# SELF-REGULATED LEARNING IN ONLINE SETTINGS

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# SELF-REGULATED LEARNING IN ONLINE SETTINGS

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# Editorial: Self-regulated learning in online settings

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Editorial on the Research Topic
Self-regulated learning in online settings

Online learning has become an increasingly popular mode of learning in today's education. With the COVID-19 pandemic resulting in stay-at-home orders worldwide, most, if not all, students will have experienced online learning to some degree. Given the high level of autonomy required with online learning, self-regulated learning (SRL) is essential for academic success when studying online (Broadbent and Poon, 2015). SRL refers to the various ways individuals plan, monitor, control, and regulate their learning, with most SRL frameworks containing three phases: preparatory, performance, and appraisal (Zimmerman, 2008).

Even though research in SRL has spanned over 50 years, online SRL is still an emerging field. The 13 selected articles for this special issue focused on online SRL. They involved 57 authors from 17 countries (Australia, Canada, China, Czechia, Estonia, Finland, France, Germany, Liechtenstein, Malaysia, Netherlands, Norway, Poland, Slovakia, Spain, United Kingdom, and the United States). Five papers focused on better understanding online SRL, and eight focused on examining interventions to support online SRL. These are outlined below.

Because of the ability to gather, synthesize and analyse huge amounts of data, technology is an avenue to examine the ways SRL strategies are used. Taub et al. investigated how students' SRL behavior and achievement-goal orientation changes over one semester. The authors highlighted the changing nature of SRL during online learning as a series of SRL events that unfold and provide guidance for developing online instructional materials that facilitate SRL for students with different motivational profiles.

In a similar effort to use technology to understand SRL, Lim et al. employed a pre-post design to measure students' SRL in an online learning environment via concurrent think-aloud protocols. Aside from identifying how students of varying success use regulation processes during learning, their study obtained evidence of relations between SRL activities and transfer performance. The authors conclude that interventions should focus on a repertoire of SRL strategies and knowing when to use them.

Non-academic learning settings, such as sports, continue to provide insights into understanding and generating new ways of supporting SRL in academic learning settings. Kleinman et al. replicated Kitsantas and Zimmerman's (2002) original volleyball microanalytical study examining the use of SRL in the online context of esports. When comparing the use of SRL processes between experts, non-experts and novices, they found that novices struggled only in the forethought phase. The authors discussed how specific features of esports, such as visualization of their cumulative data, could support novices during the performance and self-reflection phases.

Investigations on SRL during the COVID-19 pandemic showed that such disruptive events affect students' ability to perform well. Still, effective SRL interventions can serve as a buffer for these additional challenges. Kilmova et al. studied undergraduate students' online SRL during the sudden and seismic shift to online learning. They found that students reported positively on motivation, personal competencies and meaningfulness. However, students struggled with metacognitive strategies. They suggested that instructors gradually introduce SRL strategies to their students explicitly, underscoring the need to know the interaction of learning through technology and SRL in a more detailed way.

Similarly, Hadwin et al. examined whether SRL practices and intervention helped post-secondary students mitigate the impact of COVID-related psychological distress and academic challenges on their educational outcomes. They surveyed 463 students at the end of a semester on their SRL practices and then compared first-year undergraduate students who did and did not participate in an SRL intervention (a 13-weeks course on learning strategies). Findings showed that SRL practices buffered the impact of COVID challenges on students' academic performance and that an intervention can effectively support these practices.

On SRL interventions, Edisherashvili et al. conducted a systematic review on initiatives to support SRL in online higher education settings. Across the 38 studies considered, they found various effective SRL interventions, particularly in metacognitive regulation and the performance phase of learning. They found a lack of SRL interventions in emotion regulation and across the preparatory and appraisal phases of SRL.

The effectiveness of technology-based SRL interventions was tested across four papers. Two studies by Baars explored the efficacy of a mobile application called Ace Your Self-Study, which supports SRL. The first article by Baars Zafar et al. describes the design and development of the mobile application, including theoretical background, app features, embedding gamification elements and targeting all three phases of SRL. The second article by Baars et al. focused on implementing the Ace Your Self-Study mobile application in a first-year psychology course. Compared to students not using the application, students using the application had a significant increase in autonomous motivation, controlled motivation, and metacognitive self-regulation skills across the 5-week course. Qualitative interviews provided additional complementary insights into the mobile application's efficacy.

Additionally, Han et al. used a quasi-experimental design to examine undergraduate students perceived SRL strategies in three writing task conditions: two technology-enhanced groups (Icourse and Icourse + Pigai) and a control group. They found that the two technology-enhanced groups significantly outperformed the control group but performed similarly to one another. This study adds to the evidence that technologically mediated learning can support SRL and demonstrates the need to dig deeper into why and how technology can support SRL. Bellhäuser et al. conducted a randomized controlled trial to investigate the effectiveness of different web-based SRL interventions (training, learning diary and peer feedback) on improving SRL knowledge, self-efficacy, time investment and content acquisition. Web-based training was an effective intervention to improve all outcomes, except content acquisition, especially when combined with peer feedback groups. Learning diaries, on the other hand, did not affect measured outcomes.

However, as Deter et al. and Azevedo et al. pointed out in their papers, SRL is complex and requires new conceptual and methodological approaches, such as considering SRL as a complex system. This shift would allow the upcoming generation of adaptive and personalized interventions to grasp the dynamic and emergent nature of SRL fully. Dever et al. described an experiment in which the learner's navigation through a game-based learning environment was manipulated, i.e., full agency and partial agency. The Authors found that learners with restricted agency and more recurrent actions had greater learning gains. Azevedo et al. offer lessons learned and future directions for MetaTutor, an intelligent tutoring system that provides SRL-based scaffolds in the context of learning about the human circulatory system. Through studies involving MetaTutor over the past 10 years, the group has gathered an enormous amount of information on the role of cognitive strategies, metacognition, emotion, and motivation while learning with the intelligent tutoring system. They offer ideas and limitations for studying human and artificial agents and emphasize the interdisciplinarity needed for thorough examinations of SRL.

Finally, Khalil and Belokrys analyzed the online public discussion of SRL through 54,070 tweets and 29,556 users' over the last 10 years via Twitter. The authors found five overarching themes of what people were discussing about SRL online: communication and help-seeking, self-control, mindfulness, online workshops, and assessment. This paper provides valuable insights into the online public discourse of SRL and how to enhance SRL research impact.

These articles reflect the current need to keep understanding SRL as sequences of events unfolding overtime in online settings. Moreover, they call for finding innovative and effective ways to provide students with SRL support, e.g., personalized scaffolding of SRL in real-time. We hope this collection inspires upcoming SRL researchers to continue to explore SRL in online settings.

## Author contributions

PG wrote the first draft of the manuscript. All authors contributed to writing summaries of the papers, manuscript revision, read, and approved the submitted version.

## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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ORIGINAL RESEARCH
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# How Technology Tools Impact Writing Performance, Lexical Complexity, and Perceived Self-Regulated Learning Strategies in EFL Academic Writing: A Comparative Study

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Students experience different levels of autonomy based on the mediation of self-regulated learning (SRL), but little is known about the effects of different mediation technologies on students' perceived SRL strategies. This mixed explanatory study compared two technology mediation models, Icourse (a learning management system) and Icourse+Pigai (an automatic writing evaluation system), with a control group that did not use technology. A quasi-experimental design was used, which involved a pre and post-intervention academic writing test, an SRL questionnaire, and one-to-one semi-structured student interviews. The aim was to investigate 280 Chinese undergraduate English as a foreign language (EFL) students' academic writing performance, lexical complexity, and perceptions of self-regulated strategies in academic writing. One-way ANCOVA of writing performance, Kruskal-Wallis test of lexical complexity, ANOVA of the SRL questionnaire, and grounded thematic content analysis revealed that, first, both Icourse and Icourse+Pigai provided significant support for the development of SRL strategies vs. the control group, although there was no significant difference between the two groups. Second, Icourse+Pigai-supported SRL was more helpful for improving students' academic writing performance because it enabled increased writing practice and correction feedback. Third, Icourse+Pigai-supported SRL did not significantly improve students' lexical complexity. In conclusion, we argue that both learning management systems and automated writing evaluation (AWE) platforms may be used to assist students' SRL learning to enhance their writing performance. More effort should be directed toward developing technological tools that increase both lexical accuracy and lexical complexity. We conclude that the technical tools used in this study were positively connected to the use of SRL techniques. However, when creating technologically mediated SRL activities, students' psychological study preferences should be considered.

**Keywords: academic writing performance, lexical complexity, psychological study preferences, self-regulated learning, study needs, technology-mediated SRL**

# INTRODUCTION

It has been well established that technology-mediated self-regulated learning (SRL) plays an increasingly prominent role in the language learning process (Zhu et al., 2016). Previous research has indicated that students experience different levels of autonomy based on the mediation they are provided for SRL (Bouwmeester et al., 2019; van Alten et al., 2020). However, not enough is known about the effects of different technologies on students perceived self-regulated learning strategies. Technology-mediated SRL enables students by providing more personalized pre-class preparation or classroom study, after-class practice, or discussion via online platforms and tools that support numerous resources and analyze individual learner data (Tan, 2019). As technological advances occur, instructors may need to adjust teaching strategies or modify their teaching practices within classrooms (Golonka et al., 2014). Learners, in turn, need to adapt to changes in their self-learning processes and practices necessitated by different types of technological tools (Cancino and Panes, 2021). Students may experience different cognitive loads depending on the study devices that they use to complete an assignment (Ko, 2017). For example, Ko (2017) indicated that learners' working memory load may be influenced by their physical learning environment, which includes different allocations of learning resources and technologies. Therefore, it is vital to understand the effects of different technologies on students' SRL processes and practices to better address students' learning needs.

According to a previous review (Broadbent and Poon, 2015), relatively insufficient attention has been paid to the effects of technology-supported SRL on academic achievement in English academic writing programs in blended learning settings in higher education. Academic writing, which predominately involves the development of a thesis, demands complex cognitive processes that requires the effective development of SRL strategies (Lam et al., 2018). Technology changes the EFL writing process from paper-based to online and subsequently influences the development of cognitive strategies in writing (Cancino and Panes, 2021). Thus, understanding technology mediation in SRL is crucial to better support students with effective SRL strategies. However, it is unclear whether technology use changes would ultimately change learning outcomes.

In Chinese higher education, poor academic English writing quality remains an issue among undergraduate students, despite their having received at least 10 years of English instruction since primary education. For instance, students are reported to compromise complexity for accuracy in their writing. They tend to overuse basic vocabulary, such as public verbs (e.g., say, stay, talk) and vague nouns (e.g., people, things, society) and avoid using advanced words or misuse advanced words in their academic writing (Hinkel, 2003; Zuo and Feng, 2015). Furthermore, the over-emphasis of accuracy in Chinese national academic English writing tests for non-English disciplines in higher education, such as College English Test Band 4 (CET-4) and Chinese English Test Band 6 (CET-6), reinforces such behavior (Zhang, 2019). However, linguistic complexity is an essential parameter by which to assess quality of English writing (Treffers-Daller et al., 2018; Xu et al., 2019). Among the various aspects of linguistic complexity, lexical complexity is crucial, as supported by research evidence from Csomay and Prades (2018), who found that higher quality essays among their participants were those that displayed a more comprehensive vocabulary range. However, whether technology-mediated SRL effectively enhances lexical complexity in students' academic writing has seldom been mentioned in previous research (Broadbent and Poon, 2015). Therefore, effort should be directed toward determining how technology-mediated SRL may help students to produce high-quality academic writing.

To address the issues mentioned above, this study compared the effects of Icourse and Icourse+Pigai-supported SRL on writing performance, lexical complexity, and perceived self-regulated learning strategies. The Small Private Open Course (SPOC) learning management platform enables enriched exposure to authentic materials and provides online quizzes and discussion boards to support various learning subjects (Qin, 2019). However, improvement in EFL learning to write requires enriched exposure to learning input and repeated writing practice with corrective feedback (Gilliland et al., 2018). Pigai provides automatic writing evaluation (AWE) with instant feedback and revision suggestions for learners, which may supplement individual learners' needs for synchronous feedback while simultaneously reducing teachers' workload. Combining Icourse and Pigai does not necessarily improve students' writing performance and writing quality or enhance SRL. Since the combination of technology use represents an extra burden and demands higher cognitive load of students, the blend of technology use may lead to a decline in students' satisfaction with learning (Xu et al., 2019). Thus, an investigation is required to determine the effects of different technology-mediated SRL on EFL learners' writing performance and quality.

# LITERATURE REVIEW

## Self-Regulated Learning

SRL refers to self-formed ideas, feelings, and actions that help individuals achieve their objectives (Zimmerman and Schunk, 2001; Seifert and Har-Paz, 2020). Technology-mediated SRL facilitates learners with flexible learning models and improves their language learning outcomes and motivation (An et al., 2020). Prior studies primarily focused on the effectiveness of technology-enhanced language learning within classroom instruction (An et al., 2020). There is a lack of empirical investigation of the effect of technology-mediated SRL on improving language skills. Of the limited number of previous studies that addressed technology-enhanced SRL, most reported positive relationships to language learning outcomes. For instance, Öztürk and Çakiroglu (2021) compared two groups of university students with and without SRL strategies in flipped learning. The findings indicated that SRL facilitated learning English speaking, reading, writing, and grammar. Similarly, students with SRL capabilities exhibited enhanced learning outcomes in blended learning settings (Zhu et al., 2016). In contrast, Sun and Wang (2020) found low-frequency use of SRL strategies among 319 sophomores Chinese EFL students in processes of learning writing, although SRL strategies significantly predicted writing proficiency. The students were reported to lack practice in writing during classroom sessions due to large classroom size and limited class time (Sun and Wang, 2020).

In terms of the instrument to measure SRL, the Motivated Strategies Learning Questionnaire (MSLQ) is frequently used (Pintrich et al., 1993). The MSLQ has been shown to be valid and reliable for use among undergraduate students. The original MSLQ assesses cognitive, meta-cognitive, and resource management strategies (Broadbent, 2017). Cognitive strategies involve the preparation, elaboration, and management of studies. Meta-cognitive strategies primarily refer to self-control. Resource management includes time management, effort regulation, and peer learning (Broadbent, 2017). According to Broadbent's (2017) review of 12 SRL regulated online studies, meta-cognition and resource management strategies positively influence learning outcomes, while cognitive strategies have the least amount of empirical evidence to suggest their utility. As SRL theory developed from a focus on meta-cognition to recognizing its multifaceted nature, it included motivation factors that influence learning (An et al., 2020). Pintrich (2004) noted an issue of the MSLQ is that it does not include motivational and affective factors that determine essential emotional strategies (Pintrich, 2004; An et al., 2020). Therefore, this study adopted a revised version of the MSLQ that includes four SRL aspects: cognitive, metacognitive, resource management, and emotional strategies (**Supplementary Appendix 1**).

## Lexical Complexity

The ultimate goal for the technology-supported SRL, in this context, is to improve students' writing performance and writing quality. More specfically, lexical complexity is an essential indicator of EFL writing (Lemmouh, 2008; Zhu and Wang, 2013), but few studies have addressed the effect of SRL on linguistic complexity in EFL programs. O'Dell et al. (2000) suggested that lexical complexity primarily involves lexical diversity, lexical sophistication, and lexical density (the ratio of content words to tokens). The lexical diversity aims to measure lexical variability, while lexical sophistication compares the ratio of advanced words to the total tokens. Treffers-Daller et al. (2018) highlighted the importance of integrating lexical diversity, the range of words used to measure lexical complexity, and lexical sophistication, with reference to less frequently used words as defined by various standards. Previous literature on lexical complexity development is inconclusive; some studies discovered growth after training, while others did not (Knoch et al., 2014; Kalantari and Gholami, 2017). Bulté and Housen (2014) affirmed the possibility of capturing changes in linguistic complexity in L2 writing over a short period. Inquiry into the effects of various technologies on lexical complexity is necessary so that language teachers can support students with desirable technology-mediated SRL strategies, thus enabling students to achieve enhanced learning outcomes, such as better writing quality.

**TABLE 1 |** Definition of Icourse and Pigai.

| | | | |
|---|---|---|---|
| 1. | Icourse | Under the Small Private Online Course (SPOC) platform, course organizers use the platform to publish course content, learning activities and discussion topics; learners use various social learning tools, including course discussion spaces, course resource sharing tools, and online quizzes to participate in learning | Enable sharing of course materials that cater to students characteristics, allowing accessibility to content anytime, anywhere |
| | | | Enable sharing of authentic MOOC videos, with higher quality and multiple choices |
| | | | Facilitate course content organization and teacher-student and student-student communication with online discussion boards |
| | | | Foster practice with online quizzes |
| 2. | Pigai | Based on natural language processing technology and corpus technology, which analyzes the distance between students' compositions and the standard corpus to score students' English written essays instantly. Provides suggestions for improvement and content analysis | Provide immediate and large-scale online automatic corrections |
| | | | Create student corpora based on the composition assignments submitted by students, and compare errors, word frequencies, collocations, graded vocabulary, data comparison, and dimensional analysis |
| | | | Support teacher manual correction function |

## Icourse and Pigai

The technology tools adopted in the technlogy-mediated SRL in this research are the Icourse and Pigai. Based on previous studies (Golonka et al., 2014; Yang and Dai, 2015; Zhai, 2017), the definitions of Icourse and Pigai are presented in **Table 1**. Massive open online courses (MOOCs) are often criticized for high dropout rates and low student engagement (Gilliland et al., 2018; de Moura et al., 2021). Icourse, as a SPOC platform, is claimed to be a valid alternative as course designers, usually course lecturers, permit the course syllabus to be flexible in difficulty and more adaptable to different student characteristics (Ruiz-Palmero et al., 2020). Guo et al. (2021) quantitatively assessed the impact of the SPOC-based blended learning model embedded in the undergraduate course of International English Language

Testing System (IELTS) writing at a Chinese university in Beijing. IELTS is an international standardized proficiency English test for non-English speakers. Assessments were made of writing performance through classroom observation, questionnaires, and achievement tests in pre, mid, and final terms. The experimental group outperformed the control group in the final term test results, but there were no significant differences in pre and mid-term results. However, the study did not include linguistic parameters for evaluating SPOC platforms' effects on EFL learning of writing. Of the few studies that did include linguistic measurement, Cheng et al. (2017) addressed the impact of SPOC learning management systems on 35 Chinese undergraduate EFL learners' writing performance in terms of essay length, accuracy, and lexical complexity. The findings revealed that the SPOC learning platform helped the learners to write with increased accuracy and fluency and with an increased ratio of advanced academic vocabulary in the post-test compared to the pre-test. However, the study did not include comparison with a control group that did not use the SPOC platform. Overall, prior studies highlighted the positive role SPOC platforms play in assisting the EFL learning of writing, in terms of improving writing test scores, accuracy, and fluency. **Figures 1–3** illustrate how Icourse functions as a SPOC learning management system to support browsing course materials, answering online quizzes, and interacting via discussion boards.

Besides the learning management system, Pigai is used as an AWE tool in this research. AWE aims to provide prompt writing revision feedback to learners (Liao, 2016). The major difference between AWE and teacher feedback is that AWE calculates the language gap between the EFL learner's language use and that of the native speaker (Li et al., 2019). While teacher feedback mainly relies on teachers' knowledge and teaching experience. **Figures 4**, **5** illustrate how Pigai works as an AWE tool to support learning how to write proficiently in English. **Figure 4** shows how Pigai gives an overall mark to students' essays based on lexical, syntactic, semantic, and content parameters. A general remark on the vocabulary and sentence use is also displayed at the lower right corner of the screen. **Figure 5** illustrates how Pigai provides detailed feedback regarding confusing words, synonyms, and convertible sentence patterns to expand students' vocabulary and sentence use.

Overall, positive findings support the applicability and efficiency of Pigai (Lin et al., 2020). For instance, Li and Zhang (2020) reported a positive role of Pigai in improving Chinese EFL learners' writing performance and writing self-efficacy by indicating errors in students' writing in real time and thereby enabling them to acquire vocabulary and sentence-construction knowledge. In contrast, some researchers have argued Pigai has deficits (Wu, 2017). For example, Pigai is less effective at providing feedback that helps logical thinking and content structure organization, which are also crucial factors for successful compositions, in addition to vocabulary and grammar (Wu, 2017). While the technology of Pigai constantly updates and adapts to emerging pedagogical needs, Hou (2020) called for additional studies of Pigai to keep pace with its technological advances.

Determining effective ways to support EFL learning is complex. Careful consideration should be made of the combination of various technologies, rather than favoring one specific technology over another (Lam et al., 2018).

According to the research aim, the research questions of the current study were as follows:

1. To what extent does technology-mediated SRL impact undergraduate Chinese EFL learners' written performance?
2. To what extent does technology-mediated SRL impact undergraduate Chinese EFL learners' written performance in terms of lexical complexity?
3. To what extent do technology tools impact undergraduate Chinese EFL learners' use of SRL strategies?
4. What factors impact undergraduate Chinese EFL learners' perceptions of using technology-mediated SRL during their writing in English?

## MATERIALS AND METHODS

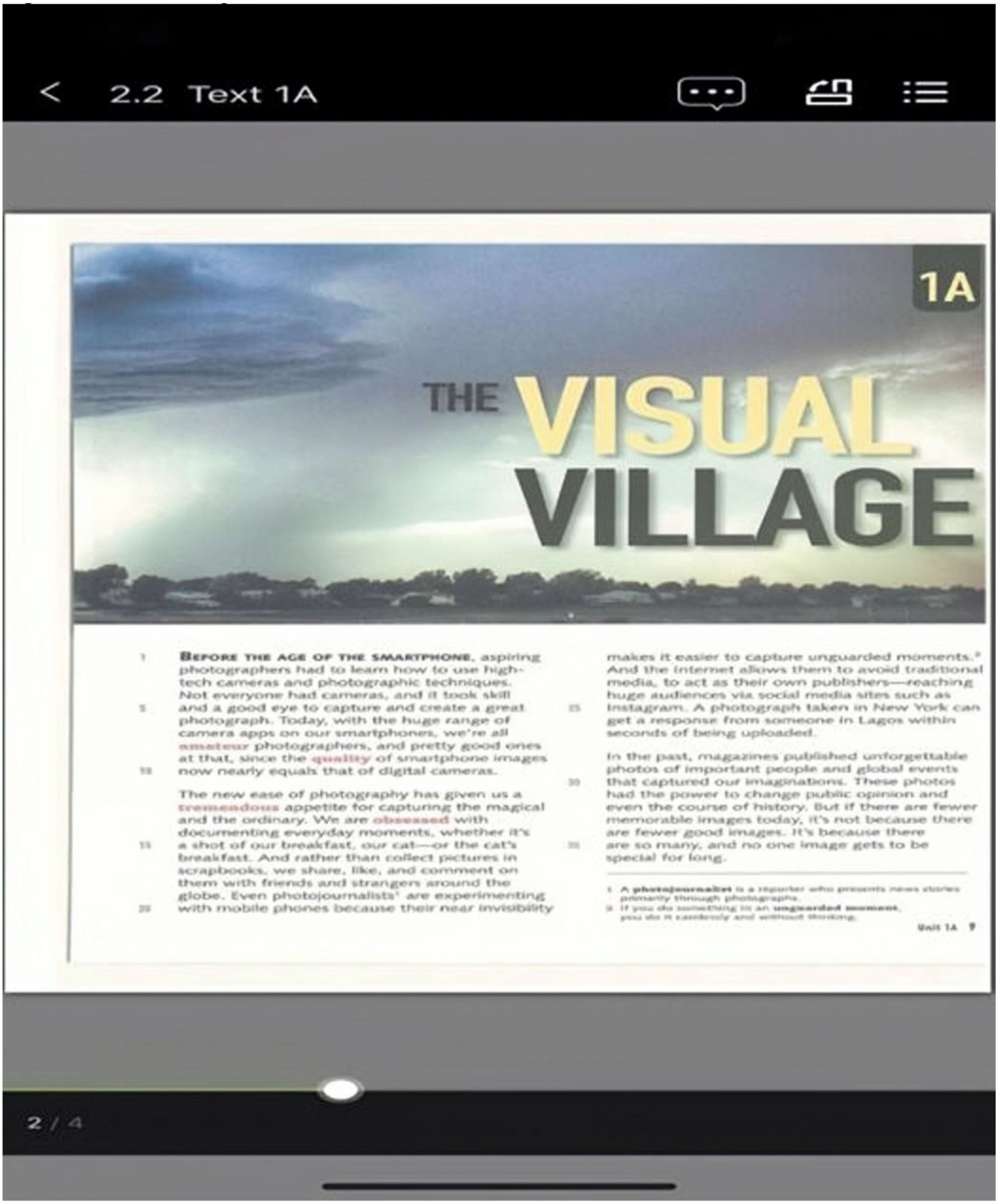
### Participants

Purposive sampling was used to recruit the participants. The initial plan was to recruit 300 sophomore students from water conservancy engineering, mechanical engineering, electronic engineering, and allied subjects. However, although the intention was to have 100 students in each group, only 280 students agreed to participate in this study. Of these students, 99 were assigned to the control group, 90 to the Icourse group, and 91 to the Icourse+Pigai group. The participants were from the same Henan province in the People's Republic of China to ensure that they shared a similar EFL learning background. Their average age was 19 years (SD = 1.169), and each had at least 10 years of EFL learning experience since their primary education.

The research complied with all ethical stipulations of the ethics committee at the University of Malaya. Before conducting the research, the relevant university administrators were fully informed, and all the students voluntarily participated in the study, and each signed an online consent form before participating in the study. All participants remained anonymous during the entire research process.

### Research Design

An explanatory sequential mixed-methods approach was used to address the research questions (**Figure 6**). First, a quasi-experimental study was conducted to obtain quantitative comparative data, with follow-up qualitative data derived from student interviews. This study assessed three groups: a control group that received no technology-mediated SRL, an Icourse-assisted SRL group, and an Icourse and Pigai supported SRL group. Icourse and Pigai supported self-regulated learning of academic writing both in and outside the classroom. The academic writing course outline is presented in **Table 2**. These




# THE VISUAL VILLAGE

**BEFORE THE AGE OF THE SMARTPHONE**, aspiring photographers had to learn how to use high-tech cameras and photographic techniques. Not everyone had cameras, and it took skill and a good eye to capture and create a great photograph. Today, with the huge range of camera apps on our smartphones, we're all amateur photographers, and pretty good ones at that, since the quality of smartphone images now nearly equals that of digital cameras.

The new ease of photography has given us a tremendous appetite for capturing the magical and the ordinary. We are obsessed with documenting everyday moments, whether it's a shot of our breakfast, our cat—or the cat's breakfast. And rather than collect pictures in scrapbooks, we share, like, and comment on them with friends and strangers around the globe. Even photojournalists[1] are experimenting with mobile phones because their near invisibility makes it easier to capture unguarded moments.[2] And the internet allows them to avoid traditional media, to act as their own publishers—reaching huge audiences via social media sites such as Instagram. A photograph taken in New York can get a response from someone in Lagos within seconds of being uploaded.

In the past, magazines published unforgettable photos of important people and global events that captured our imaginations. These photos had the power to change public opinion and even the course of history. But if there are fewer memorable images today, it's not because there are fewer good images. It's because there are so many, and no one image gets to be special for long.

1 A **photojournalist** is a reporter who presents news stories primarily through photographs.
2 If you do something in an **unguarded moment**, you do it carelessly and without thinking.

Unit 1A 7

**FIGURE 1 |** Icourse—Text preview screenshot.

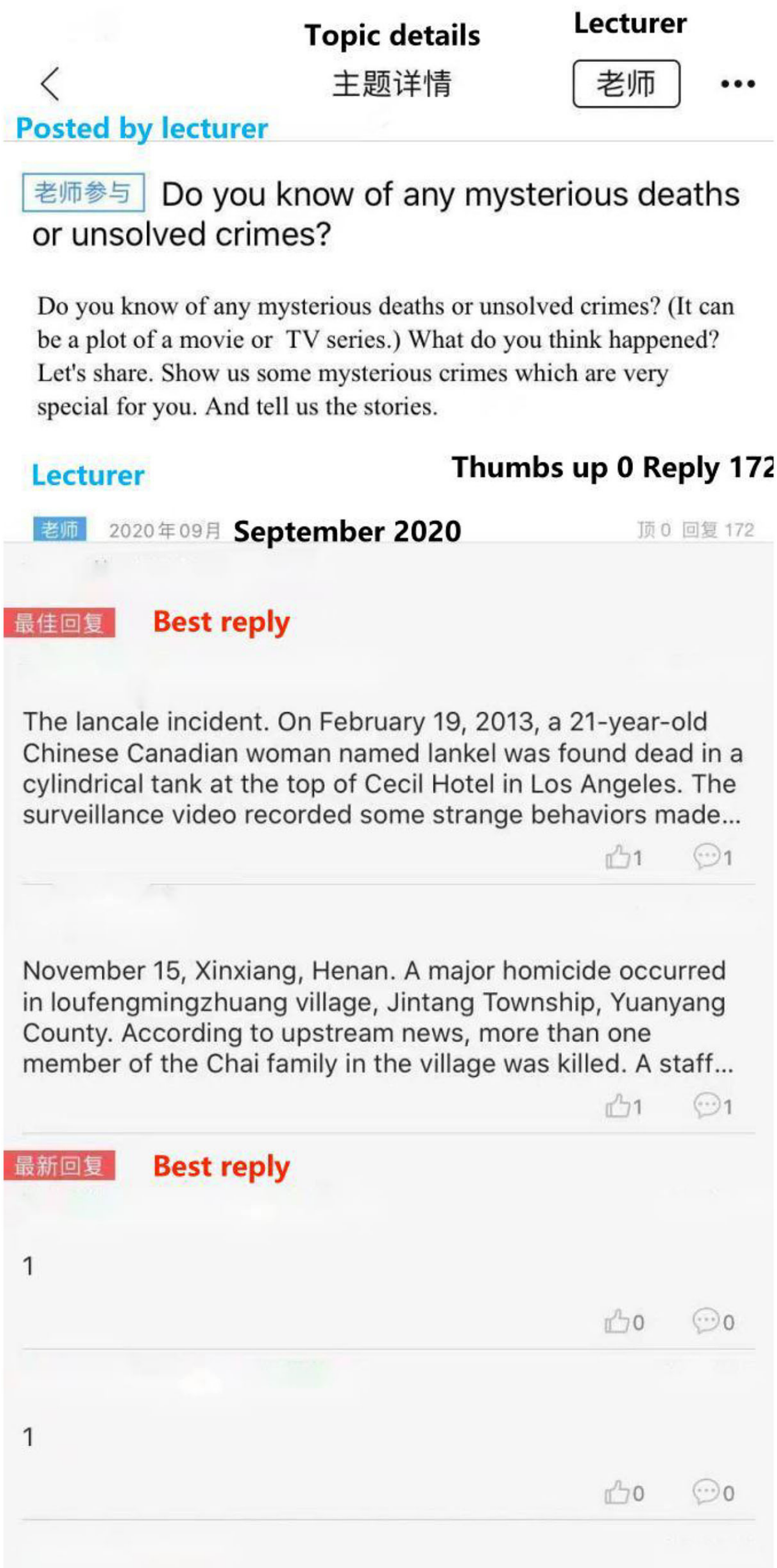



**FIGURE 2 |** Icourse—Online discussion screenshot.

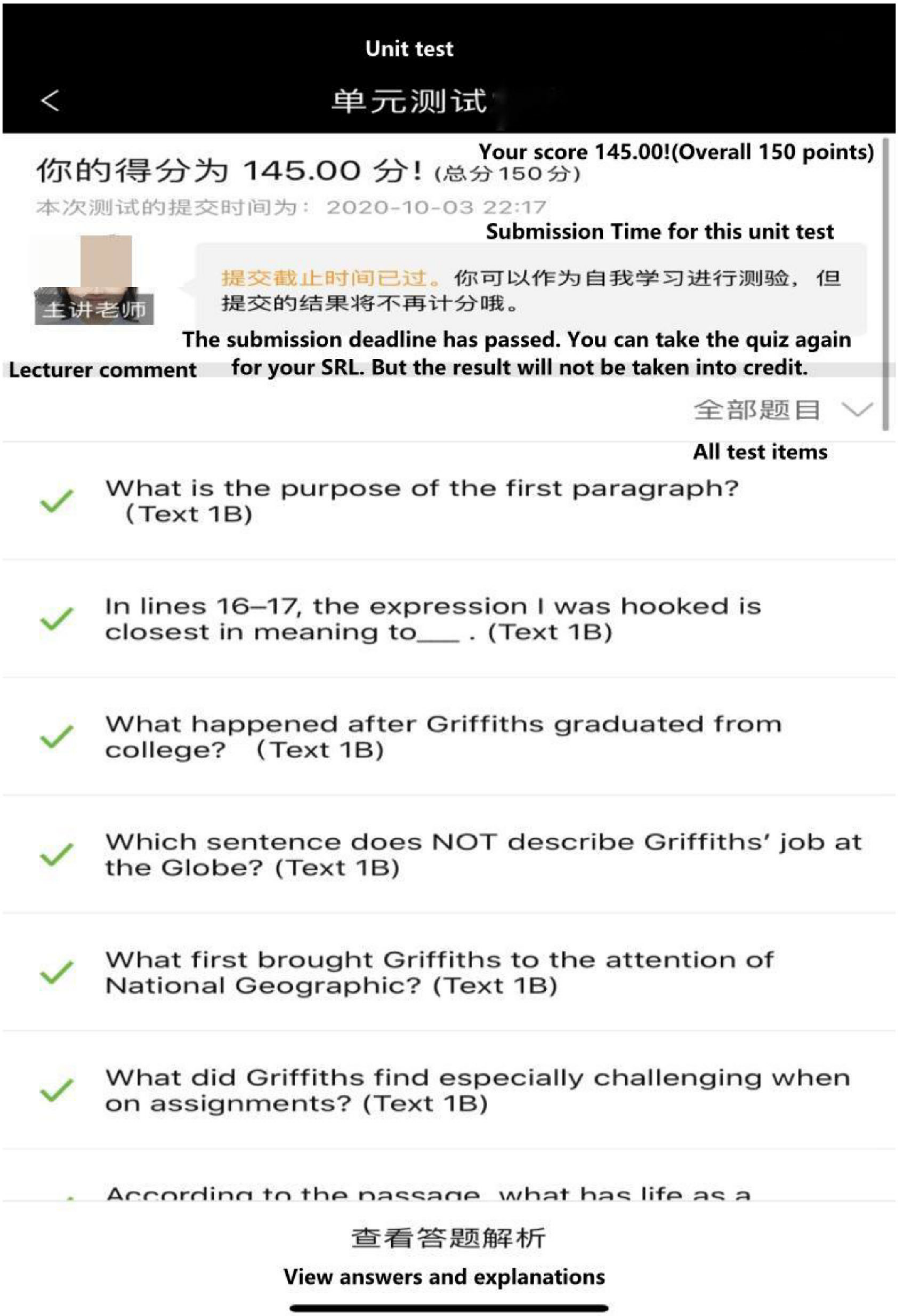



**FIGURE 3 |** Icourse—Online quiz screenshot.

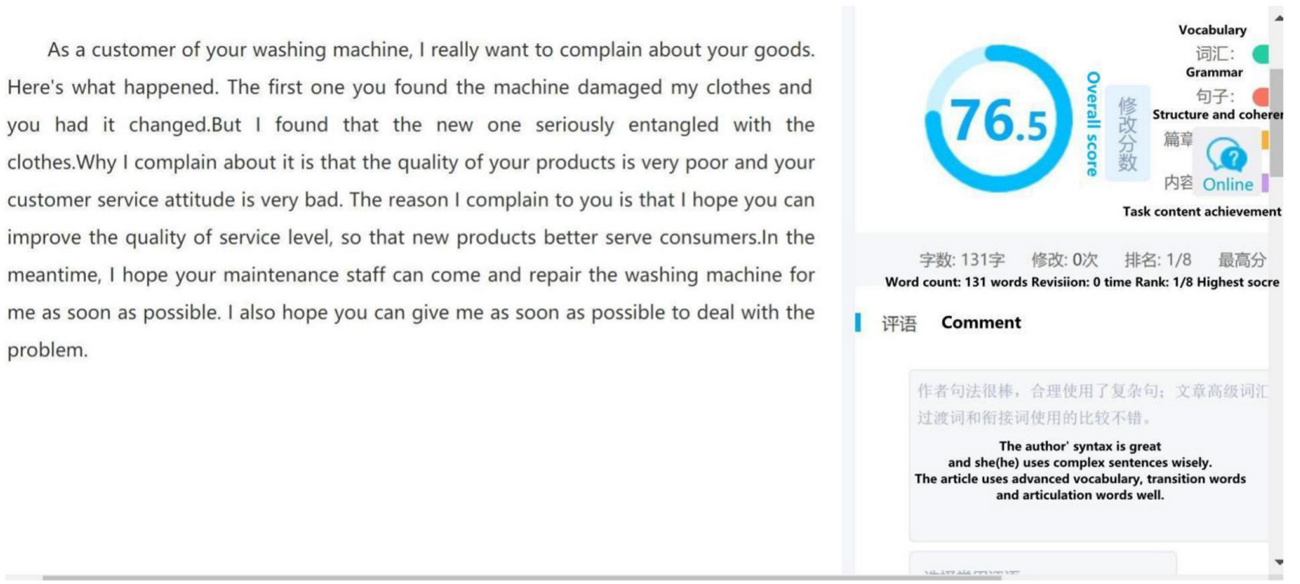



**FIGURE 4 |** Pigai—Automatic writing evaluation screenshot.

systems include pre-class online learning of vocabulary, watching online instruction videos about writing skills, lead-in quizzes, sentence paraphrase practice, online forum discussion, after-class review, essay writing online submission, and receiving feedback and revisions. The same academic writing course was delivered to all three groups, using the same textbook in classroom instruction. The same five units of content were covered in one academic term and the class frequency was the same, namely three times per week for 90 mins per class. Each group was recruited from a general polytechnic-focused university. All three universities were ranked at the same level. The three senior lecturers in the three groups shared a similar educational background, namely, holding a master's degree and having taught 10–12 courses. Lecturers similarly monitored students' SRL processes by setting up tasks, quizzes, and activities with deadlines, and answered students' questions online when needed.

### Writing Performance

#### *Instrument*

The two composition topics were revised from the academic International English Language Testing System (IELTS) Writing Task 2 (Esol, 2007). The topic was "What is your opinion on consumer complaints?" The second was "What is your opinion on distance education?" The reasons for selection of these tasks were that, first, the IELTS Writing Task 2 focuses on academic writing. Second, the grading rubrics for IELTS cater more to the research purpose of measuring students combined lexical accuracy and complexity rather than simply focusing on lexical accuracy alone. **Supplementary Appendix 2** presents the revised writing grading rubrics (Esol, 2007). A pilot study was conducted among 30 students to check validity and reliability. KMO was 0.6 and Bartlett's test $p$ value were 0.00 and Cronbach's alpha was 0.79; these values were considered acceptable for the study.

#### *Data Collection*

Both pre and post-tests were delivered online through scanning Quick Response (QR) codes. Before delivering the tests, the participants signed an informed consent electronically by scanning QR codes. The pre-test was delivered at the beginning of the academic term in September 2020, and the post-test was given at the end of the academic term in January 2021. Anti-cheating measures and a time limit of 30 mins were enforced to avoid plagiarism. If the online submission was blank or highly suspected of plagiarism, this composition was considered invalid. The number of valid cases for each group was 73 (out of 99), 70 (90), and 72 (91).

#### *Data Analysis*

Both AWE graded the tests in Pigai, as well as the researcher, and another experienced teacher. The average grade of the three grading results was regarded as the final result for each participant. After grading, the pre-test results were used as covariates in a one-way ANCOVA of academic achievement. The effect size was calculated.

### Lexical Complexity

#### *Instrument*

The student texts in each group were assessed in terms of their lexical diversity, lexical density, and lexical sophistication. The lexical diversity measure used the STTR (standard type-token ratio) as measured by Wordsmith 8.0, developed by Mike Scott. The WordSmith software was originally developed by University of Liverpool, UK, and published by Oxford University Press.


**FIGURE 5 |** Pigai—Revision suggestions.

The measurement of STTR is more accurate than the type-token ratio (TTR) because it is less dependent on the text length (Treffers-Daller et al., 2018). The lexical density and lexical sophistication were calculated using Range 32, designed by P. Nation and A. Coxhead. By calculating the ratios of content words to the total tokens, Range 32 first excludes the built-in function words (function text) as filter words and obtains lexical density ratios (Zhu and Wang, 2013). Range 32 uses Laufer and Nation's base word list for the most high-frequency words, the second 1,000-word list (hereinafter referred to as baseword 2) for the next most high-frequency words, and the third word list (hereinafter referred to as baseword 3) for advanced academic vocabulary (Laufer and Nation, 1995; Zhu and Wang, 2013). Lexical sophistication was measured by calculating the frequency of words other than Range 32, which refers to the ratio of defined baseline 2 and 3 words with no spelling errors to the total token (Gong et al., 2019).

#### *Data Collection and Analysis*

The texts were first processed to identify spelling errors and homographs. Misused words were removed from the essay entry process to ensure that all words entered were correct output words. Where words were selected correctly but spelt incorrectly or homographs, such as bat the animal or bat for baseball, the researchers corrected them and added a marker afterwards. A pre-test was conducted to examine whether there were any differences among the three groups in terms of lexical complexity before the intervention. Both between-groups and timewise comparisons were conducted to determine whether there was any significant effect of technology-supported SRL on lexical complexity. Since the Levene test hypothesis was violated, the post-test lexical complexity ratios were analyzed using SPSS 26 with Kruskal-Wallis tests.

### SRL Strategies

#### *Instrument*

Based on the literature review, a revised version of the MSLQ was applied to measure the technology-mediated SRL strategies in this study (**Supplementary Appendix 1**). MSLQ was initially developed by the National Center for Research USA after completing numerous correlational research on SRL and motivation (Pintrich, 2003). The tool consists of four sections: emotional (including motivational and affective factors), cognitive (including elaboration, rehearsal, and organization), metacognitive (including self-control), and resource management (including time management and peer learning). A five-point Likert-type scale was adopted for the self-report questionnaire, with responses ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire was in Mandarin to ensure that the participants could fully understand all items. A pilot test was conducted with 30 undergraduate students other than the participants, which revealed a Cronbach's alpha value of 0.899 and a value of 0.917 for KMO and Bartlett's test.

#### *Data Collection and Analysis*

Participants received access to the questionnaire through QR code scan. The questionnaire was collected only after the intervention. One-way ANOVA was conducted to determine whether there were any statistically significant differences among the three groups.

### Technology Use Factors Toward Technology-Supported SRL

#### *Instrument*

One-to-one interviews (**Supplementary Appendix 3**) were conducted with 10 participants (Icourse: 5, Icourse+Pigai: 5)

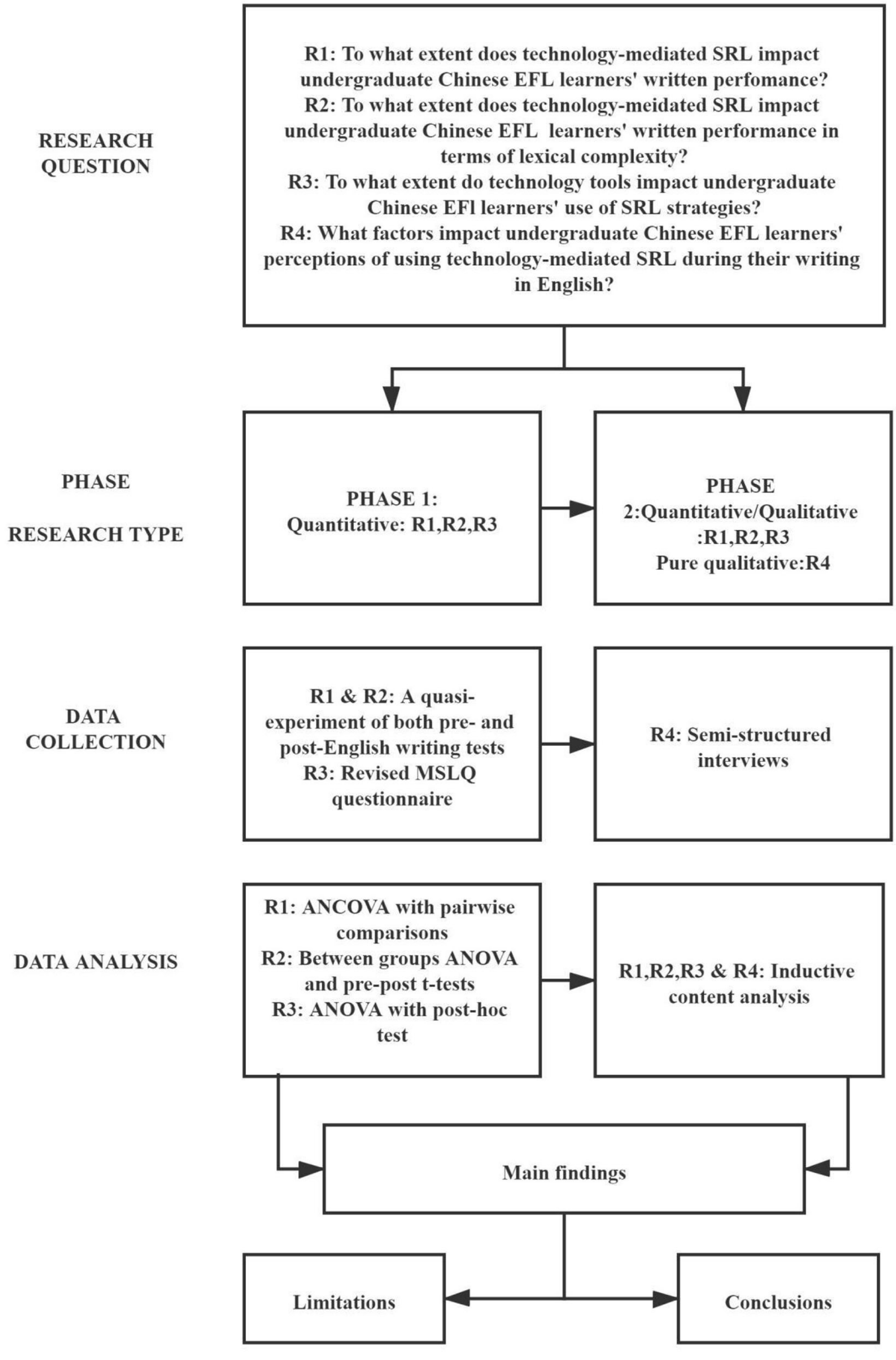



**FIGURE 6 |** Flowchart-research process.

**TABLE 2 |** The EFL academic writing course outline.

| **Course: EFL academic writing course for second year non-English major students** | | | |
|---|---|---|---|
| **Course guideline: Preview+Lecture+Assignment+Assessment** | | | |
| **Course frequency: 4 classes per week (45 mins/per class)** | | | |
| | **Control** | **Icourse** | **Icourse+Pigai** |
| Preview (before classes) | With textbook | Icourse | Icourse+Pigai |
| Lecture (in-classes) | 2 lectures+ 2SRL with textbook | 2 lectures+2 SRL with Icourse | 2 lectures+ 2SRL with Icourse+Pigai |
| Assignment (after classes) | In paper | Icourse | Icourse+Pigai |
| Assessment (both in and out of classes) | In paper | Icourse+paper | Icourse+Pigai+paper |

to explore the reasons for the quantitative data using in-depth evidence. The interviews were semi-structured, and follow-up questions such as "how" or "why" were added based on the interviewees' answers. The interviews were designed and delivered in Mandarin Chinese to ensure that the interviewees could understand all interview questions.

#### *Data Collection and Analysis*

Interviewees were randomly chosen from the experimental groups. Each interview required up to 30 mins through WeChat video chat. WeChat is a free application that Tencent launched on January 21, 2011 to provide instant messaging services. All interviews were recorded after obtaining the interviewees' permission. All records were transcribed verbatim and translated into English by a licensed professional translator. The transcripts were then coded and analyzed using Nvivo 12. Inductive content analysis was used because no predetermined codes were used. Based on preliminary analyses, the researcher established the relationships between the nodes and checked them against the data.

## RESULTS

### Writing Performance

A one-way between-groups ANCOVA was conducted to compare the effectiveness of Icourse (group 2) and Icourse+Pigai (group 3) supported self-regulated learning on the participants' writing performance as compared to the control group (group 1) after one academic term. The independent variable was the technology tools used, and the dependent variable was the post-test score. Participants' pre-test scores were used as covariates in this analysis. Preliminary checks were conducted to ensure that the assumptions of normality, linearity, homogeneity of variances, homogeneity of regression slopes, and reliable measurement of the covariate were met. After adjusting for pre-test scores, there were significant differences in mean scores among the three groups (**Figure 7**) [$F_{(1,211)} = 4.03$, df $= 2$, $p = 0.019$, partial $\eta^2 = 0.04$; **Table 3**]. According to the pairwise comparisons shown in **Table 4**, the Icourse+Pigai group ($M = 78.44$, SD $= 9.71$) significantly outperformed the control group ($M = 73.35$, SD $= 13.76$; $p = 0.01$). The difference between the Icourse group ($M = 75.16$, SD $= 11.46$) and the control group ($M = 73.35$, SD $= 13.76$; $p = 0.23$) was not statistically significant.

### Lexical Complexity

**Table 5** illustrates that the pre-test comparison indicated no statistically significant differences in lexical diversity, lexical density, or lexical sophistication among the three groups. After the intervention, significant differences were observed in all three lexical complexity indicators in the Icourse group, but only in lexical diversity and density in the Icourse+Pigai group after the intervention. The latter group showed no significant differences in lexical sophistication after the intervention. In contrast, the control group exhibited no statistically significant difference from pre-test to post-test for any of the three lexical complexity indicators.

The Kruskal-Wallis post-test revealed no statistically significant differences in lexical diversity and sophistication across the three groups (control group, $n = 73$; Icourse group, $n = 70$; Icourse+Pigai group, $n = 72$), $\chi^2_{(2,215)} = 5.53$, $p = 0.063$ (diversity), $\chi^2_{(2,215)} = 6.02$, $p = 0.049$ (density), $\chi^2_{(2,215)} = 0.06$, $p = 0.970$ (sophistication). The result leads the null hypothesis to be rejected that the distribution of lexical density is the same across the three groups, as there was a significant difference between the Icourse group and the Icourse+Pigai group in lexical density after the intervention.

### SRL Strategies

A one-way between-groups ANOVA was conducted to explore the impact of technology tools on SRL strategies. Since the assumptions required to conduct ANOVA were met and homogeneity of variances was not violated ($p = 0.36$), the three groups (control group, Icourse group, Icourse+Pigai group) were compared (**Figure 8**). There was a statistically significant difference ($p < 0.05$) in SRL strategies among the three groups, $F = 8.59$, $df = 2$, $p < 0.01$ (**Table 6**). Despite reaching statistical significance, the actual differences in the mean scores among the three groups were minor. The effect size, calculated using $\eta^2$, was 0.06. *Post-hoc* comparisons using the LSD indicated that the mean score in the control group ($M = 3.47$, SD $= 0.47$) differed significantly from that of the Icourse group ($M = 3.75$, SD $= 0.45$) and that of the Icourse+Pigai group ($M = 3.65$, SD $= 0.51$). The Icourse+Pigai group did not differ significantly from the Icourse group ($p = 0.15$).

### Technology Use Factors Toward Technology-Supported SRL

A list of 308 frequently occurring codes was found initially in the student transcripts and then reorganized into 46 categories of third-tier code families. Many of the themes identified in the initial coding concerned the qualities of Icourse and Pigai and the advantages and disadvantages of using the tools in academic writing. Likewise, other factors related to student needs and

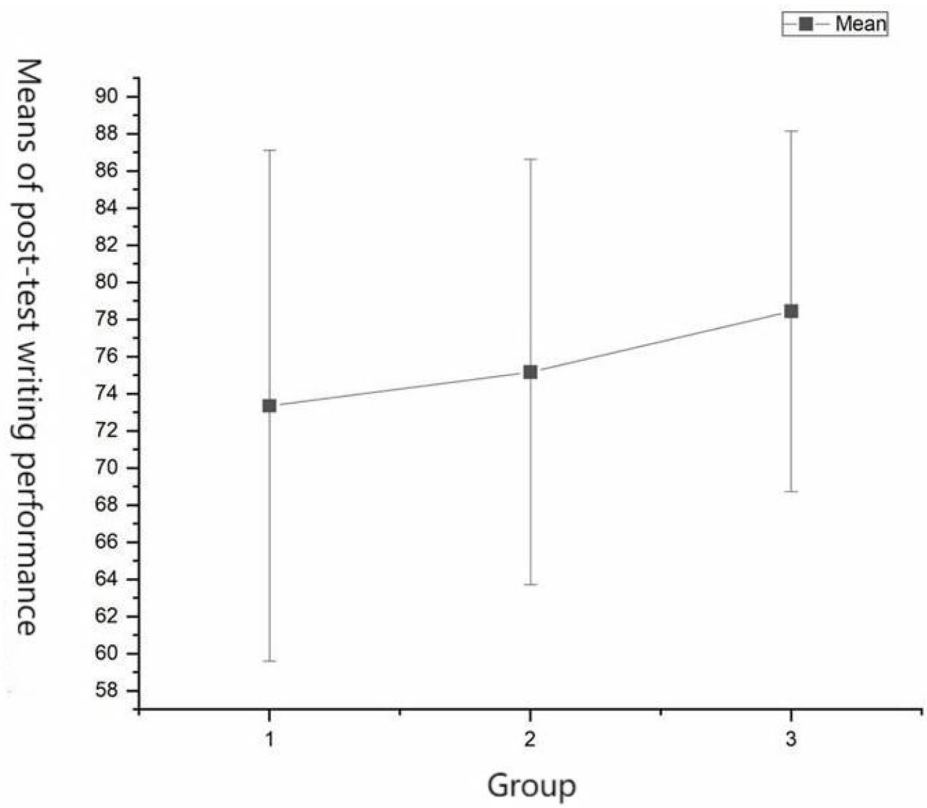



**FIGURE 7 |** Means plot of post-test writing performance.

**TABLE 3 |** ANCOVA tests of between-subjects effects at post-test for writing performance.

| Source | Type III Sum of squares | Df | Mean square | *F* | *p* | Partial eta squared |
|---|---|---|---|---|---|---|
| Corrected model | 9,154.694[a] | 3 | 3,051.565 | 30.361 | <0.001 | 0.302 |
| Intercept | 20,936.195 | 1 | 20,936.195 | 208.302 | <0.001 | 0.497 |
| Pretest | 8,192.335 | 1 | 8,192.335 | 81.509 | <0.001 | 0.279 |
| Group | 809.980 | 2 | 404.990 | 4.029 | 0.019 | 0.037 |
| Error | 21,207.337 | 211 | 100.509 | | | |
| Total | 1,260,601.250 | 215 | | | | |
| Corrected total | 30,362.030 | 214 | | | | |

[a] *$R^2 = 0.302$ (Adjusted $R^2 = 0.292$).*

**TABLE 4 |** Pairwise comparisons at post-test writing performance.

| (I) group | (J) group | Mean difference (I-J) | Std. error | $p^a$ | 95% confidence interval of difference | |
|---|---|---|---|---|---|---|
| | | | | | Lower bound | Upper bound |
| 1 | 2 | −2.012 | 1.677 | 0.232 | −5.318 | 1.294 |
| | 3 | −4.714* | 1.666 | 0.005 | −7.997 | −1.430 |
| 2 | 1 | 2.012 | 1.677 | 0.232 | −1.294 | 5.318 |
| | 3 | −2.702 | 1.684 | 0.110 | −6.021 | 0.618 |
| 3 | 1 | 4.714* | 1.666 | 0.005 | 1.430 | 7.997 |
| | 2 | 2.702 | 1.684 | 0.110 | −0.618 | 6.021 |

**The mean difference is significant at the 0.05 level.*

[a]*Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).*

**TABLE 5** | Between groups and pre- and post-test comparisons for lexical complexity.

| Lexical complexity | | Diversity | | | Density | | | Sophistication | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Between groups (Pre-test: one way ANOVA, posttest: Kruskal Wallis test) | $p < 0.05$ | Control vs. Icourse | Control vs. Icourse+Pigai | Icourse vs. Icourse+Pigai | Control vs. Icourse+Pigai | Control vs. Icourse+Pigai | Icourse vs. Icourse+Pigai | Control vs. Icourse | Control vs. Icourse+Pigai | Icourse vs. Icourse+Pigai |
| | Pre-test | 0.204 | 0.338 | 0.027 | 0.286 | 0.968 | 0.270 | 0.294 | 0.368 | 0.876 |
| | Post-test | / | / | / | 0.623 | 0.069 | 0.020 | / | / | / |
| Pretest and posttest (independent t-test) | $p < 0.05$ | | Pretest vs. Posttest | | | Pretest vs. Posttest | | | Pretest vs. Posttest | |
| | Control | | 0.881 | | | 0.874 | | | 0.254 | |
| | Icourse | | 0.016 | | | 0.003 | | | 0.000 | |
| | Icourse+Pigai | | 0.002 | | | 0.013 | | | 0.102 | |

preferences also emerged, such as increased essay practice and unwillingness toward online peer review. As the codes were grouped and sorted, 15 categories of second-tier code families were identified, such as Icourse function, Icourse quality, Pigai function, Pigai quality, study needs, teacher influence, and peer influence. The 15 categories were then grouped as 7 broader themes and then categorized as 3 main themes and ultimately classified as two main categories as internal and external factors (**Figure 9**). For example, internal factors referred to study needs and study preferences, and external factors included teacher influence and peer influence.

**Table 7** presents 22 categories from the 46 third-tier code families that distinctly show the differences and similarities among participants' perceptions between the two experimental groups. The five participants in the Icourse group expressed a stronger desire for an increased amount of writing practice (Icourse group: 11 citations, Icourse+Pigai: 5 citations). Compared to no complaints of Icourse drawbacks in the Icourse+Pigai group, students in the Icourse group complained about its drawbacks, such as lack of essay practice (5 citations) and inability to produce calligraphy (3 citations). Compared to the Icourse group, the most distinct feature in the Icourse+Pigai group was that students referred to self-regulated learning more frequently (Icourse group: 6 citations, Icourse+Pigai group: 10 citations). As seldom mentioned in the Icourse group, the Icourse+Pigai group referred more to the Pigai benefit of high efficiency of AWE (5 citations) and reduced teacher essay evaluation pressure (5 citations).

# DISCUSSION

## Writing Peformance

The Icourse+Pigai group significantly outperformed the control group in writing performance, while the Icourse group showed no significant statistical difference from the control group. The writing performance results indicate that Icourse+Pigai-mediated SRL is more conducive to enhanced writing performance than is Icourse-mediated SRL. This may be because Icourse-supported SRL fails to satisfy students' study needs for more opportunities for writing practice. As revealed by the interview results, students in the Icourse group expressed a stronger desire for frequent writing practice available through technological support.

> *If there is an online system, it can be better than the current one because we are a little weaker in English writing, and then the system can give feedback and give some suggestions.* (Interviewee 1)

> *I also feel that I need to practice my composition, I do feel that I don't have much practice now.* (Interviewee 2)

This research finding is consistent with Rüth et al. (2021), who found that testing and quizzes were more effective for learning than was repeated exposure to learning materials. Writing practice provides relevant cognitive load, that is, knowledge construction processes that unavoidably lead to learning (Sweller et al., 1998; Nückles et al., 2020). Pigai,

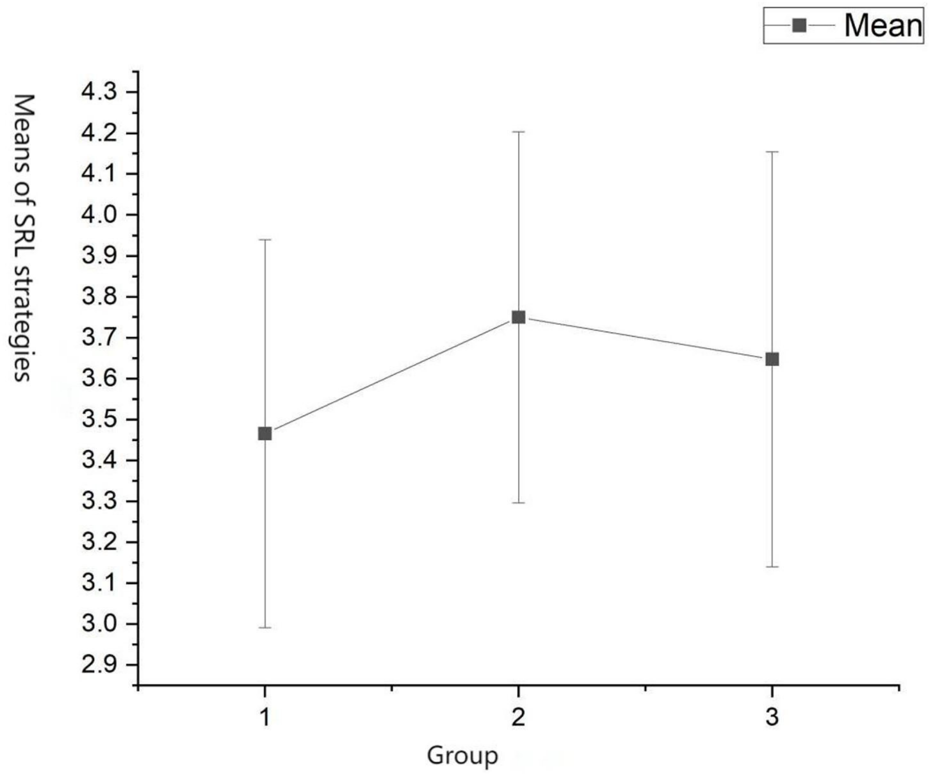



**FIGURE 8 |** Means plot of SRL strategies.

which supports online writing submission and provides AWE services, enables students to learn through self-regulated writing practice. This might partially explain the higher writing scores in the Icourse+Pigai group. However, the participants perceived Icourse, the learning management system, as essential in their SRL, since Pigai does not allow exposure to learning materials, online discussion, and MOOC learning. The participants felt that Icourse and Pigai are irreplaceable because the two technological tools play their own roles in SRL.

> *I think it is better to use two of them. Because Icourse supports online discussion, and then you can preview the lessons. Pigai, on the other hand, allows you to submit your essays and give feedback about your writing timely. I don't think the two conflicts with each other.* (Interviewee 9)

The participants' psychological study preferences also might have played a role in their SRL technological use.

> *Since it is a writing course, I tend to have Icourse and Pigai together. I am not used to relying on only one software to study the subject. I think the two have one focus for me, so I think both of them are necessary.* (Interviewee 10)

**TABLE 6 |** ANOVA for self-regulated learning strategies.

| | Sum of squares | Df | Mean square | *F* | *p* |
|---|---|---|---|---|---|
| Between Groups | 3.938 | 2 | 1.969 | 8.590 | <0.001 |
| Within Groups | 63.492 | 277 | 0.229 | | |
| Total | 67.430 | 279 | | | |

## Lexical Complexity

No statistically significant differences in lexical complexity were found among the three groups in the pre-test. From the post-test lexical complexity results, the technology-tools-supported SRL did not significantly affect students' lexical diversity and sophistication compared with the control group. The result is consistent with the participants' interview results, in that they felt negative about Icourse and Pigai's ability to significantly improve their lexical complexity. They stated that Pigai focuses more on lexical accuracy than lexical complexity in error correction.

> *It will tell you which word is misspelled, and if you misspell it, you can correct the word in your composition. In a sense, it also provides a learning opportunity. However, it does not significantly improve my lexical complexity because it cannot replace your words with*

> *more advanced words after all, and its AI technology has not yet developed to this level.* (Interviewee 7)

> *I think it is more focused on picking mistakes than lexical complexity. It does not require advanced vocabulary, and it will only say that your balance of structure is relatively simple.* (Interviewee 6)

The negative perceptions are not consistent with Jia's (2016) finding that students perceived a higher level of satisfaction regarding improving their lexical complexity of writing with Pigai mediation and used a higher frequency of Basewords 2 and 3 (less frequent words) according to Range 32 software analysis. She also stated that lexical diversity and lexical density improved after a 12-week intervention. This is consistent with Zuo and Feng's (2015) result that Pigai's scoring criteria focus more on lexical accuracy than lexical complexity. Students tend to adjust their writing strategies according to the scoring criteria applied by Pigai to obtain high scores. Our results indicate that SRL supported by both the Icourse group and the Icourse+Pigai group affected students' writing performance in terms of lexical complexity but did not significantly improve on it in the current phase of technological development.

## SRL Strategies

Finally, ANOVA of SRL strategies revealed significant differences between the control and technology-supported groups. The results indicated that both Icourse and Icourse+Pigai positively related to the participants' use of SRL strategies. This aligns with van Alten et al. (2020) study, which found that providing students with technological SRL prompts is an effective strategy for improving SRL. They found that providing online videos in the process of flipped learning was positively related to students' learning outcomes. Likewise, Öztürk and Çakiroglu (2021) demonstrated that technology-mediated SRL positively enhanced students' writing skills in a flipped learning environment. According to Broadbent and Poon's (2015) review, enhanced SRL strategies positively influence learning outcome because, despite cognitive skills having a relatively negligible influence on improving learning outcomes, metacognition, time management, and critical thinking skills are positively related to learning outcomes.

However, the Icourse and Icourse+Pigai groups exhibited no significant difference in the use of SRL strategies, indicating that variation in technology tools did not significantly affect the participants' SRL strategy use. Students' psychological study preferences may partially explain this finding. Psychological study preference is compared to physical study preferences, such as, visual, aural or kinesthetic influences on study preferences. In this research, it refers to the possible psychological factors that affects students' choices on some educational modes over others. In previous studies, study preference primarily referred to sensory modality preferences. This denotes those students make study choices physically, through vision or auditory reactions (Hu et al., 2018). However, the study preferences in this research primarily referred to students' psychological factors. For instance, the interview results reflected those participants tended not to use the peer evaluation function in Pigai, even if they were told that it could be helpful to their writing. They expressed feelings of "distrust" and "embarrassment" regarding showing their essays to classmates.

> *I think that sometimes it is challenging to evaluate others' work because of face issues. I just said that I still don't feel confident about my evaluation ability. I think this is a bit embarrassing.* (Interviewee 8)

> *I don't think it's necessary because I think my classmates have poor writing and everyone is quite clueless.* (Interviewee 5)

Our results are consistent with van Alten et al. (2020), who found that some students disliked the SRL prompts even though the SRL support encouraged students to be more conscious of their learning. Likewise, Yot-Domínguez and Marcelo (2017) found that students tended not to use mobile-related technology tools in their SRL, but rather used mobile devices for social communication purposes. Students' psychological study preferences affect their study choices regarding technology prompts, which may subsequently influence their SRL strategy use.

## Technology Use Factors Toward Technology-Supported SRL

The research shed light on the possible factors to consider when improving students' technology-enhanced SRL experience. Findings indicate that students' perceptions toward technology-supported SRL on their academic learning of writing vary, to some degree, by both internal and external factors (**Figure 9**). The state-of-art technology innovations alone do not guarantee an effective learning process and outcome (Hao et al., 2021). Chew and Ng (2021) emphasized the importance of integrating the effects of students' personality and proficiency in their word contribution in online forums. Different personality traits, such as, introverts or extroverts, may lead to different word productions in their online discussion with the same technological tool (Chew and Ng, 2021). Similarly, Lai et al. (2018) reported that various external and internal factors influence students' perceived study engagement. They proposed a new perspective in viewing technological use as diversified, which means one technological use can generate multiple forms of technology supported learning experiences. Rather than viewing technology as a whole entity in itself, students' psycho-social factors are also essential in contributing to their technologically supported learning experience (Lai et al., 2018). Our research consistently supported their finding by recognizing the importance of integrating students' internal needs and psychological factors with external factors: technological quality and performance and environmental impact are equally important as technological advances in the design and implementation of technology-supported SRL for students.

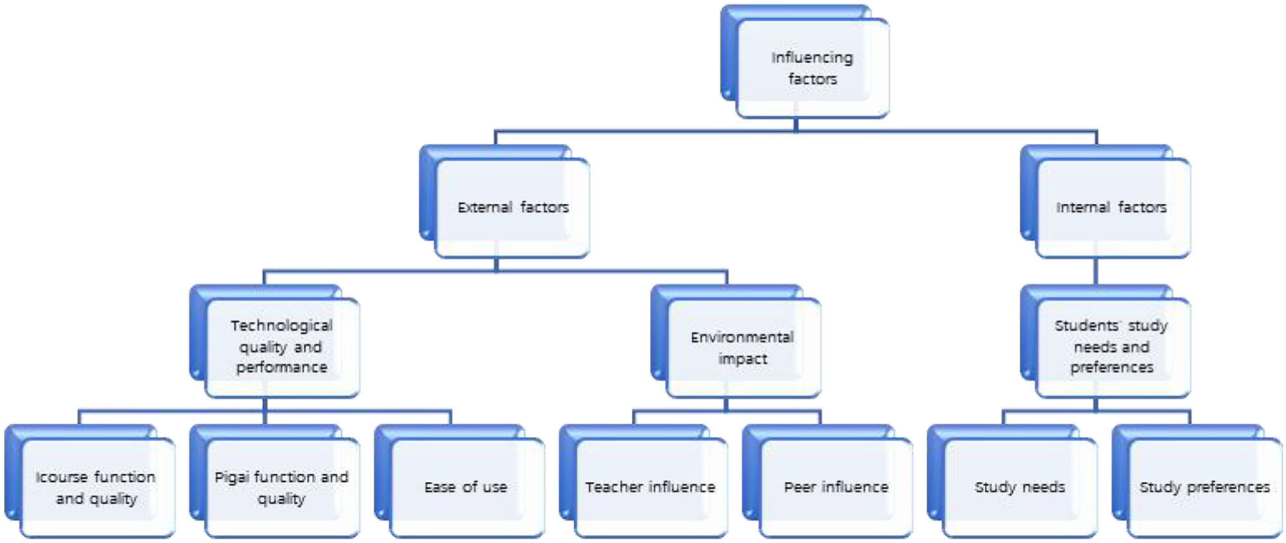



**FIGURE 9 |** Technology use factors toward technology-supported SRL.

## CONCLUSION

The study shows that the Icourse+Pigai group yielded a significantly positive result in writing performance as compared to the control and Icourse. This is partly because the Icourse+Pigai group enabled exposure to learning materials and supported more opportunities for writing practice and corrective feedback. Our research results regarding lexical complexity show that technology-supported SRL failed to significantly improve lexical diversity and sophistication. This is possibly because current feedback focuses more on lexical accuracy than on lexical complexity. Finally, the results of using SRL strategies indicated that the groups with technological support differed significantly from the control group. However, the variation in technological tools in this research did not significantly change SRL strategies. We found that students' psychological study preferences may play a role in students' choice of technological mediation of SRL strategies, all else being equal. According to student interview results, the students' perceived influencing factors were identified as external (technological quality and performance, environmental impact) and internal (study needs and preferences). We thereby conclude that it is feasible to apply both learning management systems and AWE platforms to support students' SRL learning to improve their writing performance. We call for more efforts to design technology tools that improve both lexical accuracy and lexical complexity. We conclude that the technological tools applied in this research are positively related to SRL strategies. However, students' psychological study preferences should be considered when designing technologically mediated SRL activities.

**TABLE 7 |** Some technology use factors between Icourse group and Icourse+Pigai group.

| | (A) Icourse group | (B) Icourse+Pigai group |
|---|---|---|
| 1. Slack and need for supervision | 8 | 4 |
| 2. Improve vocabulary and grammar | 3 | 4 |
| 3. Collocation and advanced expression | 6 | 3 |
| 4. Critical thinking and logic | 0 | 5 |
| 5. Self-regulated learning | 6 | 10 |
| 6. Increase the amount of essay practice | 11 | 5 |
| 7. Academic discussions | 6 | 9 |
| 8. Lack of essay practice | 5 | 0 |
| 9. Unable to practice calligraphy | 3 | 0 |
| 10. Easy access to English resources | 6 | 2 |
| 11. Strengthen communication with teachers | 3 | 2 |
| 12. Improve lexical complexity | 2 | 1 |
| 13. Improve learning motivation | 4 | 4 |
| 14. Promote knowledge gains | 3 | 7 |
| 15. Unable to increase lexical complexity | 0 | 3 |
| 16. AWE not intelligent enough | 6 | 8 |
| 17. Focus on error correction | 1 | 6 |
| 18. Reduce teacher essay evaluation pressure | 1 | 5 |
| 19. High accuracy rates of AWE | 5 | 4 |
| 20. AWE meticulously | 7 | 6 |
| 21. High efficieny of AWE | 1 | 5 |
| 22. Eases of use | 3 | 6 |

The limitations of this research lie in the heavy reliance on students' self-report questionnaires in data collection. Self-reports are sometimes biased, which reduces their validity. Future studies may add more instruments such as observation or eye-tracking techniques to triangulate the data. Furthermore, the limitations also include the possible influence of different lecturers on the group due to individual differences. Further studies may use one lecturer to teach the three groups to minimize the possible effects of the individual differences.

Another limitation is that although all participants spent the same fixed time for SRL in lecture learning, the time of their SRL process spent on the preview and assignment after classes may be different. Further studies may find ways to record students' SRL study time or ask students to report their time use in SRL study in students' residences. Moreover, future studies may focus on other technological combinations or technology types since there is a wide range of available technological tools, such as AI and mobile technologies. Further investigation is necessary to explore the effects of psychological study preferences on technologically supported SRL strategies. Overall, a fruitful avenue for future research appears to be exploration of the effects of various technological prompts on students' SRL learning.

## DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the University of Malaya Ethics Committee. The patients/participants provided their written informed consent to participate in this study.

## AUTHOR CONTRIBUTIONS

YH and SZ conceived the idea and drafted the research. YH carried out the data collection and analysis. SZ and L-LN supervised the research and provided the critical feedback. All authors read and approved the final manuscript.

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## SUPPLEMENTARY MATERIAL

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# Temporal Assessment of Self-Regulated Learning by Mining Students' Think-Aloud Protocols

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It has been widely theorized and empirically proven that self-regulated learning (SRL) is related to more desired learning outcomes, e.g., higher performance in transfer tests. Research has shifted to understanding the role of SRL during learning, such as the strategies and learning activities, learners employ and engage in the different SRL phases, which contribute to learning achievement. From a methodological perspective, measuring SRL using think-aloud data has been shown to be more insightful than self-report surveys as it helps better in determining the link between SRL activities and learning achievements. Educational process mining on the basis of think-aloud data enables a deeper understanding and more fine-grained analyses of SRL processes. Although students' SRL is highly contextualized, there are consistent findings of the link between SRL activities and learning outcomes pointing to some consistency of the processes that support learning. However, past studies have utilized differing approaches which make generalization of findings between studies investigating the unfolding of SRL processes during learning a challenge. In the present study with 29 university students, we measured SRL *via* concurrent think-aloud protocols in a pre-post design using a similar approach from a previous study in an online learning environment during a 45-min learning session, where students learned about three topics and wrote an essay. Results revealed significant learning gain and replication of links between SRL activities and transfer performance, similar to past research. Additionally, temporal structures of successful and less successful students indicated meaningful differences associated with both theoretical assumptions and past research findings. In conclusion, extending prior research by exploring SRL patterns in an online learning setting provides insights to the replicability of previous findings from online learning settings and new findings show that it is important not only to focus on the repertoire of SRL strategies but also on how and when they are used.

**Keywords: self-regulated learning, temporal patterns in SRL, process mining, fuzzy miner, think aloud**

## INTRODUCTION

A key competence for lifelong learning is self-regulated learning (SRL), otherwise known as "learning to learn," and it refers to the ability to monitor and adapt one's learning (European Union, 2019). During SRL, students actively make decisions on the metacognitive and cognitive strategies they deploy to monitor and control their learning to achieve their goals. Yet, students experience difficulties regulating their learning in digital or online settings whereby further support is necessary (Azevedo and Feyzi-Behnagh, 2011; Zheng, 2016; Wong et al., 2019; Poitras et al., 2021). Digital and online learning settings are distinct to traditional classroom learning in that learning tasks, tools, and support are often embedded (e.g., Azevedo et al., 2010; Molenaar et al., 2011; Kinnebrew et al., 2014; Poitras et al., 2021) and students navigate the learning environment autonomously and make decisions as to how their learning takes place and how the learning tasks are completed. Therefore, there needs to be more focus on SRL in digital and online learning, owing to the sharp increase in learning taking place in these settings, largely driven by the ongoing pandemic (EDUCAUSE, 2021). It has been widely theorized and empirically supported that SRL is related to more desired learning outcomes (e.g., performance in transfer tests; Panadero, 2017; Schunk and Greene, 2017). However, SRL consists of complex and dynamic activities and processes which are adapted as students regulate their learning and, therefore, need further investigation in order to support students' learning (Azevedo et al., 2010; Winne, 2010). Hence, beyond learning outcomes, research has shifted to understanding the role of SRL during learning, such as the strategies and learning activities, learners employ and engage in different SRL phases, which contribute to learning achievement (Broadbent and Poon, 2015). Context is an integral part of SRL which shapes students' learning (Winne, 2010). Consequently, students may use new operations as contexts evolve.

Using think-aloud data is a valid approach to uncover SRL processes (Veenman, 2013; Greene et al., 2018). The think-aloud method captures students' utterances of their activities as they occur, thereby generating data that can be modeled to reflect the dynamic nature of SRL processing (Greene et al., 2018). Event-based data, in this case, think-aloud protocols measured during learning, are particularly suited for investigation of SRL processes (Reimann et al., 2014). Applying process analysis gives us the opportunity to investigate learning processes as they unfold (Molenaar and Järvelä, 2014). Frequency analysis through statistical methods does not allow us to identify how SRL activities are used during learning and how the activities are arranged with respect to their temporal structures (Reimann, 2009). In this respect, educational process mining on the basis of think-aloud data enables a more fine-grained analysis and a deeper understanding of SRL processes (Sonnenberg and Bannert, 2015; Engelmann and Bannert, 2019). Although students' SRL is highly contextualized (Winne, 2018), there are consistent findings of the link between SRL activities, specifically metacognitive activities, and learning outcomes (Bannert and Mengelkamp, 2013; Bannert et al., 2014; Sonnenberg and Bannert, 2015; Müller and Seufert, 2018) suggesting that some processes are consistently beneficial to learning across different learning tasks and contexts, such as monitoring and better integration of task analysis processes including orientation, planning, and goal specification. In order to model SRL processes meaningfully, researchers in previous studies have selected representative groups of students, such as successful and less successful students (e.g., Schoor and Bannert, 2012; Bannert et al., 2014; Engelmann and Bannert, 2019; Huang and Lajoie, 2021). However, differing approaches and the corresponding analyses among prior studies investigating the unfolding of SRL processes during learning without standardized guidelines (e.g., types of data used, how learning events have been coded and their granularity, modeling methods) pose a challenge for generalizing findings. In the study reported in this paper, we investigated SRL processes which took place in an online learning environment by comparing SRL activities of successful and less successful students. Furthermore, we extended contributions from past research also conducted in digital and online learning settings by looking at the replicability of findings of SRL activities across learning contexts and tasks through the utilization of a similar approach as a previous study to ascertain if some SRL processes are consistently beneficial for learning. The general aim of the paper was to identify strengths and deficits of student's SRL activities by collecting and analyzing think-aloud data in order to build the basis for future SRL interventions.

### Models and Components of SRL

Learners regulate their learning by monitoring and controlling the processing of content and operations they apply to content's processing as they pursue goals to augment and edit prior knowledge (Winne, 2019). SRL is a process, whereby learners employ various cognitive strategies in an effective manner, which is directed by their metacognitive knowledge and skills (Boekaerts, 1999). Although there are several SRL models available (e.g., Winne and Hadwin, 1998; Pintrich, 2000; Zimmerman, 2000) offering different perspectives, they share the common assumption of SRL defined as cyclical phases comprised of several processes (Puustinen and Pulkkinen, 2001; Panadero, 2017). Based on comparison of different SRL models of Puustinen and Pulkkinen (2001), there are three common identifiable phases in the SRL process, namely the preparatory, performance, and appraisal phases. In the preparatory phase, learners analyze the task, set goals, and strategically plan their learning. Goals are the set of standards students refer to in order to monitor their learning metacognitively during the learning process. They also guide students in forming their plan (Winne, 2018). Strategic planning refers to activating prior knowledge, and analyzing the task in order to determine which cognitive strategies to use (Pintrich, 1999). During the performance phase, students monitor and regulate their learning as they employ cognitive strategies to perform the task, which are guided by their goals. Regulating of learning *via* monitoring and control processes plays a paramount role which is further elaborated by Nelson and Narens (1994). According to them, cognition is structured into a "meta-level" and an "object-level." A mental representation of one's cognition forms the meta-level; one's cognition is therefore the object-level. Monitoring and control are regulatory processes that reflect the interaction between the meta- and object levels. Monitoring leads to the mental representation of one's cognition and control processes alter the object-level (i.e., one's cognition). Dependent on the meta-level representation (e.g., judgments of their learning) derived from monitoring, one could modify control processes, such as through rereading the text or terminate the current strategy. Weinstein and Mayer (1983) identified three main cognitive strategies – rehearsal, elaboration, and organization – which are important for academic performance. Rehearsal strategies, which reflect shallow processing, enable students to take note of important information, which are kept in their working memory. For example, students may repeat out loud what they have read, or take verbatim notes. Elaboration and organization strategies involve students processing information at a deeper level. Elaboration strategies include summarizing, paraphrasing, explaining, creating analogies, etc. Organization strategies include outlining and organizing material learned, such as mapping out and connecting ideas. In the final SRL phase, known as appraisal, students evaluate and reflect on their learning which in turn lead to adaptations for their next learning cycle. Evaluation refers to one's comparison of current progress with a pre-defined goal or standard (Zimmerman, 2000). In a more elaborated model such as the COPES model (Winne and Hadwin, 1998), monitoring is also assumed to be omnipresent across all phases, which leads to control processes that reduce discrepancies between current progress and standards.

Most SRL models explain regulatory processes to occur in a time-ordered sequence but not in a specific stringent order (Azevedo, 2009). In past empirical studies investigating the temporal structure of students' SRL activities (Bannert et al., 2014; Sonnenberg and Bannert, 2015; Paans et al., 2019; Cerezo et al., 2020; Huang and Lajoie, 2021), students' SRL processes in the main SRL phases were distinguishable, particularly among students who were more successful. Moos and Miller (2015) also found that the SRL processes, planning and monitoring, are more stable across learning tasks. Therefore, in the current study, we investigated the consistency of findings of students' SRL activities and by distinguishing successful and less successful students.

## SRL and Learning Performance

Self-regulated learning has been shown to be related to academic performance, especially transfer test scores (Schunk and Greene, 2017). Students transfer their knowledge when they apply knowledge and skills to a new situation or problem (Bloom et al., 1956). Metacognitive activities can help to deepen understanding (Bannert et al., 2009). Specifically, metacognitive activities comprise of analyzing the task through orientation, planning, and setting goals for learning, regulation of cognitive activities, monitoring the processing of content and operations applied for the content's processing, and evaluation of learning (Meijer et al., 2006; Schunk and Greene, 2017). Deekens et al. (2018) found in two studies they conducted that monitoring activities, which are part of metacognitive activities, were positively associated with use of deep learning strategies. The association between metacognitive activities and learning has been repeatedly found by empirical studies investigating (and supporting) SRL activities and learning performance, with effects found particularly in transfer performance. Bannert and Mengelkamp (2013) conducted three experimental studies using a range of metacognitive prompts to support university students' SRL when learning with hypermedia. They investigated students' metacognitive activities and analyzed SRL processes. They found that experimental groups which were supported by metacognitive prompts engaged in more metacognitive activities. Furthermore, they found significant effects of metacognitive prompts on only transfer performance in two out of three studies. Bannert et al. (2014) similarly found significant positive correlation between metacognitive activities and transfer performance in a study, which measured students' learning activities with the use of think-aloud protocols. Sonnenberg and Bannert (2015) investigated the learning activities which contributed to differences in transfer performance between an experimental group supported by self-directed prompts and a control group. Their findings indicated that transfer performance was mediated by the number of metacognitive events. In particular, monitoring activities seemed to have been the driving force of the mediation (i.e., larger effect of monitoring when compared to effect of all metacognitive events) in the experimental group supported by metacognitive prompts. In the experimental study by Müller and Seufert (2018), they observed the effects of self-regulation prompts for the purpose of activating self-regulation activities on university students' learning across two learning sessions. Their findings revealed significant differences between the groups in terms of transfer performance after the first session, where students received prompts. These studies highlighted the role of SRL, particularly metacognitive activities, in improving students' transfer performance.

The success of students' learning is dependent on the skills in applying strategies in their SRL activities during learning. Yet, students are not able to produce the skills required in a spontaneous manner in a phenomenon termed production deficiency (Flavell et al., 1966). Understanding how the spontaneous unfolding of SRL activities occurs could provide us better insights on how and at which points to support students' learning. Therefore, there is a need to examine not only learning outcomes, but also the processes during learning.

## Measuring SRL Processes Using the Think-Aloud Approach

Self-regulated learning processes have been measured in several ways through self-report questionnaires (e.g., Motivated Strategies for Learning Questionnaires; Pintrich et al., 1993), think-aloud protocols (Johnson et al., 2011; Bannert et al., 2014; Vandevelde et al., 2015), micro-analyses (Cleary and Callan, 2017; Dörrenbächer-Ulrich et al., 2021; Kia et al., 2021), and increasingly, trace data (Järvelä et al., 2019; Cerezo et al., 2020; Huang and Lajoie, 2021). The reliability of self-report questionnaires in measuring SRL has been repeatedly questioned (Greene and Azevedo, 2010) and they have been shown to be poor predictors of actual SRL behavior

(Bannert and Mengelkamp, 2013; Veenman, 2016). Self-report questionnaires used are typically administered offline and measure global use of SRL strategies, which show low calibration with actual SRL behavior, though online micro-analytic (i.e., fine-grained) self-report questionnaires may show better calibration with actual SRL behavior indicators (Rovers et al., 2019). Online methods such as think aloud are strong predictors of achievement (Veenman, 2013). This could be explained by the finer grained nature of these measures (e.g., think-aloud protocols, micro-analytic questions, trace data, and eye-tracking data), in comparison with self-reports which focus on global SRL rather than specific strategies (Rovers et al., 2019). Greene et al. (2010) analyzed SRL activities of university students in a hypermedia learning environment, while they were thinking aloud. They found that measures of SRL which were coded from the think-aloud protocols using a previously established coding scheme were more advantageous than self-report instruments. Heirweg et al. (2019) used two different methods (i.e., think-aloud protocols and self-reports) for the exploration of SRL profiles in primary school students. Their findings supported past research that students overestimate their SRL behavior in self-reports. From a methodological perspective, measuring SRL using think-aloud data has been shown to be more insightful than self-reports as it helps better in determining SRL activities and learning achievements. Although research using trace data, especially with the combination of multimodal and multichannel data (e.g., logs and eye tracking, etc.) has been gaining popularity due to benefits over self-report questionnaires, working with these data comes with specific challenges, as summarized by Azevedo and Gašević (2019), such as temporal alignment of data, variations in data granularity, theoretical assumptions, and interpretations of different data streams, and so forth. Thus, in our study, we focus on the use of think-aloud protocols using an established coding scheme to measure SRL processes.

### Using Concurrent Think Aloud to Make Learning Activities Observable

Using concurrent think aloud (CTA) is a powerful approach to observe and model the dynamic nature of SRL processes (Greene et al., 2018). CTA allows students to verbalize every thought out loud without additional processing such as interpretation or judgment (Ericsson and Simon, 1984). To maximize the rigor of this approach, pre-requisites of studies implementing CTA are both adequate prior training and prompting during the session (Hu and Gao, 2017; Greene et al., 2018). This means that participants should be allowed to practice in an appropriate manner in order to familiarize with the procedure and that experimenters are required to prompt participants to continue thinking aloud in the event of silences. The disadvantage of using CTA is the additional processing time required by participants, especially with verbal encoding processes (Ericsson and Simon, 1984). Extended silences could indicate the high cognitive load participants are experiencing at the moment or the activity they are performing is highly automated (Ericsson and Simon, 1984; Elling et al., 2012). Another downside of working with think-aloud protocols is that the coding process is a labor-intensive procedure. Despite its limitations, using CTA allows researchers to see the inner workings of how learners process information as it does not alter information processing (Winne, 2018).

It is, however, important to note for whom CTA gathers valid observations and in general, whether it has a reactive effect. In review of Hu and Gao (2017) on past studies on the reactive effects of think aloud as a method, their findings suggested that older students (i.e., university students) were less inclined to alter their processes when asked to think aloud as compared to younger students such as primary school students. In meta-analysis of almost 3,500 participants in 94 independent data sets of Fox et al. (2011), they found that the use of CTA did not lead to performance changes. Bannert and Mengelkamp (2008) found no performance differences between students who were asked to think aloud during learning and the control group who learned in silence. Finally, since the activities students are engaged in are deduced from their verbalizations, the coding process calls for the use of sophisticated coding schemes derived from theory and the procedure to be performed by trained raters (Greene et al., 2018). In conclusion, CTA is a valuable method to measure SRL processes in a nonreactive manner.

## Using Process Mining to Investigate SRL Processes

Analyzing sequences of actions learners take while learning provides an opportunity to investigate SRL processes beyond learning outcomes (Roll and Winne, 2015). This has led to increased use of approaches in identifying SRL patterns by means of process mining, sequence mining, t-pattern analysis, lag sequential analysis, statistical discourse analysis, and so forth (Molenaar and Järvelä, 2014); process mining provides insights into the temporal structures of students' SRL (Bannert et al., 2014) and hence, its use in the educational context for the purpose of discovery and conformance checking of learning processes is one of the top five uses of process mining (Garcia et al., 2019). The conceptualization of SRL as a series of events which develops and unfolds over time has led to growing research exploring the temporal and sequential sequences of SRL (Molenaar and Järvelä, 2014). The variable-centered approach of frequency analysis of SRL occurrences using statistical methods assumes that independent variables are constantly acting upon the dependent variables (Reimann, 2009). As an addition to the variable-centered approach, the event-based approach in SRL research aims to increase explanatory power by identifying how SRL processes occur and develop over time (Reimann, 2009; Molenaar, 2014).

Think-aloud protocols are one way to measure SRL using the event-based perspective, whereby SRL is observed as a sequence of temporal events (Winne and Perry, 2000). Bannert et al. (2014) analyzed the process patterns of successful and less successful students who learned in a single session in a hypermedia learning environment using their think-aloud protocols as indicators of their SRL behavior. Their findings revealed that successful students not only showed more learning and regulation activities, but there were also differences in temporal structures, which were detected in the process models generated from applying the Fuzzy Miner algorithm on coded think-aloud protocols. They found that successful students engaged in preparatory activities prior to learning, learned more deeply by engaging in deeper cognitive processes such as elaboration, and evaluated their learning. They also continuously monitored various learning activities throughout their learning. In contrast, less successful students adopted a surface approach to learning, whereby superficial cognitive activities such as repetition were more dominant in their process model. Evaluation activities were notably absent from the model.

Other studies focused on using logfiles to detect SRL patterns. Although, the data streams differed, the goal was similar – investigating SRL processes by means of students' learning activities. Huang and Lajoie (2021) identified SRL patterns in teachers' acquisition of technological pedagogical content knowledge (TPACK) in a computer-based learning environment (CBLE). They collected log files which included how teachers navigated in the learning environment, as well as lesson plans which were evaluated. On the basis of TPACK application quality from the lesson plans and teachers' self-report of TPACK, they distinguished three groups which represented low to high achievements. They then applied the Fuzzy Miner algorithm for the detection of SRL patterns within and across groups. On a global level, the groups exhibited differences in how SRL activities took place. In particular, the model of high TPACK achievers showed that all SRL events were connected and they began their learning by analyzing the task and setting goals. They constantly monitored as they were performing the tasks. Additionally, when comparing high and low clusters within each group, high clusters showed iterative SRL patterns and the dominant role of monitoring of various activities.

Other than studies which were conducted in a single session in the lab mentioned above, process mining has also been utilized in other learning contexts, such as online courses. Cerezo et al. (2020) applied the Inductive Miner algorithm to discover SRL patterns in a university e-Learning course that stretched over a semester with over 100 students. They analyzed logfiles obtained from the learning platform and concentrated on the process models for passing and failing students and especially in one learning unit. They found that students who failed in this unit displayed SRL patterns which was not supported by neither SRL skills nor instructor recommendations. Students who passed had a combination of more meaningful activities such as comprehension, learning, execution, and reviewing, which demonstrated more effective SRL. Using a larger data set and additionally self-reports, Maldonado-Mahauad et al. (2018) found differences between students who completed a Massive Open Online Course and those who did not. Students who completed the course showed higher engagement with course assessments, and moreover, those who have a higher SRL profile, interacted more deeply with the materials and were more strategic in their learning.

The studies mentioned indicate similarities in the approaches used to uncovering SRL patterns, such as by comparing process models between successful and less successful groups of students. However, the challenges with comparing findings and identifying students' gaps in SRL across studies lie in the learning contexts and tasks, types of data used (e.g., think-aloud protocols, logfiles, and self-reports) as well as how learning events have been coded and their granularity. Therefore, we reflect upon our findings mainly with the study from Bannert et al. (2014) owing to the data type (i.e., think aloud) used, and coding scheme which is an adapted version of the coding scheme they used. We adopted a similar approach using the Fuzzy Miner algorithm and the parameters used in their study. Further, Saint et al. (2021) compared four prominent process mining algorithms used in SRL research, namely, Inductive Miner (Leemans et al., 2014), Heuristics Miner (Weijters et al., 2006), Fuzzy Miner (Günther and Van Der Aalst, 2007), and pMiner (Gatta et al., 2017). They systematically explored the insights provided by each of the process mining algorithms in the context of SRL research and found that Fuzzy Miner holds the highest value for interpreting SRL processes with clarity. Therefore, we assume that using Fuzzy Miner on coded think-aloud protocols is an appropriate approach to discover the key SRL processes which take place (or do not take place) during learning.

## The Present Study

Students' SRL is dependent on the learning task and context (Winne, 2018), but Moos and Miller (2015) have also found that SRL processes, such as planning and monitoring, are more consistently helpful for learning across different tasks. The consistent findings of SRL activities on transfer performance suggest the presence of processes that are beneficial across different learning contexts and tasks. Yet, comparison of findings from previous studies on how SRL processes unfold during learning can be a challenge due to differing approaches and methods. Hence, replication studies are necessary in order to generalize findings. In our study, we sought to find a more stable picture on SRL processes and learning outcomes. The findings of our study extended previous SRL research in digital and online learning settings and provided insights to whether previous findings were replicable, and whether our findings were still valid and coherent to older studies when applied to a different learning task and context. By doing so, we illustrated how we analyzed SRL processes in the online learning environment. Through these findings, we sought to identify students' gaps in SRL in order to develop better scaffolds by modeling successful and less successful students' SRL patterns. Building on this, the generated findings were further connected with those of previous process mining studies from the research field. These research questions guided our study:

### How Do Students (Spontaneously) Regulate Their Learning Activities?

Since there are similarities between our and study of Bannert et al. (2014), and that the learning task required students to engage in SRL activities across all SRL phases, we expected that we observed activities in all categories of SRL. In study of Bannert et al. (2014), students engaged in higher frequencies of metacognitive activities and monitoring activities had the highest frequencies. Other activities such as planning, goal specification, evaluation, and motivation had lower frequencies.

### How Do Learning Activities and Their Regulation Correspond to Learning Performance?

Based on past studies (Bannert and Mengelkamp, 2013; Bannert et al., 2014; Sonnenberg and Bannert, 2015; Müller and Seufert, 2018), increased metacognitive activities led to better transfer performance. Additionally, better transfer performance was mediated by monitoring activities (Sonnenberg and Bannert, 2015) in the experimental group supported by metacognitive prompts. We anticipated that metacognitive activities had a positive correlation with transfer performance.

### How Do the Temporal Structures of Learning Activities of Successful and Less Successful Students Differ?

Our study used process mining for the exploration of temporal structures of SRL activities between successful and less successful students. As we aimed to explore the consistency of findings from SRL patterns with past studies, we did not specify any hypothesis related to this research question. However, in general, we expected that similar to Bannert et al. (2014), successful students show SRL patterns closer to those proposed by SRL theories, where the main SRL phases are closely linked.

# MATERIALS AND METHODS

## Participants

Our study consisted of 36 participants from various universities in Germany. Due to poor quality in the recording of audio data and data loss, we had usable think-aloud data for 32 participants ($M_{age}$ = 26.56 years, $SD_{age}$ = 4.18 years, 66% female). We then performed a check on the proportion of participants' think aloud for the whole session and excluded two participants who were thinking aloud for less than 50% of the session to make sure only valid protocols were included. Additionally, we removed one non-native speaker. The final sample consisted of 29 participants. Participation was voluntary – all participants signed a printed consent form – and the participation criteria were that students had German as first language and were studying in a university. The participants were reimbursed with 15 euros for their participation. The participants studied a diverse range of degree majors – 25 in total – such as informatics, education, business administration, chemistry, engineering, law, and political science.

## Design

We conducted the study in single onsite sessions with participants individually. Before the session started, participants filled out a demographic questionnaire asking them for their gender, age, and degree major. We used a pre–post-design (see **Figure 1**), whereby participants completed a domain knowledge test before and after learning. During the 45-min learning phase, where participants had to think aloud, they were tasked to learn and write an essay. Afterward, they completed a transfer test.

### Learning Environment and Materials

A CBLE presented learning materials from three topics: Artificial intelligence, differentiation in a classroom, scaffolding, and an essay task. All materials were presented in German. The CBLE (see **Figure 2**) comprised of a navigation menu, a reading panel, a note-taking tool, and a countdown timer. The CBLE consisted of 37 pages, including one instruction page, an essay-writing page, an essay rubric page, three table of contents pages, one for each topic, and pages presenting learning content. Some irrelevant materials were included in each topic so students had to learn strategically. Participants navigated by clicking the title of the pages on the navigation menu. They could create, edit, and delete notes *via* the note-taking tool. The countdown timer displayed a countdown from 45 min.

The learning content contained 5,237 words and six figures. A text readability analysis (Michalke, 2012) showed the Flesch-Kincaid grade-level score and Flesch Reading Ease values (the equivalent for German texts is Amstad) of all three texts to be suitably challenging for university students. The text about artificial intelligence had a Flesch–Kincaid grade-level score of 15.56, and a Flesch Reading Ease value of 41.42. The text about differentiation in the classroom had a Flesch-Kincaid grade-level score of 21.33, and a Flesch Reading Ease value of 22.41. The text about scaffolding had a Flesch-Kincaid grade-level score of 19.84, and a Flesch Reading Ease value of 28.39. The Flesch-Kincaid grade-level score corresponds to grade levels and the higher the number, the more difficult to read is the text. The Flesch Reading Ease value has a range from 0 to 100, with lower numbers indicating more difficult reading.

## Procedure

The data collection session was conducted in a lab at a German university and lasted approximately one and a half hour with an experimenter present throughout. Participants were specifically instructed prior to starting that they would not have sufficient time to read all the materials and write the essay and they would have to learn efficiently and choose what and how they learn. We presented the learning environment on a 23.8-in monitor using a web browser. Audio data were collected *via* a clip-on microphone. Participants had access to a keyboard and mouse at all times.

The session consisted of four parts. Part 1 began with the demographic questionnaire and then pretest questions. All participants were given a maximum of 20 min to complete the pretest. In Part 2, the experimenter first introduced the learning environment and tools. Then, the experimenter demonstrated how to think aloud while navigating the learning environment. Finally, the participants were asked to think aloud and complete short exercises, where they navigated through the learning environment and used the tools. At the end of the training, the experimenter would provide a short feedback (e.g., volume needs to be louder). This took between 10 and 15 min. In Part 3, the learning phase, participants had 45 min to read the text and write an essay. During this phase, they were free in how they navigated or used the tools in the learning environment. However, they had to read and think aloud throughout. Whenever they were silent for more than 5 s, or spoke quietly, they were prompted verbally by the experimenter. Finally, in Part 4, participants completed the

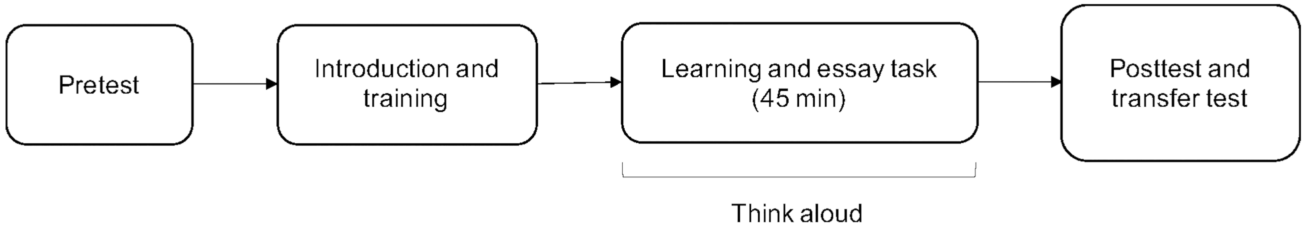


**FIGURE 1** | Research design in our present study.

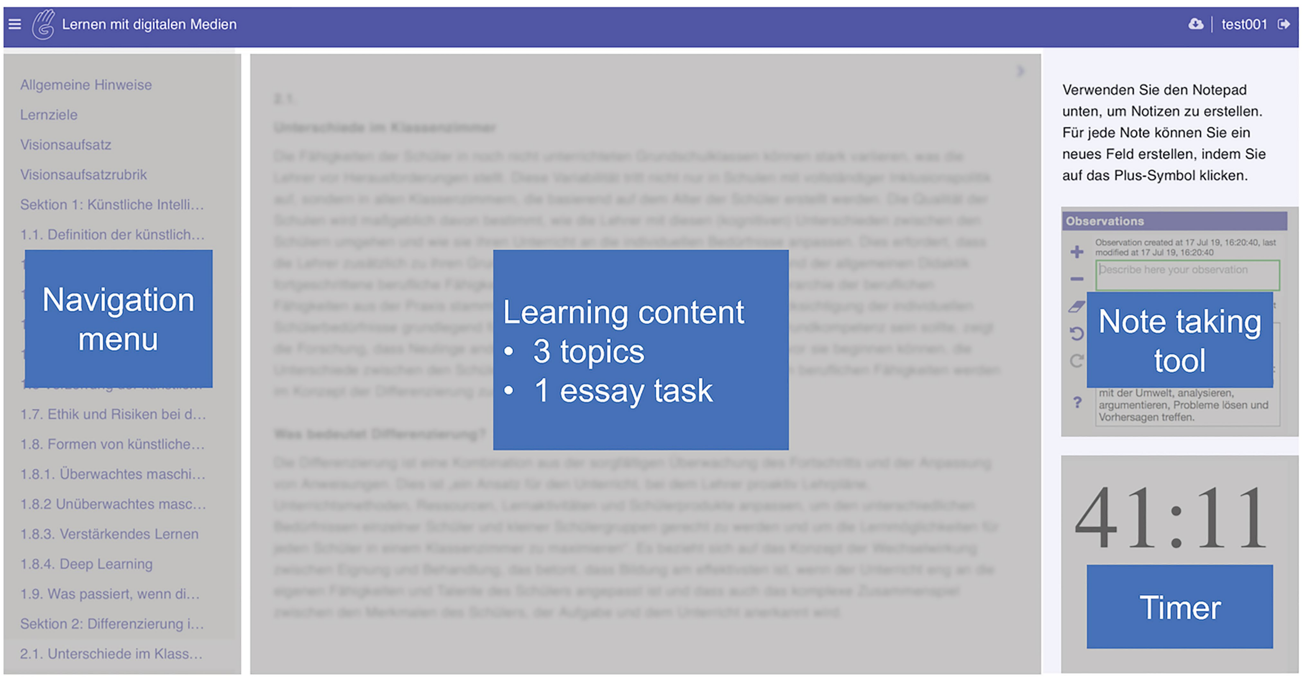


**FIGURE 2** | The computer-based learning environment (CBLE).

posttest and transfer test in this sequence. They were given a maximum of 30 min for Part 4.

## Instruments

We developed the learning performance measures based on Bloom's taxonomy of cognitive learning objectives (Bloom et al., 1956). The items in the domain knowledge test were focused on the lower levels of the taxonomy, such as comprehension of the texts, while the transfer test items were focused on the higher levels, such as application of concepts (in the medical field). All items in the tests were compulsory and could not be skipped. The domain knowledge test addressed knowledge relating to sections of the text relevant to the learning goals and consisted of 30 multiple-choice items ($\omega = 0.75$). The omega coefficient ($\omega$) has been found to be a better choice than Cronbach's alpha, especially when scores are normally distributed, as was the case in our study (Trizano-Hermosilla and Alvarado, 2016) and is less prone to over- or underestimation of reliability (Dunn et al., 2014). An example of a domain test item was: "How can an algorithm work better?" with options, (A) "By making the series longer," (B) "By building in more supervision," (C) "By analyzing more data" (correct answer), and (D) "By simulating more human behavior." The sequences of both pre and posttest items were randomized, so that items were not presented in the same order for the pre and posttests, and that items relating to the same topic did not appear together. Each item consisted of four answer options with one correct answer; each correct answer was worth one point with a total of 30 points for the whole test. We measured transfer knowledge with 10 multiple-choice items ($\omega = 0.44$). An example of a transfer test item was: "Which of the following describes how artificial intelligence has been used by the healthcare industry?" with options, (A): "Using augmented reality architecture systems to develop quicker and more efficient paths for transporting patients at the emergency department," (B): "Using natural language processing to analyze thousands of medical papers for better informed treatment plans" (correct answer), (C): "Automatic transfer of patient information whenever another hospital requests for it.," and (D): "Using robots to prepare meals that meet patients' treatment and dietary needs as indicated in the patient file." Identical to the format of the domain knowledge test, there were four options provided with one correct answer. Each correct answer was awarded one point with the total points possible being 10 points. Participants were asked to apply their knowledge of artificial intelligence in the medical field.

### Essay Task and Coding

To elicit self-regulated learning strategies, participants were tasked to write a 300–400-word essay during the 45-min learning phase of the session. Detailed task instructions and an essay assessment rubric were provided in the learning environment. The task was to apply what they had learnt from all three text topics into an essay, where they envision and suggest how learning in schools would look like in the year 2035. The essays were assessed manually by two trained coders and inter-rater reliability (weighted $\kappa = 0.68$) was calculated by randomly selecting 17 essays. According to Fleiss et al. (2003), a weighted kappa value is interpreted the same way as a kappa value and the value, we have obtained was acceptable to proceed.

## Think-Aloud Procedure and Coding Scheme

All verbalizations in the learning phase were coded using a coding scheme (see **Table 1**) adapted from prior research (Bannert, 2007; Molenaar et al., 2011; Sonnenberg and Bannert, 2015). In their theoretical framework, the authors characterized hypermedia learning into three main categories, Metacognition, Cognition, and Motivation. Furthermore, there are distinct sub-categories within the larger categories of Metacognition and Cognition. **Table 1** presents the coding categories, description, and examples. Metacognition included the subcategories, *orientation*, *planning*, *monitoring*, *search*, and *evaluation*. Cognition was further categorized into *reading*, *rereading*, *superficial processing*, *elaboration*, and *organization*. All verbalizations relating to motivational aspects of the task, situation, or self, were coded as *motivation*. The final category, *other*, included irrelevant utterances, or segments which were incomprehensible (e.g., a mumble).

Two trained research assistants coded the verbal protocols together using the procedure suggested by Chi (1997). Due to economic reasons, segmentation and coding were carried out in one step. Segmentation was performed based on meaning and multiple or nested codes were not allowed. In the event of uncertainty, the final code was decided after discussion with the first author. We found interrater reliability of $\kappa = 0.95$, representing excellent agreement (Fleiss et al., 2003).

## Data Analysis

To answer the research questions we posed, we utilized three approaches. In order to find out how students regulated their learning activities, we performed descriptive analyses of coded think-aloud events to investigate whether and which activities were captured. We also checked if students had learned by conducting a paired samples $t$-test with pre and posttest scores. For our second research question, we correlated the frequencies of activities observed *via* coded think-aloud protocols and the performance measures (i.e., comprehension and transfer tests, and essay). We conducted the Spearman's correlation due to the non-normal distribution of almost all categories of the coded activities. It is typical of this measurement method (i.e., think aloud) of SRL processes to have non-normal distributions (Greene et al., 2018). Since we expected metacognitive activities to be positively correlated with learning performance, one-tailed correlation analysis was performed for metacognitive activities and learning performance, and two-tailed correlation analysis for the rest of the analyses. Furthermore, we checked how the same SRL activities simultaneously predicted the posttest, transfer, and essay performance by means of multivariate regression analyses. For the third research question, we used the process model discovery algorithm, Fuzzy Miner (Günther and Van Der Aalst, 2007), on two groups of students categorized as successful or less successful, we created prior to the analyses. Successful learning was operationalized by using transfer performance and a median split was conducted to form the groups.

**TABLE 1** | Think-aloud coding scheme adapted from Bannert (2007).

| Initial coding category | Final coding category | Final code | Examples |
|---|---|---|---|
| **Metacognition** | | | |
| Orientation | Task analysis | ANALYSIS | I have to write an essay |
| Planning | Task analysis | ANALYSIS | First, I will read the text through. |
| Goal specification | Task analysis | ANALYSIS | I must first understand Scaffolding. |
| Monitoring | Monitoring | MONITOR | Okay, I understand it. |
| Search | Search | SEARCH | I'm looking for the concept, "Divergence." |
| Evaluation | Evaluation | EVAL | I think I have completed the learning goals. |
| **Cognition** | | | |
| Reading | Reading | READ | Reading content out loud |
| Rereading | Rereading | REREAD | Rereading content out loud |
| Superficial processing | Repeating | REPEAT | Rehearsal, writing verbatim notes from content |
| Elaboration | Elaborating | ELABORATE | That means, the students should be taught in smaller groups. |
| Organization | Organizing | ORGANIZE | Outlining important points as notes |
| Motivation | Motivation | MOT | I do not like writing essays. |
| Other | Rest | REST | I have problems with the mouse. |

**TABLE 2** | Descriptive table of coded think-aloud events, $n = 29$.

| | Min | Max | *M* | *SD* |
|---|---|---|---|---|
| **Metacognition** | | | | |
| Orientation | 23 | 147 | 67.24 | 31.41 |
| Planning | 0 | 33 | 10.28 | 9.22 |
| Goal specification | 0 | 27 | 3.55 | 6.03 |
| Monitoring | 61 | 313 | 159.48 | 65.03 |
| Search | 0 | 11 | 3.52 | 3.63 |
| Evaluation | 0 | 6 | 0.62 | 1.63 |
| Sum of metacognitive activities | 141 | 373 | 244.69 | 73.54 |
| **Cognition** | | | | |
| Reading | 30 | 207 | 93.21 | 42.69 |
| Rereading | 1 | 156 | 55.28 | 37.74 |
| Superficial processing | 0 | 56 | 4.38 | 11.66 |
| Elaboration | 6 | 299 | 90.45 | 69.16 |
| Organization | 0 | 244 | 67.59 | 57.46 |
| Sum of cognitive activities | 122 | 477 | 310.9 | 81.02 |
| Motivation | 0 | 9 | 1.83 | 2.61 |
| Others | 8 | 123 | 45.24 | 23.21 |
| Sum of all coded activities | 313 | 870 | 602.66 | 125.96 |

**TABLE 3** | Descriptive table of learning outcomes, $n = 29$.

| | Min | Max | *M* | *SD* |
|---|---|---|---|---|
| Pretest[a] | 7 | 20 | 14.14 | 3.35 |
| Posttest[b] | 8 | 25 | 17.14 | 3.72 |
| Transfer[c] | 2 | 10 | 5.97 | 1.57 |
| Essay[d] | 0 | 17 | 8.45 | 4.31 |

*Maximum possible scores for each learning measure are indicated below.*
*[a, b]30 points.*
*[c]10 points.*
*[d]21 points.*

### Process Discovery Using the Fuzzy Miner Algorithm

We imported the event logs of all coded think-aloud protocols into the ProM process mining framework version 5.2 (Verbeek et al., 2011). All event logs contained a participant ID, timestamp which indicated the start of the activity, and the activity which was coded. We then applied the Fuzzy Miner algorithm (Günther and Van Der Aalst, 2007) on the imported event logs to create two process models – one for the successful group and one for the less successful group. According to its developers, this process mining algorithm is suitable for unstructured real-life data (i.e., coded think-aloud data in our case) and produces meaningful process models which can be interpreted. Fuzzy Miner uses two key metrices to compute the process model which contains nodes and edges, and their respective significance and correlation values. *Significance* refers to the relative level of importance of the observed events and the relations between these events (i.e., edges); *Correlation* refers to "how closely related two events following one another are" (Günther and Van Der Aalst, 2007, p. 333). There are three ways guiding the process simplification approach. The process model retains highly significant events; less significant but highly correlated events are aggregated into clusters. Finally, events which are both less significant and lowly correlated are removed from the model. For our analyses, we used the following parameters as per the modeling procedure by Bannert et al. (2014): edge filter cut-off set at 0.2, utility ratio set at 0.75, node filter set at 0.75 and the significance cut-off set at 0.25. For the purpose of investigating the temporal structure of SRL activities in our model, we excluded the categories, motivation, and others.

## RESULTS

### Frequency Analysis of all Coded SRL Events

In order to answer RQ1, that is, how do students spontaneously regulate their learning activities, we calculated the descriptive results for all coded learning events (see **Table 2**). We coded a total of 17,477 activities in the 45 min learning session for the sample. On average, there were 244 metacognitive and 310 cognitive activities. The participants showed a mean of less than two motivation activities and 45 other utterances, which were not related to learning. Monitoring activities ($M = 159.48$, $SD = 65.03$) had the highest mean frequency across all categories, followed by reading ($M = 93.21$, $SD = 42.69$), and elaboration ($M = 90.45$, $SD = 69.16$). Evaluation activities ($M = 0.62$, $SD = 1.63$) had the lowest frequency, as well as motivation ($M = 1.83$, $SD = 2.61$) and Search ($M = 3.52$, $SD = 3.63$).

### Correlation Analysis of all Coded SRL Events and Learning Outcomes

For RQ2, that is, how do learning activities and their regulation correspond to learning performance, we analyzed the correlations between coded think-aloud events and performance scores. An analysis of pre- and post-knowledge tests using a paired samples *t*-test showed a significant learning gain. We found a significant difference in the pre-knowledge scores ($M = 14.14$, $SD = 3.35$) and post-knowledge scores ($M = 17.14$, $SD = 3.72$); $t(28) = 5.87$, $p < 0.001$, $d = 1.09$. The effect size was large (Cohen, 1992). **Table 3** presents the descriptive statistics for all learning outcomes.

**Table 4** presents the correlation results for SRL activities and different learning performance scores. As expected, metacognitive events had no significant correlation to all learning measures except transfer score ($r_s = 0.37$, $p = 0.024$). Of all metacognitive activities, transfer performance was significantly correlated to monitoring ($r_s = 0.44$, $p = 0.008$), as we expected, and in addition, to search ($r_s = 0.40$, $p = 0.017$) and rereading ($r_s = 0.48$, $p = 0.008$). The deeper cognitive activities, elaboration and organization, were found to be negatively correlated ($r_s = -0.62$, $p < 0.001$) to each other. Additionally, as a check for consistency, we conducted a multivariate regression analyses for the same SRL activities and learning outcomes. The results showed search to be a predictor for post-knowledge performance

($b^* = 0.68$, $p = 0.029$), monitoring to be a predictor for transfer performance ($b^* = 0.47$, $p = 0.046$), as well as evaluation ($b^* = 0.49$, $p = 0.034$). Elaboration was a predictor for essay performance ($b^* = 0.63$, $p = 0.035$).

## Temporal Structures of Learning Activities of Successful and Less Successful Students

We examined the differences in temporal structures of learning activities between successful and less successful students (RQ3) by using process mining. The details of the preparation and process mining procedures are elaborated in the sections below.

### Successful and Less Successful Students

Similar to the findings from Bannert et al. (2014), we found correlation coefficients to be the highest between the sum of counts of metacognitive activities and transfer scores, and moreover, the only significant correlation among performance measures. Hence, based on our findings, and also past research findings, we proceeded to use transfer scores to operationalize successful learning. We operationalized successful and less successful groups in terms of transfer performance by first calculating the transfer score median (six points). We then split the sample by assigning students with transfer scores above six points to the successful group and students with transfer scores below six points to the less successful group. This resulted in 10 students in the successful group and nine students in the less successful group. Both groups had similar proportion of utterances in the learning session – average of 72% for both groups.

### Comparison of Different Learning Outcomes Between Successful and Less Successful Groups

**Table 5** shows the frequency of learning performance for the successful and less successful students. Out of all performance measures, only the transfer performance showed a statistical significant difference between the successful group ($M = 7.50$, $SD = 0.97$) and less successful group ($M = 4.22$, $SD = 1.09$), $t(17) = 6.92$, $p < 0.001$. The effect size ($d = 3.18$) was largest for transfer performance.

### Comparing Overview of Coded Think-Aloud Events Between Groups

A preliminary check on both groups showed that the groups were similar on mean proportion of think aloud (successful group: $M = 0.72$, $SD = 0.10$; less successful group: $M = 0.72$, $SD = 0.11$). **Table 6** shows that the groups differed significantly on the sum of metacognitive activities, and specifically monitoring. Additionally, the groups differed on frequencies of rereading activities. Moreover, in other SRL activity categories coded, successful students had higher frequencies in planning ($M = 11.20$), search ($M = 5.20$), evaluation ($M = 0.90$), elaboration ($M = 81.40$), and organization ($M = 82.10$). Both groups had the lowest frequency in evaluation activities and highest frequency in monitoring activities.

### Process Analysis of Successful and Less Successful Students

We adopted the aggregation approach of Bannert et al. (2014) to reduce complexity and prevent "Spaghetti" process models when applying the Fuzzy Miner algorithm. "Spaghetti" models are overly complex models which pose great challenges for interpretation (Günther and Van Der Aalst, 2007). Similar to their study, we aggregated three metacognitive categories (orientation, planning, and goal specification) into ANALYSIS. They further aggregated the deeper cognitive activities, elaboration, and organization. Additionally, they had only the categories, read, and repeat. However, we opted to retain all cognitive categories due to two main reasons. First, there was a statistically significant negative correlation between elaboration and organization, possibly indicating that they did not belong to one major category of deep processing. In order to find out the temporal arrangements of these activities to unravel why there was a significant negative correlation between these categories of activities, it was necessary to keep them in their individual categories, and not group them together. Second, in our study, instead of only repeat, we differentiated between superficial processing and rereading in order to capture activities related to rereading of the learning materials, notes, and essay, and copying of learning materials by writing verbatim notes. Superficial processing was represented in the model as REPEAT and rereading as REREAD.

**Figure 3** illustrates the process models for successful students and less successful students. In both groups' model, search was omitted as it did not hit the minimum significance cut-off value of 0.25, as in Bannert et al. (2014). For the successful students' model, all activities were connected – that is, every activity was connected to at least one other activity. Successful students started with preparatory activities, then they monitored as they performed various cognitive activities (ANALYSIS → MONITOR → READ/REPEAT/ORGANIZE). The model shows a double loop with ANALYSIS, MONITOR, and READ, and a double loop with ANALYSIS, MONITOR, and ORGANIZE. The successful students engaged in monitoring and control activities (MONITOR → READ, MONITOR → ORGANIZE, MONITOR → REPEAT). There was also a chain of cognitive activities students performed, shown as ORGANIZE → REREAD → ELABORATE, whereby REREAD and ELABORATE shared a mutual link. Finally, students evaluated their learning which is then connected back to analysis (EVAL → ANALYSIS). Overall, MONITOR was a dominant SRL activity, whereby it had both a high significance value of one, indicating high frequency and was connected to multiple activities. The model of the less successful students was divided into two groups of activities, with one group containing a cluster of two cognitive activities. A cluster appears in a process model when significance cut-off values are not met and events are aggregated together (Günther and Van Der Aalst, 2007). The model shows that students in this group engaged in preparatory activities as they monitored and read the learning texts (ANALYSIS → MONITOR → READ). Like in the successful group, there were double loops between these activities. The second group of activities showed the deeper cognitive activities, ELABORATE

**TABLE 4** | Correlations for self-regulated learning (SRL) activities and learning performance, $n = 29$.

| S. No | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. | Orientation | — | | | | | | | | | | | | | | | | | |
| 2. | Planning | −0.12 | — | | | | | | | | | | | | | | | | |
| 3. | Goal specification | −0.03 | 0.35 | — | | | | | | | | | | | | | | | |
| 4. | Monitoring | −0.08 | 0.15 | 0.24 | — | | | | | | | | | | | | | | |
| 5. | Search | 0.27 | −0.01 | 0.21 | 0.33 | — | | | | | | | | | | | | | |
| 6. | Evaluation | 0.07 | −0.11 | 0.23 | −0.03 | 0.18 | — | | | | | | | | | | | | |
| 7. | All metacognitive activities | 0.30 | 0.25 | 0.36 | 0.88*** | 0.43* | 0.01 | — | | | | | | | | | | | |
| 8. | Reading | −0.06 | −0.23 | −0.17 | 0.29 | −0.23 | 0.20 | 0.25 | — | | | | | | | | | | |
| 9. | Rereading | 0.24 | 0.08 | 0.14 | 0.03 | 0.67*** | 0.05 | 0.17 | −0.26 | — | | | | | | | | | |
| 10. | Superficial processing | −0.16 | 0.17 | 0.19 | 0.18 | 0.16 | 0.11 | 0.26 | −0.06 | 0.16 | — | | | | | | | | |
| 11. | Elaboration | −0.05 | 0.20 | 0.20 | −0.20 | 0.01 | 0.18 | −0.19 | −0.22 | 0.38* | −0.20 | — | | | | | | | |
| 12. | Organization | −0.03 | −0.21 | −0.14 | 0.18 | 0.30 | −0.22 | 0.15 | 0.20 | 0.03 | 0.18 | −0.62*** | — | | | | | | |
| 13. | All cognitive activities | −0.13 | −0.04 | 0.12 | 0.24 | 0.26 | 0.03 | 0.22 | 0.36 | 0.39* | −0.01 | 0.42* | 0.23 | — | | | | | |
| 14. | Motivation | 0.47** | −0.05 | 0.07 | 0.04 | 0.20 | −0.06 | 0.23 | −0.04 | 0.43* | −0.06 | 0.14 | −0.03 | 0.21 | — | | | | |
| 15. | Pre-test | 0.04 | −0.01 | 0.05 | −0.12 | 0.19 | 0.24 | −0.15 | 0.06 | 0.28 | −0.31 | 0.57** | −0.18 | 0.22 | 0.15 | — | | | |
| 16. | Post-test | 0.24 | −0.17 | −0.02 | 0.00 | 0.57††† | 0.25 | −0.01 | −0.03 | 0.34 | −0.38* | 0.30 | 0.03 | 0.19 | 0.24 | 0.69*** | — | | |
| 17. | Transfer | −0.20 | 0.04 | 0.09 | 0.44†† | 0.40† | 0.15 | 0.37† | 0.08 | 0.48** | 0.27 | 0.14 | 0.07 | 0.18 | 0.17 | 0.38* | 0.25 | — | |
| 18. | Essay | −0.06 | 0.33† | 0.39† | −0.14 | 0.25 | 0.28 | −0.11 | −0.54** | 0.39* | −0.02 | 0.69*** | −0.43* | 0.17 | 0.10 | 0.36 | 0.30 | 0.21 | — |

*As we anticipated that increased metacognitive activities lead to better learning performance, we used a one-tailed correlation analysis for all metacognitive activities and learning measures and a two-tailed analysis for the rest.*
*$p < 0.05$, two-tailed.
**$p < 0.01$, two-tailed.
***$p < 0.001$, two-tailed.
†$p < 0.05$, one-tailed.
††$p < 0.01$, one-tailed.
†††$p < 0.001$, one tailed.

**TABLE 5** | Comparison of learning measures between successful ($n = 10$), and less successful students ($n = 9$).

| | Successful students ($n = 10$) | | Less successful students ($n = 9$) | | $t$ | $p$ | $d$ |
|---|---|---|---|---|---|---|---|
| | $M$ | $SD$ | $M$ | $SD$ | | | |
| Pretest[a] | 15.70 | 3.50 | 12.89 | 3.98 | 1.64 | 0.120 | 0.75 |
| Posttest[b] | 18.80 | 2.86 | 16.00 | 3.94 | 1.79 | 0.092 | 0.82 |
| Transfer[c] | 7.50 | 0.97 | 4.22 | 1.09 | 6.92 | <0.001 | 3.18 |
| Essay[d] | 8.30 | 4.60 | 6.56 | 4.13 | 0.87 | 0.398 | 0.40 |

[a, b]*30 points.* [c]*10 points.* [d]*21 points.*

and ORGANIZE, and the metacognitive activity, evaluation (EVAL), weakly linked to the cluster which contained REREAD and REPEAT. Similar to the successful group, MONITOR had a high significance value of one, but in contrast, was linked to only two other activities.

To sum up, monitoring had a high frequency in both groups but the models looked distinctly different; the successful students' model contained a SRL cycle with all activities connected but the less successful students' model was disjointed and had deeper cognitive activities and evaluation isolated from analysis and monitoring.

## DISCUSSION

In the study presented, we investigated how students spontaneously regulated their learning, how their learning activities corresponded with learning performance, and the temporal order of SRL activities by means of process mining of *post hoc* coded think-aloud events. We compared our findings to previous studies to search for generalizability through replicability of findings with regard to SRL activities in order to identify gaps for the development of future SRL interventions. Although most of our results were parallel to previous studies, which we expected, they also pointed to some differences. We discuss our findings in more detail with respect to the specific research questions we introduced at the beginning.

With regard to our first research question, we observed activities in all categories of our coding scheme which indicated that students engaged in a range of activities in all three major phases of SRL throughout the learning session. In contrast to Bannert et al. (2014), there were more cognitive than metacognitive activities observed in our study. Frequency of monitoring activities was highest, as in their study. Frequencies of specific activities, such as planning, goal specification, evaluation, and motivation were similarly lower in our study. During the learning session, the students' main learning task was to read the text and write an essay. This is contrary to the study of Bannert et al. (2014) which had no writing task during learning. Writing is a complex and challenging task which encompasses a variety of recursive cognitive processes (Kellogg, 1987). This could have led to the students engaging in higher frequency of cognitive activities to facilitate the essay writing process, as seen in our study.

In our second research question, we investigated the relationship between SRL activities and learning outcomes by means of correlation analysis. In our analyses, we zeroed in on the transfer performance to establish coherence of findings with past studies (i.e., Bannert and Mengelkamp, 2013; Bannert et al., 2014; Sonnenberg and Bannert, 2015; Müller and Seufert, 2018). Our findings replicated the link between metacognitive activities and transfer performance as we had expected. Additionally, we found the metacognitive activity, search, and the more superficial cognitive activity, rereading, corresponding positively with transfer performance. Transfer performance was subsequently used to distinguish successful and less successful students for the last research question. A secondary finding which we did not expect was the significant negative correlation between elaboration and organization activities. A possible explanation was that due to limited time to complete the task, some students may have opted to prioritize one activity over the other. For example, some students organized their learning by taking notes extensively, while other students focused on elaborating on their learning and ideas in the essay and while learning. However, in order to understand how these activities took place during the learning session, we modeled the temporal arrangement of learning activities for the third research question.

We examined the frequencies and temporal structures of learning activities between successful and less successful students for the third research question. We first compared the frequencies of the two groups and found the SRL activity with the highest frequency for both groups to be monitoring, like in the study of Bannert et al. (2014). We also found similarly low frequencies of evaluation, goal specification, and planning, for both groups of students in our study. Although, our study used different learning tasks and materials, we found comparable patterns in the frequencies of SRL activities. Successful students engaged in higher frequencies of metacognitive activities in conjunction with deeper cognitive activities, resembling the findings by Bannert et al. (2014) who found that successful students adopted a deep level approach to learning. Rereading was also a specific activity that successful students in our study engaged significantly more frequently in than the less successful students, which we did not anticipate as it is typically known to be less effective than other strategies such as elaboration (Dunlosky, 2013). Rereading is a superficial cognitive activity (Weinstein and Mayer, 1983) usually executed by less successful students with lower deep knowledge performance (i.e., transfer; Bannert et al., 2014). Nevertheless, students who perform well include rereading strategically (i.e., when to use it) in the repertoire of activities they perform when learning (Matcha et al., 2019). Moreover, students who are skilled in text reading "not only look for

**TABLE 6 |** Absolute, relative frequencies, and test statistics of coded learning events for successful and less successful students.

| | Successful ($n = 10$) | | | | Less successful ($n = 9$) | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***M*** | ***SD*** | **Absolute frequency** | **Relative frequency** | ***M*** | ***SD*** | **Absolute frequency** | **Relative frequency** | ***t/U*** | ***p*** | ***d*** |
| **Metacognition** | | | | | | | | | | | |
| Orientation | 67.60 | 41.17 | 676 | 10.15 | 73.78 | 12.64 | 664 | 13.60 | 33[a] | 0.356 | 0.46 |
| Planning | 11.20 | 10.22 | 112 | 1.68 | 10.44 | 10.33 | 94 | 1.92 | 0.16 | 0.875 | 0.07 |
| Goal specification | 2.40 | 3.60 | 24 | 0.36 | 4.44 | 8.89 | 40 | 0.82 | –0.67 | 0.512 | –0.31 |
| Monitoring | 199.10 | 62.88 | 1991 | 29.9 | 123.78 | 58.19 | 1,114 | 22.81 | 2.7 | **0.015** | 1.24 |
| Search | 5.20 | 3.99 | 52 | 0.78 | 2.11 | 3.41 | 19 | 0.39 | 1.8 | 0.089 | 0.83 |
| Evaluation | 0.90 | 2.02 | 9 | 0.14 | 0.33 | 0.71 | 3 | 0.06 | 0.8 | 0.438 | 0.37 |
| Sum of metacognitive activities | 286.40 | 71.30 | 2,864 | 43.01 | 214.9 | 61.28 | 1934 | 39.60 | 2.33 | **0.032** | 1.07 |
| **Cognition** | | | | | | | | | | | |
| Reading | 96 | 20.34 | 960 | 14.42 | 106.9 | 58.39 | 962 | 19.70 | 43[b] | 0.905 | 0.08 |
| Rereading | 72.60 | 36.64 | 726 | 10.9 | 32.89 | 28.61 | 296 | 6.06 | 2.61 | **0.018** | 1.20 |
| Superficial processing | 3.20 | 4.73 | 32 | 0.48 | 6.33 | 18.63 | 57 | 1.17 | –0.52 | 0.613 | –0.24 |
| Elaboration | 81.40 | 51.16 | 814 | 12.22 | 70.56 | 68.25 | 635 | 13 | 0.4 | 0.698 | 0.18 |
| Organization | 82.10 | 72.11 | 821 | 12.33 | 68.78 | 54.33 | 619 | 12.67 | 0.45 | 0.658 | 0.21 |
| Sum of cognitive activities | 335.30 | 76.73 | 3,353 | 50.35 | 285.4 | 84.64 | 2,569 | 52.60 | 1.35 | 0.196 | 0.62 |
| Motivation | 2.20 | 3.22 | 22 | 0.33 | 1.33 | 1.80 | 12 | 0.25 | 0.71 | 0.490 | 0.33 |

*p values in bold are significant.*

[a, b]*assumption of homogeneity of variance violated, nonparametric test Mann-Whitney U reported.*

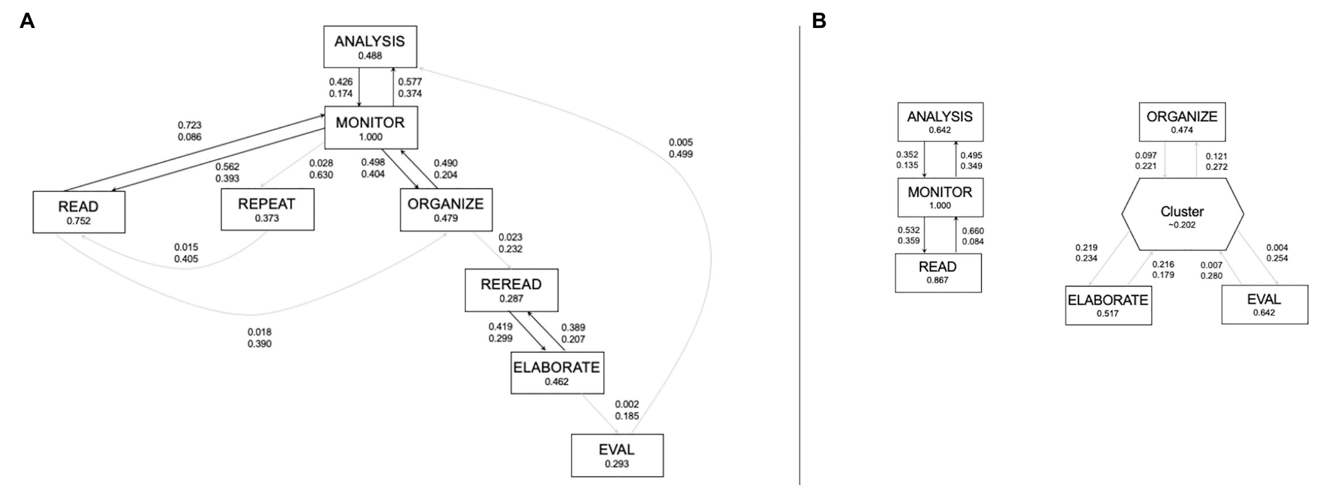


**FIGURE 3 |** Process models of **(A)** successful ($n = 10$) and **(B)** less successful ($n = 9$) students. Metacognitive activities are: orientation, planning, and goal specification (ANALYSIS), monitoring (MONITOR), and evaluation (EVAL). Cognitive activities are: reading (READ), rereading (REREAD), superficial processing (REPEAT), elaboration (ELABORATE), and organization (ORGANIZE). The cluster in the right model aggregated REREAD and REPEAT due to low significance values. Significance refers to relative importance of observed events (i.e., nodes) and the relations between them (i.e., edges). Correlation refers to how closely related two consecutive events are. Both values have a maximum of one.

important information, they process that important information differentially (e.g., rereading it, underlining it, paraphrasing it"; Pressley, 2002, p. 295). Selective rereading is often performed by skilled readers (Pressley, 2002). As shown in the process model of the successful students in our study, rereading was preceded by organization, which shared a mutual relation to monitoring. Furthermore, monitoring shared a mutual relation to reading. Successful students read the text, monitored their learning and comprehension, and processed the content deeply *via* organizational strategies and selectively reread parts of the text. Less successful students, on the other hand, read the text, monitored their learning and comprehension, but carried out other cognitive strategies subsequently, such as organization and elaboration, in an unconnected manner. To summarize, our findings indicated that successful students employed rereading strategies differently, in addition to using organization strategies an intermediate learning activity, and better integrated these strategies into their learning.

Although both groups of students utilized organizational strategies with similar frequencies during their learning, their process models revealed differences in the temporal arrangement of their activities. According to Weinstein and Mayer (1986), organizational strategies differ between basic and complex learning tasks. In basic learning tasks, students may group items into categories to remember them better. On the other hand, for complex learning tasks like in our study, students select and connect key ideas as they are learning. For example, in our learning task, successful students took notes and organized what they have learnt while monitoring their learning. Furthermore, good readers monitor their comprehension more than poor readers (Weinstein and Mayer, 1986). In the process model of the successful students, we observed that all activities, cognitive and metacognitive, were linked, as well as both superficial and deep cognitive activities, suggesting that they were able to combine and deploy different strategies during learning. Based on their monitoring, they employed various corrective strategies (i.e., reading, repeating, organizing, rereading, and elaboration). In contrast, despite the less successful students engaging in similarly diverse activities, also deeper processing of information, they demonstrated difficulty in combining these activities, leading to groups of activities which were detached from each other. Particularly, monitoring was not linked to both the deeper cognitive activities and evaluation was not linked to analysis. However, we also observed that more can be done to support the successful students. For example, the link between elaboration and evaluation was weaker and less significant than other processes such as monitor and read, and in comparison with findings from Bannert et al. (2014). To sum up, the process model of the successful students showed more congruence to SRL models proposed from theory, comprising of the three main SRL phases we introduced in the beginning. Based on the differences identified between the process models of the more and less successful students, we are able to identify SRL gaps as a basis for interventions to support SRL.

## Implications for Research and Practice

The findings we have presented illustrated some SRL processes are consistently beneficial for learning across tasks and contexts, while adopting similar methods used in Bannert et al. (2014). By means of doing so, we mitigated issues arising from granularity and categories used in the coding scheme, as well as, parameters applied during process mining. Our findings provide us insights as to which SRL processes are still lacking during learning. For example, less successful students monitor to a high extent based on frequencies, but limited to specific processes (i.e., reading and analysis) as illustrated by their process model. According to Winne and Hadwin (1998), monitoring is fundamental to SRL and occurs throughout all phases, as reflected in the process model of successful students in our study. In the current SRL models (e.g., Winne and Hadwin, 1998; Zimmerman, 2000; Panadero, 2017), students are assumed to engage in activities and processes across different SRL phases in a recursive manner. This was exemplified in the process model of the successful students, and conversely, students who did not do so, were less successful in their learning. We found that SRL needs to be performed in strategic combinations for higher effectiveness with regard to transfer performance. Therefore, our findings corroborated with previous studies which found that students who performed better regulated their learning strategically through a meaningful combination of SRL activities (Saint et al., 2018; Matcha et al., 2019). Our findings set the groundwork for developing scaffolds through the SRL gaps we have identified, which consisted not only of individual activities, but also SRL processes and patterns.

Through our study, we were able to further validate the use of think aloud as an SRL measurement approach through replication of findings from Bannert et al. (2014). Increasingly, researchers in the field of SRL have advocated for the use of nonobtrusive measurement methods and the use of trace data using various combinations of data streams has shown promising advances to detect SRL processes (Winne and Perry, 2000; Siadaty et al., 2016; Taub et al., 2017; Azevedo and Gašević, 2019). However, the issue of validity and reliability of trace data remain a challenge (Winne, 2020). Using current valid measures as presented in our study as the basis for validating other measurement protocols, such as with trace data, is one way to circumvent the issues, as per the procedure from (Fan, van der Graaf, et al., submitted) who used the think-aloud protocols as the “ground truth” for mapping SRL activities measured through trace data.

## Limitations and Future Research

Our present study had a relatively small sample size, particularly in the successful and less successful group. Despite this limitation, we considered our findings meaningful for the following reasons. First, we had a reasonably large number of data points for the coded SRL activities. Second, our results supported previous research findings, and third, we addressed the research aim of identifying students’ gaps in SRL in order to develop better scaffolds. Nevertheless, replication studies should be conducted. Our study investigated the frequency and temporal structure of SRL activities by coding and analyzing presence of these activities. However, we observed that monitoring had a significant role in students’ SRL for both successful and less successful students, but the resulting control measures differed. Our findings indicated that monitoring was linked to four activities in the successful group but limited to two activities in the less successful group. This suggests that the connection of monitoring activities with other activities (i.e., what students monitor) led to differential transfer performance. In tasks which require text comprehension, monitoring is a core skill but metacomprehension (accuracy) tends to be underdeveloped (Prinz et al., 2020) and poor monitoring accuracy have consequential effects on the use of effective control and remediation measures (Serra and Metcalfe, 2009). The present study’s learning task involved intensive text reading and comprehension through which students had to make decisions on what to read, how to read, how to proceed with the materials they have read. However, the quality of monitoring (i.e., how students monitor) was not assessed and could have led to differences in the control measures successful and less successful students carried out. We recommend that future research include further distinction of the quality of monitoring.

Although it has been established that CTA protocols do not interfere with information processing, students are only able to verbalize thoughts that are conscious (i.e., in working memory; Ericsson and Simon, 1984). Wirth et al. (2020) highlighted the issues with assuming that students are consciously self-regulating their learning at all times. Wirth et al. (2020) argued that SRL models should not be limited to active and conscious SRL but also reactive and unconscious SRL which does not induce additional cognitive load. They proposed a three-layer model (i.e., content, learning strategy, and metacognitive) respectively corresponding to the structural components of memory (i.e., sensory, working, and long-term). They propositioned that consciousness of learning and regulation occurs when they reach the working memory, through sustained and strong resonance. The term, resonance, refers to the automatic processing of information in the sensory memory through information-expectations alignment *via* interaction with the long-term memory. Whenever sensory information in a resonant state remains in the sensory memory, interaction can occur with the long-term memory without entering the working memory, thus, contributing to learning and application of SRL strategies without consciousness (and inducing cognitive load on working memory). At the metacognition layer, metacognitive regulation can occur (through resonance) without reaching consciousness. Therefore, using CTA for the measurement of SRL processes poses a challenge for the observation of unconscious SRL. Future studies need to include measurement of SRL activities beyond one methodological approach to fill the gaps present in only one data stream, such as the limitations of CTA. However, it is equally pertinent that SRL activities are measured in a valid manner, hence the complementary roles of different data sources (Fan, Lim, et al., submitted) combined and compared trace data and think aloud and calculated “match rates” – whether SRL activities detected in trace data and think aloud were congruent. They analyzed which SRL activities were observed in both data channels, and also which activities were not observed in one data channel, but the other. Through studies like these, we are able to compensate for the shortfalls of a single measurement approach.

# CONCLUSION

In conclusion, our present study investigated the consistency of findings when applying new learning contexts and tasks, in terms of SRL processes and learning outcomes, in order to continually improve our understanding of students’ SRL gaps to better design scaffolds. Process models give deeper insight to how SRL activities are connected and arranged, beyond frequency counts. Our findings demonstrated that some processes, especially when occurring in a specific sequence, are consistently beneficial even when learning in a new context and task. Future interventions need to focus not only on repertoire of SRL strategies but also knowing when to use them.

## DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

## AUTHOR CONTRIBUTIONS

LL performed the conceptualization and design of the study, data collection, coding, and analysis, and writing of the manuscript and revisions. LL and JG designed the learning environment and instruments. MB and IM provided the original think aloud coding scheme and supported the adaption of the final version. MB supervised the conceptualization and design of the study and reviewed the writing and editing. YF, JG, and JK contributed to the revision of the manuscript. MB, IM, DG, and JM conceptualized and designed the project which this study is a part of, and the revision of the manuscript. All authors contributed to the article and approved the submitted version.

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# "Because I'm Bad at the Game!" A Microanalytic Study of Self Regulated Learning in League of Legends

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Self-regulated learning (SRL) is a form of learning guided by the student's own meta-cognition, motivation, and strategic action, often in the absence of an educator. The use of SRL processes and skills has been demonstrated across numerous academic and non-academic contexts including athletics. However, manifestation of these processes within esports has not been studied. Similar to traditional athletes, esports players' performance is likely correlated with their ability to engage SRL skills as they train. Thus, the study of SRL in the context of esports would be valuable in supporting players' learning and mastery of play through specialized training and computational support. Further, an understanding of how SRL manifests in esports would highlight new opportunities to use esports in education. Existing work on SRL in games, however, predominantly focuses on educational games. In this work, we aim to take a first step in the study of SRL in esports by replicating Kitsantas and Zimmerman's (2002) volleyball study in the context of League of Legends. We compared the self-regulatory processes of expert, non-expert, and novice League of Legends players, and found that there were significant differences for processes in the forethought phase. We discuss three implications of these findings: what they mean for the development of future computational tools for esports players, implications that esports may be able to teach SRL skills that transfer to academics, and what educational technology can learn from esports to create more effective tools.

**Keywords: self-regulated learning, online learning, technology enhanced learning, gamified learning, esports, esports in education, League of Legends**

## INTRODUCTION

Self-regulated learning (SRL) broadly refers to the phenomenon by which students can self-regulate their learning process without the direct guidance of an educator (Zimmerman and Pons, 1986; Panadero, 2017) and has been shown to have a positive impact on engagement and outcome (Cleary et al., 2006; Lee et al., 2010; Liu, 2016). There are several frameworks for SRL (Hadwin et al., 2011; Panadero, 2017), but one of the most influential is Zimmerman's cyclical phase model, which splits the processes of SRL into three phases: forethought, performance, and self-reflection (Zimmerman and Pons, 1986; Panadero, 2017). Forethought encompasses skills used to plan or set goals for a learning activity, performance encompasses skills used to complete the activity and monitor one's progress toward goals, and self-reflection encompasses skills related to evaluating one's performance and adapting it for future iterations of the activity. This model, and variations of it, have been used to study SRL in several academic contexts (Zimmerman and Pons, 1986; Magno, 2010) as well as athletic contexts including basketball (Cleary and Zimmerman, 2001; Cleary et al., 2006), dart throwing (Zimmerman and Kitsantas, 1997), and volleyball (Kitsantas and Zimmerman, 2002). These studies provided valuable insights into how SRL manifests in athletics, which sparked additional exploration of SRL outside of traditional academic contexts, such as SRL in educational games (Sabourin et al., 2013; Nietfeld et al., 2014; Nietfeld, 2017).

However, there is currently no work examining how individuals apply SRL processes in the context of esports. This is in spite of the fact that esports have evolved into a multi-billion dollar industry (Media, 2021) and demonstrated real world benefits for players (Hilvoorde and Pot, 2016; Wu et al., 2021). This popularity and perceived benefits have led to esports' recognition as an official sport (esports.net, 2021) and their adoption in educational contexts (Cho et al., 2019; Lee et al., 2020). Similar to traditional athletics, esports skill is highly dependent on a player's ability to learn and master gameplay mechanics (Donaldson, 2017; Fanfarelli, 2018), and thus, SRL processes are likely correlated with one's chances of becoming a successful player. That being said, without knowledge of how SRL manifests within esports, it is currently difficult to make informed decisions about how to support learning in the context of esports play.

There are several ways that the formal study of SRL in esports could benefit both the learning and games communities. For games, and especially for esports, knowledge of how SRL manifests within the domain could highlight opportunities to more effectively support learning through specialized training or computational tools that target SRL processes (Kuan et al., 2017; Afonso et al., 2019). Further, knowledge of where SRL processes are not being leveraged by players, or where they differ across skill levels, may highlight elements of the gameplay experience where learning is more difficult. These elements may act as obstacles to novices seeking to move into higher skill-level play. As such, identifying these pain points, and developing support systems that can address them, can help prevent feelings of frustration or inadequacy, which have been known to result in discontinuation of play (Brusso et al., 2012; Esteves et al., 2021). When implemented into the games themselves, such support may result in lower churn rates.

For learning, there are two areas where more formal understandings of SRL within esports could have substantial implications. First, there could be an opportunity to use esports to train SRL skills that could then transfer to academic contexts. Existing work has already demonstrated that esports play can improve players' emotional regulation (Wu et al., 2021), fine motor skills (Toth et al., 2021), and academic performance (Rothwell and Shaffer, 2019). As such, esports have seen increased adoption as extracurricular activities in schools (Cho et al., 2019; Lee et al., 2020). If esports players are demonstrating strong SRL skills, such as reflection or goal setting, it may be that their engagement with the games themselves is teaching these skills, and this may be another benefit warranting their inclusion in schools.

Second, esports interfaces could inspire the design of future e-learning technologies that more effectively engage students. There already exist numerous data-driven tools to improve and enhance students' learning, including Open Learner Models (OLMs) (Hooshyar et al., 2020) and Learning Analytics Dashboards (LADs) (Bodily and Verbert, 2017; Bodily et al., 2018). As esport games often include data visualization systems reminiscent of these learning technologies, a better understanding of how SRL skills manifest in relation to these could provide OLMs and LADs with valuable design insights for engaging, and even playful, systems. This, along with the previous two implications, however, requires a stronger understanding of how SRL skills and processes manifest among esports players.

The work presented here is, to the authors' knowledge, the first study to empirically examine the manifestation of processes from Self Regulated Learning in the context of esports. Specifically, we replicate the study of Kitsantas and Zimmerman (2002) that examined SRL differences between novice, non-expert, and expert volleyball players. In place of volleyball, we recruited 30 League of Legends players (10 novices, 10 non-experts, and 10 experts) and collected data regarding their self-regulatory processes and gameplay practices following the exact protocol of the original study, adapted to the new context.

Our results found that the three groups differed significantly in their execution of goal setting and planning, which are termed forethought processes by Zimmerman (Zimmerman and Pons, 1986; Panadero, 2017), but not in the other phases. We suggest that League of Legends' in-game interface features, as well as external tools that are easily accessible by players at all skill levels, may be nurturing SRL skills in the performance and self-reflection phases simply through interaction with them. By contrast, skills in the forethought phase are not prominently supported by existing tools and would instead require interaction with a team or coach to develop, making them more common among expert players. Based on these conclusions, we present three implications and avenues for future work. First, we suggest that the forethought phase presents an opportunity for the development of new computational support tools for players that could help bridge the gap between novice and expert play. Second, we suggest that esports could be used to train SRL skills that may transfer to academic contexts, and propose to explore this further in future work. Third, we suggest that data-driven systems for learning may be able to leverage design standards from esports interfaces to better engage students.

## RELATED WORK

In this section we will frame the contribution of this work by providing an overview of previous work on Self-Regulated Learning (SRL) and SRL in games.

### Self Regulated Learning

There are several different theories of SRL, which, broadly, all encompass the processes and skills related to analyzing tasks, setting goals, developing strategies to reach those goals, monitoring progress toward those goals, and reviewing performance and outcomes (Puustinen and Pulkkinen, 2001; Boekaerts and Corno, 2005; Künsting et al., 2011; Winne, 2011; Panadero, 2017). The models vary, however, in how they conceptualize each aspect of SRL and what skills they emphasize (Panadero, 2017). Perhaps the most influential of SRL models, however, is Zimmerman's Cyclical Phase Model, which has influenced much of the SRL work and models that have come after (Zimmerman, 2000; Puustinen and Pulkkinen, 2001; Zimmerman and Campillo, 2003; Panadero, 2017). The Cyclical Phase Model is often used in the literature to study SRL in various academic contexts (Barnard-Brak et al., 2010; Lee et al., 2010; Malmberg et al., 2017; Min and Foon, 2019) and has been built upon by more recent SRL models (Hadwin et al., 2011; Panadero, 2017).

Building on Zimmerman's earlier models of SRL (Zimmerman and Pons, 1986; Zimmerman and Kitsantas, 1997; Magno, 2010), The Cyclical Phase Model organizes SRL processes into three phases: forethought, performance, and self-reflection (Zimmerman, 2000; Zimmerman and Campillo, 2003). An overview of this model can be seen in **Figure 1**. The forethought phase includes processes such as analyzing the task, setting goals, and planning how to reach them. The performance phase encompasses execution of the task and progress monitoring along with strategies to maintain engagement and motivation. The self-reflection phase encompasses the processes by which the learner assesses how they performed the task (Zimmerman, 2000; Zimmerman and Campillo, 2003; Panadero, 2017).

Zimmerman and his research partners also demonstrated the relevance of the Cyclical Phase Model beyond academics, through several studies that used it to examine SRL in athletic contexts (Zimmerman and Kitsantas, 2005; Zimmerman, 2006). In a 2001 study, Cleary and Zimmerman found that expert basketball players set more specific goals and technique-oriented strategies during the forethought phase and more often attributed failure to faulty technique during the self-reflective phase than non-expert or novice players (Cleary and Zimmerman, 2001). Building on this, in 2006, Cleary and Zimmerman used the Cyclical Phase Model in a study that examined the impact of the additive effects of self regulation training in forethought, performance, and self reflection processes on basketball free-throws (Cleary et al., 2006). They found that those who practiced all three phases of SRL had a significantly better shooting performance than those who only practiced one phase or none, indicating that SRL had a significant impact on overall performance (Cleary et al., 2006).

Most relevant to this work, however, is a 2002 study by Kitsantas and Zimmerman (2002) that used the Cyclical Phase Model to study differences in SRL between expert, non-expert, and novice volleyball players. They conducted a micro-analytic study in which players were asked questions about their general practice techniques for learning and mastering overhand serves. They were then asked to perform before the researchers and answer additional questions about how they felt they did and why they may have failed (Kitsantas and Zimmerman, 2002). The results found that experts set better goals and had better planning during the forethought phase, better strategy use and self-monitoring during the performance phase, and better evaluations, attributions and adaptations during the self-reflection phase than either non-experts or novices (Kitsantas and Zimmerman, 2002).

Together, this literature paints a clear picture of the significant role that SRL plays in athletics, which can be used to better understand how to help athletes gain expertise (Zimmerman and Kitsantas, 2005; Zimmerman, 2006). However, with the rise of esports comes the question of whether or not these findings are applicable to the new domain. Unfortunately, this remains an open question, as much of the work on SRL in the context of digital games focuses almost exclusively on educational games (Nietfeld, 2017).

## Self Regulated Learning in Games

In the context of digital games, SRL is notably under-studied, and much of the existing work focuses almost entirely on educational games (Nietfeld et al., 2014; Nietfeld, 2017). For example, Sabourin et al. (2013) generated SRL scores for students who played the educational game *Crystal Island* (Rowe et al., 2009) based on their responses to a reflective prompt. They found that SRL scores were significantly predictive of post-test learning gains and that high-SRL students appeared to make more use of the in-game curricular resources than low-SRL students and reported more immersion, interest, and enjoyment (Sabourin et al., 2013).

Reflective, or self-explanation prompts, are, in fact, one of the most common ways that self-regulated learning has been implemented in educational games, and some of the literature has studied the impact of this design (Nietfeld, 2017). For example, ONeil et al. (2014) added a self-explanation prompt, which encouraged self-reflection processes, to an educational math game and found that students who responded to the prompts tended to have higher mean post-test scores than those who did not. Similarly, Fiorella and Mayer (2012) found that adding prompts to a game that taught electrical circuits significantly increased student performance.

Another area of interest for SRL in games is goals (Nietfeld, 2017). This is unsurprising, given that gameplay is often driven by the pursuit of goals (Lankoski, 2011). Several studies have examined the impact of different kinds of goals on performance in game-based learning. For example, Künsting et al. (2011) examined the impact of type and specificity of goals in a game-based learning environment that taught buoyancy concepts. Their results found that non-specific problem-solving goals yielded substantially more frequent strategy use from learners, but that this was not the case when the goals were learning goals (Künsting et al., 2011). Feng and Chen (2014) examined a similar question, but in the context of educational game design through Scratch (Resnick et al., 2009). Their results demonstrated that students with non-specific goals outperformed those with more specific goals and that students with structuring scaffolds demonstrated worse SRL (Feng and Chen, 2014).

While all of this work demonstrates the role that SRL can and does play in games, it focuses entirely on educational games and, in most cases, on the impact SRL has on players' learning of the educational content (Künsting et al., 2011; Fiorella and Mayer, 2012; Feng and Chen, 2014; ONeil et al., 2014). In contrast, there is currently little work that examines the role that SRL plays in

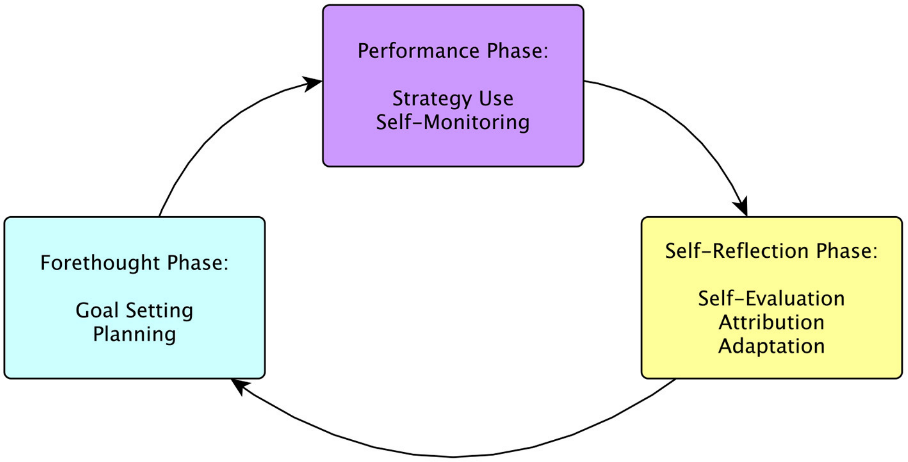


**FIGURE 1 |** An overview of the cyclical phase model of self-regulated learning highlighting the specific processes examined in this work and which phase they belong to.

learning the skills and mechanics involved in playing a game. Brusso et al. (2012) provide one of the only examples of work that examines SRL skills in relation to gameplay performance itself. In their study, they investigated the impact of unrealistic performance goals on player performance in a first-person-shooter game (Brusso et al., 2012). They found that those whose performance fell short of their goal would perform significantly worse in subsequent levels than those whose performance more closely matched their goal. Further, they found that this was significantly more common for those players with high video-game self-efficacy (Brusso et al., 2012). This demonstrates that SRL plays a role in games beyond education. Specifically, SRL skills, such as goal setting, can have an impact on gameplay performance. In the context of esports, knowledge of the role and impact of SRL would be invaluable to helping players more effectively learn and gain expertise, which is often cited as the primary motivation for the development of computational support tools for esports (Wallner and Kriglstein, 2016; Kuan et al., 2017; Afonso et al., 2019).

**FIGURE 2 |** The league of legends game map. On the bottom left is the base for the green team, on the top right is the base for the red team. These are linked by three lanes, and the areas between the lanes are the jungles. The lanes contain towers that fire at enemy players and must be destroyed to advance toward the enemy base. Image reproduced with permission from Riot Games Inc. This image is copyrighted to Riot Games Inc.

# METHODS

We chose Kitsantas and Zimmerman (2002)'s study as it provided a foundational overview of how SRL skills relate to expertise in athletics, which we felt was transferable to the esports context. Additionally, we found the protocol to be easily translatable to League of Legends, a digital, online game. The study was carried out from May to July 2021 and COVID19 required the study to be conducted remotely over Zoom. In this section we will outline the steps we took to recreate this study.

## League of Legends

League of Legends is an esport game developed by Riot games and belonging to the Multiplayer Online Battle Arena (MOBA) genre. The game is played by two teams of five on a square map (see **Figure 2**) where each team has a base in either the lower left (for the green team) or upper right (for the red team) corner of the map. The bases house a crystal called a "Nexus" and the goal for each team is to reach and destroy the opposing team's nexus. The rest of the map consists of three lanes which extend from base to base and are referred to as top (for the one that follows the left and top edges of the square map), middle (for the one that cuts diagonally across the center of the square), and bottom (for the one that follows the bottom and right edges of the square map). There are also forested areas between the lanes, referred to as the "jungle."

A League of Legends team typically has players play on one of five designated roles: top (usually a high defense character, starts in the top lane), mid (usually a powerful attacker, starts in the mid lane), jungler (usually a character with high mobility and skills like health regeneration that help it survive, moves around the jungles), adc (another powerful attacker, starts in the bottom lane), and support (usually has healing or shielding abilities, helps the adc in the bottom lane). The three lanes each house six towers (three for each team) that fire lasers at opposing entities and must be destroyed in order to reach the enemy base. The jungle, by contrast, is home to various monsters that can be killed for gold or experience points.

In order to win a match of League of Legends, players must gain experience to level up their characters, gold to buy items to make their characters stronger, and win battles against enemy players in order to destroy the opposing towers and advance across the map. We chose League of Legends for the study due to its immense popularity as an esport game (leaguefeed.net, 2021). Additionally, because it is part of the extremely popular MOBA genre of esports, which also includes titles such as DOTA2 and Heroes of the Storm, we believed the results of this study would be indicative of general trends across multiple games.

## Last Hitting

We chose last hitting as the skill to focus on in this study, whereas the original study focused on overhand serves. In League of Legends, there are small non-player character (NPC) entities called minions or "creeps," which march down the lanes from the two bases and attack nearby enemy minions, players, or towers and grant gold and experience to players when killed. More gold and experience are awarded to the player who deals the finishing blow, which is advantageous to players as the experience allows them to level up and the gold can be used to buy equipment, both of which make them stronger. The act of intentionally dealing finishing blows is referred to as "last hitting" and is a strategic maneuver that involves carefully timing one's attacks to ensure that the finishing blow to an enemy minion can be dealt by the player rather than their own minions or tower. The number of minions a player has last hit is referred to as their creep score (CS). Last hitting is widely considered to be relatively easy to understand, but difficult to master from a technical standpoint, which makes it similar, conceptually, to the overhand serves that were the focus of Kitsantas and Zimmerman's volleyball study (Kitsantas and Zimmerman, 2002).

## Recruitment

30 League of Legends players were recruited to participate: 10 experts, 10 non-experts, and 10 novices, following the participant breakdown of the original study. In the context of League of Legends, the line between expert, non-expert, and novice is not as clear as it is in traditional sports contexts. Further, complete beginners would lack the technical knowledge (i.e., how to navigate or attack in-game) to complete the study's steps. Thus, we worked with a collegiate League of Legends coach to define the three skill levels based on criteria appropriate to the esports context. These were as follows:

- Expert referred to someone who currently played (or had played in the past) on an established, competitive team and participated (or had participated in the past) in formal competitions.
- Non-Expert referred to someone who currently played (or had played in the past) with one or multiple informal teams (i.e., a team comprised of a group of friends) in a recreational manner, who may have played ranked games but did not participate in formal competitions.
- Novice referred to someone who only played on pick-up teams (i.e., solo-queue) and did not play competitively at any point.

Skill level was self-reported by prospective participants when filling out an online recruitment form. The 10 experts were recruited from collegiate League of Legends teams at several North American universities. The non-experts and novices were recruited through convenience sampling and social media ads. All participants received a 30$ Amazon gift card as compensation.

27 participants identified as male, 2 as female, and 1 as non-binary. Age ranged from 18 to 39 and the average age was 22. Race information was not collected. The average age for experts was 20.1, for non-experts was 21.9, and for novices was 24.5. On average, expert players had 5.75 years of experience, non-experts had 4.8, and novices had 4.9. Novices had a slightly higher average due to several players who had been playing for a long time but never beyond the novice level. Across the entire sample, 2 players played jungle (both experts), 8 played top lane (two experts, three non-experts, and three novices), 5 played mid lane (three non-experts and two novices), 9 played adc (five experts, one non-expert, and three novices), 5 played support (one expert, two non-experts, and two novices), and one (a non-expert) played fill (all positions).

To assess their general knowledge of last hitting, participants were asked to describe a last hit "as if they were explaining it to someone who did not know what it was." Responses were written down verbatim by the lead researcher. These were scored according to a rubric developed in collaboration with a League of Legends coach. Participants' responses were awarded a point for each of the following they mentioned:

- Timing (when to strike the minion)
- Wave management (pushing, pulling, or freezing the wave)
- Trade patterns/opponent presence (knowing how to last hit around an enemy)
- Champion/role differences (different characters and roles CS differently).

As there were four elements, participants could score up to four points, however, no player scored perfectly. The mean of experts' knowledge of last hitting was 1.8, the mean of non-experts' knowledge was 1.3, and the mean for novices' knowledge was 1.4. The low means are likely the result of the lack of a definitive definition of the skill within the gameplay community, with many players knowing what it is and how to perform it but struggling to articulate it in words. The low means are not of concern to this study, as all players were shown the same instructional video on how to perform a last hit after giving their description.

## Procedure

Following the collection of demographic data and knowledge of last hitting, in line with the protocol used by Kitsantas and Zimmerman (2002), all participants were shown the same video about how to execute a last hit. They were then asked a set of questions regarding their self-efficacy, perceived instrumentality of last hitting, intrinsic interest in last hitting, goal setting, and planning (measures described below).

Following these questions, participants were instructed to open the League of Legends practice tool, where they could create a custom, solo game with no other players and practice last hitting for 10 min. Participants were instructed to share their screen at this point so the attending researcher could observe. Participants used their own accounts and were instructed to select any character that they were comfortable last hitting with, to ensure that familiarity with the character's skills would not confound the results. They were instructed to buy their usual starting equipment when the game loaded and proceed to the middle lane. They were also instructed not to leave the lane to explore the jungle or buy more equipment. This was to ensure that all participants spent the same amount of time last hitting in the lane. Following the practice session, participants were asked about their strategy use, self-monitoring, self-evaluation, and self-satisfaction during the session (measures described below).

Participants were then tested for last hitting skill, and asked to create a second game in the practice tool with the same arrangement. This time, however, they would only last hit until they missed a last hit. All participants did miss a last hit. At this point they were asked about their attributions, adaptation processes, and self-efficacy perceptions (measures described below). Participants were then debriefed and thanked by the researcher, who also answered any questions they had about the study. Participants received their payment via email after completion of the session. The protocol was carried out by one researcher and was reviewed and approved by the university's institutional review board.

## Measures

### Last Hitting Skill

League of Legends tracks how many last hits a player has achieved in a user-interface (UI) element in the upper right corner of the screen. Last hitting skill was evaluated based on this number at the point at which the player missed the last hit during the second custom game.

### Measures of Self Motivation

The questions for the measures of self-motivation were adapted directly from those used by Kitsantas and Zimmerman (2002). All participants were asked the following questions to measure the respective factors:

- "On a scale from 0 to 100 with 10 being Not Sure, 40 being Somewhat Sure, 70 being Pretty Sure, and 100 being Very Sure, how sure are you that you are able to last hit every creep in a given wave?" (Self-Efficacy). This was asked once before practice and again after missing a last hit during the second custom game.
- "How interesting is last hitting to you on a scale from 0 to 100 with 10 being Not Interested, 40 being Somewhat Interested, 70 being Pretty Interested, and 100 being Very Interested" (Intrinsic Interest). This was asked once before practice.
- "How important is last hitting skill in attaining your future goals on a scale from 0 to 100 with 10 being Not Important, 40 being Somewhat Important, 70 being Pretty Important, and 100 being Very Important" (Perceived Instrumentality). This was asked once before practice.
- "On a scale from 0 to 100 with 10 being Not Satisfied, 40 being Somewhat Satisfied, 70 being Pretty Satisfied, and 100 being Very Satisfied, how satisfied are you with your performance during this practice session?" (Self-Satisfaction). This was asked once after practice.

### SRL: Forethought Phase

**Goal Setting:** Before practice, all participants were asked "Do you set any specific goals for your sessions when practicing last hitting and if yes, what are they?" The researcher recorded the answer verbatim. The goals were then coded independently by two researchers into one of the following categories: outcome goals, technique of process goals, other, and no goals, the same scale used by Kitsantas and Zimmerman (2002). For the context of League of Legends, the categories were considered as follows:

- "Outcome goals" referred to statements related to getting a certain number of last hits or amount of gold.
- "Process goals" referred to statements related to managing opponent presence or number and positioning of creeps in the lane.
- "Other" referred to any statements that did not discuss either of the above.

These definitions were developed and agreed upon by two researchers with extensive League of Legends experience. Cohen's kappa (Cohen, 1960) was used to check for agreement and resulted in a score of .9, indicating very strong agreement (Landis and Koch, 1977).

**Planning:** Also before practice, participants were asked "Do you have a regular routine that you follow when you practice on your own?" The responses were again recorded verbatim and coded by two researchers into one of the following categories: completely structured routine, partially structured routine, or unstructured routine, the same scale used by Kitsantas and Zimmerman (2002). For the context of League of Legends, these were defined as follows:

- A "completely structured routine" referred to discussions of regular practice using the practice tools or regularly playing warm up games in less competitive game modes.
- A "partially structured routine" referred to discussions of staying in practice by just playing regularly or irregular practice sessions.
- An "unstructured routine" referred to discussions of not practicing.

These definitions were developed and agreed upon by the same two researchers with extensive League of Legends experience. There were no disagreements in the code applications resulting in a kappa value of 1, indicating perfect agreement (Landis and Koch, 1977).

### SRL: Performance Phase

**Strategy Use:** Two questions were asked regarding strategy use, echoing Kitsantas and Zimmerman's protocol (Kitsantas and Zimmerman, 2002). These were:

- "What do you need to do to accomplish your goals?" (Asked before practice)
- "What do you need to do to successfully execute the last hit next time?" (Asked after missing a last hit during the second custom game).

These were again recorded verbatim and coded by two researchers into one of the following categories: specific technique, visualization strategies, concentration strategies, both, and practice/no strategies, the scale used by Kitsantas and Zimmerman (2002). For the context of League of Legends these were defined as follows:

- "Specific technique" referred to discussions such as getting the timing right, using the right skill, or targeting the right minion.
- "Visualization strategies" referred to any discussion of visualizing or imagining oneself doing it correctly.
- "Concentration strategies" referred to any discussion of focusing or concentrating either in general or on a specific aspect of gameplay.
- "Technique and concentration" referred to responses that included both.
- "Practice/no strategy" referred to answers that just discussed practicing or did not discuss any strategy.

These definitions were developed and agreed upon by the same two researchers. Cohen's kappa resulted in a score of .91 for the first question and .83 for the second, both indicating very strong agreement (Landis and Koch, 1977).

**Self-Monitoring:** After the practice session, all participants were asked "How did you monitor your performance and progress during the practice session?" These were again recorded verbatim and coded by two researchers into one of the following categories: creep score alone (corresponding to Kitsantas and Zimmerman's 'service outcome points alone'), use of technique or form and its outcomes, do not know, or other, the scale used by Kitsantas and Zimmerman (2002). For the context of League of Legends these were defined as follows:

- "Creep score alone" referred to discussions of tracking the number of last hits achieved, either in one's head or using the UI's CS score board.
- "Use of technique or form and its outcomes" referred to discussions of technical execution of the skill, such as making sure the minions were in the right spot or managing their numbers.
- "Do not know" referred to statements indicating that they did not monitor their performance or were not sure if they did.
- "Other" referred to any self monitoring strategy that did not correspond with the above.

These definitions were developed and agreed upon by the same two researchers. There were no disagreements in the code applications resulting in a kappa value of 1, indicating perfect agreement (Landis and Koch, 1977).

### SRL: Self-Reflection Phase

**Self-Evaluation:** Also after the practice session, participants were asked "Did you evaluate your performance during the practice session? If so, how?" These were again recorded verbatim and coded by two researchers into one of the following categories:

- Self-evaluator (if they responded yes and gave a reasonable example of self-evaluation)
- Non-self-evaluator (if they responded no or failed to give a reasonable example of self-evaluation).

These are exactly the categories used by Kitsantas and Zimmerman (2002) and did not need to be adjusted to the context of League of Legends due to the general definitions. There were no disagreements in the code applications resulting in a kappa value of 1, indicating perfect agreement (Landis and Koch, 1977).

**Attributions:** After missing a last hit, participants were asked "Why do you think you missed the last hit?" These were again recorded verbatim and coded by two researchers into one of the following categories: form or technique, power, ability, practice, concentration, and do not know, the scale used by Kitsantas and Zimmerman (2002). For the context of League of Legends, these were defined as follows:

- "Form or technique" referred to discussion of strategic failures such as wave or health management or player positioning.
- "Power" referred to discussion of physical failures such as reaction time or mis-clicks.
- "Ability" referred to discussion of one's gameplay skill.
- "Practice" referred to discussions of practice (i.e., needing more).
- "Concentration" referred to discussions of focus.

These definitions were developed and agreed upon by the same two researchers. Cohen's kappa resulted in a score of 0.78, indicating strong agreement (Landis and Koch, 1977).

**Adaptation:** After missing a last hit, all participants were asked the following three questions, answered with either a "yes" or "no," following Kitsantas and Zimmerman's protocol (Kitsantas and Zimmerman, 2002):

- "After missing last hits, do you think about why you missed?"
- "When you miss a last hit, do you change anything during your next attempt?"
- "If you repeatedly miss last hits, do you ask your coach or teammates to give you feedback or advice?"

## RESULTS

Shapiro-Wilk tests were used to check for normal distributions of the numerical self-motivation data. Test results indicated that the data was not normally distributed, and thus non-parametric Mann-Whitney tests and Kruskal-Wallis tests were used for these data. Chi-square tests were used to assess differences for categorical data.

Between knowledge of last hitting, years of experience, and age, only years of experience was normally distributed. According

**TABLE 1 |** The means and standard deviations for creep score for each group.

| Group | Mean | STDEV | Median |
|---|---|---|---|
| Experts | 17 | 12.9 | 11.5 |
| Non-experts | 15.1 | 19.1 | 9 |
| Novices | 8.4 | 12 | 5 |

**TABLE 2 |** The means and standard deviations for the five measures of self-motivation.

| Variable | Experts | Non-experts | Novices |
|---|---|---|---|
| **Self-efficacy (Before practice)** | | | |
| Mean | 79 | 58 | 58 |
| St. dev | 14.5 | 21 | 15.5 |
| Median | 70 | 70 | 70 |
| **Self-efficacy (After missing)** | | | |
| Mean | 76 | 55 | 55 |
| St. dev | 19 | 25.5 | 25.5 |
| Median | 70 | 70 | 55 |
| **Intrinsic interest** | | | |
| Mean | 64 | 43 | 70 |
| St. dev | 31 | 26.3 | 24.5 |
| Median | 70 | 40 | 70 |
| **Perceived instrumentality** | | | |
| Mean | 91 | 79 | 82 |
| St. dev | 14.5 | 20.2 | 25.3 |
| Median | 100 | 70 | 100 |
| **Self-satisfaction** | | | |
| Mean | 73 | 73 | 58 |
| St. dev | 17 | 17 | 25.3 |
| Median | 70 | 70 | 70 |

to two-tailed $t$-tests used for years of experience, and Mann-Whitney tests used for knowledge and age, there were no significant differences between groups.

## Last Hitting Skill

Last hitting skill was determined using the creep score, or number of creeps last hit, each player earned during the second custom game (when they were asked to last hit until they missed one). The means and standard deviations for each group are shown in **Table 1**. Kruskall-Wallis results indicate that the differences between all three groups are not statistically significant ($p > 0.05$).

## Measures of Self-Motivation

Due to the non-normal distribution of the data, Kruskall-Wallis tests with Bonferroni corrections were used to check for significant differences for each variable. The means and standard deviations are shown in **Table 2**. Kruskall-Wallis results indicated that the differences between groups were not significant ($P > 0.05$) for all measures except for the Self-Efficacy (Before Practice) measure ($H = 8.35$, $P = 0.01$, Degrees of Freedom = 2). Mann-Whitney pair-wise test results with Bonferroni corrections indicate that experts had significantly higher self-efficacy at this point than novices ($U = 79$, $P = 0.01$). Non-experts did not differ significantly from novices or experts at this point ($P > 0.016$). There were no significant differences between groups at the second self-efficacy measurement due to the changes in mean and standard deviation. Mann-Whitney results indicate that these changes from before to after were also not significant.

**TABLE 3 |** An overview of how different types of goals were set across the three skill levels.

| Forethought: Goal setting | Experts | Non-experts | Novices |
|---|---|---|---|
| Outcome goals | 5 | 6 | 0 |
| Process goals | 3 | 2 | 7 |
| Other goals | 0 | 2 | 1 |
| No goals | 2 | 0 | 2 |

**TABLE 4 |** An overview of how different routines were used across the three skill levels.

| Forethought: Planning | Experts | Non-experts | Novices |
|---|---|---|---|
| Completely structured | 5 | 1 | 0 |
| Partially structured | 4 | 5 | 2 |
| Unstructured | 1 | 4 | 8 |

## Self-Regulated Learning Processes

In the following sub-sections we discuss the results regarding how players at different skill levels engaged SRL processes across the three phases of Zimmerman's model.

### Forethought Phase

**Goal Setting:** There were significant differences in goal setting among the three expertise groups [$\chi^2_{(6)} = 13.1$, $P = 0.04$]. The counts for each goal type for each skill level can be seen in **Table 3**. Cramer's V was calculated to determine effect size and the result ($w = 0.46$) indicates a medium to large effect size.

**Planning:** There were significant differences in planning among the three expertise groups [$\chi^2_{(4)} = 14$, $P = 0.007$]. The counts for each goal type for each skill level can be seen in **Table 4**. Cramer's V was calculated to determine effect size and the result ($w = 0.48$) indicates a medium to large effect size.

### Performance Phase

**Strategy Use:** There were no significant differences for strategy use before practice [$\chi^2_{(8)} = 6.94$, $P > 0.05$] or after missing last hits [$\chi^2_{(4)} = 4.26$, $P > 0.05$]. The counts for each strategy type for each skill level can be seen in **Table 5**. For the second question, asked after missing last hits, "Visualization Strategies" and "Practice/No Strategy" were never applied to the participants' statements by the two researchers.

**Self-Monitoring:** There were no significant differences between the groups for self-monitoring [$\chi^2_{(4)} = 5.97$, $P > 0.05$]. The counts for each technique for each skill level can be seen in **Table 6**. "Do Not Know" was never applied to the statements by the two researchers.

**TABLE 5 |** An overview of how different strategies were used across the three skill levels at both question times.

| Performance: Strategy use | Experts | Non-experts | Novices |
|---|---|---|---|
| **Before practice** | | | |
| Specific techniques | 2 | 4 | 4 |
| Visualization | 2 | 0 | 0 |
| Concentration | 3 | 3 | 1 |
| Technique and concentration | 1 | 1 | 1 |
| Practice/None | 2 | 2 | 4 |
| **After missing** | | | |
| Specific techniques | 5 | 6 | 6 |
| Concentration | 1 | 3 | 3 |
| Technique and concentration | 4 | 1 | 1 |

**TABLE 6 |** An overview of how different self-monitoring techniques were used across the three skill levels.

| Performance: Self-monitoring | Experts | Non-experts | Novices |
|---|---|---|---|
| Points | 9 | 5 | 6 |
| Technique | 1 | 5 | 3 |
| Other | 0 | 0 | 1 |

**TABLE 7 |** An overview of how self-evaluation occurred across the three skill levels.

| Reflection: Self-evaluation | Experts | Non-Experts | Novices |
|---|---|---|---|
| Yes | 9 | 8 | 10 |
| No | 1 | 2 | 0 |

**TABLE 8 |** An overview of attribution types across the three skill levels.

| Reflection: Attributions | Experts | Non-experts | Novices |
|---|---|---|---|
| Form and technique | 5 | 5 | 5 |
| Power | 3 | 3 | 4 |
| Concentration | 2 | 2 | 1 |

### Self-Reflection Phase

**Self-Evaluation:** There were no significant differences between the groups for self-evaluation [$\chi^2_{(2)} = 2.2$, $P > 0.05$]. The counts for self-evaluation for each skill level can be seen in **Table 7**.

**Attributions:** There were no significant differences between the groups for attribution [$\chi^2_{(4)} = 0.6$, $P > 0.05$]. "Ability," "Practice," and "Do Not Know" were never applied to the attribution statements by the two researchers. The counts for the remaining attribution types across the skill levels can be seen in **Table 8**.

**Adaptation:** The responses for the three adaptation questions can be seen in **Table 9**. Chi square tests indicated no significant differences between groups (all $P > 0.05$).

**TABLE 9 |** The number of people in each group who said yes and no for each of the adaptation questions.

| Reflection: Adaptation | Experts | Non-experts | Novices |
|---|---|---|---|
| Do you think about it? | | | |
| Yes | 6 | 5 | 5 |
| No | 4 | 5 | 5 |
| Do you change anything? | | | |
| Yes | 4 | 7 | 7 |
| No | 6 | 3 | 3 |
| Do you ask for help? | | | |
| Yes | 3 | 4 | 4 |
| No | 7 | 6 | 6 |

## DISCUSSION

Our findings suggest that the only significant differences in SRL processes between League of Legends skill levels exist in the forethought phase. In this section, we discuss possible reasons for these findings, and their implications on future work.

### Differences Between Expertise Levels and Contexts

We observed significant differences in how players engaged SRL processes in the forethought phase. Specifically, novices discussed process goals more than non-experts and experts. This is in line with previous work that found that players seemed to shift from process to outcome goals as they obtained more skill (Zimmerman and Kitsantas, 1997). We also saw, however, that there was one more non-expert than expert who mentioned outcome goals. While we can make no real claims based on a one-participant difference, it is possible that, in the domain of esports, there may be a shift back toward process goals at the highest skill levels. This is somewhat supported by some of the statements made by expert players who discussed process goals, for example "I'm not that focused on last hitting to get the minions because I find that somewhat easy, like it comes second nature to me now, there's other stuff I take into more account when I play and try to secure my farm. So like uh wave management, mainly, that's more important to me than last hitting to secure minions, and obviously just like not screwing up the lane and dying randomly" (Participant 16, Expert). This may be because the desired outcome for last hitting is generally understood to be about 10 creeps per minute (for a total of 100 at 10 min). It may be that high-level players understand this as their desired outcome and revert to focusing on process in order to identify execution errors that may hinder it. Another quote from an expert player that suggests this is "[I will] see if I can get all of the CS when the wave is sitting in the middle, when I'm pushing, freezing, when I'm under tower. There's so many scenarios for where the minion wave is at and I want to make sure I can adjust and reach goals in every situation." (Participant 4, expert).

For planning, we observed that more advanced players had significantly more structured practice routines than novice players. This is likely the result of novice players being less

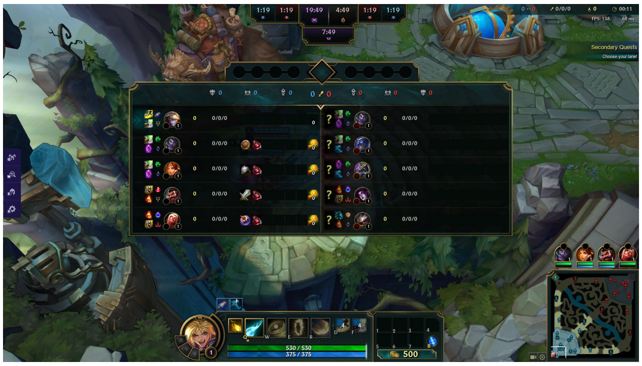

**FIGURE 3 |** The League of Legends in-game UI presents information about player performance including kill counts, gold, experience earned, and creeps killed while playing the game. Image reproduced with permission from Riot Games Inc. This image is copyrighted to Riot Games Inc.

interested in competitive play, and therefore less motivated to pursue structured practice, instead choosing to play games for leisure, as articulated by Participant 22 (novice): "No, usually I just jump right into a game and go from there." Further, advanced players are more likely to play in formal contexts, on teams or with coaches, making it easier for them to access structured practice routines, or those who can design them, than novices, who are often playing on their own. These findings are consistent with those discussed by Kitsantas and Zimmerman (2002), suggesting that this is an area where esports and traditional sports share common ground. In other words, our results indicate that novice League of Legends players, like novice volleyball players, are more often engaged in casual play than structured training.

Interesting, however, is that there were no significant differences in SRL processes for any other phase of SRL or for the measures of self-motivation, which are in sharp contrast to the findings of Kitsantas and Zimmerman (2002), which indicated significant differences across all phases. A likely explanation for the lack of differences in the performance and self-reflection phases may be found in the design of League of Legends itself. During play, the game tracks all participating players' progress information including gold amounts, level, enemy players killed, and, of course, creeps killed. This information is visible to any player in the game either in small menus on the boarder of the screen or through a dashboard that can be accessed with the press of a button, see **Figure 3**. Participant responses to the self-monitoring and self-evaluation questions indicated that they were making use of these interface elements to monitor their progress during play, and that they do so on a regular basis. For example: "biggest thing is just looking at my CS vs. time elapsed" (Participant 19, non-expert) and "Mainly I just check the scoreboard, check my CS and stuff" (Participant 29, novice). Thus, it is possible that the design of the game itself is encouraging players to engage in self-monitoring practices whenever they play.

A similar situation may be the reason for the lack of significant differences in the self-reflection phase. When a match of League of Legends ends, all players are brought to a post-game screen that depicts how much each player in the game contributed and offers an assessment of their performance, see **Figure 4**. Additionally, the game client features a statistics interface that stores players' performance data over time and presents it to the player in aggregate graphs that depict how the player performs in comparison to other players, see **Figure 5**. There also exist a number of third-party tools that present players with similar information, outside of the game client (Blitz.gg, 2021; Mobalytics, 2021; SENPAI.gg, 2021). While participant responses did not mention these screens or tools in the context of the study, it is likely that their presence encourages players to reflect on their performance, especially the post game screen, which is automatically shown to all players upon completion of a match. Players who are particularly motivated to improve at the game likely spend a fair amount of time interacting with these screens in order to extract actionable insights. In other words, these screens likely encourage players to engage in self-reflection processes.

These observations resonate with existing theoretical discussions on the role of visualized data within the player experience (Medler, 2011; Medler and Magerko, 2011; Bowman et al., 2012; Hazzard, 2014) and personal informatics and quantified self in the context of games (Kou and Gui, 2018; Rapp, 2018). Specifically, previous work has discussed how game data visualization, specifically player dossiers, which present players with data on their gameplay performance over time, motivates continuous play and facilitates improvement (Medler, 2011; Bowman et al., 2012). The results of this study suggest that the improvement that comes about as a result of interaction with this visualized data may be because the visualizations encourage the execution of self-regulated learning processes. This suggests further opportunities to support players seeking to improve at gameplay through the development of visualizations of their gameplay data.

In summary, players are engaging SRL processes in the performance and self-reflection phases simply through interaction with the game's interface. Because all players at all skill levels interact with the same interface, there are few significant differences. With this in mind, the significant differences in planning and goal setting are likely the result of the game lacking any interface or interaction that supports SRL during the forethought phase. League of Legends itself provides little guidance on how to practice effectively, meaning that players must turn to external resources. Existing literature acknowledges this phenomenon of players seeking out external resources (Taylor, 2006; Consalvo, 2009), and it is likely that there is a connection between SRL processes and skills and one's ability to seek out the correct resources. It may be that most novice players have not sought these resources and therefore have not developed the same SRL skills for the forethought phase as their more skilled counterparts. Also worth noting is that most of the third-party tools that exist for League of Legends do not aim to help players with goal setting or training routines. Coaches are ultimately the best resource in this area, but non-expert and novice players are less likely to have access to coaches than expert players, resulting in significant differences. This may be a point of concern, as uncertainty in how to gain skill or set realistic goals could result in frustration and discontinuation of play (Brusso et al., 2012; Esteves et al., 2021), leading to higher churn rates.

It is also necessary to acknowledge that the differences between the results of this study and the results of Kitsantas and Zimmerman (2002)'s study are likely also influenced by the nature of the game and what it means to be a novice of that game. League of Legends requires players to complete a tutorial before beginning play, meaning that complete beginners, and certainly novices, possess some basic knowledge of gameplay and terminology. By contrast, volleyball novices recruited from a public court, such as those in Kitsantas and Zimmerman (2002)'s study, may or may not have ever looked at any formal documentation on how to play. While this does not necessarily make one game easier than the other, it does suggest an inherent difference in the knowledge level of novice players, which may explain the lack of statistical difference in knowledge of last hitting.

## Implications

We identify three main areas where our findings have noteworthy implications for future research and development, which we discuss below. We also note that our findings and the implications we discuss in this section may not be unique to esports and may apply to digital games at large. We hope to explore this further in future work.

### Computational Support for Esports

The first area in which these results have implications is in the domain of computational support for esports. A great number of computational tools for esports exist, which broadly provide players with assistance in decision making (Chen et al., 2018a,b; Christiansen et al., 2019; Eger and Sauma Chacón, 2020) and review of gameplay (Wallner and Kriglstein, 2016, 2020; Kuan et al., 2017; Afonso et al., 2019). These tools are often explicitly motivated by the desire to help players learn and master their game. Based on our results, future tools can be designed with SRL in mind. Specifically, we see that novices differ greatly in their execution of SRL processes in the forethought phase compared to non-experts and experts. Thus, a targeted and effective way to assist novices through computational support may be through the development of tools that directly address this specific phase. Specifically, tools that can help novices with goal setting and practice regimens may be beneficial, especially since previous work has shown that unrealistic goals can lead to worse performance (Brusso et al., 2012). While computational tools designed for the other phases may also be helpful to players, the lack of statistically significant differences in SRL processes in these phases indicates that players, especially novice players, may not need additional support in these areas.

### Transferring SRL Skills From Esports to Academics

The second implication of these results is that esports may be an engaging way to train SRL skills that can transfer to academic contexts. In the learning literature, transfer is defined as the extent to which a student can apply a learned knowledge or skill to new situations different from the learning context (Perkins and Salomon, 1992). The literature also defines two types of transfer: near transfer, referring to transfer occurring in a new situation that resembles the learning context where the knowledge or skill is learned, and far transfer, referring to transfer occurring in situations where the learning context is very different (Schuster et al., 2020). So far, transfer of SRL from games to academics has predominantly focused on educational games (Nietfeld, 2017), which are primarily examples of near transfer. By contrast, transferring SRL from esports to academic contexts would be an example of far transfer. Previous work on SRL transfer suggests that far transfer is often less successful (Dignath and Veenman, 2021). For example, Raaijmakers et al. (2018) found that SRL skills taught in biology did not transfer to math, which they considered an example of far transfer.

Despite this evidence, however, there have been arguments in favor of far transfer. McCardle (2015a) argues that much of the work on transfer looks at what the students learn rather than how they learn, and suggests that how they learn, which is a critical component of SRL, would successfully transfer even in circumstances where what they learn does not. This argument aligns with the defining traits of far transfer from Schuster et al. (2020), discussed above. This argument is further supported by previous work that found that athletes who engage SRL skills within their sport tend to engage the same skills in academic contexts. For example, in a case study of a table tennis player who was also a university student, McCardle (2015b) found that the athlete leveraged the same SRL skills, such as task-understanding and goal setting, in both contexts. Previous work on the academic impact of esports highlighted similar trends to McCardle (2015b)'s case study. For example, students who were interviewed by Cho et al. (2019) explicitly stated that they would take the skills and logic they used to communicate or make decisions in-game and use them in the classroom. These findings from previous work are encouraging and suggest that SRL skills may also successfully far transfer to academic contexts.

While esports for SRL training would not necessarily train specific cognitive strategies that could directly transfer to academic contexts, they may be able to provide students with an opportunity to develop more general meta-cognitive skills, providing them with a foundation upon which academic context-specific strategies can then be built. As White and Frederiksen (2005) demonstrate, developing strong meta-cognitive knowledge is beneficial to academic performance and as Bartolomé and Steffens (2011) argue, these skills do transfer across domains. As esports can be played at home and in the absence of a teacher, they may provide students with more opportunities to practice using meta-cognitive skills. Further, since esports are engaging, and, as demonstrated by our results, players at all skill levels are highly motivated to succeed, getting students to play would likely not be difficult. In future work, we hope to explore this further and empirically examine the phenomenon of transfer of SRL between esports and academics.


**FIGURE 4 |** The League of Legends post-game UI presents information regarding how each player performed during the game. Image reproduced with permission from Riot Games Inc. This image is copyrighted to Riot Games Inc.


**FIGURE 5 |** The game client stores and aggregates statistical data to present players with overviews of their gameplay over time. Image reproduced with permission from Riot Games Inc. This image is copyrighted to Riot Games Inc.

## Data-Driven and E-Learning

The third area where these results have implications is data-driven and e-learning environments, where data is used to motivate, encourage, and assist students. These environments may be able to help promote SRL in students by emulating esports-style interfaces within their applications. The results of our study suggested that the presence of League of Legends' in-game UI, which tracks gold, experience, kills, and creep score among other points, promoted SRL in the performance phase. Similarly, the post-game statistics screens, which display aggregate counts of all players' performances, promoted SRL in the reflection phase. Using this design approach as inspiration, e-learning applications, especially those that take a gamification approach, could potentially support the engagement of SRL skills in students by developing similar UI elements for their applications. Some applications have already begun to explore this possibility space through Open Learner Models (OLMs), which are conceptually similar to these UIs, in that they display measures and evaluations of a students' performance. OLMs have demonstrated great promise in supporting SRL in learning contexts (Hooshyar et al., 2020). Future work can explore opportunities to use esports and esports UIs to expand, and even gamify, open learner model design and support SRL and learning in more engaging and motivating ways. This suggestion is in line with observations made by previous work on personal informatics that have turned to games to identify opportunities for developing more engaging data visualization systems (Kou and Gui, 2018; Rapp, 2018).

These results also have implications for the implementation of Learning Analytics Dashboards (LADs) (Bodily and Verbert, 2017; Bodily et al., 2018). While many LADs seek to motivate and aid students through comparison of their own progress against that of their peers (Fritz, 2011; Santos et al., 2013; Park and Jo, 2015), previous work also found that such comparison is often undesired by students or can have the opposite effect, either de-motivating them or making it harder for them to set goals and follow plans (Reimers et al., 2015; Aguilar, 2016; Rets et al., 2021). Similar to these LADs, League of Legends' UI elements provide players with critical information about their performance, which includes comparisons with other players, most notably post-game. The results of our study suggest that the post-game comparison does not have detrimental effects on students' motivation, and LADs may be able to leverage design insights from esports UI's in order to overcome this challenge. Most notably, presenting comparative information only at the end of the term, the academic equivalent of "post-game", may provide students with valuable information that can motivate a desire to overcome shortcomings in the following term.

## LIMITATIONS AND FUTURE WORK

We acknowledge the sample size as a limitation of this work. We chose to replicate the sample size of the original study to ensure that the results of this work could be directly compared to the original results, and claims about how SRL compares between traditional athletics and esports could be made. However, we recognize that a larger sample size may reveal more significant differences between expertise levels.

Further, like the original study, we do not question players about their experience with other games. This may result in inherent differences between players in a given expertise level, i.e., those who have played another game before may perform better than those for whom League of Legends is their first esport. We hope to address this limitation through further exploration of this topic in future work.

We also acknowledge that we have only looked at a single esport game, and that other games may present different findings. This may be especially true if our assumption that League of Legend's in-game elements are teaching players SRL skills is correct. While we argue that these results are likely generalizable given that many esports games, including DotA2 and Heroes of the Storm, follow a similar design framework, we acknowledge that future work is necessary to ensure the generalizability of the results.

With this in mind, we present this work as an exploratory first look at SRL in an esports context, how it differs from traditional sports, and the implications of SRL's manifestation within esports. We hope to follow it with a larger scale study in future work. We also hope to expand the study of SRL in esports to look at individual processes and phases as well as SRL in the context of other games and models. Further, in future work, we hope to explore and expand upon the three implications we discussed in the previous section.

## CONCLUSION

In this work, we replicated Kitsantas and Zimmerman (2002)'s micro-analytic study in the context of League of Legends, in order to examine differences in SRL processes between expert, non-expert, and novice players. Our results found that there were significant differences in the forethought phase, but none in the performance and self-reflection phases. We discuss that these findings, which are different from those of the original study, may be the result of the design of the game, and suggest that League of Legends, and similar esport games, may be training players in SRL skills. Based on these conclusions, we identify opportunities for computational support for esports, suggest that esports may be a potential avenue for training SRL skills, and suggest ways in which data-driven and e-learning environments may be able to learn from esports to improve learning and SRL skill acquisition. In future work, we hope to explore these three implications and expand on our understanding of SRL in esports.

## DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article can be made available by the authors upon request.

## ETHICS STATEMENT

The studies involving human participants were reviewed and approved by UC Santa Cruz Office of Research. The patients/participants provided their written informed consent to participate in this study.

## AUTHOR CONTRIBUTIONS

EK led the study, conducted the interviews, collected and analyzed the data, and wrote the manuscript. CG acted as the second researcher for the qualitative analysis and assisted in the development and writing of the discussion. MS was the PI on the project and EK's Ph.D. advisor, offering feedback throughout the study, and providing guidance in writing the manuscript. All authors contributed to the article and approved the submitted version.

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# Supporting Self-Regulated Learning in Distance Learning Contexts at Higher Education Level: Systematic Literature Review

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Shifting learning to distant formats especially at the higher education level has been unprecedented during the past decade. Diverse digital learning media have been emerging which allow learner autonomy, and at the same time, require the ability of efficient regulation of various aspects of the learning process for sustainable academic progress. In this context, supporting students in self-regulated learning (SRL) in an optimal way becomes an important factor for their academic success. The present study attempts through a systematic review of 38 studies to provide an overview of the interventions identified as supporting all areas of SRL (metacognitive, cognitive, motivational and emotional), in its three phases (preparatory, performance, appraisal) in distance education environments at the higher education level. As the study results show, there are a number of SRL support interventions available with proven positive effect on SRL. However, their distribution has been found to be uneven. Whereas metacognition regulation and the performance phase of learning is vastly investigated, the emotion regulation, and the preparatory and appraisal phases of the SRL cycle are somewhat underexplored. As complex and multi-component as the process of SRL is, the combination of various interventions, and specific features, for more comprehensive support has also been found beneficial. Additionally, it has been revealed that the emotion regulation, in most cases, is closely related to motivation regulation, and similar interventions support these two. Future studies can further explore the efficiency and relevance of the identified interventions, taking closer look at the effects of various digital media, learner characteristics as well as different levels of education on learners' self-regulation needs.

**Keywords: self-regulated learning, support interventions, distance learning, higher education, systematic review**

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## INTRODUCTION

Digitalization and shifting to distant modes of operation have affected the 21st century living, studying and working dramatically. However, the start of the COVID-19 pandemic triggered even stronger, irreversible reliance on digital technologies, in general, and the largest "online movement" in the history of education, in particular. The current tendencies in the field of education indicate that operation in the distance learning environment is becoming more and more common and will eventually turn into a new normal beyond the era of the COVID-19 pandemic. Consequently, relevant adaptations and finding new ways to cope with the new reality in the field of education are emerging (Chick et al., 2020; Daniel, 2020). In the field of education, the shift to distance learning is especially visible and more widely adopted at the higher education level. At this stage, students are already expected to have some degree of competence to function independently, and thus, as long as the proper instructional design is put in place, and learners are further supported in their self-regulated learning needs, the chances of success become feasible (Broadbent and Poon, 2015).

In this era of unprecedented digitalization and distance learning, reconsideration of the ways that have been used to support learners in their study process has become crucial. Even though self-regulated learning (SRL) is relevant for face-to-face (F2F) learning formats as well, it is distance learning that makes the importance of SRL more pronounced (Breslow et al., 2013; Jordan, 2014). In the absence of the instructor's direct supervision and guidance witnessed in many distance learning formats, the importance of SRL becomes even more crucial and a determining factor for the successful implementation of the learning process and learners' improved academic outcomes (Veenman, 2011; Broadbent and Poon, 2015; Wong et al., 2019). Unlike some decades ago, when learning technologies were just environments where highly structured information was presented electronically, today, learners have to actively get involved in planning their own learning paths, setting their goals, using the best strategies to get to those goals, monitoring their progress, reflecting upon their learning and adapting accordingly (Carter et al., 2020). It has been demonstrated that the lack of ability to self-regulate and operate efficiently under new education norms and circumstances is causing learning difficulties for students (Baticulon et al., 2021). A huge discrepancy between the enrollment and completion rates in Massive Open Online Courses (MOOCs), for instance, is a further indication of the importance of the support learners need in the process of distance learning (Breslow et al., 2013).

Self-regulated learning becomes even more important at the university level, when studying becomes more intense and complex (Khiat, 2019). Higher education was heading toward the shift to distance learning even before the pandemic, and at present, does so in a more accelerated manner. Additionally, it is at the higher education level where the distance learning model is expected to hold most extensively beyond the COVID-19 pandemic (Gallagher and Palmer, 2020).

Further, engaging in self-regulated learning in an efficient manner, in a digital environment which is open-ended, non-linear and information-rich (Duffy and Azevedo, 2015), and especially in the ones characterized by "massiveness and heterogeneity of the participants" (Pérez-Álvarez et al., 2018, p. 17), does not happen automatically. It is claimed that learners' SRL competence should be developed and supported in a targeted way (Panadero and Alonso Tapia, 2014). Thus, the selection of the SRL support mechanisms has to be conducted in a thorough manner, bearing in mind that the provided help should not only technically support the learner in the given learning context, making them reliant on the given support mechanisms, but rather be conducive to the development of learners' transferable SRL skills.

# BACKGROUND

## Self-Regulated Learning

Over the past two decades, SRL has become one of the major areas of research in educational psychology, and it is often referred to as the driving competence needed for transforming individuals into successful independent learners (Boekaerts, 1999). SRL has been widely explored by many authors, proposing various angles of seeing the process. What the existing different models of SRL have in common, though, is its cyclical, multi-phase and multi-component nature (Panadero and Alonso Tapia, 2014). The SRL model adopted in the current review (see **Figure 1**) is based on the version suggested by Panadero (2017), and is also applied in the study by Hooshyar et al. (2020).

The given model is detailed enough to cover all aspects of SRL: all three of its phases (preparation, performance and appraisal) as well as the areas (cognition, metacognition, motivation and emotion). Exploration of SRL along these lines will allow a comprehensive analysis of the whole process and identification of the targeted support interventions.

## Self-Regulation and Distance Learning

As repeatedly witnessed during COVID-19 pandemics, where the emergency shift toward online learning became a necessity at each level of education, succeeding academically in distant contexts requires a different set of skills on learners' part from the ones they were used to in f2f learning formats (Shnaubert and Herold, 2020). In f2f context, the presence of the teacher helps learners throughout all phases of learning — planning and preparation; monitoring and supporting of the learning process through close observation and just-in-time feedback provision. Additionally, the physical presence of the

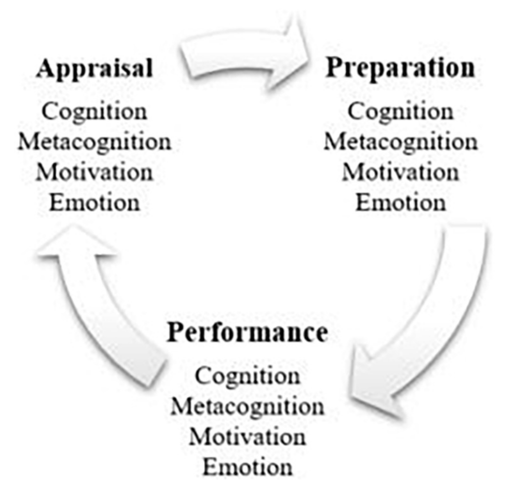


**FIGURE 1 |** Cyclical model of Self-regulated learning (SRL) adapted from Panadero (2017).

instructor as well as peers has been found to be conducive to transforming learning into emotionally and motivationally more accommodating process. It is exactly emotions and motivation that have been found particularly challenging to support in the distance learning formats, requiring special adaptations and instructional design planning (Shnaubert and Herold, 2020). Thus, the SRL skills needed in f2f and distant environment cannot be equated, and should be investigated separately.

## Self-Regulated Learning at Higher Education Level

Another important factor to be considered while narrowing down the scope of SRL research is the education level. Learners of different ages differ considerably by the way they learn – the methods that help them prepare for their studies, the ways they process information, stay focused and motivated. The factors that contribute to the initiation and support of SRL learning also differ across different age groups. If in case of children and school contexts it is the teacher who plays the defining role for learners' successful SRL, in case of adults, the instructional design is seen to be a driving factor (Oates, 2019). Also, whereas it is implicit approaches that have been found to be working for developing SRL skills in case of young learners (Wagener, 2013), more explicit interventions have been found helpful for adults (Raaijmakers et al., 2018). Academic demands and expectations also differ across the age groups (Taylor and Hamdy, 2013; Kellenberg et al., 2017). at the higher education level, learners are expected to be more autonomous, and in need of taking control of their own learning process (Zimmerman, 2000; Dillon and Greene, 2003), while also dealing with more "high stakes" tasks (e.g., tests, interviews, preparing for the job), and require specific SRL skills to be able to effectively manage one's learning behavior as well as motivation and emotions (Shnaubert and Herold, 2020). Anxiety levels involved in the learning process have been found to be higher in case of adult learners, calling for more attention toward identifying adequate and sustainable supporting measures in this regard (Kellenberg et al., 2017).

## Previous Research and an Existing Gap

For the past decade, an increasing number of literature reviews has been conducted on the interventions supporting SRL in online learning. The focus of the research available has varied, however. Some studies have focused on identifying as many concrete tools/platforms supporting SRL as possible without particularly checking their actual impact (Pérez-Álvarez et al., 2018; Yen et al., 2018) on learners' abilities or performance. Some have aimed at providing focus on one particular type of online learning environment (Pérez-Álvarez et al., 2018) or how to support a particular area (metacognition and its specific aspects) of SRL (Dabbagh and Kitsantas, 2004); others have centered around the efficiency of concrete interventions, such as prompts, feedback and/or their combination (Wong et al., 2019), around concrete technological features (Yen et al., 2018), specific study domains (Devolder et al., 2012) or concrete types of tasks (Azevedo et al., 2011). Other studies have reviewed SRL support interventions during a concrete period of time (Tsai, 2013) or focused on the design recommendations of SRL support interventions (Pérez-Álvarez et al., 2016). Yet more recent studies have looked at how SRL measurement tools can be employed for SRL support purposes, a new interesting trend in measuring and supporting SRL simultaneously (Panadero et al., 2015; Araka et al., 2020). The potential of the measurement and support of SRL, the Open Learner Model (Hooshyar et al., 2020) and Learning Analytics (Marzouk et al., 2016; Matcha et al., 2020) have also been explored. However, there are missing reviews focusing on the effects of interventions on different phases and areas of SRL comprehensively and systematically.

## The Aim of the Current Study

It was deemed important to keep the scope of the study focused, and explore SRL in the context of distance learning at the higher education level (see also Section "Further Research and Limitations" on the study limitations). Such approach facilitates capturing the specific nature of the given contexts comprehensively (see section "Self-Regulation and Distance Learning" and "Self-Regulation and Higher Education Level" above), and making the findings context-specific and readily applicable.

Thus, the current study investigates how SRL can be best supported in distance learning environments at higher education level. It aims to identify the interventions, or combination of interventions, that have been found to have a demonstrated effect on supporting each area of SRL at each of its phases. Study further tries to locate the features with which various interventions can be enhanced. To explore the most recent findings, the present literature review looks into studies conducted in the period from 2010 to 2020.

Taking into consideration the objectives described above, the following research questions have been formulated:

### Research Questions

1. Which interventions support various areas of SRL in its three phases in the context of online learning at higher education level?
2. Which technical features and representations of SRL support interventions, and which combinations of interventions are effective for SRL support?

# METHODOLOGY

The present systematic literature review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) approach (Moher et al., 2009). Consequently, the study selection process consisted of several phases: article identification, screening, checking for eligibility and final rigorous full text analysis (see **Figure 2**). The analysis was conducted according to the data analysis framework developed by the authors specifically for this study.

## Search and Selection Procedures

### Search Terms Defined and Databases Selected

In an attempt to thoroughly cover all aspects of the research, first, the main concepts covered in the RQ were clearly identified. The table below presents the concepts along with their synonymous terms used under each concept category.

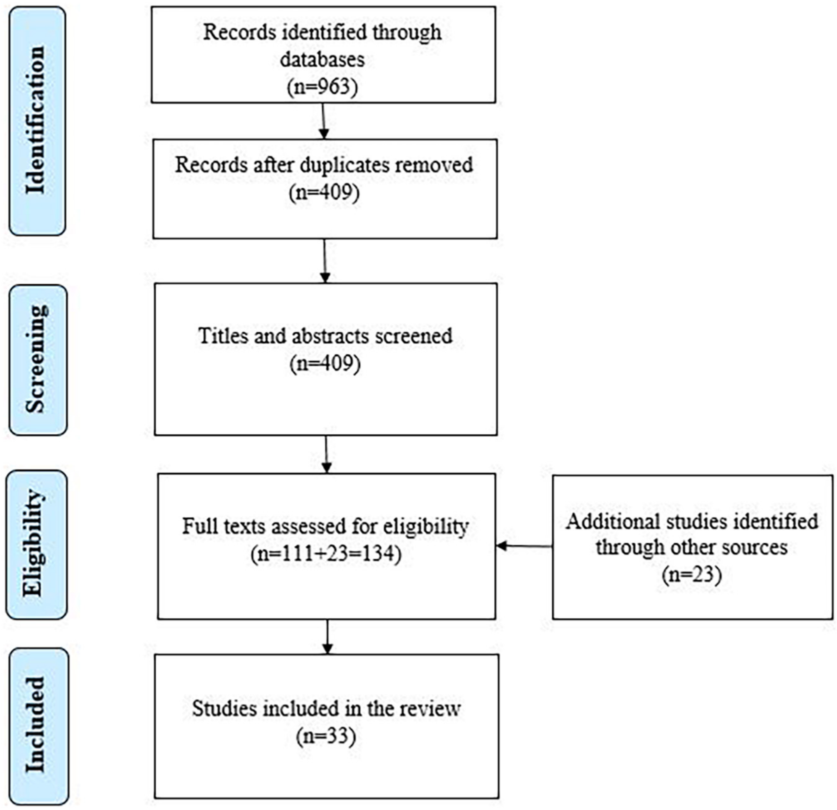


**FIGURE 2 |** Selection process of the studies.

**TABLE 1 |** Concepts explored and included in the search.

| Concept 1 | Concept 2 | Concept 3 |
|---|---|---|
| Supporting<br>Scaffolding<br>Facilitating | Self-regulated<br>Self-control | Distance learning<br>Web-based learning<br>Online learning<br>E-learning<br>Digital learning |

Based on the identified concepts and related terms, a relevant search phrase was created, which is presented below:

("support*" OR scaffold*" OR "facilitat*") AND ("self-regulat*" OR "self-control" OR "SR" OR "SRL" OR "self-regulated learning") AND ("distance learn*" OR "web-based learn*" OR "online learn*" OR "e-learn*" OR "digital learn*").

Since the aim of the search was to detect any potential SRL support mechanism, no search words such as tool, framework or intervention were specified. Rather, the word *Support/Scaffold/facilitate* was expected to naturally lead to the identification of the diverse possibilities of SRL support methods. Further, even though the concept of SRL can be further broken down into smaller constituent categories (cognition, metacognition, motivation, emotion), such elaboration was considered unnecessary based on the assumption that the term *self-regulated learning* would be sufficient for locating studies covering various constituents of SRL.

The search for studies focusing on the supporting intervention of SRL was conducted in the Web of Science and EBSCO, two of the biggest database platforms focusing intensively, among other areas, on the field of education. The platforms were expected to have the most relevant articles for our study purposes. Advanced search was used in both databases using the search formula presented above.

Since the focus of the study was to identify the interventions most up to date in nature, the search was restricted to the period from 2010 to 2020. The studies selected had to come from peer-reviewed journals, conference publications and dissertations. Another limitation applied during the search was with regard to language—only those articles published in English were targeted. Besides other obvious reasons, English is the common language for all authors involved in this study and facilitated the required validation processes involved in the study.

## Study Selection Criteria

The following inclusion criteria were used for the study selection purposes at the abstract as well as full text screening level:

1. The study makes an explicit link to SRL and focuses on at least one area of SRL (cognition, metacognition, emotion, motivation).
2. The study is empirical in nature, and attempts to measure the effect of an intervention(s) on SRL.
3. The study focuses on distance learning (covering all types of digital media).
4. The study is conducted with students at higher education level.

### Search Process

Searching Web of Science and EBSCO for relevant articles resulted in identifying 351 and 729 articles in each database, respectively. EBSCO database automatically eliminated the duplicates identified in its search result, leaving the total at 512 articles. EBSCO and Web of Science articles together amounted to a total of 963.

When both search result sets were exported to the web version of EndNote, an additional search for duplicates was performed, and 496 articles were eliminated automatically as well as additional 58 ones manually, leaving the total of merged database results at 409. As a result of further screening – browsing the titles and abstracts of the articles – 111 studies were found to be meeting the established inclusion criteria and selected for further eligibility check. In the process of full text screening, 23 additional relevant studies were identified through the references of the selected articles and added to the pool of 111. After the final full text analysis, 33 articles were selected as meeting the inclusion criteria. The reviewed articles include four that describe two or more studies, looking at differentiating effects of certain features and/or combination of features (Kauffman et al., 2011; Bannert and Mengelkamp, 2013; Lehmann et al., 2014; Wäschle et al., 2014) of an intervention. Thus, the total number of actual studies investigated amount to 38. Additionally, there are three studies in the review which focus on the same intervention, *MetaTutor*, each focusing on the effects of the given platform on SRL from a slightly different perspective. The multifunctional and explicitly SRL support directed nature of the given medium must be the reason of the recurring interest. More information about the articles can be found in **Supplementary Appendix B**. The whole systematic literature review process is captured in **Figure 2**.

### Validity

Two authors examined the studies separately. The validation was conducted at title and abstract as well as full text level (30 articles validated at each level) according to the inclusion criteria outlined. Cohen's Weighted Kappa test revealed the range of.82 to.92 reliability at the title and abstract, and from full agreement to.88, in the full text level.

## Data Analysis

A frame of analysis was created by the authors to facilitate systematic capturing of the information related to the studies included in the present literature review. The validation was ensured through the rounds of discussions and refinement of the frame, as well as actually applying it to 5 studies before its employment for wider scale study analysis (see **Supplementary Appendix B**). For validation purposes, the authors held a discussion with regard to the components included in the table and finalized its structure. Additionally, two authors analyzed 5 studies using the given table and compared the extracted data for consistency and validity checking purposes.

### Key Term/Concept Definitions

In the context of this study, several terms are of high importance and recurring throughout the study. Firstly, the term *intervention* will be used to refer to all possible methods of SRL support, including the concrete digital tools as well as more general support types such as pedagogical frameworks, platform designs and quality factors explored for SRL support. Another key umbrella term used in the current study is *distance learning*, which refers to all types of learning not taking place in F2F format and implemented distantly with the help of technology, ranging from Massive Open Online Courses (MOOCs) and Learning Management Systems (LMS) to Hypermedia Learning Environments (HLE).

As for the key concept involved in the present review, *self-regulation,* it is defined, in general terms, as a process through which self-generated thoughts, emotions and actions are planned and adapted to reach the established goals (Zimmerman, 2000). As for SRL, according to Panadero (2017), it is an extraordinary umbrella under which a considerable number of variables that influence learning (e.g., self-efficacy, volition, cognitive strategies) are included within a comprehensive and holistic approach [.]. [It is a] core framework to understand the cognitive, motivational and emotional aspects of learning (p. 1).

In the present study, in accordance with the definition of Panadero (2017), SRL is perceived as a multi-component, cyclical process, involving several stages and areas (see also section "BACKGROUND").

### Study Component Categories Clarified

#### *Framework of Analysis*

Descriptive data about the articles includes the information about the study *domain,* which requires further categorization. Disciplines such as Biology, Chemistry and Geography are classified under *Science*; technology-related disciplines such as Computer Science and Programming under *Technology*; Research, Educational Sciences and Educational Psychology falls under *Education*; and *Medicine* is presented separately. As for the study medium, different ways of referring to it was adopted in various studies. Whereas in some studies learning environment was described in broader terms (e.g., LMS), in others the course type (e.g., MOOC) or the qualities of the systems working behind the platform were reported (e.g., Hypermedia). This made clear, broader categorization of the information about the learning media challenging. Thus, the analysis framework captures the information as it is presented in the studies reviewed.

With regard to the research quality related section of the table, the following categories were formed: *Longitudinal,* referring to the course-long and more extensive studies, and *Cross-sectional*, referring to shorter studies, conducted during one or more learning sessions.

Outside the analysis framework, the interventions were further categorized with terms *Micro* and *Macro— Micro*, focusing on helping learners at the task level, and *Macro,* facilitating SRL throughout the course and/or at the study cycle level, types, which are then further grouped according to the phase and area of SRL they support.

As for the more concrete categories related to the interventions, broadly, they fall into following categories (a). *Prompts*, which are largely defined as "recall and/or performance aids" (Bannert, 2009). They do not teach new information, rather the assumption is that students have previously mastered the concept/knowledge, and need help with learning execution. According to Bannert, they "are scaffolds to induce and stimulate students' cognitive, metacognitive, motivational, volitional and/or cooperative activities during learning" (2009). Other larger categories of the reviewed interventions include (b) *various tools* (time logging, note taking, group awareness, assessment), which are embedded instruments facilitating the process of SRL in various ways. (c) *Instructional designs* built on SRL principles are other interventions providing broader, framework-based support, affecting the whole dynamics of the learning experience. (d) Other interventions include technical features/additions to the system/tool such as *visualization*, *social comparison*, as well as *video/text enhancement* functionalities. Learning environment related *quality factors* (system, service, information) are yet other components to consider while identifying SRL support mechanisms (e). For more clarity and better understanding of the interventions explored, descriptions of intervention related terminology is provided in **Supplementary Appendix A** as well as in the Results section below. As for the terminology used for referring to the *effects* of the interventions included in **Tables 3–5**, these have been extracted from the original articles and are common in the field needing no further interpretation or categorization.

### Effect Size Calculation

To present comparable effects of the SRL interventions explored in the included studies, the effect size of these intervention on learners' SRL skills (for concrete examples of dependent variables, see **Tables 3–6**) was calculated using standardized *Cohen's d* (*d*).The effects were calculated based on the presented data in the particular studies: *t*-value, *f*-value, $\chi 2$-value or *p*-value of the tests along with sample sizes reported. In a few cases, where not enough analysis data was provided, calculation of the effect size was not possible.

# RESULTS

## Descriptive Data

The studies included in the review come from peer-reviewed scientific journals, dominated by the journal Computers in Human Behavior (8), and several from the International Conference proceedings (3) and one dissertation. The study domains involved are mostly from the field of education (14), technology (12), science (7) and medicine (4); thus, the study topics/tasks as well are complex in nature and require intense support in distance learning formats. As for the learning media, they range from MOOCs and Learning Management Systems (LMS) to adaptive multi-agent hypermedia learning environments. Most of the studies are conducted in countries with highly developed educational technologies infrastructure (i.e., 24% in Germany, 24% in the United States).

As for the methods applied, as defined by the inclusion criteria, studies reviewed are empirical in nature. In vast majority of cases data collection tools and data analysis methods were largely reported. The data for analysis was collected through a combination of various sources such as log data, video protocols, observation protocols, archived forum discussions and various types of validated targeted questionnaires (e.g., Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich and de Groot, 1990); Perceived Stress Questionnaire (PSQ) (Levenstein et al., 1993) and procrastination questionnaires (Lay and Silverman, 1996), Intrinsic Motivation Inventory (IMI) and the PANAVA inventory (Schallberger, 2005). However, the level of detail and consistency when referring to certain areas/concepts involved varied across the studies. While the domain of the study, as well as participant number and age was almost always reported, there were some gaps with regard to the information about the validity check procedures of the data collection instrument(s). As for the study variables, for instance, the learner-related characteristics which might have a differentiating effect on the efficiency of certain SRL interventions in given contexts, were not consistently reported in the studies reviewed, and were only investigated in a few cases (Ifenthaler, 2012; Verpoorten et al., 2012; Bannert and Mengelkamp, 2013; Lehmann et al., 2014). Thus, due to the lack of enough data in this direction, we could not include this information in a systematic manner in our analysis framework.

The interventions identified focus both on micro (task/activity, e.g., Matrix note-taking tools; Kauffman et al., 2011) and macro (study cycle) level (e.g., Planning and Reflection Protocol; Wäschle et al., 2014). The micro level interventions tend to be the shorter term investigations, whereas macro level interventions are investigated in the context of the longer term designs (e.g., Alexiou and Paraskeva, 2015; Yeomans and Reich, 2018). See more in **Supplementary Appendix B**.

## Interventions Supporting Various Areas of Self-Regulated Learning in Distance Learning Environments at Higher Education Level

**Table 2** summarizes the findings in a numerical format with regard to the SRL support interventions, which are categorized and presented according to the SRL phases (preparation, performance, appraisal) and areas (cognition, metacognition, motivation, emotion) they target and have an effect on. The subsequent sections further elaborate on the details of the interventions identified in the studies reviewed.

As can be observed from the table below, by far the biggest number of the studies explore interventions that support metacognition regulation, followed by motivation and cognition. The biggest gap detected concerns emotion regulation.

**TABLE 2 |** Self-regulated learning (SRL) phases and areas targeted by the SRL support interventions[1].

| SRL Areas | SRL Phases | | | Total |
|---|---|---|---|---|
| | Preparation | Performance | Appraisal | |
| Cognition | 0 | 13 | 0 | 13 |
| Metacognition | 9 | 15 | 5 | 29 |
| Motivation | 2 | 13 | 1 | 16 |
| Emotion | 0 | 6 | 0 | 6 |
| Total | 11 | 47 | 6 | |

[1] *The total numbers presented in this table do not reflect the amount of each unique intervention but rather the multiple SRL areas and phases they target (in most of the cases an intervention affects more than one area of SRL and/or more than one phase).*

As for SRL phases, the biggest emphasis can be seen with regard to the performance phase, whereas preparatory as well as appraisal phases are underexplored in all areas of SRL except for metacognition, where preparation phase support is also well covered.

## Interventions Supporting Cognition Regulation

Prompts have been identified as among the most widely researched interventions to support cognitive (as well as metacognitive) areas of SRL. *Adaptive Content and Process Scaffolds* involving human tutor (Azevedo et al., 2011) have been proven to be an effective SRL support intervention. Process-embedded, adaptive scaffolding, delivered by course assigned tutors in real time, in a personalized manner, has a positive impact on learners' cognitive (content evaluation, note-taking, hypothesizing, re-reading) as well as metacognitive (planning, monitoring progress, reflection, goal directed search, help-seeking) strategy use. However, at the same time, the study reveals the fact that even though extra help provided with regard to the content, in addition to the process support, is conducive to declarative knowledge gain and has a positive effect on cognition regulation, too much support (content as well as process) might result in overdependence, and hence, lesser transferable SRL skills. See **Table 3** below.

Another study by Duffy and Azevedo (2015), investigating the online learning platform *MetaTutor*, focuses on adaptive prompting and subsequent feedback provision coming from its platform-embedded pedagogic agents covering different areas of SRL strategy support. Agents prompt participants to deploy specific SRL strategies— goals and sub-goal setting and staying mindful of their overall learning goal. The learners are also prompted to activate their prior knowledge, write summaries, assess the relevance of the content, take notes, assess their understanding and re-read sections of the text. The agents then give feedback regarding the accuracy and relevance of the practices employed, which has a positive impact on cognition regulation strategy improvement such as note-taking, summarizing and inferring skills as well as content evaluation ability (for metacognition and motivation related effects, see below in sections "Interventions Supporting Metacognition Regulation" and "Interventions Supporting

**TABLE 3 |** Cognition regulation support intervention and the areas affected.

| SRL Phases | Intervention[1] | Strategy/Area Affected | Effect[2] |
|---|---|---|---|
| **Preparation** | N/A | N/A | N/A |
| **Performance** | Tutor provided adaptive Content and Process Scaffolds (5) | Reading/note-taking<br>Re-reading<br>Hypothesizing | *d* = 0.71, CI[0.34, 1.0]<br>*d* = 0.71, CI[0.33, 1.0]<br>*d* = 0.70, CI[0.33, 1.0] |
| | Pedagogical agent scaffolding (instructional prompts and feedback) (9) | Note-taking, summarizing, content evaluation | *d* = 0.51, CI[0.07, 0.94] |
| | Matrix and outline note-taking tools (11a) | Accurate and relevant information localization | *d* = 2.4, CI[1.3, 3.5] |
| | Note-taking tools combined with self-monitoring prompts (11b) | Note-taking (more notes taken) **monitoring component - for conventional note-taking* | *d = 0.96*, CI[0.56, 1.3] |
| | Peer-peer formative feedback in asynchronous fora, stimulated and monitored by tutor (12) | Sharing and comparing content understanding, Meaning construction | N/A |
| | Generative learning strategy prompts and metacognitive feedback (15) | Highlighting main information, note-taking, refining knowledge by revisiting materials | *d* = 0.26, CI[0.02, 0.52] |
| | Personalized e-journals + self-reflection prompts (18) | Elaboration, rehearsal | *d* = 0.89, CI[0.33, 1.4] |
| | The negative impact of media diversity (21) | Increased cognitive load | *d* = −0.32, CI[−0.40, 0.24] |
| | Learning Framework *(SR-INSPIRE us)* with adaptive presentation support technique (25) | Improved cognitive processing and cognitive achievement | *d* = 0.71, CI[0.00, 1.4] |
| | Group awareness tool (26) | Information processing<br>Selection of main ideas | *d* = 0.96, CI[0.54–1.38]<br>*d* = 0.86, CI[0.44–1.27] |
| | Prompts on help-seeking (28) | Help-seeking activity about relevant content | *d* = 0.26, CI[0.01–0.52] |
| | Instructional design workflow – PBL and SRL combined (32) | Rehearsal,<br>elaboration,<br>organization | *d = 0.60*, CI[0.12–1.0]<br>*d* = 0.81, CI[0.32-1.2]<br>*d* = 0.70, CI[0.22-1.1] |

*(Continued)*

**TABLE 3 |** (Continued)

| SRL Phases | Intervention[1] | Strategy/Area Affected | Effect[2] |
|---|---|---|---|
| | Planning and reflection protocol (1) | Rehearsal Organization, elaboration | *d* = 0.59, CI[0.01–1.1] |
| **Appraisal** | N/A | N/A | N/A |

[1] *The numbers in this and subsequent* ***Tables 2-4*** *refer to the studies in* ***Supplementary Appendix B****.*
[2] *95% Confidence Interval (CI) is set for the effect size.*

Motivation Regulation"). Since the study also investigated the effect of the learner goal orientation, as a factor, it revealed that such support is more useful for performance- rather than mastery-oriented learners, the authors speculating that intensive prompting and feedback provision might not be creating a challenging enough learning experience for mastery-oriented students. *The Planning and Reflection Protocol*, embedded in an LMS, which primarily focuses on metacognition regulation support, helping learners in the process of planning, goal setting and reflection, proved to have a positive effect on cognition regulation strategy use as well. Learners, by setting specific goals and then reflecting on what has been learned and what needs further adaptation, manage to engage in more targeted and conceptual learning (Wäschle et al., 2014).

The interventions which enhance learner cognitive regulation (as well as have an effect on metacognition, motivation and emotion regulation, see Sections "Interventions Supporting Metacognition Regulation," "Interventions Supporting Motivation Regulation," and "Interventions Supporting Emotion Regulation" below) through group awareness mechanisms applied in collaborative contexts include *pie chart* reflecting learners' posting for behavioral awareness and *group interaction diagram* for social awareness as well as *cloud tags* capturing the main concepts coming up in the process of collaboration (Ma et al., 2020). Application of these interventions resulted in better information processing by learners as well as more accurate identification of and focus on the relevant information in the process of learning. The benefits of collaborative practice were further demonstrated in other studies. Receiving and offering constructive peer feedback in discussion forums helps learners build a new understanding and perspectives, leading to the construction of new knowledge (Gikandia and Morrowa, 2016). Collaboration also helps with elaboration and rehearsal strategy improvement, the practice which is especially helpful in less structured contexts such as problem-based learning (Paraskeva et al., 2017).

Further, at the task level, the interactive nature of the tools used (available functionalities such as note-taking, text highlighting, annotation and summarizing), which allow learners to get actively engaged in the learning process rather than remain in a passive recipient's role, improves their cognitive regulation strategies. The *Video Mapper* and *MetaTutor's* reading platforms offer such environments (Lee et al., 2010; Delen et al., 2014). Note-taking tools, especially the multi-dimensional ones (Matrix and Outline), which contribute to putting learners in charge of collecting the right information for learning and processing, have also been found helpful with cognition regulation. While taking notes, learners engage in prioritizing and trying to discern what is essential and what is secondary level information. Capturing the main concepts in such a structured manner makes information processing easier, allows more focused revision and elaboration (Kauffman et al., 2011) and, ultimately, is conducive to improved learning and information retention.

Another important factor to be considered while trying to help learners with cognitive processing and avoidance of negative overload is to carefully plan the learning environment using well-structured modes of information presentation as well as efficient use of diverse media formats. Even though there is evidence pointing to the positive effects of multimedia use in the instructional process on learners' cognitive processing and increased level of learning, overall, inefficient application of the diverse media can have reverse effects. Using multimedia for delivering the content/messages irrelevant to learning and/or providing redundant/overlapping information through various forms of media (e.g., text, visuals, audio, graphical) leads to diverting learners' attention from the essential to non-essential information processing. This results in extraneous cognitive workload and confusion on learners' part, which further hinders self-regulation and is conducive to lower levels of knowledge acquisition (Mayer et al., 2001; Lange and Costley, 2019).

### Interventions Supporting Metacognition Regulation

Information about metacognition regulation support interventions is captured in **Table 4** and further elaborated in the text that follows to provide further details.

As in the case of cognition, with regard to metacognition as well, prompts have been found to be among the most prominent interventions supporting metacognition regulation. The findings with regard to prompts indicate that specific prompts (e.g., pop-up prompts at various SRL phases reminding learners of using relevant SRL strategies) are significantly more efficient and conducive to more positive effects on metacognition regulation, especially when combined with feedback (Duffy and Azevedo, 2015), than prompts that are generic in nature (Bannert and Mengelkamp, 2013). The importance of carefully designing prompts and attributing them context specific nature is especially pronounced in less structured learning contexts, and with less experienced learners (Verpoorten et al., 2012).

Further, training with regard to understanding and following the prompts has also been found helpful. However, the positive effect of such explicit training can be observed only with less experienced and less motivated learners, whereas almost a reverse influence can be observed on more advanced learners with high intrinsic motivation (Bannert and Mengelkamp, 2013). Similar findings were also reported in the study by Duffy and Azevedo (2015) with regard to over supporting learners with high mastery orientation (intrinsic motivation). The authors speculate that it might be the lack of challenge inherent in the scaffolding that undermines mastery-approach learners' interest and makes them overwhelmed rather than motivated. Despite being conducive to better knowledge gain and better metacognition regulation strategy use (planning, monitoring

**TABLE 4 |** Metacognition regulation support interventions and areas affected.

| SRL Phases | Metacognition | Strategy/Area Affected | Effect[1] |
|---|---|---|---|
| **Preparation** | Planning and reflection protocol (1) | Reduced procrastination<br>Improved goal specificity | $d$ = 0.62, CI[0.04, 1.2]<br>$d$ = 0.68, CI[0.10, 1.2] |
| | Metacognitive prompts (3b) | Orientation, planning and goal setting | $d$ = 0.84, CI[0.19, 1.4]<br>$d$ = 0.86, CI[0.21, 1.5] |
| | Metacognitive prompts + training in their use (3c) | Planning<br>Goal specification | $d$ = 0.58, CI[0.04, 1.2]<br>$d$ = 1.0, CI[0.48, 1.8] |
| | Fading/adaptive prompts (4) | Content-goal relevance and existing knowledge evaluation | $d$ = 0.50, CI[0.18, 0.81] |
| | Tutor provided adaptive Content and Process scaffolds (5) | Planning-prior knowledge activation, setting sub goal | $d$ = 1.0, CI[0.63, 1.4] |
| | Pedag. agent provided instructional prompts and feedback (9) | Planning and prior knowledge activation | $d$ = 0.50, CI[0.07, 0.94] |
| | E-portfolio based on SRL framework (16) | Planning | $d$ = 0.84, CI[0.20, 1.4] |
| | Instructor and institutional support and Course quality (19) | Independent goal setting, planning | $d$ = 0.34, CI[0.18, 0.50]<br>$d$ = 0.30, CI[0.15, 0.46] |
| | Pedagogical agent-supported monitoring/reflection prompts (23) | Goal setting, planning | $d$ = 1.9, CI[1.5, 2.4] |
| **Performance** | Metacognitive prompts (3b)<br>+ training in their use (3c) | Monitoring<br>Search and judge | $d$ = 0.92, CI[0.27, 1.5]<br>$d$ = 0.69, CI[0.06, 1.3] |
| | Fading/adaptive prompts (4) | Management of progress toward goal | $d$ = 0.50, CI[0.18,0.81] |
| | Tutor provided adaptive content and process scaffolds (5) | Time and effort planning<br>Goal directed search | $d$ = 1.0, CI[0.63, 1.4]<br>$d$ = 0.61, CI[0.24, 0.98] |
| | Automated adaptive time management enabling system (6) | Less procrastination and cramming | $d$ = 1.2, CI[0.68, 1.8] |
| | Time logging tool (7) | Time management and planning | $d$ = 0.65, CI[0.09, 1.2]<br>$d$ = 0.50 CI[0.04, 1.0] |
| | Pedag. agent provided instructional prompts and feedback (9)<br>Fading effect (4) | Help-seeking, content evaluation, judgments of learning<br>Progress toward goal | $d$ = 0.51, CI[0.07, 0.94]<br>$d$ = 0.50, CI[0.18, 0.81] |
| | Radar visualization (10) | Starting<br>Earliness of submission | $d$ = 0.43, CI[0.01, 0.81]<br>$d$ = 0.24, CI[0.15, 0.64] |
| | Visualized feedback with social comparison (13) | Timeliness (reduced procrastination) | N/A |
| | E-portfolio based on SRL framework (16) | Time management<br>Monitoring | $d$ = 2.1, CI[1.3, 2.9]<br>$d$ = 2.8, CI[2.0, 3.7] |
| | Pedagogical agent-supported monitoring/reflection prompts (23) | Performance stage skills<br>Self-observation | $d$ = 1.7, CI[1.2, 2.1] |
| | Group awareness tool (26) | Time management, self-testing, study aids | $d$ = 1.2, CI[0.77, 1.6]<br>$d$ = 1.1, CI[0.74, 1.6]<br>$d$ = 0.98, CI[0.56, 1.4] |
| | Self-assessment scripts (30) | Learning strategies | $d$ = 0.55, CI[0.07, 1.0] |
| | Instructional design workflow – PBL and SRL combined (32) | Metacognition<br>Help-seeking | $d$ = 0.44, CI[0.03, 0.91]<br>$d$ = 0.42, CI[0.05, 0.89] |
| | Self-directed metacognitive prompts (31) | Goal orientation (visiting and spending time on relevant pages; non-linear navigation)<br>*More transferable skills* | $d$ = 0.65, CI[0.17, 1.1]<br>$d$ = 0.58, CI[0.10, 1.0]<br>$d$ = 0.63, CI[0.15, 1.1]<br>$d$ = 0.44, CI[03, 0.91] |
| **Appraisal** | Metacognitive prompts (3b)<br>+ training in their use (3c) | Evaluation | $d$ = 0.79, CI[0.15, 1.4]<br>$d$ = 0.57, CI[−0.57, 1.2] |
| | Fading/adaptive prompts (4) | Knowledge evaluation | $d$ = 0.96 CI[0.52, 1.4] |
| | Peer feedback in asynch. forum (12) | Self-assessment | N/A |
| | Pedagogical agent-supported monitoring/reflection prompts (23) | Self-reflection | $d$ = 2.4, CI[1.93, 2.96] |
| | E-portfolio with techno-pedagogic design (29) | Deeper reflection and revisiting learning evidence | N/A |

[1] *For the studies marked as N/A not enough data was available to calculate the effect size.*

progress, reflection, goal directed search, help-seeking), tutor-provided content and process directed support can result in learners' overdependence on external help and hence, lesser transferable SRL skill development (Azevedo et al., 2011).

*Adaptability* and *self-directed* nature are other features that have been found to make prompts more effective. An adaptable, initially more frequent but progressively fading prompting contributes to the increase of SRL strategy deployment (Bouchet et al., 2016). Another way identified to support the metacognition regulation process is through *self-directed prompting*, which involves learners themselves in the process of configuring their own prompts by selecting relevant SRL strategies from a template and determining the time stamps for the prompts to pop up and support them in the process of learning. Such self-directed metacognitive prompts have been found to help learners engage in platform navigation in a more targeted rather than linear manner—learners identified and visited more relevant pages/materials and, overall, spent more time on learning. Further, both adaptive and self-directed prompting have also been found to have a transferable effect, manifested through the fact that at a later stage, in the context of reduced or no metacognitive prompting, learner-initiated regulatory activities still increased (Bannert et al., 2015).

The positive effect of the comprehensive and personified approach adopted with regard to prompting was witnessed in the study by Yılmaz et al. (2017). During the learning process, questions were directed to the learners by an animated and audible video-based *Pedagogical Agent* (PA) at macro SRL-phase level, encouraging planning, monitoring and reflection (at first, prior knowledge prompts are asked, expectations are set with regard to the course content; then, self-monitoring prompting takes place, and at the end of the week, reflection happens), as well as at micro, learning material level (prompting about how well the videos and/or texts have been understood). The intervention was found effective for metacognitive strategy improvement across all SRL phases. However, the biggest effect was observed with regard to the performance phase.

Interventions specifically focusing on and positively influencing time management strategies include systems that help learners stay conscious of their time spent on learning and avoiding cramming and procrastination. In this regard, the *Automated Adaptive Time Management Enabling System* (Khiat, 2019) with special features such as visual reinforcement (e.g., visual representation of the study plan on the main page), adaptive release of study materials, learning monitor and learning motivator messages was found helpful. The personalized nature of the notifications sent via a mobile linked application system and the optimal timing of the sent reminders, together with the social comparison feature enabling learners to analyze their own progress against their peers and teacher-set expectations, have also been shown to be helpful for learners to better organize their time while learning (Tabuenca et al., 2015; Jivet, 2016; Ma et al., 2020).

There are interventions that focus on SRL and particularly on metacognition regulation support in a more comprehensive manner, such as portfolios and platforms with specific SRL instructional workflow design. E-portfolio α*pot2iMySelf*, for instance, requires learners to reflect on their SRL skill use throughout all three learning phases and complete the portfolio with relevant information throughout the course, which helps learners with consistent and systematic planning and monitoring of their progress (Alexiou and Paraskeva, 2015). E-portfolio *Transfolio* with techno-pedagogical designs, coupled with teacher led procedural guidance as well as the need on the learners' part to dialog with the teacher and provide learning evidence was also found to be conducive to learners' increased reflection, self-assessment and learning adaptation strategies (Torras and Mayordomo, 2011). Additionally, an online platform with comprehensive *SRL instructional workflow design* (*apT2CLE*), founded on PBL collaborative model, and having instructor support available as needed, was also found to be supportive to learners through the learning process with their metacognition regulation strategies (Paraskeva et al., 2017). Pedagogic design as well as the overall quality of the learning system, instructor provided support and intuitive course structure helps learners to better self-regulate in an online learning environment (Albelbisi and Yusop, 2019).

The benefits of instructor supervision of the learning process in distance learning environments as well as the self-regulatory power of cooperative learning contexts have been demonstrated by Gikandia and Morrowa (2016). Specifically, learners' active participation and collaboration within (a) the topical asynchronous discussion forum, (b) open forum to share developing thinking and work in progress and (c) forum for students to share their polished artifacts and receive *peer formative feedback*, while the whole process is being stimulated and monitored by the teacher, was found to be conducive to learners engaging in more targeted goal setting, intensive reflection, self-monitoring and self-assessment.

The potential of assessment instruments such as assessment scripts and rubrics has been investigated and shown to be helpful for SRL (Panadero et al., 2013). Namely, while the scripts were helpful with more complex tasks and deep learning—better goal setting, deeper reflection and self-assessment— the rubrics were useful for staying focused on the learning process, monitoring and meeting the set expectations (specified in the rubrics) in the context of low to medium complexity tasks.

### Interventions Supporting Motivation Regulation

As the results of the current literature review show, the motivation regulation support has been largely associated with clarity with regard to learning objectives, learner autonomy, collaboration, the opportunities to analyze and compare one's own learning to standard performance and the quality of the learning environment. The information about motivation regulation support interventions is captured in **Table 5** and further elaborated in the text that follows.

Engaging learners in setting their learning goals and planning their study process has been proven to have a positive effect on learners' self-efficacy (Wäschle et al., 2014). Assessment rubrics and scripts also help with managing learning expectations and lay out the path toward achieving the goals. Such clarity with regard to the upcoming learning experience and set expectations positively impacts learner motivation—they become more engaged in the learning process due to reduced stress related to the complex tasks and have also been found to avoid difficult tasks they encounter in the process of learning less. However, increased self-efficacy and the feeling of contentedness have not been witnessed with regard to self-assessment rubrics and scripts, authors speculating that this can be explained by the absence of the feedback involved in the process, which would likely make the learning experience more fulfilling (P). Pre-planning prompts, which encourage learners to make learning

**TABLE 5 |** Motivation regulation support interventions and areas affected.

| Phases | Intervention | Strategy/Area Affected | Effect |
|---|---|---|---|
| **Preparation** | Directed pre-flection prompts (2b) | Positive activation through step-by-step guidance | *d* = 0.39, CI[0.09, 0.87] |
| | Planning and reflection protocol(1) | Self-efficacy | *d = 0.63*, CI[0.06, 1.2] |
| **Performance** | Mastery grids *with social comparison* (8) | Engagement and effort allocation | *d* = 1.05, CI[0.61, 1.4] |
| | Pedag. agent provided instructional prompts and feedback (9) | Engagement (time viewing materials) | *d* = 1.1, CI[0.72, 1.4] |
| | Peer feedback in asynch. topical fora, stimulated and monitored by tutor (12) | Increased engagement/interaction Self-value | N/A |
| | Visualized feedback with social comparison (13) | More access to videos, attempts at *graded* quiz questions, forum visits | N/A |
| | Pre-planning prompts (17) | Greater persistence and completion | *d* = 0.61, CI[0.08, 1.1] |
| | Online platform with learner-style oriented instructional design (14) | More time spent on materials | *d* = 0.34, CI[0.32, 1.0] |
| | Enhanced video tool (20) | More engaged: spent more time on video material | *d* = 2.5, CI[1.9, 3.2] |
| | Group awareness tool in collaborative environment (24) | Increased number of contributions and interaction with peers | *d = 0.49*, CI[0.05, 0.93] *d* = 0.76, CI[0.31, 1.2] |
| | Learning framework based on learner preferences (25) | Increased self-efficacy for learning and performance | *d* = 0.71, CI[−0.01, 1.4] |
| | Group awareness (visualized feedback) (26) | Self-efficacy More time learning Attentive learning | *d* = 0.52, CI[0.21, 0.83] *d* = 1.9, CI[1.5, 2.3] *d* = 2.5, CI[2.0, 2.9] |
| | E-learning WEB 2.0 (System, inform., service quality) (27) | Interaction/cooperation increase (with peers and content) | *d* = 0.37, CI[0.12, 0.62] |
| | Prompts on help-seeking (28) | More active participation Initiating discussions | *d = 0.64,* CI[0.03, 1.2] |
| **Appraisal** | Automated adaptive time management enabling system (6) | Improved completion rate (persistence) | *d* = 0.58, CI[0.01, 1.1] |

plans at the beginning of the learning process and which then stay visible for learners' further reference, have also been identified as having a positive effect on learners' subsequent learning experience and persistence during the process (Yeomans and Reich, 2018). By being better prepared from the very outset, learners feel more empowered and choose not to "surrender" (persistence) in the face of potential challenges. Hence, the provided support assumes a predictive (and thus, preventive) nature and helps learners elaborate implementation strategies for achieving the set objectives while the intention is still strong. Another feature of such prompts that makes them effective is their targeted nature, which contributes to learners' positive activation (Lehmann et al., 2014). The intervention was found to be particularly useful for novice learners in open learning environments such as MOOCs. The effect of the pre-planning prompts is further enhanced.

The benefits of systematic planning implemented through *weekly e-journals* and further supported by *reflective prompts* have been demonstrated by Fung et al. (2019). Careful planning and then reflection on the challenges encountered during the week and analyzing the methods applied/not applied to overcome those difficulties were found to be conducive to learners spending more time studying as well as making more effort during the online learning process. Such persistence and increased motivation is especially important for learners engaged in longer term courses.

Systematic reminders about the progress made, and explicit encouragement to make more effort helps learners stay mobilized and motivated. An Automated Adaptive Time Management Enabling System (also discussed in section "Interventions Supporting Metacognition Regulation") sending learning monitors (reminder emails about progress) and learning motivators (personalized emails sent out to learners to compliment them on their achievements and/or encourage learners who are falling behind to do better) was found to be conducive to learners spending more time on material and more students completing the course successfully (Khiat, 2019). Similarly, explicitly reminding learners of the possibility and the need to ask for help in the process of learning by placing the prompts along learners' individual workspace proved to be an encouraging factor for students' increased participation and involvement in the study process (Schworm and Gruber, 2012).

Adaptability achieved through Open Learner Modeling (OLM) and its benefits have been demonstrated in several studies reviewed. In the *Mastery Grids* system, an intelligent interface for online learning content that combines Open Learner Modeling (OLM), adaptive navigation support and a navigation-oriented social comparison feature, learners can click on any topic cell of the interface and access diverse web-based "smart" practice content. The system can then process learner activity, estimate progress and incorporate feedback based on the log data. The adaptable and interactive nature of the system, possibility of receiving individualized feedback in a visual format and the comparison feature have proven to have a positive effect on learner engagement and overall efficiency (Guerra et al., 2016). Similarly, Learning Tracker (Jivet, 2016), using the low-level data from learner trace logs and condensing those into indicators, provides learners with individualized feedback on their performance through the spider chart visualization and allows social comparison. Such individualized and visual nature of feedback has proven to have a positive effect on learners' persistence, translating into increased time spent on completing the quizzes as well as higher course completion rates. The study also revealed a longer term as well as a transferable effect (certain SRL aspects that were not explicitly targeted by the provided feedback, still improved over time) of the given intervention. The explanation could be, as the author suggests, interconnectedness of the learning activities involved in the SRL which cannot be completed independent of one another, and thus, the intervention acquiring a holistic effect on SRL.

An online collaboration environment with *Group Awareness (GA)* functionality, in a somewhat similar way to *Learning Tracker*, has been found helpful for boosting learners' motivation regulation (Lin and Tsai, 2016). The intervention stimulates higher levels of peer-to-peer interaction and contribution to the learning process while allowing learners to observe group activity in the process of cooperative learning through their visualized log data (number of personal contributions made; feedback/evaluation provided; replies written; "likes" given in the process of cooperative learning). To remind students of using GA information, the given function is automatically displayed whenever students log in the system and is available upon demand. The motivational effect of GA has been found to be stronger and more sustainable with learners with higher self-regulation skills. Another intervention providing group awareness functionality was explored by Ma et al. (2020), which, alongside cognition and metacognition regulation (see sections "Interventions Supporting Cognition Regulation" and "Interventions Supporting Metacognition Regulation"), was also confirmed to be helpful with motivation regulation—the data indicates that the visualized feedback about one's own as well as other students' collaborative activities, provided to learners in a timely manner, can encourage students to work harder. The benefit of collaborative learning format on motivation regulation has also been proven by yet another study (Gikandia and Morrowa, 2016): namely, peer-to-peer interaction as part of the collaborative learning experience and the formative feedback, delivered in an asynchronous forum under the instructor stimulated discussion session, have been found to further stimulate learner engagement in the learning process.

Higher engagement in an online learning can also be induced by delivering learning materials through formats/tools which are interactive and allow diverse means of information processing. *MetaTutor* and *Video Viewer* tools, identified in the present study, offer such interactive learning opportunities. *Video Viewer*, for instance, allows interactive note-taking, viewing of supplemental resources, bookmarking and comprehension check opportunities during and after the viewing process, followed up with immediate feedback, which helps students to monitor and evaluate their learning progress (Delen et al., 2014). Similarly, an interactive reading tool (see also sections "Interventions Supporting Cognition Regulation" and "Interventions Supporting Metacognition Regulation" above) with text summarizing, annotating, bookmarking and highlighting, alongside cognition regulation strategy improvement, contributes to increasing learner engagement in the learning process and the sense of autonomy (Duffy and Azevedo, 2015).

Learning platforms having learner-directed, adaptive and individualized nature have been proven to have a positive effect on learners' intrinsic and extrinsic motivation. For instance, *SR-INSPIRE us* is a *Learning Framework* supporting learners' motivation (and emotion) regulation through a learner style-based, individualized approach. It aims at enabling learners to define and manage their learning path by means of providing a set of generic strategies and customized learning activities based on their learning preferences throughout the three phases of SRL (Souki et al., 2015). Learners are offered individualized content by changing the sequencing of the modules included in each content page (adaptive presentation support technique). Similarly, platforms allowing diverse modes of presentation of materials (watching, discussing, conceptualizing, trying out) and giving learners the choice to select the modes of instruction and materials of their preference, and each mode providing extra help for additional skill development specific to that mode (e.g., note-taking, for watching mode), motivated learners to spend more time on learning (Lee et al., 2016).

Other factors more general in nature have also been found to have a positive impact on motivation regulation— *system/tutor provided support* as well as *quality of the course* (design, appropriateness of outputs and ease of understanding of course materials) (see also section "Interventions Supporting Cognition Regulation" above). Especially with novice learners, with less developed technology skills, such factors determine the level of learner engagement and the anxiety level in the study process. Interestingly, factors such as information quality and service quality did not show any significant impact on learner SRL strategies in the same study (Albelbisi and Yusop, 2019), which can be explained by the fact that if the overall system (platform) quality and course design is not good enough, learners cannot even get to the stage of properly processing the information offered.

### Interventions Supporting Emotion Regulation

The fewest interventions have been identified with a proven effect on emotion regulation in the present study. Information about the emotion regulation interventions is presented in **Table 6** below.

As revealed by the present study, emotion regulation is in most cases closely related to motivation regulation, and similar interventions support these two SRL areas. As in the case of motivation regulation, collaborative and interactive learning environments, with open social comparison functionalities allowing learning about peers' cognitive, behavioral and social activity patterns, result in reduced anxiety and boosted self-esteem. Cooperative activities also contribute to decreasing the feeling of loneliness and increasing the sense of relatedness and belonging to a learning community (Ma et al., 2020).

As in the case of motivation regulation, easy-to-navigate and well-designed course structure, together with instructor and system provided explicit support, as well as a simple interface have been shown to be conducive to less anxiety and emotional overload (Albelbisi and Yusop, 2019; Lange and Costley, 2019). Learner-directed online environments, allowing learners more autonomy and flexibility in the process of learning through

**TABLE 6 |** Emotion regulation support interventions and areas affected.

| Phases | Intervention | Strategy/Area Affected | Effect |
|---|---|---|---|
| **Preparation** | N/A | N/A | N/A |
| **Performance** | Planning and reflection protocol (1) | Lower stress level (related to reduced procrastination) | *d* = 0.63, CI[0.06, 1.2] |
| | Learner style directed online platform (14) | More positive learning experience Controllability | *d* = 0.48, CI[0.18, 1.1] *d* = 0.76, CI[0.07, 1.4] |
| | Learner preference directed online platform (25) | Control of learning beliefs Less test-related anxiety | *d* = 42, CI[0.16, 1.0] |
| | Group awareness tool (26) | Anxiety control and reduced sense of loneliness | *d* = 0.52, CI[0.21, 0.83] |
| | Instructor and institution support Course quality (19) | Confidence, enjoyment, interest | *d* = 0.56, CI[0.40, 0.72] |
| | System, information, service quality) (27) | User satisfaction | *d* = 0.39, CI[0.13, 0.64] |
| | Assessment rubrics (30) | Reduced task anxiety/avoidance | *d* = 0.57, CI[09, 1.0] |
| **Appraisal** | N/A | N/A | N/A |

personalized (learning style- and preference-oriented), adaptive modes of instruction have been proven to have a positive effect on emotion regulation. Learners in such environments have more control over their learning beliefs, higher self-efficacy, and consequently experience lower levels of test-related anxiety (Souki et al., 2015; Lee et al., 2016).

Additionally, interventions such as *assessment rubrics* that support learners to better prepare and orient themselves for the upcoming learning process help reduce negative emotions and task avoidance practice (Panadero et al., 2012). Likewise, lowered stress levels and reduced confusion were witnessed as a result of *Planning and Reflection Protocol* application (see also in section "Interventions Supporting Metacognition Regulation" above), which encourages learners to plan and set their learning goals before engaging in the learning practice, which results in better implementation of the learning process and less procrastination related anxiety (Wäschle et al., 2014).

## Technical Features, Representations of Interventions and Combination of Those Effective in Supporting Self-Regulated Learning

### Identified Effective Technical Features of Self-Regulated Learning Support Interventions

*Open Learner Model* allows more individualization and adaptation of the online learning experience by tracing learners' activities and making them available for analysis to the interested parties (i.e., teachers, learners). To make the raw data more easily digestible, v*isualization* comes into play, which has been proven to have a positive effect on learners' metacognition as well as motivation regulation (Jivet, 2016)[1]. With the visualization, the type of visual being selected also becomes important. Since SRL is a multifaceted, multidimensional process, visualizations allowing multi-dimensional and multi-layered representation, such as radar graphs, line charts, heat maps, mastery grids, cloud tags and interaction diagrams come into play (Wäschle et al., 2014; Guerra et al., 2016; Jivet, 2016; Ilves et al., 2018; Ma et al., 2020), with the intentional use of different colors to denote different aspects and quality of learning (Wäschle et al., 2014; Guerra et al., 2016). Ilves et al. (2018) tested the effect of *radar* versus *textual feedback* on performance and mastery-oriented students' SRL skills (starting the learning process and earliness) and found a positive effect of radar visualization over the textual one ($d = 0.43$, CI[0.01, 0.81]) as well as the advantage of the textual visualization over no visualization option (in case of performance-oriented learners—$d = 0.1.5$, CI[1.1, 2.0] and mastery-oriented students – $d = 0.42$, CI[0.08, 0.77]). Interestingly, textual visualization did not have a favorable effect on scheduling, i.e., dividing the work across multiple days—the visualizations did not increase the number of days during which the students worked on the assignments, the difference between the groups being statistically significant ($p = 0.031$). The authors speculate that the possible explanation could be that the performance-oriented learners may have tried to gain all the exercise points as fast as possible, ignoring the feedback related to spacing out their effort over a longer period of time. Additionally, when it comes to academic performance, the highest performing students, regardless of the visualization, earned the highest scores, giving grounds to speculate that students who have strong task related or self-regulatory skills do not benefit from the external feedback provided by the visualizations as much as students with weaker skills (Ilves et al., 2018).

The *social comparison* feature, which allows analysis of students' performance against standard expectation/class average/previous successful learners, was also explored in combination with the learner log data based visualization function, and was found beneficial for learners' motivation, metacognition as well as cognition skills (Guerra et al., 2016; Jivet, 2016; Ma et al., 2020; see also studies N13, 26, 8, 13 in **Tables 3–6** above). Further, the study by Ilves et al. (2018) described above investigated the effect of the *comparison feature* administered through layered radar graphs (student's performance displayed in a blue layer and the average performance of all students in the course in a gray layer) and found that while beneficial for all types of learners, visualization without such comparison function might even have a reverse impact on performance-oriented students, who draw their motivation from outperforming others ($d = -0.26$, CI[−0.68, 0.14]. With regard to the social comparison feature, it has to be further observed that alongside its positive effect, it might also have a somewhat restricting influence on the diversity of student navigation, resulting in learners mimicking each other's

[1]However, these results should be taken with caution because, due to lack of relevant data, it was not possible to calculate the comparable effect size in the mentioned study.

behavior and following unified learning patterns. To address the given downside of this feature, authors suggest combining it with personalized recommendation technologies (Guerra et al., 2016; Jivet, 2016).

### Combination of Interventions for an Enhanced Self-Regulated Learning Support Effect

Some studies explicitly emphasize the necessity of combining several interventions in order to have a significant effect on SRL. Examples identified in the present study include *planning e-journals* combined with *self-reflection prompts* closely mapped with curriculum activities and assessment (Fung et al., 2019). *Note-taking tools* (Matrix, outline and conventional) when combined with *self-monitoring prompts* that encourage students to review their notes before moving on to the next activity have proven to have an enhanced effect on learners' cognitive strategy use (more rehearsal and deeper analysis of the taken notes) as well as self-monitoring efficiency. Such combination is especially helpful with least supported (conventional note-taking) learners and more observable in the case of more complex tasks ($d$ = 0.96, CI[0.56, 1.3]), (Kauffman et al., 2011), a fact that might indicate that more elaborate interventions on their part have more enhanced effects when combined with further scaffolding tools. Yet another study (Lee et al., 2010) showed the effectiveness of the task-based *generative learning strategy prompts* in combination with *the monitoring feedback* only ($d$ = 0.26, CI[0.02, 0.52]). The generic nature of prompting, which, used on its own, was found not to have a significant effect (Bannert and Mengelkamp, 2013), seems to be boosted with more details and individualization coming in the form of monitoring feedback.

In a qualitative study by Gikandia and Morrowa (2016), the effect of *peer-to-peer feedback* in collaborative online learning contexts was shown to be enhanced with the detailed *assessment guidelines and analytical rubrics*. Such rubrics play a key role in supporting students to monitor their peers' progress, and provide valuable feedback. The process further benefits from tutor supervision.

The important role of teacher involvement has also been proven with regard to the SRL interventions which are more complex in nature. SRL e-portfolio is a multifunctional and multi-component tool, the functionality and use of which need to be properly understood in order to reach the intended effect (Torras and Mayordomo, 2011). The preliminary preparation of students for the efficient use of the intervention has also been confirmed by another study on metacognitive prompting by Bannert and Mengelkamp (2013), which focuses on combining the administration of prompts with training on their use.

## DISCUSSION

Operating efficiently in online learning environments is not an inherent competence that higher education students possess. Rather, it is a skill that needs to be developed in the process of learning and requires explicit support and training at an initial stage. The less experienced the learner and the more conceptually rich the learning domain, the more such help is needed. The present study investigated the SRL interventions that were found helpful for supporting various areas of SRL at its various phases. The study also attempted to identify technical features and a combination of interventions which were found to be effective for SRL support. As a result, the potential inventory of interventions was drawn up in the form of tables (see **Tables 3–6**).

### General Overview of the Findings of the Interventions Targeting Various Areas of Self-Regulated Learning

In the current study, the distribution of the interventions explored focusing on various SRL areas has an unbalanced nature, with metacognition regulation scaffolds being by far the most explored, whereas emotion regulation interventions are the least investigated (see **Table 1** above). As for the focus on SRL phases, the overwhelming majority of the interventions target SRL areas in the performance phase, even though the planning phase is considered as the most important of the three (Greene et al., 2012; Yılmaz et al., 2017), especially for novice and less motivated learners, who need extra support, particularly at the "set up" stage. This finding is not in line with a study by Viberg et al. (2020) where the planning phase is claimed to be equally well supported. This can be explained by the fact that in this study, no differentiation is made between SRL areas and phases, and the interventions targeting preparation phase of the metacognition regulation (and which are well covered according to the present review as well), compensate for the interventions largely absent from the preparation phases of other SRL areas.

Additionally, SRL is a multi-component and complex construct; it is a cyclical process, and the activities in each phase, which are also non-linear or lacking a subsequent nature, affect one another (Zimmerman, 1990). Under supporting any given component or phase can have a disruptive effect on the whole SRL support process. Thus, "the connectedness" (Wong et al., 2019, p. 369) in the process of support among all SRL areas and phases needs to be born in mind, and the comprehensiveness of the support designs must be ensured (Greene et al., 2012). The fact that none of the support interventions explored in the current study were found to be covering all SRL areas as well as phases is in line with the above claim about its complex nature. Hence, to achieve optimal outcomes with regard to SRL support, it becomes necessary to engage in careful mixing and matching of various interventions while keeping in mind the context, the learner as well as the task characteristics at hand.

However, if a single most flexible and comprehensive intervention had to be selected, that would be prompts. As shown in the present study, prompts can come in different forms (e.g., text, pedagogical agents) and at different times (planning-, learning process- and reflection-oriented prompts). Various prompts are also presented in combination with other interventions (e.g., with the feedback) for an enhanced effect. They can be of varying levels of specificity (personalized vs general), and delivered at micro (task-level) as well as macro level (study cycle level). Prompts also vary according to the level of individualization and flexibility (e.g., adaptive/personalized prompts), learners' involvement (e.g., self-directed prompts) and intensity of support they provide. Prompts have been found the most useful for learners with fewer skills and competence as well as for more complex tasks (Kauffman et al., 2011). However, the studies reviewed also revealed the importance of taking into account various factors to ensure the successful application of prompts in specific contexts and with specific learner groups. For instance, whereas more detailed and more frequent prompts have been found to be efficient with more inexperienced learners, prompts that are more strategic and generic in nature have been proven to work better with more experienced learners, avoiding unnecessary overload and distraction.

To broadly summarize the findings with regard to the areas of SRL that the identified interventions cover, it can be observed that cognition regulation seems to be supported at the task level in most of the cases and at the performance stage of the learning process; the findings are in line with previous studies (Devolder et al., 2012). The interventions targeting cognition regulation largely support learners with engaging more deeply with the content through being reminded to revisit the materials, ask for further clarifications, prompting and giving the tools to summarize, highlight, take notes and thus interact with the content as much as possible. Such interactive practice is in line with the claims of the learning theorists that learners should "do something" with learning materials rather than just be exposed to them and stay in the role of the passive recipient (Jonassen et al., 1998). As for metacognition, it is the most comprehensively supported and investigated SRL area. The biggest fascination with metacognition can be explained by the fact that regulation is mostly associated with planning and actual performance-related learning strategy use. Thus, the need for metacognitive support might seem more prominent. However, the importance of supporting cognition, motivation and, especially, emotion regulation, which are more associated with internal learning processes, seems to be somewhat underestimated. In the current review, motivation and emotion regulation support have been found to be closely interconnected as well as related to other areas of SRL (cognition and metacognition). In none of the studies was the motivation or emotion component the only and explicit target of the exploration but rather investigated together with other areas of SRL. This could be explained by the fact that motivation and emotion regulation, besides external and learner-related characteristics, are also largely defined by cognition and metacognition regulation as well as influencing one another (Weiner, 1985). With regard to motivation, as part of the current review, it can be further observed that motivation is investigated not only as a dependent variable but, in a couple of cases (e.g., Bannert and Mengelkamp, 2013; Duffy and Azevedo, 2015; Ilves et al., 2018), as an independent variable having its differential effect on other SRL area outcomes, indicating an excessive interdependence of motivation regulation with various aspects of self-regulated learning and underlining the necessity to look at it in combination with other areas of SRL. For instance, when learners feel totally lost facing complex content which is beyond their "reach," then, if they are unequipped with special metacognitive strategies that would help them navigate through the online learning experience, they might find a more feasible alternative—to avoid the failure by just giving up.

The present literature review revealed a positive association of motivation and emotion regulation with goal setting and planning conducted at the preparatory phase of the SRL cycle. This observation is supported by the Goal Orientation theory, according to which goal setting is a key motivational process (Locke and Latham, 1984). Since the set goals define the ultimate outcome that individuals are trying to achieve, they are more likely to engage in activities that are believed to lead to those goals. Goals that are specific, realistic and adapted to learners' needs are highly motivational and translate into increased learner self-efficacy at the preparatory phase. It also has the potential to reduce learners' anxiety levels by engaging them in setting goals that seem more realistic and feasible. Further, motivation is maintained during the performance phase by learners being more prepared and less anxious about what comes next. Thus, it is no surprise that interventions such as planning and reflection tools, assessment rubrics and planning prompts, aimed at clarifying the expectations and setting out clear paths for learners to follow, have been shown to have a positive effect on motivation and emotion regulation. Even in the face of challenging tasks, knowing what to expect and what the priorities are results in reduced stress levels and increased motivation to persist in the learning process.

Unlike motivation regulation, which has been well explored at the performance phase of SRL, emotion regulation has been vastly under investigated. Fortunately, it seems that the existing gap has been identified in other studies as well (Duffy and Azevedo, 2015; Hooshyar et al., 2020), the realization of the need to integrate affective components of SRL into instructional settings are beginning to emerge (Belland et al., 2013) and more and more calls have been made to develop "systems that care" (Du Boulay et al., 2010, p. 197).

## Effective Combination of Interventions and Their Technical Features for Self-Regulated Learning Support

### Combination of Interventions

As shown by the findings of the current review, the most optimal and feasible way to provide comprehensive support for self-regulated learning in distance learning environments is by accurately and thoughtfully combining various interventions. Additionally, it is important that each intervention is carefully crafted, paying attention to each of its feature as well as taking into account a myriad of factors emerging from the context at hand. Otherwise, potentially very powerful tools might turn into useless or even hindering measures. For instance, directed pre-flection prompts (Lehmann et al., 2014) were found to be positively affecting novice learners' motivation, but less efficient with more advanced and experienced learners, whereas a study by Ifenthaler (2012) proves the efficiency of generic prompts with more advanced learners more pronounced (Wong et al., 2019). In the present review, generic reflection prompts used on their own without reinforcement of their effect with feedback, and used with less experienced learners, proved to have no effect on SRL (Verpoorten et al., 2012; Bannert and Mengelkamp, 2013). According to Verpoorten et al. (2012), the prompt, a potentially powerful SRL intervention, can turn into a "featherweight technique" (p. 8), unless designed efficiently and used with the right audience. Thus, it becomes very difficult to design a one-of-a-kind intervention that can "do magi" in all these cases. The solution may be attributing the online learning process a more individualized nature (see discussion below).

As for an impactful combination of SRL interventions, it was found that reflection prompts enhance the effects of planning e-journals by encouraging further reflection on learners' part with regard to their metacognitive strategy use. Also, a note-taking tool highly benefits from add-on monitoring prompts, and the combination results in more intensive processing and analysis of the notes taken. Generic prompts benefit from being reinforced by monitoring feedback for significant effects, whereas the feedback itself has a stronger effect if delivered in the visual form. In the case of SRL, multidimensional visualizations, such as radar graphs, are of most use, and a further combination of the visual feedback and the comparison feature (see detailed discussion in the paragraph below) makes the interpretation of the results easier and more productive.

Another efficient combination of interventions identified is supplementing system delivered SRL support with tutor involvement in the support process, a practice that proves to be useful in the case of complex SRL interventions and, again, particularly with learners lacking experience in operating efficiently in online learning environments independently. Peer-to peer interaction and the provision of feedback, which is a useful SRL practice, can also be further supported by employing well-defined assessment rubrics, which are expected to secure the needed quality of the feedback given and alignment of the feedback with the learning outcomes. This is an especially useful practice in the absence of intensive teacher presence.

## Effective Technical Features

The "empowering features," which were found to be contributing to boosting the impact of the SRL support and, in some cases, being a critical determining factor of success, are summarized below.

### *A. Personalization, Adaptability and Learner-Directed Nature of the Interventions*

Personalization and adaptability of the distance learning experience can be achieved with the help of designs of the tools and learning environments that involve learners themselves in elaborating support interventions for themselves. Such practice contributes to making learners more engaged and motivated in the learning process (Bannert et al., 2015; Lee et al., 2016), the finding which is also in line with the previous studies in this area (Poot et al., 2017). Teacher involvement in providing help on an individual basis is another possibility of such support. However, even though the latter is an efficient and personalized way of support (Azevedo et al., 2011; Torras and Mayordomo, 2011; Gikandia and Morrowa, 2016), such approach might not always be a feasible solution in the present day of massive online learning. Luckily, these days, advanced technologies offer possibilities of mediating the given challenge. In the present study, interventions described as individualized and/or adaptive were the ones largely based on system generated learning analytics and Open Learner Model technologies. Open Learner Models have great potential to transform the nature of SRL support dramatically by making it possible for the system to analyze learner behavior through log data and, in the case of clearly defined indicators for each SRL area, provide a personalized and well-timed targeted support. In the present study, such technologies helped attribute the prompts (Duffy and Azevedo, 2015), feedback (Lee et al., 2010; Wäschle et al., 2014; Ilves et al., 2018) as well as the study materials (Guerra et al., 2016) an individual/adaptive nature. Within the study environments, such systems enabled automatic re-designing of the learning format—the sequence of activities, the mode of delivery of learning practices and materials based on learning styles and preferences, pre-determined based on learners' profiles (Souki et al., 2015).

Providing students with adaptive scaffolding in the OLM environment then also means measuring learners' levels of SRL and providing personalized support. Accordingly, clearly defining the indicators related to concrete SRL strategies becomes necessary for the system to be able to accurately deliver targeted support to the learner. The trend of combining the measurement and support of SRL is emerging in the field of self-regulated learning, and is referred to as "the third wave" (and the most efficient) of SRL support, "when measurement and intervention come hand in hand" (Panadero et al., 2016, p.1), and help provide just the right level of support. SRL is about finding "the right balance between freedom and guidance during the learning process" (Nussbaumer et al., 2014, p. 17) after all.

### *B. Social Comparison*

The social comparison feature has been explored by a number of studies as a useful feature to have in distance learning environments. The motivational and time management related benefits of social comparison were identified in the studies reviewed (Guerra et al., 2016; Jivet, 2016; Ilves et al., 2018) and this finding is also in line with the previous research (Papanikolaou, 2015). Papanikolaou observed that comparing one's behavior to a target performance largely determines how learners react to their success or failure, and helps to identify differences in their learning process. In case of success, the comparison helps learners recognize the learning strategies they adopted and optimize their strategies. On the other hand, in case of failure, the desired state motivates learners to re-evaluate and change their strategies. However, the "dangers" of using the social comparison feature have also been emphasized. Namely, while proven to make learners more engaged in the study process, such comparison, if done on a peer-to-peer basis, might be conducive to the development of a more competitive spirit among students, which might be more acceptable in some cultural contexts than in others. As for comparisons based on other students' navigation patterns, such practice might have a unifying effect, and prevent learners from adopting new and creative ways on the way to achieving their goal (Guerra et al., 2016). Moreover, certain forms of social comparison could put pressure on learners who are lagging behind and contribute to them giving up the course instead of encouraging them to pursue their goals.

Thus, one potential way to go about the comparison issue and to encourage mastery rather than performance orientation

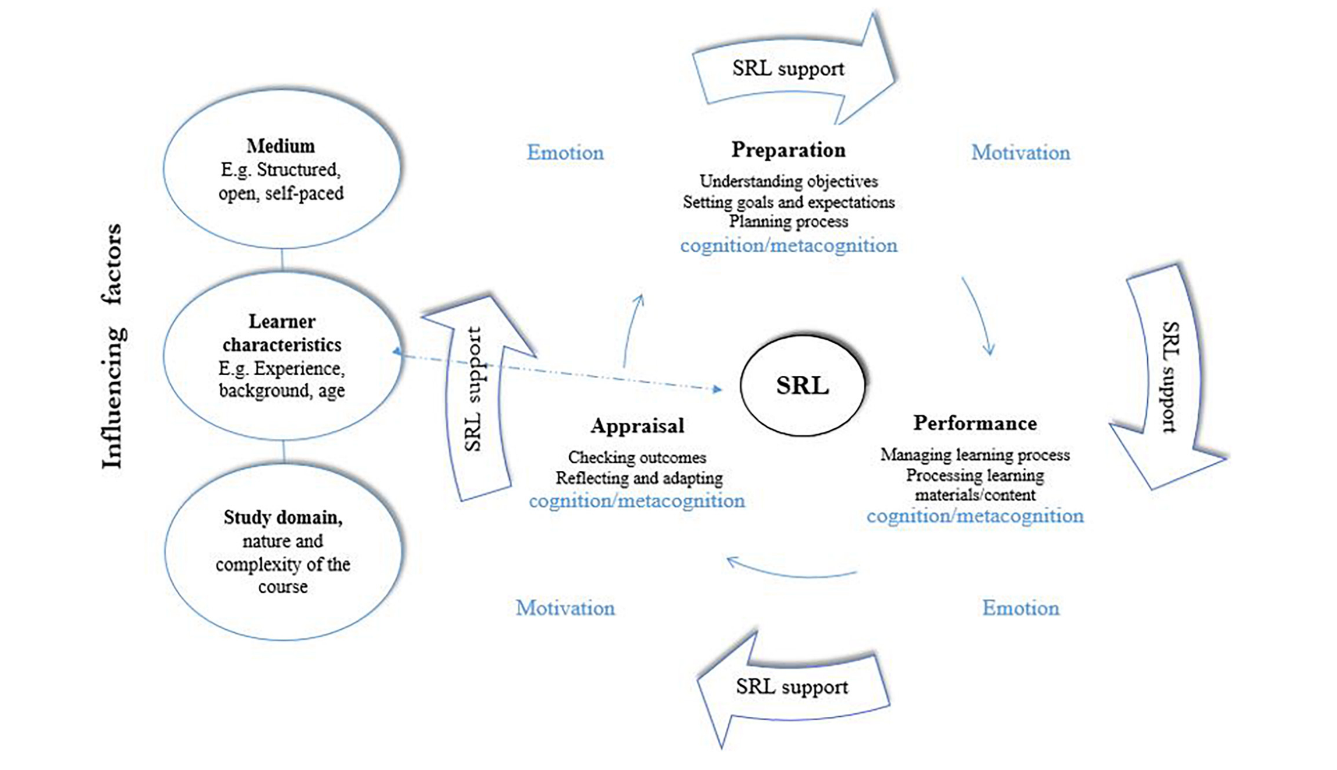


**FIGURE 3 |** Self-regulated learning process: SRL stages and areas, strategies used, the dynamics of support provision and external factors involved.

among learners is to focus on making the comparison more general in nature. Comparison can be made of a students' outcomes against a standard expectation level, a 'neutral average' rather comparing students' success to one another, which can have a detrimental effect on low-achieving learners, and result in increased anxiety levels. Another potential approach to help learners stay focused on their own progress rather than worry about being 'behind' or being demotivated by progressing too 'far ahead' of the others is to follow up the comparative data with the textual feedback focusing on the learner's own improvement and individual effort as much as possible. Further, to attribute this feature an adaptable nature, it can be offered to learners on an on-demand basis, by making the function optional.

## FURTHER RESEARCH AND LIMITATIONS

The gap observed in the research of the SRL support was with regard to emotion regulation in online learning environments. It can be speculated that the reason for the under-investigation of this area might be due to its highly 'hidden' nature. For this reason, the ability to accurately detect the need for emotion regulation becomes important (Viberg et al., 2020). For the purpose of accurate measurement of emotion regulation a multidimensional approach has been suggested (Panadero et al., 2016), such as self-assessment, or naturalistic approaches, such as observation (if feasible), as well as facial expression analysis (Järvenoja et al., 2017), applied alongside with exploiting the potential of OLM. As for the potential of OLM, the need to define accurate indicators becomes crucial, which requires further research and evidence base.

The fact that the study is limited to looking at SRL in higher education level and distant learning context, implies that the findings of the given study cannot be automatically applied in other settings (e.g., young learners and f2f formats) and these areas require further investigation. Similarly, learner-related variables might have a differentiating effect on the efficiency of certain SRL interventions. The current review revealed that the studies investigating this aspect in a systematic and thorough manner with regard to concrete interventions are scarce and need more attention.

Additionally, the present study does not compare or explore the differentiated effects of the identified interventions in the various identified learning environments. For instance, platforms that are open and non-linear in nature and allow interaction and communication and self-directed choice of materials for learning purposes would benefit more from technology provided step-by-step scaffolding, OLM technology adoption and individualization of the learning process. In contrast, distance learning environments which serve more as repositories of knowledge and leave little space for creativity or autonomy due to their passive and straightforward nature are likely to benefit from different types of support, e.g., feedback on their level of engagement with the course material and learning performance (Jivet, 2016). Hence, further exploration with regard to how concrete interventions function in different distance learning environments would provide deeper insight and facilitate the choice of optimal interventions for concrete digital learning media.

Also, since the wider context (countries where the studies included in the current literature review were conducted) is dominated by highly developed countries (see **Supplementary Appendix B**), it can be assumed that we are looking at places with a high level of technological development and learners with a higher level of digital competences, and thus, the effects of the interventions explored may be of a different nature in dramatically different circumstances.

## CONCLUSION

The central aim of the present study was to investigate what interventions have been studied as part of the recent research conducted in the area of SRL, with a particular focus on distance learning and higher education level. The cyclical nature of SRL makes the comprehensive, and continuing support necessary for ultimate success. Additionally, since the SRL processes are largely determined by a number of more global, objective factors as well as learner-related characteristics, a careful account of all of these variables need to be taken into account while designing SRL support systems in online learning environments. In this direction, further, more consistent and focused research is needed for more concrete assumptions (for this reason, the relationship between these factors and SRL is presented with a dashed arrow in **Figure 3**). In the meantime, for the optimal and targeted learning support, the interventions that integrate personalized and adaptive features should be considered, as they were found to have the best potential to flexibly serve multiple purposes in various contexts. Customized support becomes possible with the systems that help track learner performance comprehensively, and allow adaptation of the learning process as well as more active involvement of learners themselves by giving them the access to their learning data, and allowing self-assessment and reflection. The potential of Open Learner Model systems in this direction cannot be underestimated (Hooshyar et al., 2020). Another thing to be pointed out is somewhat different nature of affective aspects (motivation and emotion) of SRL, which seem to be closely interconnected, on the one hand, as well as largely, and on an ongoing basis, affected by the factors related to the success/failure related to the cognitive and metacognitive regulation. Thus, the need for careful measurement and support of the motivation and emotion aspects of distance learning is rather pronounced. The figure below captures the above discussed points in a form of a concluding framework, which is now an expanded version of the one (see **Figure 1** above) that has been used as the theoretical basis for the current study.

On a final note, amid the abundance of the SRL supportive interventions, and facing the temptation of adopting multiple technologies while trying to make the online learning environments highly supportive, it has to be born in mind that the systems and designs should stay simple, whereas the learner, their needs and the process of learning always needs to occupy the central part.

## DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author/s.

## AUTHOR CONTRIBUTIONS

NE, KS, MP, and ÄL all contributed to conception and design of the study. KS took an active part in data validation, and together with MP and ÄL, to the development of the framework of analysis. NE wrote the first draft in close collaboration with other authors. KS, MP, and ÄL provided detailed feedback and contributed to the revision process of the manuscript. All authors approved the final version of the manuscript to be published.

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## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2021.792422/full#supplementary-material

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# What Does Twitter Say About Self-Regulated Learning? Mapping Tweets From 2011 to 2021

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Social network services such as Twitter are important venues that can be used as rich data sources to mine public opinions about various topics. In this study, we used Twitter to collect data on one of the most growing theories in education, namely Self-Regulated Learning (SRL) and carry out further analysis to investigate What Twitter says about SRL? This work uses three main analysis methods, descriptive, topic modeling, and geocoding analysis. The searched and collected dataset consists of a large volume of relevant SRL tweets equal to 54,070 tweets between 2011 and 2021. The descriptive analysis uncovers a growing discussion on SRL on Twitter from 2011 till 2018 and then markedly decreased till the collection day. For topic modeling, the text mining technique of Latent Dirichlet allocation (LDA) was applied and revealed insights on computationally processed topics. Finally, the geocoding analysis uncovers a diverse community from all over the world, yet a higher density representation of users from the Global North was identified. Further implications are discussed in the paper.

**Keywords: self-regulated learning (SRL), Twitter analysis, topic modeling (LDA), geocoding analysis, descriptive analysis, self regulation**

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## INTRODUCTION

Self-Regulated Learning (SRL) has gained much attention recently. Researchers have presented theories of SRL in various contexts of modern educational models, including SRL in formal learning, SRL in informal learning, and SRL in non-formal learning settings. Most of these learning models have been shaped by the digital revolution of education (i.e., teaching and learning) through the introduction and usage of learning management systems, smart devices, Massive Open Online Courses (MOOCs), and other data-driven applications such as learning analytics. In addition, social media has emerged as a popular forum for learning and sharing information as well as discussing activities that are related to education, concepts, and classrooms (Clarke and Nelson, 2012). The term microblogging in social media forums is seen as a new form of blogging activity for the general public that enables rapid dissemination of information and exchange of artifacts and opinions among diverse communities.

Twitter is one of the most popular microblogging services that entails a vast corpus of contextual data. According to Ahlgren (2020), there are over 500 million tweets each day generated by 350 million active users. Twitter structure is simple. Users are allowed to tweet short messages that are only 280 characters in length (previously in the early times of Twitter, users were allowed to tweet only 140 characters). Twitter permits users to interact with microblogs in various ways: posting on one's profile page (tweet), sharing a microblog on their profile (retweet), replying to someone's microblog (reply), clicking the action button of a "heart" (like), a mention of someone (user hashtag), and linking to a context (topic hashtag).

In the scientific domain, Twitter has been actively used to raise scholarly discussions and exchange of scientific information (Darling et al., 2013). That is, research shows that scholars tend to use Twitter for sharing activities and providing quick and direct reflections on conferences, publications, and getting into debate (Collins et al., 2016). Relying on the increasingly respected practice of science communication with the public, evidence has been found on microblogging in general and Twitter in particular as a means for outreach and increasing science literacy (Parsons et al., 2014; Collins et al., 2016). Since Twitter is gradually becoming a venue for academic microblogging (Dhir et al., 2013; Collins et al., 2016), knowledge about research topics, interest and scholarly interactions are becoming immense, and "fortunately" automatically recorded. The availability of such a rich repository of data on research topics offers valuable insights to discover and understand trends within scientific domains (Chen et al., 2015). As an important theory in the field of education, SRL can benefit greatly from such an intuitiveness approach. In fact, understanding the discussions around SRL in the scope of one of the most popular social networking services can help identify themes and changes. In addition, the analysis can provide a determination of critical gaps and yet plan for future steps by involving a different voice from outside academia.

Recently, several studies have reviewed scholarly works on SRL (Winne, 2021; Yusufu and Shakir, 2021). Nevertheless, we do not know how the theory of SRL is discussed on social media in general and Twitter in particular. Whereas Twitter has been found to stimulate interest in certain topics (Han et al., 2021), no study reviewed Twitter to explore the SRL theory. We want to take advantage of this social media platform and offer an alternative approach to investigating and exploring SRL communication and discussion. Our exploration includes investigating Twitter conversations on SRL, the main topics of interest raised by the public discussion, and where do they originate from?

A big challenge of analyzing social media data is how to excerpt valuable insights from a large amount of data. However, the fast development of data science technologies allows to analyze a large amount of unstructured content data and gain insights in a short time (Blazquez and Domenech, 2018). In particular, and besides descriptive and content analyses, this work uses Natural Language Processing (NLP) techniques, including unsupervised methods and analyze 54,070 tweets collected in a time frame between 2011 and 2021.

Therefore, the main contribution of the paper is to potentially reflect on the SRL theory and reveal new insights about the community discussions on SRL by analyzing the Twitter microblogging data with particular key search terms. The exploration of Twitter data is not new, however, to our knowledge, this is the first study of such an approach on SRL to be conducted, demonstrating a gap of knowledge that should be tackled. As a result, this work brings in interesting findings to fill the research gap. First, the paper bridges the research gap on SRL by leveraging user-generated data which is commonly unfiltered information and uses a unique source other than those available from general derivations (i.e., scholarly publications, practices). Second, we extract some interesting topics on SRL from unsupervised topic modeling, including five main themes that could demonstrate a different direction on social media than what is used to account in academic shares. Last but not least, the article reinforces originality by bringing in geocoding, a technique that indexes particular information to a geographical position, and unveils that discussion on SRL is more prevalent in some particular geographical regions than others.

The remainder of the paper is structured as follows. In section "Related Work," we discuss related work. Section "Theoretical Framework" covers the theoretical framework that shaped our understanding of the research problem and analyses. Section "Methodology" and "Results" draw insights into the used methodology and results, respectively. Section "Discussion" discusses the results and bring in our answer to the research questions. Finally, the paper concludes with implications, limitations, and future directions.

## RELATED WORK

Self-regulated learning is a skill of self-thought, plan, and action that has been identified as one of the critical factors affecting student success in learning processes (Zimmerman, 1990; Winne, 2021; Yusufu and Shakir, 2021). While there are various models of SRL, most of the models agreed that SRL is cyclical and clustered into three phases, namely forethought, performance, and reflection. One of the grounds for the relevant interest in SRL is the growth of digital, online, and virtual courses in the context of formal and informal learning environments (Lim et al., 2021). The reason of which returns to the students who are in needed skills to "actively make decisions on the metacognitive and cognitive strategies they deploy to monitor and control their learning to achieve their goals" (Lim et al., 2021, p. 2). SRL strategies such as goal setting, time management, and help-seeking are useful and common practices used to explore and investigate SRL processes (Yusufu and Shakir, 2021).

Encouraging online collaborative activities through social media platforms to seek help from other colleagues was identified as relevant and essential for SRL (Yen et al., 2021). Yen et al. (2021) also found that blogging on social media effectively engages students in self-evaluation and self-reflection, which, as mentioned earlier, are fundamental parts of the SRL phases. With that in mind, social media may encompass important discussions on the theoretical and practical approaches for better self-regulation.

Recently, there have been a growing number of Twitter-related research works. Some of the studies powered up Twitter and used the huge collection of microblogs contextual data to address interesting research questions. For example, Chen et al. (2015) analyzed tweets of 4 years period of the official learning analytics and knowledge conference to gain insights into the community. The analysis revealed that Twitter was helpful to identify trends of learning analytics as well as identify major personal experiences. Chen et al. (2015) were able to characterize an escalating trend of student-centered topics on engagement and assessment as well as cluster tweets into topics using topic modeling to show the diversity of the field of learning analytics.

The conversational nature of Twitter has been identified to be useful in detecting user networks to discover scientific knowledge across different communities. The study by Díaz-Faes et al. (2019) provided novice evidence on Twitter studies to break new ground for systematic analysis around science. Díaz-Faes et al. (2019) analyzed over 1.3 million unique users' data and 14 million tweets on scientific publications to outline the general activities of Twitter communities and their interactions with scientific outputs based on social media metrics. Some of the major findings of their study has revealed the significant disciplinary differences of how researchers behave in the social media realm and the development of scholarly identity of researchers.

Another example is the study by Garcia and Berton (2021) who used sentiment analysis to explore a large number of tweets in Brazil and United States on related microblogs to COVID-19. The researchers identified a general negative emotions dominancy during the COVID-19 pandemic for almost all the topics in United States and Brazil. A key contribution of Garcia and Berton (2021) study was enriching the library of the Portuguese language with keywords related to positive and negative emotions as well as gap the literature with new sentiment content for the development of new techniques for processing languages other than English.

Perhaps some of the most popular analysis methods of Twitter from the literature are content analysis and topic modeling (Giachanou and Crestani, 2016). The latter method has been immensely used to identify topics from complex yet short textual data. One interesting example of how topic modeling has been used with a large tweets database is the study by Dahal et al. (2019). The researchers were able to infer different topics of discussion on the issue of climate change and how it is perceived by the general public. Dahal et al. (2019) found that the discussions of climate change in the United States are less focused on policy topics than other countries in Europe. Other examples from the literature used topic modeling to examine themes discussed on Twitter about the COVID-19 pandemic (e.g., Boon-Itt and Skunkan, 2020; Wicke and Bolognesi, 2020).

Topic modeling helped Saura et al. (2021) divide a large corpus of nearly 900,000 tweets on security issues in smart living environments. The result of this study identified 10 topics related to privacy and security breaches and smart living environments such as the Internet of Things. One of the significant implications that took advantage of Twitter microblogs using topic modeling is identifying key concerns raised by users. For example, Saura et al. (2021) determined that malware, data cloud storage, and cyber-attacks are among the major issues Twitter users reported and require further attention by manufacturers.

With respect to content analysis, Twitter offers various possibilities, for example hashtag analysis. Hashtags enable users to identify other users based on their interest in parallel topics (Kimmons et al., 2017). As such, hashtags provide sharing of information in an organized manner with which resources are curated based on shared interest. Another research study by Kimmons et al. (2021) examined tweets that incorporate a hashtag of #EdTech, found out that discussions of educational technology have been changing with the present pandemic. It seems that the COVID-19 has triggered the emerging usage of new terms in educational technology such as "remote learning." The study by Kimmons et al. (2021) also stated that trends of educational technology (i.e., EdTech) had been largely influenced by a small group of active Twitter users during the time of the pandemic.

A less popular but interesting analysis method is location analysis based on microblogs (i.e., geocoding). Using social media data for geographical research can be used to identify trends, explain patterns and describe various geographical phenomena (Goldberg, 2008). In Twitter, researchers have used geolocation analysis to map the felt area by earthquakes by examining the tweets generated after a particular time (Earle et al., 2010). Others used geolocation to identify accidents reported on Twitter in large cities (Milusheva et al., 2021).

In general, we learned from the literature that exploring the public discussions surrounding the SRL theory using Twitter analysis methods could offer useful information and present alternative perspectives to the theory. Provided that, the current study aims to gain a broader understanding of how the SRL theory is discussed in the public affinity space and how it has been argued over the last 10 years. To achieve this goal, our analyses will attempt to answer the following research questions:

- What are the general characteristics of Twitter conversation on SRL?
- What are the main topics of interest that are related to SRL from Twitter public discussion?
- Where do English-based SRL discussions originate from?

## THEORETICAL FRAMEWORK

Our understanding of investigating SRL using Twitter is grounded in Gee's (2012) theoretical framework of *affinity spaces*. Gee identifies affinity spaces when typical geographical boundaries are humbled. He conceives spaces as physical, blended or digital spaces where individuals share common interests and endeavors. In these spaces, individuals also communicate and interact with each other. Unlike traditional contexts, affinity spaces provide wide areas for involving individuals that are open for everyone.

According to Carpenter et al. (2020) study, the phenomena of infinity space can be articulated on social media, and Twitter is one of these. In the context of this paper, we follow a similar approach and use "Twitter space" and "Twittersphere" interchangeably to link to Gee's grounding of *affinity spaces*.

## METHODOLOGY

As stated earlier, the objective of this research study is to carry out analyses on Twitter tweets with a particular emphasis on the SRL theory from the time span of 2011 till 2021. As a consequence of this study goal and after the data collection, we performed key steps to clean and prepare the dataset. We then followed three main methods to answer the research questions, descriptive analysis, geocoding analysis, and topic modeling.

In the context of this work, the term "tweet" refers to a microblog message from a Twitter account that consists of a limited number of characters, 140–280 characters. The term "organic tweet" refers to original microblog tweets, while a "retweet" means a re-post of a tweet that is shared among one's followers. In this paper also appears terms of "hashtags" and "likes." The hashtags are words that start with "#" and when used by an author, it becomes linked to other tweets that share-alike. Finally, "likes" are Twitter interactions that are represented by a small heart referring to one's appreciation for a particular tweet.

## Data Collection

The data collection process was carried out using the well-known programming software, Python with scripts that belong to the standard indexed libraries[1] (e.g., json, requests, os, and time). To retrieve the tweets from Twitter, we used the Twitter Application Programming Interface of (API) using private tokens and keys. The majority of the API functions were optimized to pull out the needed raw data from Twitter database (e.g., text, likes, retweets, hashtags, etc.) to proceed with the analysis.

In order to retrieve the needed information, we created a corpus of search terms directly connected to SRL as the following:

```
keywords = "self_regulated_learning" OR "selfregulatedlearning" OR
"self-regulated learning"
```

The return results include those tweets that use the trigram word of "self-regulated learning" with and without hyphen, underscore, dash. . .etc., so-called regex check.[2]

In addition, we search a numerous number of hashtags that could be linked to SRL as the following:

```
keywords = "(#selfregulatedlearning OR #learning OR #education OR
#metacognition OR #elearning OR #edchat OR #highered
OR #learninganalytics OR #edtech OR #teaching OR #srlcanada OR
#university OR #universidad OR #teachertraining OR #onlinecourse OR
#motivation OR #selfregulation OR #mooc OR #moocs OR #teachers OR
#onlinelearning OR #srl2 OR #students OR #assessment OR
#activatedlearning OR #blendedlearning OR #feedback OR #pedagogy OR
#formativeassessment OR #metacognitive OR #technologies OR #teacher OR
#middleschool OR #teach OR #hybridlearning OR #selfreg OR #reflection OR
#agency OR #flippedlearning OR #analytics OR #technology OR
#self_regulated_learning OR #bigdata OR #teachingandlearning OR
#educators OR #selfregulatinglearning OR #training OR #student OR
#edpsych OR #computers OR #behavior OR #learner OR #mlearning OR
#multimodal OR #experientiallearning OR #collaboration OR #data OR
#psychology OR #personalizedlearning OR #selfreflection OR
#asynchronouslearning OR #flipclass OR #highereducation OR #dashboards
OR #independentlearning OR #remotelearning OR #digitallearning OR
#learninganddevelopment OR #flippedclassroom OR #lifelonglearning OR
#academic) AND ("self-regulation" OR "self-regulated" OR "self-regulate")"
```

This large corpus of hashtags was constituted based on screening particular academic article keywords relevant to SRL. Later in the study, we will investigate whether some of these hashtags are among the top discussed by the public on the Twittersphere.

Provided that the Twitter API has a quota of 900 tweets per 15 min, the automated process of retrieving the whole dataset of the tweets took around 37 h. The time frame of the search for the tweets is 10 years. That is, the exact date is between January 1, 2011, to September 30, 2021. The total number of retrieved tweets from the search terms within the specified time period is 54,070 tweets. These tweets are posted by 9,951 unique authors and interacted (i.e., likes, retweeted, etc.) by a population size of 29,556 users.

## Data Cleaning and Preparation

Similar to many studies, such as Dahal et al. (2019), we carried a substantial work to process and filter the tweets before applying the Twitter analysis. To extract and clean the tweets from the stop words, which is a common practice in microblog analysis, we used the Natural Language ToolKit (NLTK) library. Such removed stop words from the corpus are "and, or, has, have, are, is, etc." In addition, we used the Python regex to remove emojis and digital expressions like dash and underscore.

It is also common in microblogs to include short words. For that reason, we exclude those that are less than four letters. However, and to preserve popular short academic abbreviations related to SRL and education, we created a whitelist that includes several short words (see section "Topic Modeling" for examples). This whitelist is created manually by scanning the top 200 short words from the retrieved tweet dataset. Empty sentences and duplicate records have also been removed. To align well with our universal Twitter analysis in this study, we removed so-called low TF-IDF (term frequency-inverse document frequency) as recommended by Tajbakhsh and Bagherzadeh (2016). Further data customizations were done to fulfill our needs for the geocoding and the topic modeling analyses. More details are provided in the sections below.

## Descriptive Analysis

The first analysis method used in this study is descriptive analysis. This analysis includes further investigation of listing top tweets, number of tweets, source of tweets, language used, common tweet words (i.e., word cloud), number of likes, retweets and hashtag analysis.

## Geocoding

Geocoding is the procedure of indexing a description of particular information that can be linked to a geographical position on a world map (Fatima et al., 2021). There are several advantages of using geocode analysis such as identifying trends and explaining patterns based on geographical phenomena. While Twitter made it possible for users to enable their location

[1]For more information, see https://docs.python.org/3/library/ (last accessed October 2021).

[2]For more information on search patterns of regex, see https://en.wikipedia.org/wiki/Regular_expression (last accessed October 2021).

when tweeting, not so many tweeters used that function. For that reason, in June 2019, Twitter decided to stop users from tagging their locations.[3]

The form when users enable the location of their tweets is called geotagged tweets. In this paper, we could not identify more than 15% of locations based on geotagged tweets. To overcome that, we followed the direction of what is so-called geotagged users referring to our ability to extract the location of users based on their self-reported position.

To display a world map of users who used the terms of SRL, we needed to distill the names of cities and countries from the self-reported profiles ($N$ = 29,556) and then identify their geographic location. Such a process can be complicated because Twitter offers users to freely designate their place of living instead of choosing a country/city from a pre-selected list. For example, some users could state that their place of living is Germany; some other users may state that Berlin is their place of living. For humans, this is easily understood but not for machines. To surpass this issue, we had to follow Natural Language Processing (NLP) techniques.

We used several computational solutions to carry out the NLP techniques for the geocoding analysis. For purposes of tokenization of texts, we used spaCy.[4] For purposes of obtaining geographical coordination of countries, we deployed a local geocoding service called Nominatim[5] to identify locations on the world map. Furthermore, we employed Nominatim docker[6] to speed up the process of identifying positions on Earth.

## Topic Modeling

The third method of analysis in this study is topic modeling which is a common text mining technique used to discover hidden semantic of textual corpora (Blei et al., 2003). There are several algorithms in topic modeling, nevertheless, the unsupervised modeling of Latent Dirichlet Allocation (LDA) considered to be one of the most popular ones that has been widely used in social sciences (ibid). In the light of its simplicity and efficiency, we used LDA to extract relevant themes and topics through document collections of the tweets. To do the LDA, we first had to identify the number of topics, which could be done by several approaches. In this work, we picked the coherence method to calculate the consistency of topics and validate the optimal number of generated topics (Stevens et al., 2012).

Before doing the topic modeling analysis, we cleaned and filtered the tweets as described before in the Data Clearning and Preparation section. Moreover, the following steps were performed:

- Applied two dictionaries to improve topic extraction, blacklist of words (e.g., today, yesterday, look, will) and white list (e.g., SRL, MOOC, AI) of words.
- Removed non-English tweets.
- Performed light lemmatization, which is a technique to return the verbs and words to the base form. The reason is to analyze different forms of words by a single item instead of several.
- Cleared tweets from hashtags so that the topic modeling is not affected by retweets.
- Excluded retweets to reduce generating biased topics.

After the cleaning and filtration process, we imported the refined dataset into Python and ran the topic modeling algorithm using Gensim's LDA (Rehurek and Sojka, 2011) and built the model.

## Privacy Consideration

The data collection in this study used the Twitter API, which prevents mining any private and protected information. We stress two main points that define our commitment to privacy and data protection consideration:

- Twitter is a public social networking service where users cast their microblogs online and therefore the data collected by the Twitter API is considered "public data" (Deacon et al., 2021).
- The collected Twitter data has not been engineered to extract other than the published information by the users.

# RESULTS

## Descriptive Analysis

The first analysis method conducted is descriptive. The descriptive analysis provides a general overview of the dataset in terms of the tweet count, tweet sources, number of likes and retweets, hashtags used, and the language of each. With respect to the number of tweets, **Figure 1** shows a breakdown of the counts per year. The $x$-axis shows the time span between 2011 and 2021, and the $y$-axis shows frequency. It is observed that there is a steady increase in the number of tweets for the time period between 2011 and 2017. A strong spike in the mined tweets happened between 2017 and 2018. However, we see a dramatic decrease after 2018.

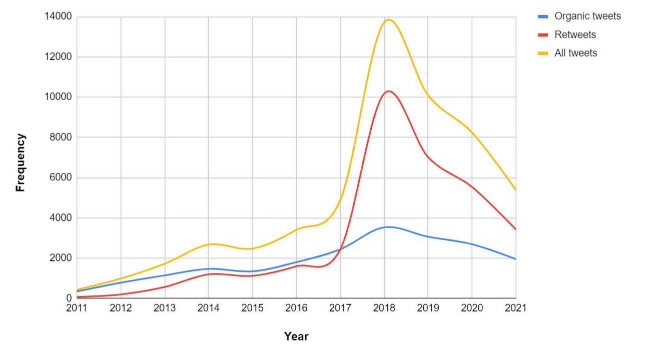


**FIGURE 1 |** Breakdown of all the retrieved tweets (yellow line), original tweets (blue line) and retweets (red line) of SRL (2011–2021). Best viewed in color.

[3] https://twitter.com/TwitterSupport/status/1141039841993355264?s=20 (last accessed January 2022).

[4] Open-source library for NLP.

[5] Open-source geocoding service.

[6] https://github.com/mediagis/nominatim-docker (last accessed August 2021).

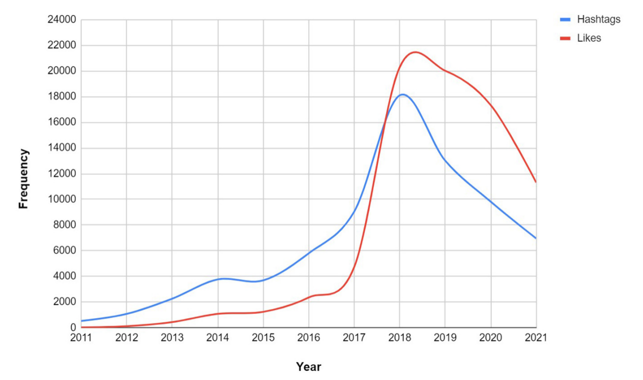


**FIGURE 2 |** Comparison of likes and hashtags of tweets on SRL (2011–2021).

**TABLE 1 |** Breakdown of the average number of retweets, likes, and hashtags.

| Year | Average number of retweets | Average number of likes | Average number of hashtags |
|---|---|---|---|
| 2011 | 0.2436 | 0.0774 | 1.2118 |
| 2012 | 0.2608 | 0.1265 | 1.0894 |
| 2013 | 0.4996 | 0.258 | 1.3135 |
| 2014 | 0.8158 | 0.406 | 1.4057 |
| 2015 | 0.8358 | 0.5008 | 1.4895 |
| 2016 | 0.8872 | 0.6924 | 1.6998 |
| 2017 | 0.9988 | 0.9685 | 1.8507 |
| 2018 | 2.8765 | 1.4793 | 1.3196 |
| 2019 | 2.2856 | 1.9839 | 1.2899 |
| 2020 | 2.0541 | 2.1038 | 1.1916 |
| 2021 | 1.7517 | 2.1003 | 1.2917 |

To get an insight into the number of tweets and retweets, we depict a line graph of the two, as also shown in **Figure 1**. In total, there are 20,647 organic tweets and 33,423 retweets in the dataset. Aligning with the number of the general tweet stats, both the number of organic tweets and retweets has been steadily increasing in the first 6 years. In a parallel manner, organic tweets keep a continuous growth in 2018 while a strong spike in the number of retweets is clearly visible in that particular year. In the time period of 2019–2021, we record a decreased traffic of SRL tweets and retweets.

Next, **Figure 2** depicts the distribution of likes and hashtags of the collected tweet dataset on SRL. In total, there are 74,106 hashtags and 72,631 likes used. Overall, there has been a growing number of both till 2018. The number of likes exceeded the hashtags in 2018. Nevertheless, the number of likes and hashtags started to decrease after 2019 till 2021.

**Table 1** shows a breakdown of the average number of retweets, likes and hashtags per year.

Following that, we looked at the data sources of our Twitter dataset. Out of the 54,070 tweets, we were able to identify 87% of the tweet sources which are broken down in **Table 2**. Around 50% of the Twitter sources belong to mobile phone systems (i.e., iPhone and Android). The usage to tweet on SRL directly from a web client equals 12.4% of the total quota. Interestingly,

**TABLE 2 |** Top 10 sources of the tweets.

| Source | Number of tweets |
|---|---|
| Twitter for iPhone | 18,588 |
| Twitter for Android | 7,695 |
| Twitter Web Client | 6,719 |
| Twitter Web App | 4,835 |
| Twitter for iPad | 3,006 |
| TweetDeck | 1,867 |
| Hootsuite | 1,331 |
| Buffer | 1,286 |
| Hootsuite Inc. | 1,011 |
| SocialOomph | 912 |

around 12% of the tweets used to blog on Twitter came from tweet management applications such as TweetDeck, Buffer, and Hootsuite, which are commonly used to schedule tweets and connect with other social networking services than Twitter. The rest of the identified tweet sources come from the Twitter app on the iPad system.

Furthermore, we looked at the hashtags that were populated by the community. **Table 3** shows the top 5 hashtags per year. The use of #edchat is observed to be very popular in the early years. When investigated, #edchat is a hashtag that encompasses a small part of education community blog that is interested in making learning better for kids.[7] In the last couple of years, hashtags of #selfreg and #selfregulation were dominant in the context. Other interesting used hashtags in the community are conference hashtags (e.g., #icalt2011, #change11), disciplines (e.g., #education, #psychology), primary and secondary education (e.g., #children, #70playactivities, # sd61learn), and educational technology (EdTech) communities (e.g., #edtech).

Given that the raw dataset we have is multilingual, another aspect we used of the descriptive analysis is a synthesis of the tweets' language on SRL. As expected, the most used language is English (97.6%), followed by Indonesian (0.56%), Spanish (0.37%), and Dutch (0.23%). The Twitter API could not identify some tweets languages (0.56%). The rest of the used languages (0.82%) belong to Japanese, Russian, French, Swedish, Catalan, Arabic, Filipino, German, Finnish, Portuguese, Danish, Romanian, Korean, Hindi, Norwegian, Turkish, Polish, Bulgarian, Latvian, Estonian, and Hebrew. These count for 390 tweets only.

At the final stage of the descriptive analysis, we looked at the content. **Table 4** presents some examples of public tweets used from the SRL tweets pool. While content varies like any other discussion board, we decided to create a word cloud of each year's tweet bundle without any computational algorithmic correction except processing the corpus for data filtration as presented in section 3.2 (see **Figure 3**). The greater the size of the word appears in the figure, the greater occurrences exist in the corpus. In 2011, words "research, video, and environment" appear more often than the other. In 2012, "digital and theory," in 2013, "value,

[7] https://teach.com/blog/what-is-edchat/ (last accessed November 2021).

**TABLE 3 |** Top 5 hashtags per year.

| Year | Hashtag (frequency of occurrences) |
|---|---|
| 2011 | #edchat (28), #psychology (24), #children (22), #icalt2011 (18), #elearning (16) |
| 2012 | #edchat (116), #edtech (56), #education (37), #elearning (36), #change11 (21) |
| 2013 | #edchat (182), #bigdata (162), #education (116), #teachers (55), #srlcanada (52) |
| 2014 | #edchat (566), #education (114), #bced (107), #sd61learn (92), #marketing (87) |
| 2015 | #edchat (286), #psychology (109), #bced (108), #sd16learn (95), #education (73) |
| 2016 | #education (406), #70playactivities (358), #edchat (194), #children (134), #therapy (98) |
| 2017 | #education (1070), #70playactivities (912), #children (335), #schoolpsych (269), #edchat (233) |
| 2018 | #education (1092), #edchat (927), #edtech (720), #elearning (644), #ukedchat (466) |
| 2019 | #edchat (360), #education (290), #exercise (248), #metacognition (244), #learning (232) |
| 2020 | #education (307), #metacognition (225), #teaching (215), #edchat (180), #cpd (159) |
| 2021 | #education (174), #learning (128), #edchat (120), #metacognition (101), #alratv (73) |

**TABLE 4 |** Selected high rating (i.e., in terms of like, retweet, and quote counts) tweets from the dataset.

| Year | Tweet |
|---|---|
| 2011 | By dgasevic: "Best paper award for our paper "A Semantic Web-enabled Tool for Self-Regulated Learning in the Workplace" at #icalt2011" |
| 2012 | By PivotLearning: "@davidwees @lookforsun @mbteach What grade level do you think students would be able to self-regulate for online learning? #edchat" |
| 2013 | By edutopia: "Interesting read. MT @TechnologyToday: Self-regulation technique helps students focus in class: http://t.co/GMDBCShnoq #ntchat #edchat" |
| 2014 | By knowledgequest: "Self-regulation is not self-control: @StuartShanker #bced #edchat #sd61learn http://t.co/PKvYw8ZRvR" |
| 2015 | By utafrith: "You may have suspected it, but here is evidence: Self-regulated learning can be undermined by rewards. http://t.co/kPVdefeRZM" |
| 2016 | By misscs_teach: "Peri Peri Challenge.excellent recap of topic, encourages challenge and self-regulated learning #PedagooFriday https://t.co/dLy1rNweVQ" |
| 2017 | By Dylanwiliam: "Activities promoting self-regulated learning may be more effective in individualistic than collectivist cultures https://t.co/jUF2gpviZv" |
| 2018 | By MindShiftKQED: "This is when we want them to be challenged and pushed because this is when we can develop advanced thinking, as well as self-regulation," said @ldsteinberg https://t.co/XFwQJNXY3v #edchat #teens #hschat #parents #teaching" |
| 2019 | By MindShiftKQED: "I love the strategy of "eating the frog," or doing the most difficult thing on your to-do list first, so everything else will feel easier @edutopia #edchat #executivefunction https://t.co/uKn5cQGRO8" |
| 2020 | By Kemguro: "We are faculty members from the University of Santo Tomas who are currently working on an independent research focused on the relationship of students' online learning readiness and self-regulated learning" |
| 2021 | By edutopia: "SRL is much more than just learning strategies to regulate emotions." It's also learning how to learn. https://t.co/L0yKtzuoVK" |

school, and focus," in 2014, "secret, support, and research," in 2015, "skill, learner, and watch," in 2016, "worksheet, child, and environment," in 2017, "child and skill," in both 2018 and 2019, "metacognition and skill," in 2020, "metacognition, online, and teacher," and finally in 2021, "skill, strategy, and support."

## Geocoding

In the geocoding analysis, we were able to classify 20,446 user origins out of the 29,556 users from the dataset, identifying 154 countries. Users in Twitter are meant to be who engaged within the dataset including those who tweeted, retweeted, liked, replied, quoted, or hashtagged. As mentioned earlier in the Geocoding section in the methodology, we used NLP techniques to identify Twitter users self-reported free text locations. **Figure 4A** depicts a normalized view of Twitter geotagged user distribution. The results show that the number of users differs among the countries. The top 10 countries with the highest number of geotagged users are United States (7,149 users), United Kingdom (4,268 users), Canada (3545 users), Australia (942 users), Spain (332 users), India (332 users), Netherlands (282 users), France (211 users), Germany (203 users), and Ireland (181 users). For those who stated their cities in their profiles, the geocoding analysis reports the following top cities London (704 users), Toronto (560 users), New York (312 users), Sydney (217 users), and Melbourne (200 users).

To get a more detailed view of the geographical distribution of Twitter users, we analyzed data from the major continents of the world (see **Figure 4B**). For North America, with the exception of New York, cities of Canada are leading Twitter microblogging on SRL. Cities of Toronto (560 users), Ottawa (199 users), and Vancouver (184 users) are among the highest. New York (312 users), Washington (180 users), and Los Angeles (123 users) lead US tweeting on SRL. In Europe, the geocoding analysis shows that London (704 users) scores the highest number of Twitter users of all cities and Europe. Other major cities are also from the United Kingdom, namely Birmingham (142 users) and Manchester (96 users).

Concerning Africa and Australasia, cities of Australia are placed on the top of the number of users, such as Sydney (217 users) and Melbourne (200 users). Some other cities from Asia are Dubai (60 users) and New Delhi (51 users). From Africa and South America are Bogotá (30 users) and Cape town (26 users).


**FIGURE 3 |** Word cloud of the most common words in the corpus of 54,070 tweets on SRL discussions divided by year (the larger the word print, the more frequent it occurs).

We also looked at another variable of interest, namely the number of SRL-related tweets per country as seen in a normalized view in **Figure 4C**. The results of this figure align primarily with the outcome from **Figure 4A** except for a relevant appearance of two more Asian countries. The most tweeting countries are as follows, United States (5,712 users), United Kingdom (3,201 users), Canada (2,816 users), Australia (803 users), Germany (326 users), Netherlands (302 users), Spain

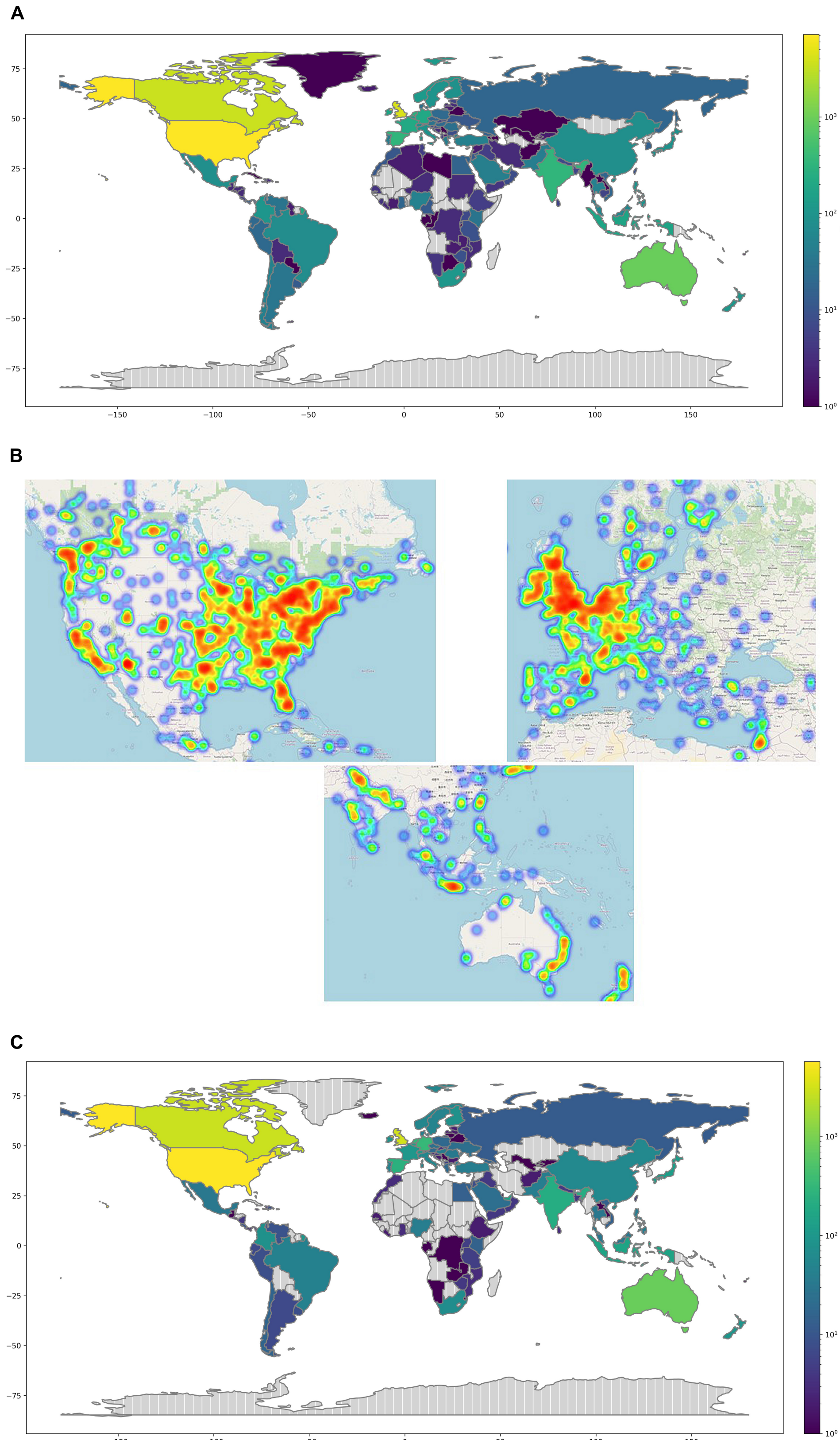


**FIGURE 4 |** SRL geocoding stats. **(A)** Top, log scaled normalization of Twitter geotagged user. **(B)** Middle, from left to right, geotagged users heatmap of North America, Europe and the Middle East, and eastern Australasia. **(C)** Bottom, log scaled normalization of tweets per country.

(255 users), India (209 users), United Arab Emirates (154 users), and Indonesia (154 users).

For more information on other metrics per country, see **Supplementary Material** of this article.

## Topic Modeling

### Coherence and the Number of Topics

At the first step of the topic modeling, we initially looked at identifying a number of topics. Such a process requires further testing of each number to detect the optimal value using the coherence score (Stevens et al., 2012). We used Gensim's model for that purpose. The highest coherence score means the best word co-occurrence consistency. In order for us to differentiate the coherence value of each topic, we trained the topic modeling of LDA and examined up to 68 topics. At the end of the process of models training, we identified that 10 topics are the optimal number. As **Figure 5** depicts, the coherence score (0.3707) was at the highest value on 10 topics, declining strongly after that, then became again higher at 18 topics (0.362). Nevertheless, 10 topics appear to be reasonable for our dataset size (Risch, 2016).

### Themes and Topics

After addressing the number of topics to 10, we ran the LDA model and set the $\lambda = 1$ (lambda means that the relevance is defined entirely by appearing keywords). While we attempted to name the generated topics automatically, we discovered that the automatic labeling results are imprecise because of the scarcity of proper dictionaries on SRL and the need for manual edit knowledge. This result aligns with the studies by Lau et al. (2011) and Qiang et al. (2017), who stress that automatic labeling does not guarantee coherence. To produce meaningful results from the topic modeling, we decided to manually name themes that incorporate common topics based on the intertopic distance map, in spite of being more labor intensive. Themes were named based on the content of the top 30 words of each topic and the consensus judgment of the authors. To ease human intervention of identifying themes, the most common appearing words such as "child" and "skills," which show up in several generated topics, were excluded.

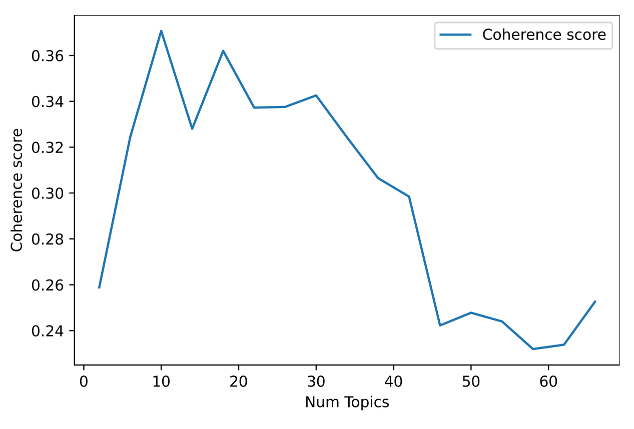


**FIGURE 5 |** Coherence score for optimum number of topics in the topic modeling (retweets excluded).

**Figures 6**, **7** depict Gensim's model through sets of visualizations. **Figure 6** shows the map design of the topic model, in which 10 divergent topics are plotted as circles. The zone of the circles designates the general prevalence, and the center of the circles is determined by computing the distance between topics (Chuang et al., 2012). The intertopic distances are depicted on a 2D plane via multidimensional scaling. The principal component 1 (PC1) represents the transverse axis, and the PC2 represents the longitudinal axis. It is noteworthy that some of these topics overlap within the same dimensional scaling, like topic 4 and topic 8 which include keywords related to development and guidance. Other topics are entirely far away like topic 7 that has keywords on assessment and topic 10 which consists of words related to behavior and self-control. Yet, we matched the topics (i.e., through human intervention) into themes corresponding to similarity of the keywords. We followed the results of the intertopic distance map but also qualitatively agreed the themes together and gave relevant names grounding in the SRL tweets. Finally, the overall themes are labeled as the following: communication and help seeking (3 topics), self-control (2 topics), mindfulness (2 topics), online workshops (2 topics), and assessment (1 topic); The results of the topic modeling indicate some common appearing words in all the topics such as "child," "skills," "read," "strategy," and "metacognition." See **Table 5** for a detailed view.

**Figure 7** shows an example of the relevant top 30 keywords of topic 4. The coding results for all the topics are available in **Supplementary Material**.

# DISCUSSION

In this work, we made a bold attempt to leverage open social network discussions from Twitter on SRL in the time period of 2011 till 2021. The analyzed dataset consists of 54,070 tweets created by 29,556 users and the current reporting on the analyses provides three main findings that answer the following research questions.

## What Are the General Characteristics of Twitter Conversation on Self-Regulated Learning?

The descriptive analysis showed a "moderate" increasing interest by the social media population of Twitter on SRL. That is, the breakdown of the dataset revealed a quite relevant tweet growth from 2011 until 2017 and a strong positive skew in 2018 (280% increase than 2017). Nevertheless, the analysis shows that the tweets markedly decrease as time goes by. The result of which the rate of fluctuation of the volume of the organic tweets, retweets, and engagements such as the number of hashtags and likes of SRL, do not quite align with the promising thoughts of academic researchers from the various fields of education who reported that the usage of SRL is garnered to be more popular (Paris and Paris, 2001; Matcha et al., 2019; Khalil, 2022). Perhaps, this conclusion is not a definite assumption given that discussions of

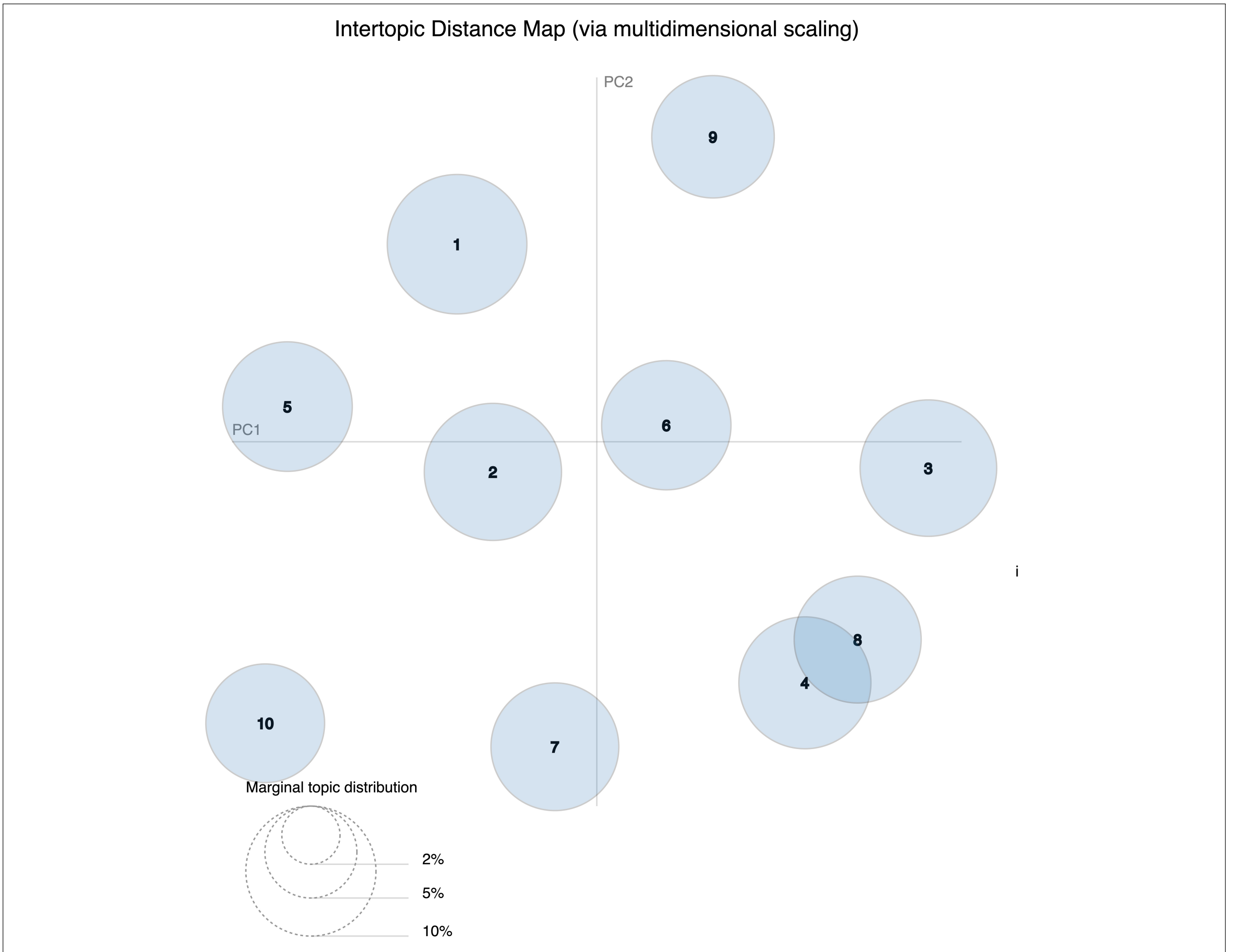


**FIGURE 6 |** Intertopic distance map (*N* = 10 topics, retweets excluded). PC, principal component.

SRL might tend to be more academic-oriented (e.g., conferences, research) than non-academic (professional, business, applied), however, not yet documented in previous studies to date. As a result, the public discussions on Twitter that cover SRL might be more allocated in other sources of information. Still, more retweets than organic tweets starting from 2017, suggesting a broader network of members sharing ideas from individuals. This decrease of organic tweets and the increase of retweets my denote some kind of a trend where users tend to shift toward resharing of content, showcasing more amplification of content and ideas (Greenhalgh et al., 2020).

The spike in the number of tweets from 2017 till 2018 could have a technical interpretation because of the extended character count limit from 140 to 280 characters in November 2017. As explained by Gligorić et al. (2018), users dealt with the character limit in different ways. Nevertheless, the drop of tweets in general after 2018 does not necessarily mean users should tweet more but could have led to more engagement in terms of more likes, retweets, and hashtags, as depicted in **Figure 1**.

Another interesting finding that we realize is the breadth of hashtags that our dataset addresses. It seems to be that there are education communities (e.g., #edchat) who contribute to discussions on SRL. This space is important for scholars to explore (see for e.g., the study by Staudt Willet, 2019) given that our examination of some of the linked tweets provides interesting points of view from practitioners and experts aligning well with Gee's (2012) theoretical framework on affinity spaces. One more implication of this finding is that such spaces enable asynchronous communication unlike educational meetings that require a pre-set time. Interested parties on SRL may collaborate with new networks and engage in further conversations and exchange ideas (Manno, 2012). However, as Staudt Willet (2019) and Carpenter et al. (2020) discussed, it might be challenging for novices interested in a certain educational topic and looking into the Twittersphere to move their taste to hashtags like "#edchat." Staudt Willet (2019) infers this challenge to the complex and overwhelming of information they could face as an entry point to new topics.

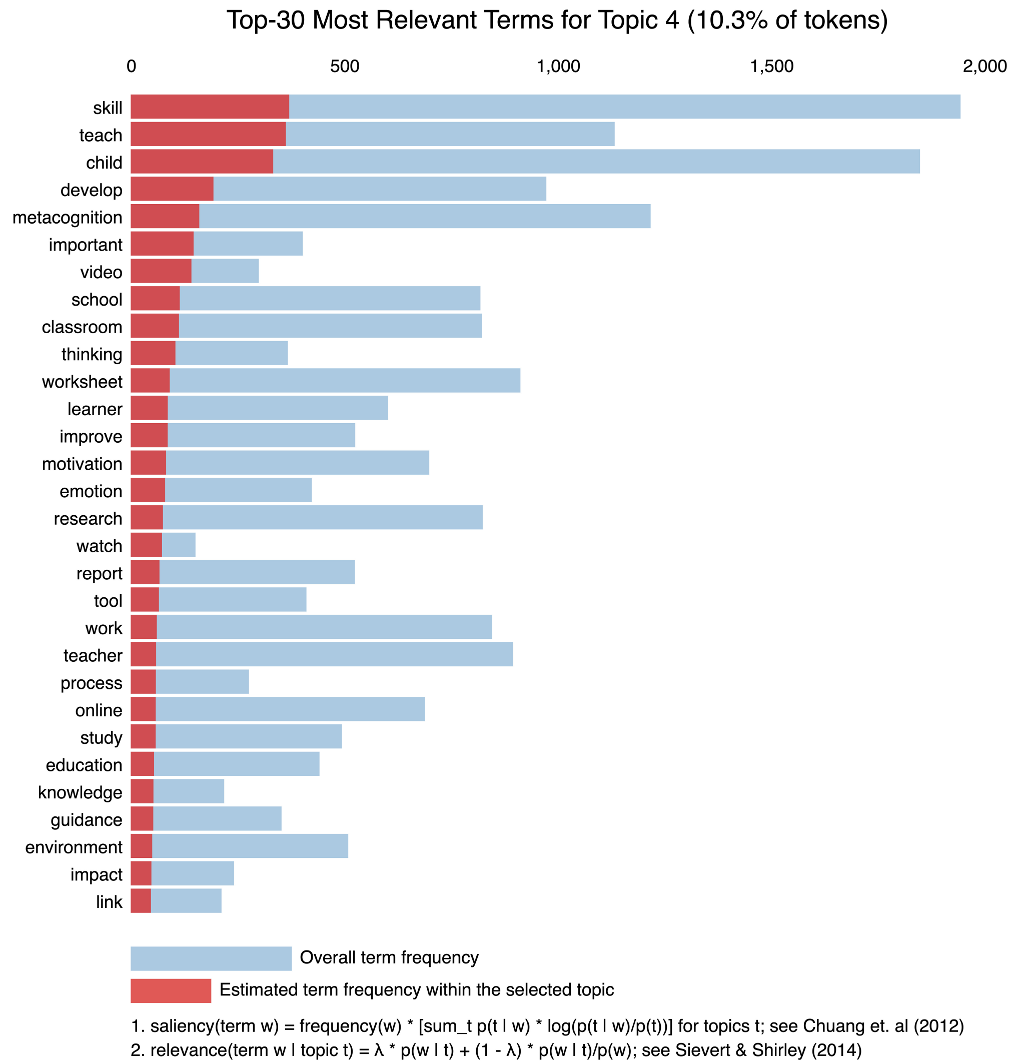


**FIGURE 7 |** Most relevant terms for topic 4 (10.3% of the tokens).

**TABLE 5 |** Topic classification, keywords, and size based (common appearing words excluded).

| Theme | Topic | Keywords* | Size |
|---|---|---|---|
| Communication and help seeking | T3 | Task, sequence, read, management, guidance, communication, check, knowledge, conversation, check | 11% |
| | T4 | Develop, video, important, study, online, guidance, improve, watch, report, tool | 10.3% |
| | T8 | Develop, thinking, social, report, read, guidance, time, early, circle, activity | 9.5% |
| Self-control | T2 | Promote, control, read, high, report, training, course, study, model, assessment | 11.2% |
| | T10 | Guide, calm, build, learner, work, start, behavior, improve, session, report | 8.3% |
| Mindfulness | T5 | Stress, goal, development, practice, work, study, foster, share, read, time | 9.9% |
| | T6 | Calm, develop, online, encourage, achievement, read, theory, tool, session, promote | 9.9% |
| Online workshops | T1 | Work, article, practice, share, join, develop, success, academic, blog, impact | 11.4% |
| | T9 | Research, group, tool, bring, foster, online, learner, share, digital, thinking, promote | 8.9% |
| Assessment | T7 | Worksheet, article, assessment, develop, tool, time, formative, design, environment, idea | 9.6% |

**Keywords are selected randomly from the pool of the top 30 words in each topic.*

As academic scholars, we were interested in exploring hashtags relevant to academic venues. We found few hashtags linked to conferences, such as "#icalt2011," the International Conference on Advanced Learning Technologies. There might be two explanations for the low representation of academic venues. First, the trend of which at academic venues, microblogging streams strongly at particular time spans and relatively stops when events finish. On the contrary, other discussions may sustain for longer periods, such as "#edchat," and "#edtech." The second explanation is that the tweets of SRL could implicitly appear in other contexts that are not directly used by tweeters in venues.

## What Are the Main Topics of Interest That Are Related to Self-Regulated Learning From Twitter Public Discussion?

Concerning the second research question, we relied on the word cloud of the most common words from the dataset as well as the computational process of topic modeling to provide an insight into the topics. Both analyses showed that there are common words sharing terms alike.

It was noticeable that words related to "child" are much more apparent in the context of the tweets. When investigated, it seems that discussions into employing self-regulation and interventions of self-monitoring are important for pupils at schools (Reid et al., 2005). Reid et al. (2005) explain that self-regulation is proposed as "an effective and efficient means for increasing students' attention and academic productivity" (p. 361). In this work, we clearly understand that SRL is a key part of self-regulation. Apparently, the collected tweets included both and users were using them interchangeably.

Moreover, the word cloud has a strong demonstration of the words "metacognitive" and "metacognition" in the last few years. As commonly known, metacognition is central to SRL. Yet, it is interesting to see that metacognition is relatively mentioned than other terms, for example efficacy and awareness. Perhaps this aligns with the recent calls for focusing more on metacognition as a key trait for successful learners of SRL (Zhang and Zhang, 2019).

Both the topic modeling and word cloud sustain for repetitive demonstration of "skill" and "strategy." According to Zimmerman (1990), SRL is a set of skills and strategies that guide learners' future study and work paths. Twitter discussions are consistent with the further calls for improving these skills to succeed. Still, the frequent mentions of skills might imply time management, awareness, and self-monitoring which were not relatively considered by the Twitter users in the dataset.

Building on the strong coherence value, the topic modeling of the tweets resulted in 10 topics which were then organized into 5 themes. It is worth to note that this quantitative approach of algorithmic categorization has its own limitation, therefore inappropriate to generalize the results (see section "Limitations and Future Direction" for more details). The bigger theme which accounts for nearly 31% of the clusters size indicates a growing discussion on communication and asking for help. Relatively appearing words of "communication, help, guidance, worksheet" suggests that help-seeking, which is commonly known as an important skill for SRL (Karabenick and Berger, 2013), is well connected with communication. The open sphere of Twitter may have implied the growth of topics in relation.

An interesting theme that we allocated is mindfulness. This theme came at a surprise when other key terms did not exist in sight (e.g., self-evaluation). Our analysis of this finding is consistent with prior research which found out that Twitter functions for venting out one's stress (Doan et al., 2017). In relation to education, stress might be a result of exam burdens and mismanagement. Withal, SRL and mindfulness has been proven to help students to cope up with stress (Ramli et al., 2018). It is possible that bloggers, including students, have used Twitter space to reflect upon stress and bad management. As some studies like (Carpenter et al., 2020) discovered that users valued Twitter to reduce not only stress, but also isolation, the appearance of this theme suggests a very interesting area for scholars to further investigate.

The prevalent words formation of "time," "management," and "metacognition" in the topic modeling may provide valuable insight on planning (Wong et al., 2019) and academic procrastination (Limone et al., 2020). This is an interesting area of research in SRL since several studies have found that SRL can provide the needed skills to reach wise decisions and solve problems which is positively correlated not only to one's academic life, but also to wellbeing (Limone et al., 2020). The same derived words may suggest associated talk on anxiety despite the word itself has not emerged in our context but linked to discussions on stress as previously mentioned. Apart from that, we also labeled Online workshops for two topics from the topic modeling. We looked at some of the tweets in this theme and found out that several share disseminating of information in conferences and workshops. Others communicated workshops to foster metacognitive skills in technology-domain settings. This finding shed considerable light on how the Twitter community facilitate supporting SRL and contribute to disseminating SRL research, practices and work.

Even though self-evaluation is imperative for SRL in social media channels (Yen et al., 2021), relevant words and topics to self-evaluation were nearly absent from the topic modeling and word cloud analysis of the tweets. This finding coordinates well with the systematic review study by van Houten-Schat et al. (2018), who found out that there is a dearth of SRL interventions on self-evaluation for students. This may suggest a gap that triggers interest for further exploration by those interested in SRL theory.

Finally, further inspection of the topics uncovers two areas from the public discussions on Twitter, self-control and assessment. Both themes might be quite linked to each other, as seen in **Figure 6** and as has been reported by Zhu et al. (2016). The link of which self-control may have a "significant impact" on students' performance (ibid). As an implication, we foresee those discussions around self-control and SRL together with assessment could be predicted to be an intriguing forum on Twitter.

## Where Do the English-Based Self-Regulated Learning Discussions Originate From?

With the expansion of the Internet, social media and the Web, social media analytics is a key tool that function not only as a support to diverse decision systems, but also as a geographic location data revealing how microblogging data can be used at different scales.

To answer our third research questions, the geocoding analysis unveiled interesting results. The presence of high-density geotagged users in some particular countries was obvious from the heatmap shown in **Figure 4**. One of the main findings is that most of the tweets on SRL originate from the Global North rather than the Global South countries, with some exceptions. For example, some Global South countries such as India, Indonesia, Mexico, and Brazil show a high density of users who tweet on SRL. Provided that these countries are the largest in the Global South in terms of population, it is fairly more common to reach this outcome. However, some countries in the Global South were not as active as the ones mentioned, such as China. Our interpretation of this low presence aligns with other studies such as Wu et al. (2016) which report that many countries use an assortment of censors and blockage means to disrupt sharing of sensitive information over the social network services. Users from some countries like North Korea and China might use Virtual Private Networks (VPNs) to overcome firewalls. Therefore, the geocoding analysis identified this low representation. For Africa and South American continents, relatively fair traffic produced from the countries of South Africa and Colombia suggests that SRL awareness is expanding and becoming more diverse.

For the Global North, we discovered that some geographic regions are not as active as the others. Speaking of which, the user representation of the United States, United Kingdom, and Canada alone accounted for over 50% of the total number of users. The other half goes for the rest of the countries. This presence of a high density of tweets of only three countries of the world was unexpected. Perhaps an explanation for such a finding relates to the popularity of Twitter in these countries (Wu et al., 2016). However, it could also be explained that SRL research and discussions are more popular in these geographical regions given that known theories and practices on SRL such as Zimmerman (1990) and Winne and Perry (2000) originate from these particular areas. Another common point between the United States, United Kingdom, and Canada countries is that 50% of the geotagged users derive from English native speaking countries, which could be another interpretation for this particular outcome.

The geocoding results from this study may raise concerns on the dominance of self-regulation and SRL discussions by high-income countries, thus limiting context on the theory from many other parts of the world. This issue has been previously discussed by Haslam et al. (2019), who found out that high-income countries have conducted the majority of research studies and discussions on self-regulation. Although SRL is one domain of self-regulation, our results from geocoding match Haslam et al.'s (2019) conclusion. We argue that more insights are needed from low and middle-income countries to draw a broader perspective on SRL.

## CONCLUSION

This research provides useful insights by analyzing Twitter discussions on SRL from various perspectives of geolocation, content, hashtags, users, topics, and themes. Considering 54,070 tweets and 29,556 users, we introduced and provided a broader understanding of public discussions on SRL from a relatively new research direction (i.e., Twitter) in the last 10 years.

The approach of conducting this research allowed us to explore a wider public view on SRL and highlighted some interesting insights on content, topics, and geolocations. We conclude that there are intriguing public discussions on SRL and communities interested in knowing more and discussing SRL strategies outside scholarly venues. However, the recent drop in tweets in the last couple of years (may) conclude a lack of interest in SRL for several reasons discussed in the study.

We conclude that topic modeling with LDA inferred different topics and aspects of communication, help-seeking, mindfulness, workshops, self-control and assessment, yet with differed tweet quantities per each. Also and even though estimating the location of the users from our dataset was a non-trivial task, geocoding of the SRL tweets has provided us with new insights that socioeconomic gradients, technology advancement, and theory-originating of some countries may have affected the higher density of geotagged users from high-income countries and the Global North than the Global South. This dominance of discussion on Twitter concludes that SRL and its wide domain of perceived subtopics (e.g., self-control, self-evaluation, goal settings) might be reticent by particular countries, thus confounded.

The research work also contributes to established research on using Twitter as an affinity space and extends this exploration by quantifying contents using computational processes of topic modeling, geocoding and descriptive analyses.

Last but not least, this research opens up several questions to be further explored by practitioners and scholars, such as self-evaluation and the mindfulness domain (e.g., stress, anxiety).

### Implications

Further research can use the identified topics and analysis to understand SRL from a different perspective. Indeed, the ideology of using affinity spaces on Twitter may provide a hospitable sphere to find interesting thoughts that are outside typical scholarly publications (i.e., book and research papers) and static medium. Scholars, teachers and practitioners can tap affinity spaces on Twitter to chase diverse sources of information on SRL. Additionally, through the analysis, we found that social media may allow novices to take advantage of microblogs and the vast experiences available from a larger pool of fellow scholars and educators and enrich their own (Carpenter et al., 2020). A likewise practical implication we distill from this study is that the generated topics based on the topic modeling and the most commonly appearing words show that Tweets suggest new areas that demand further SRL examination. This implication aligns with (Marcelo and Marcelo, 2021), who found that particular types of users, such as influencers, may act as "knowledge brokers" and intermediate content by sharing and creating elegant materials on SRL.

Finally, our work has also potential implications related to the geographical distribution of interest on SRL on Twitter. The geographical disparities in Twitter's microblogging from specific parts of the worlds require further bridging between the

Global North and the Global South on knowledge and expertise exchange on SRL. Provided the broad growth of this theory, there is a persistent need to invite scholars, educators, and practitioners to a global virtual carnival of knowledge share not only from a specific region, but from all over the world.

## LIMITATIONS AND FUTURE DIRECTION

This work incurs some limitations. Because the research study has been carried out on a social network service, the current limitations may have affected our overview of the research results. First of all, even though the dataset is not very large as we expected, it is worth noting that perhaps some tweets were not mined by the Twitter API. This might be due to that fact that some tweets were deleted right after being posted by the user. Another related aspect, the Twitter API may have also mined some tweets that were already been deleted by users at a later stage, therefore, this study may have considered tweets despite being deleted by their owner(s).

Second, the used search terms may have failed to crawl SRL tweets as intended to be. That is, some users may have used a venue or specific hashtags that are not used in the search keywords. In a related aspect to the limitations to the search terms, the trigram search of "self-regulated learning" may have scrapped some tweets that are irrelevant to the context of the study. Also, our main search terms were done in English, as a consequence, we may have missed some important microblogs that are relevant to this study.

The third and fourth limitations of this study are related to the geocoding and topic modeling analyses. For geocoding, even though we tried to show the locations of the users who tweet specifically on SRL, the absence of some countries such as China and Russia was notable. Such causes are a common practice given the complications between US politics and some other countries; for further elaboration on the issues see Twitter Safety (2020). Another limitation of our geocoding analysis is the sampling bias since the collected tweets are originated from English-based search term. Finally, the topic modeling may have exaggerated specific phenomena while overlooking other ones. However, we tried to overcome this issue by qualitatively examining the top 30 words of each topic and introducing white and black lists. Still, human intervention was required to choose the best model, name themes from topics, and depict results in a meaningful manner.

As a future direction of this work, we may improve the data collection process by examining academic papers, mainly on SRL, building an additional list of complementary keywords from the SRL theory, and then searching specifically for wordings and hashtags consisting of such. In this case, we can increase the size of our dataset, and by then, our conclusions can be more accurate. Another future direction is related the geocoding analysis. We plan to normalize the total number of tweets and link that to the country population. As a result, we foresee that representation of the countries on the heatmap (as shown in **Figure 4**) will be more accurate and less biased. Furthermore, the analysis can be extended to other social media platforms for better mapping and understanding of self-regulation.

## DATA AVAILABILITY STATEMENT

The analysis script source code of the topic modeling and the word cloud is available on GitHub (https://gist.github.com/slate-dev/8f59772a790e5a3ed70788fab70d5343). The datasets analyzed for the geocoding in this study can be found in Datasheet 1.CSV and Datasheet 2.CSV. All research metrics per country are available in Datasheet 3.CSV. Tweet ids are available in Datasheet 4.CSV. The overall topic modeling analysis code results are available in Datasheet 5.CSV.

## ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent for participation was not required for this study in accordance with the national legislation and the institutional requirements.

## AUTHOR CONTRIBUTIONS

MK conceived the presented idea, carried out analysis, verified the analytical methods, interpretation of the results, and handled writing the whole article. GB carried out the data collection, analysis, and further discussions. Both authors contributed to the article and approved the submitted version.

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## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2022.820813/full#supplementary-material

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# University Students and Their Ability to Perform Self-Regulated Online Learning Under the COVID-19 Pandemic

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The COVID-19 pandemic has affected all aspects of the educational system, including students' learning styles, which are heavily dependent on self-regulated studying strategies and motivation. The purpose of this study was to discover whether Central European students, in this case the Slovak and Czech students, were able to perform self-regulated learning during online learning under the COVID-19 pandemic to achieve their learning goals and improve academic performance, as well as to propose a few practical recommendations how to develop and maintain students' self-regulation learning in this new online environment. The methodology was based on a questionnaire survey conducted among 268 students at two Central European universities in February and March 2021. The findings indicate that Central European students seemed to be able to perform their online self-study, especially in regard to personal competencies, meaningfulness and motivation. They reported higher awareness of their strengths and weaknesses in learning, time management, and/or the usefulness of making an effort to study. However, the findings reveal an urgent need for more work to be done in the area of metacognitive strategies, such as reflective and critical thinking, analyzing and evaluating. In this respect, the teacher's role is replaceable since s/he serves as a facilitator and promotes these metacognitive strategies by providing students with constructive feedback, monitoring their learning, reviewing their progress, and/or providing opportunities to reflect on their learning. There were not any striking differences between the Czech and Slovak students. Nevertheless, Slovak students (females in particular) seemed to be more self-disciplined and goal-oriented in their learning.

**Keywords: self-regulated learning, online learning, motivation, metacognition, meaningfulness, personal competences, higher education**

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## INTRODUCTION

The COVID-19 pandemic has brought changes for university students. Face-to-face teaching has been replaced by remote teaching with students getting used to a new academic environment. Students had to suddenly transit to more independent learning and self-study (Stradiotova et al., 2021; Zamborová et al., 2021). Self-regulated learning can be defined as one's ability to understand and control one's learning environment (Schraw et al., 2006). Kisac and Budak (2014) contend that self-regulation is proceeded by setting appropriate goals, selecting an effective learning approach, and monitoring progress toward these goals. As Paris and Paris (2001) put it, effective learners self-regulate, analyze task requirements, set productive goals, and select, adapt or invent strategies to achieve their objectives.

Exploration of self-regulation in learning has been a concept that still attracts the attention of a vast number of scholars worldwide (Hertel and Karlen, 2020; Jivet et al., 2020; Kryshko et al., 2020; Miná et al., 2021) and is applicable during these turbulent changes in education due to the pandemic. Particularly in the COVID-19 pandemic students have to do a lot of self-study, which requires much effort, self-determination and motivation on students' side. And if they are not able to do this, they fail. Therefore, this study wants to explore whether students are able to conduct this self-study under new, challenging conditions, as well as discover whether there are differences between the students entering the university and those who have been there for some time already. The reason is that it is especially significant to introduce it to first-year students in higher education who are exposed to various challenges when entering a university. As a result, the dropout rate (e.g., 21% in Netherlands in 2016) is higher in the first year than in later years (Fokkens-Bruinsma et al., 2020). The reason lies in the importance of the foundation of knowledge and strategies in the first and later years. Especially attention needs to be paid to a smooth transition from secondary institutions to higher education. It concerns challenges in new students' educational environments, new academic tasks, networking, acquiring a new identity, and competitiveness among peers (Fokkens-Bruinsma et al., 2020). Therefore, students need to be prepared for the expectations of studying at a university in the preparation phase, which currently has a lack of research (Fokkens-Bruinsma et al., 2020). Research conducted among first-year students concludes that time management and autonomous motivation are favorable predictors of achievement, while classroom engagement seems important later on. Students should have personalized trajectories from the moment they enter a university (Fokkens-Bruinsma et al., 2020). Thus, the authors of this study also want to propose a few practical recommendations how to develop and maintain students' self-regulation learning in a new online environment to help them achieve their learning goals and successfully complete their university studies.

Self-regulation is comprised of four strategies/concepts that this article examines in the research section: motivation, personal competence, metacognitive strategies, and meaningfulness of learning. Recent research findings demonstrate that motivational regulation strategies increase students' academic effort, their academic performance and reduce dropout intention (Kryshko et al., 2020). Motivation plays a role in the facilitation of learning and is connected to the integrity and quality of learning. Thus, *students with high motivation for success are usually successful students* (Ekşi et al., 2020). The research suggests that *there is a positive significant correlation between motivation for success and personal professional competence as well as a positive significant relationship between lifelong learning and personal-professional competency* (Ekşi et al., 2020). Students become intrinsically motivated if their psychological needs of autonomy, competence, and relatedness (based on the premise of self-determination theory) are satisfied in the academic context (Hensley et al., 2020). It is important to underline the fact that competence is the perception of being capable (Hensley et al., 2020). If the environment supports competence, students feel more confident in performing learning tasks and the teacher's role is to support it. Therefore, students will not withdraw from trying (Hensley et al., 2020). Furthermore, personal competence includes several layers: cognitive, metacognitive, motivational, social/emotional, learning habits, mastery, enhancement, reinforcement, and contexts [see more in Redding (2014)]. The research by Hensley et al. (2020) showed evidence that to develop competence, there is a need for instructor scaffolding, required effort and analysis, and layers of meaning. Consequently, to reach a high level of self-regulation, proper **metacognitive strategies** should be utilized (Kisac and Budak, 2014). They refer to conscious monitoring, control learning, higher-order executive skills, and decision-making (Mitsea and Drigas, 2019). Their implementation encourages higher-order cognitive abilities, attentional and memory control, and self-confidence leading to independent and meaningful learning (Mitsea and Drigas, 2019). Kisac and Budak's (2014) study investigated whether there was a link between university students' metacognitive strategies and their perceived self-confidence levels about learning. They found that students who had higher self-confidence were more in favor of strategies like notetaking, summarizing, reflecting, reciting, and reviewing what they learned to things they had already known. It has been demonstrated that students with using effective metacognitive strategies can learn easily and effectively and have higher motivation and more self-confidence. Additionally, research by Hayat and Shateri (2019) showed that students with a strong belief about their ability to learn and complete the assignments are more effective in meeting requirements than students who are more skeptical. The last concept of self-regulated learning is **meaningfulness of learning**. One of the first studies by Nehari and Bender (1978) confirms that the meaningfulness and value of a course as judged by students are important factors in the cognitive-subject matter, affective-personal, and behavioral domains. Meaningfulness was explored in a study of 118 first year graduate social work students in the United States regarding the relationship among life satisfaction, peer support, and meaningfulness of the learning experience in connection to differences in gender, marital status, stress, and peer and family support. The study concluded that *receiving higher peer support was associated with perceived meaningfulness of the learning experience, whereas being female, being married, having lower perceived stress, and receiving higher family support were associated with life satisfaction* (Fakunmoju et al., 2016). To define meaning is to relate it to different ends beyond pleasure and the satisfaction of biological and material needs. Finding meaningfulness goes hand in hand with activities students consider worth pursuing, which leads to creating meaning for the entire life (Reber, 2018).

As mentioned, the COVID-19 outbreak has had an impact on the self-regulation learning practices of university students worldwide. As study in Spain evaluated how confinement at the beginning of pandemic affected the self-regulation of motivation

(SRM) of university students and that the SRM was decreased by the shift from in-class teaching to virtual, and females outperformed males, although both genders showed SRM level reduction (Santamaría-Vázquez et al., 2021). Furthermore, a survey of college English learners' self-regulation in an online environment in a Presentation-Assimilation-Discussion (PAD) class in China was carried out to examined self-preparation, self-management and self-evaluation. It was found that more colleges were well prepared for online English learning, and students had the ability to handle online learning (self-management) with suitable goals, plans, and most importantly, a good mood for learning. Their scores in self-evaluation stemmed from determination, right choice of strategies, reasoning through their learning progress, and adaptation to the PAD class (Zhenhua and Yanping, 2020). Interestingly, the study by Mayda et al. (2020) that examined the self-regulated learning skills of 209 sport science students in an online learning environment showed findings about females being more successful than males.

In the whole process of self-regulation learning, the role of a teacher is paramount (Oates, 2019). The findings of research studies (Boori and Ghanizadeh, 2011; Partovi and Tafazoli, 2016) show that it is especially emotional intelligence, self-efficacy, self-regulation, and critical thinking, which should be promoted by teacher. As Boori and Ghanizadeh (2011) state, the teacher should be equipped with them and model it to the students. Those are, for example, *goal setting, intrinsic interest, performance goal orientation, mastery goal orientation, self-instruction, emotional control, self-evaluation, self-reaction, and help seeking* (see Yesim et al., 2009). Oates (2019) expands that the teacher should model self-regulatory practices to stimulate students' motivation for their own learning by engaging them in collaborative work and interventions. Naturally, there are other factors, which can also support the whole process of self-regulated learning, such as students' abilities and willingness to engage in self-regulated learning, classroom environment, resources, curriculum, home and family background, parents, culture, and community (Alvi and Gillies, 2020).

Therefore, this study aimed to discover whether Central European students, in this case Slovak and Czech students, were able to perform self-regulated learning during their online classes in the period of the COVID-19 pandemic to achieve their learning goals and improve academic performance. In addition, the authors of this study want to discover whether there are any differences between these students as far as the year of study is concerned, gender or nationality. Finally, they also want to propose a few practical recommendations how to develop and maintain students' self-regulation learning in a new online environment.

The research questions were as follows:

*(1) Were Czech and Slovak students able to perform self-regulated online learning under COVID-19 pandemic in order to achieve their learning goals?*

*(2) Which of the four self-regulation factors, i.e., motivation, personal competences, metacognition, and meaningfulness of studying, appeared to be most problematic?*

*(3) Were there any differences between the Czech and Slovak students?*

*(4) How can teachers support students' self-regulation learning in a new online environment?*

# METHODOLOGY

## Participants

The research was performed in February and March 2021 at two Central European universities: one located in the Czechia (i.e., Faculty of Informatics and Management of the University of Hradec Králové) and one in Slovakia (Faculty of Applied Languages of the University of Economics in Bratislava). Both universities were of similar size. At the time of the survey, both groups of students had experience with self-study under the COVID-19 pandemic, since the previous semester was fully online as well. The survey was collected from 268 university students from the Czechia ($N$ = 139) and Slovakia ($N$ = 129) in their specialized courses of English as a foreign language. The research sample included students of economics and management, economic informatics, national economy, applied informatics, information management, and management of tourism. Their age predominantly ranged from 19 to 23 years.

## Instruments

The research instrument was a questionnaire developed by Hrbáčková (2011) containing demographic data (i.e., age, gender, year of study, form of study, and subject studied) and a list of 40 statements rated on a scale from 1 to 7 (1 denoting the least agree with the statement; 7 denoting most agree with the statement). All 40 statements are presented in four categories (motivation – 8 statements; personal competence – 16 statements; metacognition – 8 statements, and meaningfulness of learning – 8 statements).

Principal component analysis (PCA) was performed to reduce the 40 statements into fewer categories. Then the factors highlighted were used in further analysis of the approach to learning.

1. Verification of the PCA assumptions:
   a. KMO measure of sampling adequacy: **0.897** – this value means that reducing the number of categories makes sense.
   b. Bartlett's test of sphericity: **4258.074 ($p$ < 0.001)** – this value means the variables are correlated and, therefore PCA is justified.
2. Assumption of the number of extracted factors:

The following criteria were verified to extract a meaningful number of factors:

a. Sufficient proportion criterion: it assumes that the value of the cumulative percentage of the explained variance of the analyzed variables should be at least 75%. This would mean a reduction to **17 factors**.

b. Kaiser criterion: it implies the inclusion of the components that have eigenvalues higher than 1.0. This would mean a reduction to **8 factors**.
c. Cattell criterion: it is based on finding the factor scree, i.e., the location showing a gentle decrease of eigenvalues in a plot of eigenvalues grouped as non-descending. This means a reduction to **4 factors**.

Although the Kaiser criterion is recommended for 20 or more variables, it was decided to adopt the Cattell criterion (**Figure 1**). This decision was dictated by the easier interpretation of the 4-factor model. Furthermore, the fact of the original classification of the statements into four thematic groups was taken into account.

### Analysis of Factor Loading Matrix After Rotation

To classify the variables and obtain a clear arrangement of the loadings, the factor structure was rotated and the results were interpreted. The factor loading analysis allowed the creation of four scales, which were given the symbols C1, C2, C3, and C4. The distribution of the items is almost in accordance with the original structure of the survey questionnaire; therefore, the names of the factors were given according to the titles of the thematic groups:

- **C1** – *Motivation orientation,*
- **C2** – *Personal competence,*
- **C3** – *Metacognitive strategies,*
- **C4** – *Meaningfulness of studying.*

## Data Collection

When collecting data, all participants expressed agreement to participate in the online survey by taking part in it. It was fully voluntary and no instruction was given to them by the researchers. All GDPR regulations were strictly followed. The only demographic data we collected are presented in this manuscript without any personal identification. This research was approved by the Ethics Committee no. 2/2021 of the University of Hradec Králové.

## RESULTS

The database to be statistically analyzed consisted of 139 records of Czech nationality students and 129 records of Slovak nationality students. In the next step, it was decided to aggregate the following data:

- **Age:** the raw database contains information about each respondent's age without any division into ranges. For readability of the data interpretation, it was decided to aggregate the data into five ranges:
  - **A1** – respondents aged 17–19 years,
  - **A2** – respondents aged 20 years,
  - **A3** – respondents aged 21 years,
  - **A4** – respondents aged 22 years,
  - **A5** – respondents aged 23–36 years.
- **Year of study:** the raw database contained information about the year of study. Due to the low number of the respondents in their third, fourth, and fifth years of study, it was decided to combine the respondents into one group, i.e.,
  - **Y1 –** respondents in their first year of study,

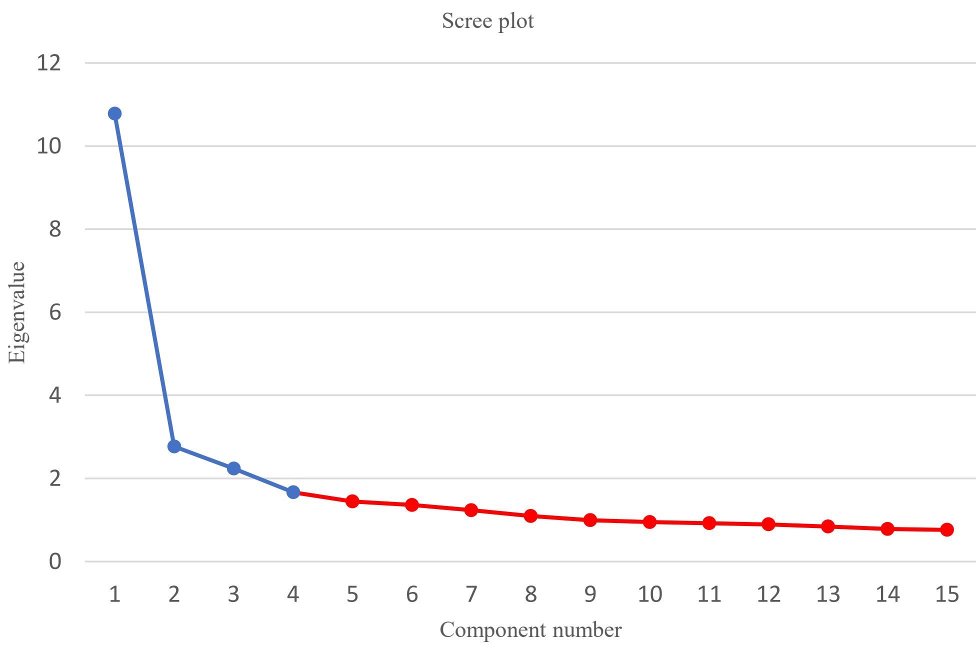


**FIGURE 1 |** Reduction of factors: Cattell criterion. The red part shows that "gentle" decrease begins and at what point the reduction to a higher number (5 and more) of factors is pointless.

- **Y2 –** respondents in their second year of study,
- **Y3 –** respondents in their third or higher years of study.

## Characteristics of the Respondents

The results in **Table 1** show there were almost twice as many women as men in the Slovak group, while men outnumbered women among the Czechs. This is not surprising since students at the Faculty of Informatics and Management are predominantly males involved in computer science. However, eventually, the whole sample was characterized by a slight advantage of women (53.7 to 43.3%). The respondents were a mean age of less than 21 years and were most often in their first or second years of study (44.4 and 36.6%, respectively). Almost four-fifths of the Slovak group were first-year students, which was directly related to a lower mean age (20.2 years). Slightly more than half of the Czech students declared the second year of study, and this group was also older (mean age 21.6).

## Analysis of the Results by Using Descriptive Statistics

The following table provides descriptive statistics for individual statements concerning the approaches to the self-regulated learning process. To ensure the readability of interpretation of the results, the scores for S1, S2, and S23 were reversed, as these statements, unlike the others, had negative overtones. The respondents agreed most with the statement "I know my strengths and weaknesses in learning" (total mean: 5.76), while the sentences with which they agreed least were "I buy or borrow additional recommended literature because I want to understand the field more" and "On my own initiative, I read the supplemental literature although it is not mandatory" (total means of 2.76 and 2.77, respectively). In addition, **Table 2** below illustrates five statements with the largest differences between both group of students.

No statistically significant differences were found for most statements. Item numbers, Mann–Whitney *U*-statistics, and *p*-value for the statements in which significantly different responses were observed between Czechs and Slovaks are presented in **Table 3**. In all the statements, a higher average score was observed for Slovak students.

**TABLE 1 |** Characteristics of the respondents.

| Nationality | Personal data | Number of indications (N) | % Distribution | % Distribution by country |
|---|---|---|---|---|
| Czechia (CZ) | | 139 | 51.9% | |
| Slovakia (SK) | | 129 | 48.1% | |
| **Sex** | | | | |
| CZ | Woman | 59 | 22.0% | 42.4% |
| | Man | 80 | 29.9% | 57.6% |
| SK | Woman | 85 | 31.7% | 65.9% |
| | Man | 44 | 16.4% | 34.1% |
| **Age** | | | | |
| CZ | A1 | 4 | 1.5% | 2.9% |
| | A2 | 24 | 9.0% | 17.3% |
| | A3 | 44 | 16.4% | 31.7% |
| | A4 | 37 | 13.8% | 26.6% |
| | A5 | 30 | 11.2% | 21.6% |
| SK | A1 | 30 | 11.2% | 23.3% |
| | A2 | 63 | 23.5% | 48.8% |
| | A3 | 28 | 10.4% | 21.7% |
| | A4 | 5 | 1.9% | 3.9% |
| | A5 | 3 | 1.1% | 2.3% |
| **Year of study** | | | | |
| CZ | Y1 | 17 | 6.3% | 12.2% |
| | Y2 | 72 | 26.9% | 51.8% |
| | Y3 | 50 | 18.7% | 36.0% |
| SK | Y1 | 102 | 38.1% | 79.1% |
| | Y2 | 26 | 9.7% | 20.2% |
| | Y3 | 1 | 0.4% | 0.8% |

*Source: authors' own study.*

## Factor Analysis

**Table 3** shows the final classification of the variables and the reliability coefficients of the scales for each nationality. The least consistent was the *Metacognitive strategies* scale, with a Cronbach's alpha coefficient of 0.795 for Czech students and 0.774 for Slovak students. The best reliability was recorded for the *Personal competence* scale. In the Czech survey, it was 0.860, whereas in the Slovak survey, it was 0.885. No statement was excluded during the analysis (the values of the coefficients after removing the items were at most at the same level, but most often lower).

### Analysis of Demographic Variables

As **Table 4** illustrates, the Slovak students rated *Metacognitive strategies* ($p < 0.001$) and *Motivation orientation* ($p = 0.016$) significantly higher than the Czech students.

No statistically significant differences were found in either women or men (**Table 5**).

For the 1st, 4th, and 5th age groups, significance tests were not conducted due to the insufficient sample size. There was a correlation in the case of age group 3: students from Slovakia rated the approach to self-regulated learning significantly higher in terms of *Motivation orientation* ($p = 0.016$).

Students in their first year of study from Slovakia rated the *Personal competence* aspect higher than their peers from the Czechia. For students in their third and higher year of study, significance tests were not conducted due to the insufficient sample size of Slovak students (**Table 6**).

# DISCUSSION

The findings described above indicate that **Central European students seemed to be able to perform their online self-regulated study, especially as far as personal competence, meaningfulness and motivation are concerned**. And this is generally true regardless students' gender, year of study and nationality. Overall, students reported higher awareness of their strengths and weaknesses in learning, time management, and/or

**TABLE 2 |** Descriptive statistics of items included in the research questionnaire by nationalities.

| Statement | Country | *M* | SD | MED | MOD |
|---|---|---|---|---|---|
| S1. I have to force myself to learn | CZ | 3.39 | 1.54 | 3 | 4 |
| | SK | 3.81 | 1.45 | 4 | 3 |
| S2. It often happens that I think of other things while learning | CZ | 2.82 | 1.47 | 2 | 2 |
| | SK | 3.30 | 1.63 | 3 | 2 |
| S3. I study even though I do not have to | CZ | 3.12 | 1.64 | 3 | 2 |
| | SK | 3.51 | 1.63 | 4 | 2 |
| S4. While studying, I fulfill the obligations beyond the requirements set by the teachers | CZ | 3.63 | 1.64 | 4 | 2 |
| | SK | 4.02 | 1.53 | 4 | 4 |
| **S5. On my own initiative, I read the supplemental literature although it is not mandatory** | **CZ** | **2.41** | **1.49** | **2** | **1** |
| | **SK** | **3.16** | **1.89** | **3** | **2** |
| S6. I like learning | CZ | 4.41 | 1.50 | 4 | 4 |
| | SK | 4.46 | 1.58 | 5 | 5 |
| S7. I buy or borrow additional recommended literature because I want to understand the field more | CZ | 2.59 | 1.51 | 2 | 1 |
| | SK | 2.94 | 1.75 | 2 | 1 |
| S8. I read study materials (notes from lectures, university textbooks, etc.) on an ongoing basis | CZ | 4.18 | 1.71 | 4 | 5 |
| | SK | 4.18 | 1.57 | 4 | 4 and 5 |
| S9. I can estimate the demands placed on me during my studies | CZ | 4.52 | 1.30 | 5 | 4 |
| | SK | 4.80 | 1.16 | 5 | 4 |
| S10. I know which style of learning is most appropriate in a given situation | CZ | 4.61 | 1.41 | 5 | 5 |
| | SK | 4.98 | 1.37 | 5 | 5 |
| S11. I know my strengths and weaknesses in learning | CZ | 5.81 | 1.13 | 6 | 6 |
| | SK | 5.77 | 1.22 | 6 | 6 |
| **S12. I can organize my study materials so I can study them well** | **CZ** | **5.00** | **1.43** | **5** | **5** |
| | **SK** | **5.50** | **1.44** | **6** | **7** |
| S13. I expect to do well in my studies | CZ | 4.95 | 1.37 | 5 | 6 |
| | SK | 5.24 | 1.21 | 5 | 5 |
| S14. I have my studies under control and I know how well I understand the issues studied | CZ | 4.72 | 1.29 | 5 | 5 |
| | SK | 4.80 | 1.35 | 5 | 5 |
| S15. I do not give up easily, even I do not understand something | CZ | 5.09 | 1.32 | 5 | 6 |
| | SK | 5.28 | 1.27 | 5 | 6 |
| S16. I know what information is the most important and which is of less importance | CZ | 4.95 | 1.28 | 5 | 5 |
| | SK | 4.96 | 1.16 | 5 | 5 |
| S17. I have a good memory | CZ | 4.50 | 1.53 | 5 | 5 |
| | SK | 4.84 | 1.42 | 5 | 5 |
| S18. I believe when I decide to succeed, I can | CZ | 5.45 | 1.39 | 6 | 6 |
| | SK | 5.50 | 1.29 | 6 | 7 |
| S19. I can organize my time to learning in a way to succeed on exams | CZ | 5.05 | 1.45 | 5 | 6 |
| | SK | 5.23 | 1.25 | 5 | 5 |
| S20. If I know what makes it difficult for me to learn, I can resolve or easy the challenge | CZ | 4.27 | 1.19 | 4 | 4 |
| | SK | 4.55 | 1.21 | 4 | 4 |
| S21. I am not afraid to start with the more demanding tasks needed to complete what I am studying | CZ | 4.31 | 1.43 | 4 | 4 and 5 |
| | SK | 4.52 | 1.36 | 4 | 4 |
| S22. I think I am better at studying than most of my classmates | CZ | 3.43 | 1.42 | 3 | 3 |
| | SK | 3.19 | 1.37 | 3 | 4 and 3 |
| S23. I often have a feeling that I don't understand anything and won't master the study | CZ | 4.11 | 1.71 | 4 | 4 |
| | SK | 4.58 | 1.68 | 5 | 6 |
| S24. The moment I complete the test, I know I passed it successfully | CZ | 3.94 | 1.33 | 4 | 4 |
| | SK | 3.81 | 1.53 | 4 | 4 |
| S25. When learning, I need to make sure I am moving in the right direction | CZ | 4.75 | 1.40 | 5 | 6 |
| | SK | 4.94 | 1.33 | 5 | 5 |
| S26. I often find myself stopping while learning to check that I understand everything | CZ | 4.27 | 1.40 | 4 | 5 |
| | SK | 4.68 | 1.53 | 5 | 4 |
| S27. When learning new information, I ask myself questions to find out how I am doing | CZ | 3.81 | 1.65 | 4 | 3 |
| | SK | 3.82 | 1.68 | 4 | 4 |
| S28. Before I start learning, I describe what I will do to myself (now and later) | CZ | 3.66 | 1.88 | 4 | 3 |
| | SK | 3.98 | 1.81 | 4 | 3 |
| **S29. When I am learning, I constantly test myself to see if I have really understood the subject matter** | **CZ** | **3.92** | **1.49** | **4** | **4** |
| | **SK** | **4.56** | **1.52** | **5** | **5** |
| **S30. I often ask myself if I have done everything I can to understand the subject** | **CZ** | **3.62** | **1.59** | **4** | **3** |
| | **SK** | **4.39** | **1.48** | **5** | **5** |
| S31. It often happens that when I am learning, I analyze or evaluate myself | CZ | 3.72 | 1.52 | 4 | 4 |
| | SK | 3.99 | 1.50 | 4 | 4 |
| **S32. When learning, I usually divide the learning materials into several parts, which I learn gradually** | **CZ** | **4.56** | **1.87** | **5** | **5** |
| | **SK** | **5.19** | **1.59** | **5** | **6** |
| S33. I try to relate the information I learn in one subject to other subjects | CZ | 5.00 | 1.51 | 5 | 5 |
| | SK | 5.09 | 1.42 | 5 | 5 |
| S34. I like the content of subjects studied in this field | CZ | 4.69 | 1.40 | 5 | 5 |
| | SK | 4.91 | 1.31 | 5 | 6 |
| S35. I think it is useful to make effort to study | CZ | 5.49 | 1.37 | 6 | 5 |
| | SK | 5.31 | 1.31 | 5 | 5 |
| S36. I am interested in the subjects studied in this field | CZ | 4.91 | 1.44 | 5 | 5 |
| | SK | 4.98 | 1.34 | 5 | 6 and 5 |
| S37. It is very important for me to understand the issues studied | CZ | 4.96 | 1.41 | 5 | 5 |
| | SK | 5.29 | 1.36 | 5 | 5 |
| S38. I learn by combining information from several sources (notes from lectures, university textbooks, recommended literature, etc.) | CZ | 4.72 | 1.55 | 5 | 5 |
| | SK | 4.88 | 1.67 | 5 | 6 |
| S39. I study as a hobby | CZ | 3.12 | 1.76 | 3 | 2 |
| | SK | 3.22 | 1.88 | 3 | 1 |
| S40. I think that what I am learning in my studies can be used in practice | CZ | 4.92 | 1.54 | 5 | 6 |
| | SK | 5.22 | 1.43 | 5 | 5 and 6 |

*Source: authors' own study. Bold letters indicate the largest differences between both groups of students.*

usefulness of making an effort to study. In addition, they feel able to interconnect the knowledge of one subject with the knowledge of another subject, which confirms their awareness of interdisciplinary knowledge.

On the contrary, **they appeared to have problems with their metacognitive strategies**, although Slovak students did slightly better. This includes, for example, less reflecting on

**TABLE 3 |** Final classification of statements into scales and reliability of scales.

| Scale | Items | Cronbach's alpha | |
|---|---|---|---|
| | | CZ | SK |
| Full scale | – | 0.914 | 0.934 |
| Motivation orientation | S1 S2 S3 S4 S5 S6 S7 S8 S39 | 0.804 | 0.844 |
| Personal competence | S9 S10 S11 S12 S13 S14 S15 S16 S17 S18 S19 S20 S21 S22 S23 S24 | 0.860 | 0.885 |
| Metacognitive strategies | S25 S26 S27 S28 S29 S30 S31 S32 | 0.795 | 0.774 |
| Meaningfulness of studying | S33 S34 S35 S36 S37 S38 S40 | 0.819 | 0.846 |

*Source: authors' own study.*

**TABLE 4 |** An overview of the analysis by nationality.

| Scale | CZ ($n$ = 139) | | SK ($n$ = 129) | | Significance of differences |
|---|---|---|---|---|---|
| | *M* | SD | *M* | SD | |
| Motivation orientation | 3.3 | 1.0 | 3.6 | 1.1 | $U$ = 7441.5 $p$ = 0.016* |
| Personal competence | 4.7 | 0.8 | 4.8 | 0.8 | $U$ = 8161.0 $p$ = 0.205 |
| Metacognitive strategies | 4.0 | 1.0 | 4.4 | 1.0 | $U$ = 6873.0 $p$ < 0.001*** |
| Meaningfulness of studying | 4.7 | 1.0 | 4.9 | 1.0 | $U$ = 8424.0 $p$ = 0.393 |

*Source: authors' own study.*
*The "*" symbol means that p-value is between 0.01 and 0.05.*
*The "**" symbol means that p-value is between 0.001 and 0.01.*
*The "***" symbol means that p-value is lower than 0.001.*

one's own learning or analyzing what they are going to do next – skills necessary for higher-order cognitive skills (cf. Mitsea and Drigas, 2019). They are not well-prepared for self-study from their institutions of secondary school learning where they were more used to memorization and fewer discussions. The students were suddenly given a huge amount of literature and assignments to do their own, whereas there were still tendencies to be fully guided and checked by their teachers at their former schools. Therefore, there is an urgent need to start developing self-regulated behaviors for studying in the early years and accentuate its importance at the secondary institutions by encouraging students to do their own research, to prioritize their tasks, and to organize their time and ability to work with much information. Furthermore, the Slovak students seemed to be more motivated, particularly in their second year of study as they experienced the school load in their first year, got to know the teachers and formed social clubs in their study groups to share and exchange information and study materials. After the first-year experience, they could better organize their study time, assignments, and requirements so they could enjoy free-time activities. Ambitious students could take advantage of exchange study trips, and some might have found a part-time job in their area of studies so they had hands-on experience to utilize in their studies and careers after graduation. Nevertheless, overall, the findings of this study indicate that metacognitive strategies improve with higher motivation and personal professional competence, which was also confirmed by Kisac and Budak (2014). In addition, students in both countries perceived their studies as meaningful, such as usefulness of studying.

**There were not any striking differences between the Czech and Slovak students.** Nevertheless, Slovak students (females in particular) seemed to be more self-disciplined and goal-oriented in their learning. This result could have been also affected by a higher proportion of boys in the Czech sample. However, as shown in the PISA testing, Slovak females generally score higher than males. Similar findings about female students were also confirmed by Mayda et al. (2020) and Santamaría-Vázquez et al. (2021).

Although learning does not seem to be the students' principal hobby, they thought it was useful to make effort to study. Both group of students seemed to be motivated by the competitive salaries possible in their fields of study. They take part-time jobs as their school load and schedule allow them to earn extra cash and get experience. They also realize that without the university diploma, the doors to the job market are closed.

Since there are abundant learning materials online, students prefer not to buy or lend any course materials, as the findings of this study revealed. They appear to be more ecologically friendly than their former peers. Even though there are enough information and resources online, students do take notes, highlight the most important information and learn the given material by heart.

Therefore, the **teacher should gradually introduce self-regulated strategies** from Day 1 so that students are aware of consciously working toward them. One needs to, however, realize that it is a life-long learning process but good basis can be grounded even within a semester of studying. Additionally, as the study by Partovi and Tafazoli (2016) reveals, the more experienced EFL teachers are, the more self-regulatory traits they have in altogether with more resilience in the students' point of view. Therefore, teachers as a model in developing their own self-regulation with time might be an encouraging and decisive factor in students' learning development.

On the basis of the findings of this study and with respect to the findings of other research studies (e.g., Alvi and Gillies,

**TABLE 5 |** An overview of the analysis by age.

| Scale | A1 | | | | | A2 | | | | | A3 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CZ (*n* = 4) | | SK (*n* = 30) | | Significance of differences | CZ (*n* = 24) | | SK (*n* = 63) | | Significance of differences | CZ (*n* = 44) | | SK (*n* = 28) | | Significance of differences |
| | *M* | SD | *M* | SD | | *M* | SD | *M* | SD | | *M* | SD | *M* | SD | |
| Motivation orientation | 3.7 | 0.7 | 3.6 | 1.1 | | 3.4 | 1.0 | 3.6 | 1.0 | $U = 737.5$ $p = 0.860$ | 3.2 | 1.1 | 3.9 | 1.2 | $U = 408.0$ $p = 0.016^{*}$ |
| Personal competence | 4.4 | 0.8 | 5.1 | 0.6 | | 4.7 | 0.8 | 4.8 | 0.9 | $U = 739.0$ $p = 0.872$ | 4.8 | 0.7 | 4.9 | 0.8 | $U = 600.5$ $p = 0.858$ |
| Metacognitive strategies | 4.8 | 0.9 | 4.6 | 0.8 | | 4.2 | 1.2 | 4.5 | 0.9 | $U = 678.5$ $p = 0.461$ | 4.1 | 1.1 | 4.4 | 1.2 | $U = 526.0$ $p = 0.298$ |
| Meaningfulness of studying | 4.9 | 1.1 | 4.7 | 1.0 | | 4.9 | 1.1 | 4.7 | 1.0 | $U = 638.0$ $p = 0.262$ | 4.8 | 1.0 | 4.9 | 1.1 | $U = 615.5$ $p = 0.995$ |

*Source: authors' own study.*
*The "*" symbol means that p-value is between 0.01 and 0.05.*
*The "**" symbol means that p-value is between 0.001 and 0.01.*
*The "***" symbol means that p-value is lower than 0.001.*

**TABLE 6 |** An overview of the analysis by year of study.

| Scale | Y1 | | | | | Y2 | | | | | Y3 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CZ (*n* = 17) | | SK (*n* = 102) | | Significance of differences | CZ (*n* = 72) | | SK (*n* = 26) | | Significance of differences | CZ (*n* = 50) | | SK (*n* = 1) | | Significance of differences |
| | *M* | SD | *M* | SD | | *M* | SD | *M* | SD | | *M* | SD | *M* | SD | |
| Motivation orientation | 3.5 | 1.0 | 3.6 | 1.1 | $U = 838.5$ $p = 0.829$ | 3.5 | 1.0 | 3.9 | 1.1 | $U = 700.0$ $p = 0.057$ | 3.0 | 0.9 | 2.0 | 0.0 | |
| Personal competence | 4.2 | 0.8 | 4.9 | 0.8 | $U = 487.5$ $p = 0.004^{**}$ | 4.8 | 0.7 | 4.8 | 0.9 | $U = 875.0$ $p = 0.623$ | 4.6 | 0.8 | 4.1 | 0.0 | |
| Metacognitive strategies | 4.1 | 1.3 | 4.5 | 0.9 | $U = 700.0$ $p = 0.204$ | 4.1 | 1.1 | 4.4 | 1.1 | $U = 774.0$ $p = 0.192$ | 3.9 | 0.9 | 5.4 | 0.0 | |
| Meaningfulness of studying | 4.7 | 1.1 | 4.9 | 1.0 | $U = 796.0$ $p = 0.589$ | 4.9 | 1.0 | 4.8 | 1.2 | $U = 868.0$ $p = 0.586$ | 4.5 | 1.0 | 3.8 | 0.0 | |

*Source: authors' own study.*
*The "*" symbol means that p-value is between 0.01 and 0.05.*
*The "**" symbol means that p-value is between 0.001 and 0.01.*
*The "***" symbol means that p-value is lower than 0.001.*

2020), the following practical recommendation could be provided in order to successfully develop and maintain students' self-regulated learning, especially their metacognitive strategies that they still lack at this level:

- Being at students' disposal in a timely manner to keep them motivated in their studies, as well as guiding them in their online learning environment,
- Helping students link new experiences to prior learning by applying their newly acquired knowledge and skills in broader contexts and in the case of foreign language learning to expose them to authentic environment (e.g., involving native speakers),
- Providing students with corrective and timely feedback by focusing on the task of learning, not on the learner,
- Giving students opportunities to communicate with each other, not only the teacher in order to share their expertise and emotions about their learning,
- Promoting students' reflection, for example, by writing self-reflection diaries or essays in a critical manner, and thus developing also their critical thinking,
- Adjust assessment criteria due to the new learning environment, as well as encourage students to keep a track of their own self-assessment rubrics which may help them find a gap in their new and past acquired knowledge,
- Put an emphasis on the new product outcome due technological innovations and needs of the current generation of students (e.g., record a video, create an interactive presentation, work with the mobile apps and softwares).

The limitations of this study consist of unbalanced gender samples, i.e., in the Slovak sample was predominantly females and the relatively small scale of the research, as it was conducted in only two neighboring European countries. Therefore, it would be necessary to replicate the research on a much larger scale to obtain more generalizable results. Nevertheless, this research generated statistically relevant and reliable results. Future research should focus on verification of our findings on a larger scale and in a larger geographical area.

## CONCLUSION

Generally, it can be concluded that the present pandemic students in Central Europe who had to study only online for the entire academic year seemed to be able to perform self-regulated online learning. However, the findings show that much more work must be done in developing their metacognitive strategies, such as reflective and critical thinking, analyzing or evaluating, the strategies that are crucial for successful academic performance. In this respect, it is the teacher who can serve as a facilitator and promote these metacognitive strategies among his/her students by providing students with constructive feedback, monitoring their learning, reviewing their progress, and/or providing opportunities to reflect on their learning.

## DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

## ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Ethics Committee no. 2/2021 of the University of Hradec Králové. The patients/participants provided their written informed consent to participate in this study.

## AUTHOR CONTRIBUTIONS

BK, KZ, AC-E, and SD drafted, analyzed, wrote, and read the whole manuscript. All authors contributed to the article and approved the submitted version.

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# Exploring Students' Use of a Mobile Application to Support Their Self-Regulated Learning Processes

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Being able to self-regulate one's learning is essential for academic success but is also very difficult for students. Especially first year students can be overwhelmed with the high study load and autonomy in higher education. To face this challenge, students' monitoring and self-regulated learning (SRL) processes are crucial. Yet, often students are not aware of effective SRL strategies or how to use them. In this study, the use of a mobile application with gamification elements (i.e., Ace Your Self-Study App) to support first-year university students' SRL processes was investigated. In Study 1a, the Ace your self-study app was implemented in a first-year psychology course, and students' SRL skills, motivation, self-efficacy, app use and satisfaction, and performance were measured. The results showed a significant increase in autonomous motivation, controlled motivation, and metacognitive self-regulation skills (MSR-R) across the 5-week course. Moreover, students who used the mobile application with gamified elements showed higher autonomous motivation. Nevertheless, most students used the app only for a limited number of self-study sessions. In Study 1b, students' self-study experiences were captured using focus group interviews to shed some more light on why students did or did not use the app. The results show that if students feel they do not need support for their SRL processes during self-study, they are less inclined to use the app. Specifically, regarding using study strategies, it was found that only if students' strategies do not work well in their perception, they feel the need to change their way of studying and choose another strategy. These results are discussed in the context of theory on SRL and how to support it.

**Keywords: self-regulated learning, mobile application, motivation, self-efficacy, monitoring**

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## INTRODUCTION

First year students starting in higher education can be overwhelmed by the course load they encounter and the challenges this poses to their study skills. To self-regulate their study process, students need to be able to accurately keep track of their own learning process (i.e., monitoring) and use that information to regulate their learning process (e.g., Zimmerman, 2002, 2008). Yet, research has shown that students are often not capable of self-regulating their learning processes. That is, without instructional guidance, they find it difficult to accurately judge their own learning processes (e.g., Dunning et al., 2003; Dunlosky and Lipko, 2007) and consequently, regulation of the learning processes is hampered (e.g., Pressley, 1995; Dunlosky and Rawson, 2012). This problematic cycle of suboptimal *self-regulated learning* (SRL) could stand in the way of academic success and the goal to become life-long learners. Especially because students often do not get instruction about how to study and are largely unaware of *learning strategies* that could help them to study effectively (e.g., McCabe, 2011; Bjork et al., 2013; Dirkx et al., 2019). Therefore, the main aim of this study is to investigate the use of a mobile application with *gamification* elements to support SRL processes of first year students in higher education.

## Self-Regulated Learning and How to Support it

Self-regulated learning can be defined as the degree to which people are "metacognitively, and behaviorally active participants in their own learning process" (Zimmerman, 1989, p. 4). Zimmerman (2008) describes a cyclical model of SRL which entails three phases: the forethought, performance, and reflection phase. First, students start the cycle with the forethought phase during which they can prepare their study session by, for example, setting a goal for the session or analyzing the task for that session. After the forethought phase, the performance phase follows. During this phase, students use strategies to process the learning materials (e.g., summarizing or self-explaining) and keep track of their learning processes (i.e., self-monitoring). Finally, in the reflection phase, students evaluate their study session, for example by making self-judgments about their learning and satisfaction.

Research has shown that metacognitive processes, such as monitoring and control, which allow students to self-regulate or self-manage their learning processes and choose which cognitive strategies to use, are crucial for academic success (e.g., Thiede et al., 2003; Broadbent and Poon, 2015; Dent and Koenka, 2015). These findings align with the model of SRL by Zimmerman (2002, 2008) as both cognitive and metacognitive processes are crucial in going through the three phases of SRL. Metacognitive processes for example are, students setting learning goals, self-monitoring learning processes, and regulating or managing their learning processes. Using study strategies, for example during the performance phase, entails all kinds of cognitive processes, such as summarizing, elaboration, or self-testing but also management strategies such as time management.

Yet, very often students are not aware of metacognitive or cognitive strategies that they can use to regulate their own learning (McCabe, 2011; Bjork et al., 2013; Dirkx et al., 2019). Moreover, research has shown that if students do not get instructional support on how to monitor their learning processes, their insight in their own learning process and how to proceed is generally very poor. Specifically, students were found to overestimate their understanding of learning materials (such as texts, e.g., Thiede et al., 2009) and their memory of learning materials (such as word pairs, e.g., Dunlosky and Lipko, 2007) when no additional instructional support was provided. Inaccurate self-monitoring can have detrimental effects on the learning process. For example, in a study by Dunlosky and Rawson (2012), retention of the learning materials was lower because of premature termination of study by students who overestimated their performance.

Importantly, providing instructional support to help students self-regulate their learning has shown to be beneficial in terms of SRL processes (e.g., Devolder et al., 2012), strategy use, and learning outcomes (e.g., Dignath and Büttner, 2008). Interventions to support SRL processes based on metacognitive theories, like metacognitive reflection (Dignath and Büttner, 2008) and planning strategies (Dignath et al., 2008), were found to improve strategy use and learning outcomes. In a review by Devolder et al. (2012) on supporting SRL in computer-based learning environments, it is concluded that SRL scaffolds support SRL processes of the learners. Yet, very often studies only prompted cognitive strategies (e.g., self-explaining) and did not prompt aspects from the other phases of SRL. Another review on supporting SRL in online learning environments concluded that prompting SRL processes such as planning benefitted students SRL behaviors and performance (Wong et al., 2019). The authors also noted that many studies only prompted and measured behaviors related to one of the SRL phases and that it might be better to prompt and measure aspects from multiple SRL phases.

In addition, more recent work stresses the importance of combining cognitive and metacognitive prompts to support SRL (Nückles et al., 2020). Prompting cognitive (e.g., summarizing and note taking) and metacognitive (e.g., planning, monitoring, and reflection) strategies were found to be most effective to support SRL. Moreover, research has shown that the most optimal sequence of prompts consists of metacognitive prompts first followed by cognitive prompts (Roelle et al., 2017a).

Next to prompting students to use cognitive and metacognitive strategies, student's self-efficacy plays an important role in SRL (e.g., Panadero et al., 2017). That is, if students' self-efficacy beliefs about their capabilities are low they are likely to avoid tasks compared to students who have high self-efficacy beliefs which make it likely they will participate in tasks (e.g., Schunk, 1990). This could mean that students with low self-efficacy will not use the cognitive or metacognitive strategies that are prompted as much as the students who have higher self-efficacy beliefs. On the other hand, students with higher self-efficacy and who use more learning strategies were found to have higher task performance. In turn, higher performance was linked to higher self-efficacy on subsequent learning tasks (Wilson and Narayan, 2016). Yet, engaging in SRL could provide students with a deeper understanding of the learning task, which could enable them to perform better and experience success. This could result in increased feelings of competence which in turn positively affect self-efficacy beliefs (e.g., Schunk, 1996; Paris and Paris, 2001).

In sum, it seems promising to support students' SRL processes by designing effective instructional support in which both metacognitive and cognitive strategies are elicited and students are stimulated to go through all the SRL phases accordingly.

## Mobile Technology to Support SRL

To make sure that these instructional prompts will be provided just in time during the learning processes (see Van Merriënboer et al., 2002), mobile technology seems promising to support SRL. That is, almost every student has a mobile phone and with this mobile device SRL support can be brought close to the student's learning process at anytime and anywhere. Yet, there has been very little research about the use of mobile devices to support SRL processes. In a study by Tabuenca et al. (2015) graduate students used a mobile device to track time during their learning processes. The results of their study showed that tracking time during the learning process had a positive effect on time management. These results suggest that using mobile devices to support SRL processes such as time management are very promising (Tabuenca et al., 2015). Similarly, a recent study by Broadbent et al. (2020) found that combining an online SRL training module with a mobile application to capture daily diaries on study activities and affect, had positive effects in terms of resource management (i.e., time and space), and metacognitive and cognitive strategies. This study has shown that a domain-independent intervention was successful in improving students' SRL strategies. Interestingly, when students only used the mobile-app for daily diaries on their study activities, they did not seem to improve their SRL strategies compared to a control condition. The authors highlight that only self-monitoring *via* a daily diary is probably not enough if someone does not know *how* to self-regulate his or her learning. Hence, the online training on SRL containing information on the three SRL phases combined with prompts *via* the mobile application at the beginning and ending of a study session seem to really support students to self-regulate their learning.

In addition to the few studies on using mobile technology to support SRL, there is abundant literature on supporting SRL in computer-supported or online environments. For example, in a review by Wong et al. (2019), it is reported that 14 out of the 35 studies reviewed used prompts as a means to support SRL. Another six studies out of 35 used a combination of prompts and feedback to support SRL. Also, 10 studies used integrated systems in the learning environment to support SRL. Other approaches that were reported in this review study were self-monitoring form (one study), e-learning (one study), training (two studies), or conceptualization of learning outcomes (one study). Hence, this review shows that although there is a variety of SRL support used in online learning environments, prompting or a combination of prompting with for example feedback is a well-researched way of supporting SRL.

Next to using mobile technology to provide instructional support for SRL, it can also provide the students with gamification elements to boost their motivation and SRL performance. Gamification can be defined as adding game elements to a non-game context (Buckley et al., 2018). Levels, points, and scoreboards are examples of gamification elements that can increase students' motivation and performance. Specifically, these gamification elements can provide students with clear goals and rewards, which in turn keeps them engaged and motivated to use the materials offered (e.g., Su and Cheng, 2015; Mekler et al., 2017).

Building upon the model of SRL (Zimmerman, 2002, 2008) and extending earlier studies on using mobile applications or computer-supported applications to support SRL, a mobile application to support SRL strategies during self-study was developed (see Baars et al., submitted)[1]: the Ace Your Self-study App (**Figures 1–3**, download *via* App store or Play store). The App was designed to help users go through three phases of SRL: forethought, performance, and evaluation. To support the forethought phase, in the App, students are prompted to start a study session and create a study plan by selecting the type of task; a suitable study strategy, deciding how much time they will need for the session, and filling out a goal of their study session (see **Figure 1**).

In the app, users can choose evidence-based cognitive strategies (e.g., note taking, summarizing, and concept mapping) and receive an explanation on how to use them (see **Appendix A**). This way they can enter the performance phase well-prepared. Moreover, if during the performance phase students need to look at their study plan, the app provides a brief overview of their choices (see **Figure 2**).

Once students decide to stop their current session, they are prompted to reflect on their learning process. They rate their satisfaction with learning in general and with the strategy they have used. Also, students select whether they worked alone or together with other students. Then, a log appears providing a summary of a single session or across sessions (see **Figure 3**).

In the Ace your self-study app, 22 cognitive study strategies are offered. As research has shown, students are often not aware of the different types of study strategies they can use (McCabe, 2011; Bjork et al., 2013; Dirkx et al., 2019). Therefore, gamification elements were added to the app to stimulate students to use a variety of study strategies during their self-study. In the tab "Tasks" in the app, students can find all the types of tasks and the strategies that can be used for those tasks (**Figure 4**). Stars were added to each strategy to create levels in using the study strategies from the app. The tab "Challenges" provides the student with some challenges in terms of using a variety of learning strategies. For example, "Lucky number, use seven different strategies" (see **Appendix B**).

## Motivation to Self-Regulate Learning

According to the self-determination theory (SDT; Deci and Ryan, 2000; Ryan and Deci, 2000a,b, 2020; Pelletier et al., 2001), intrinsic motivation and the internalisation of originally extrinsic behaviors can be enhanced if the basic psychological needs are satisfied. The three psychological needs are the need for autonomy, relatedness, and competence. The need for autonomy refers to the need to feel a sense of initiative and ownership in one's actions. Autonomy can be supported by experiences of interest and value, but it can be undermined by being externally controlled (by punishment or rewards).

[1]Baars, M., Zafar, F., Hrehovcsik, M., de Jongh, E., and Paas, F. (submitted). Ace your self-study: A mobile application to support self-regulated learning. Manuscript submitted for publication.

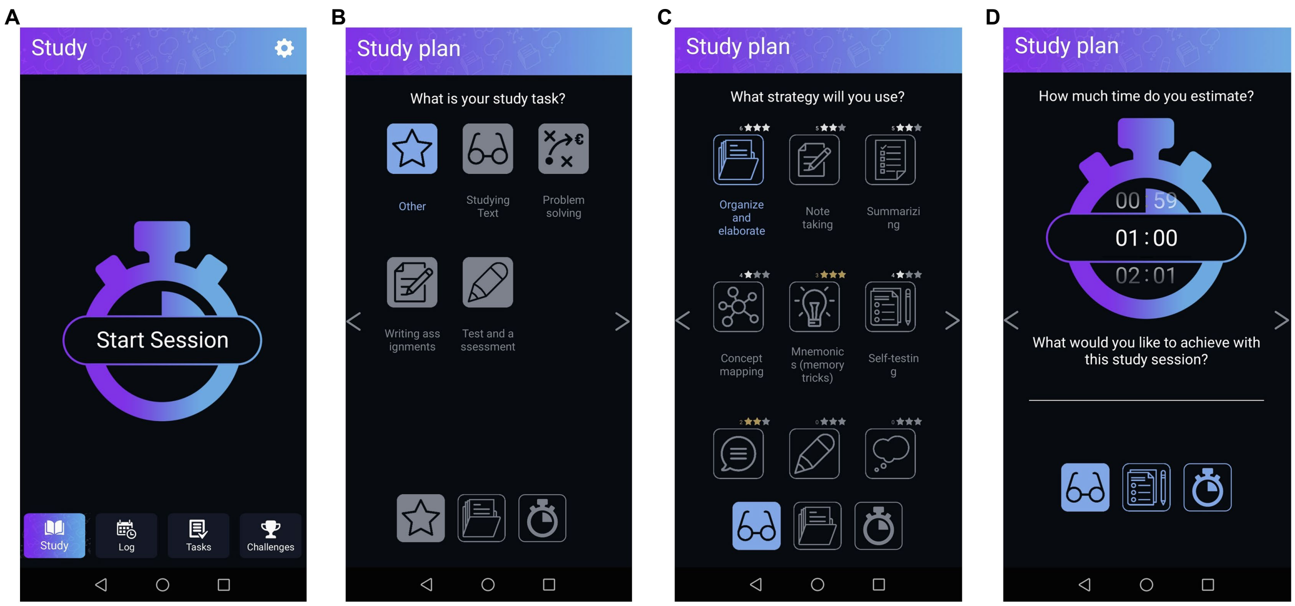


**FIGURE 1 |** Screenshots from the forethought phase. **(A)** shows the first "study plan" screen to sta1t a session. **(B)** Shows the second "study plan" screen at which students choose the type of task. **(C)** Shows the third "study plan" screen at which students choose a strategy. **(D)** Shows the fourth "study plan" screen at which students can set the time and fill out their goal [adapted from Baars et al., submitted (see footnote 1)].

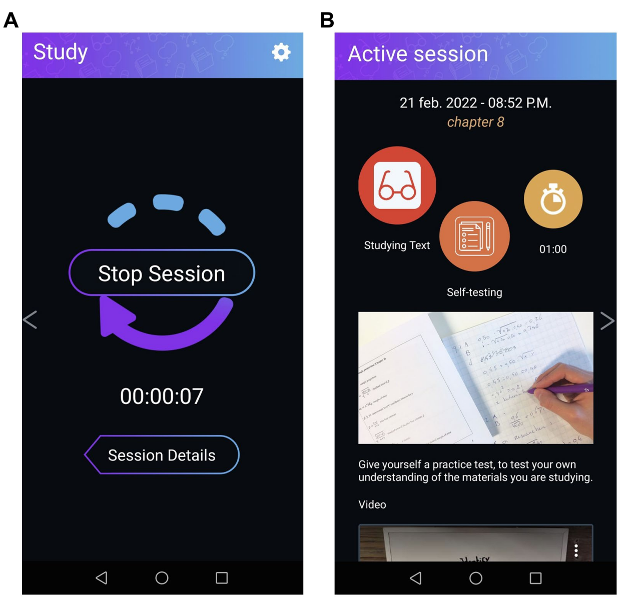


**FIGURE 2 |** Screenshots from the performance phase. **(A)** Shows the defaults screen during the performance phase, which shows a timer. **(B)** Shows the summary of the "study plan" made in the forethought phase [adapted from Baars et al., submitted (see footnote 1)].

The need for relatedness refers to the need to feel connected to others and have a sense of belonging. Relatedness is supported by conveying respect and caring. The need for competence refers to the feeling of mastery, and being able to grow. Competence can be supported in well-structured environments that allow for opportunities for growth, positive feedback, and challenges (Ryan and Deci, 2020).

In the SDT of motivation the quality of motivation which is determined by the reasons driving students behavior, is considered more important than the total amount of motivation when predicting psychological health and well-being, effective performance, and conceptual and deep learning (e.g., Vansteenkiste et al., 2006; Deci and Ryan, 2008). There is an important distinction between self-determined and controlled motivation. Students would engage in self-determined motivated actions if they would do this freely and volitionally. In contrast, students would engage in controlled motivated actions because of interpersonal or intrapsychic force. If student behavior is self-determined, regulation of learning would be based on choice, whereas if student behavior is controlled, regulation of learning would be based on compliance (Deci et al., 1991).

Hence, motivation of students can be expressed in terms of autonomy (Ryan and Deci, 2000a,b, 2020). Deci and Ryan (2000) proposed a self-determined continuum ranging from amotivation to intrinsic motivation. On this continuum of the degree of experienced autonomy, there are several types of motivation that can be conceptualized. Students with a high degree of autonomous motivation experience volition and psychological freedom. They study because it brings them satisfaction or because the subject is interesting to them (i.e., intrinsic motivation). Studying could also be valuable for development or attaining personal goals (i.e., identified motivation). More to the other side of the continuum of the degree of experienced autonomy, students who score high on

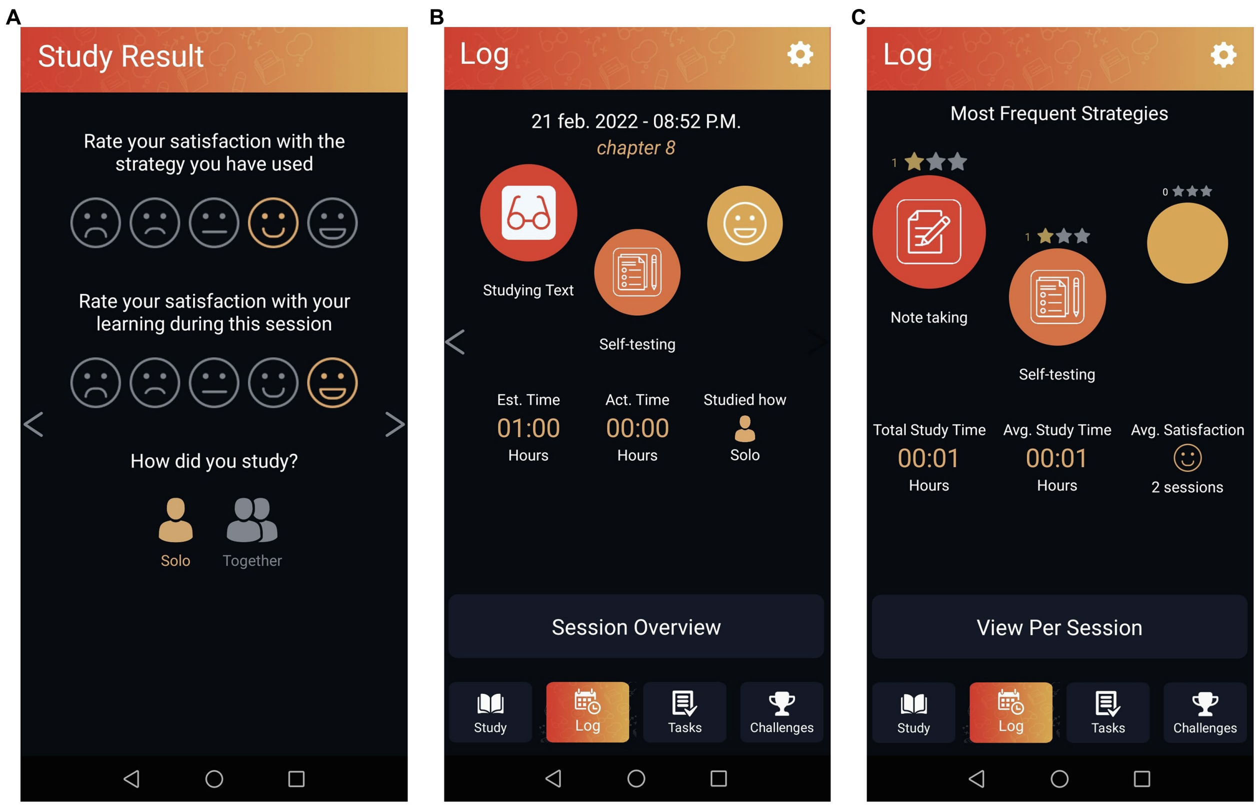


**FIGURE 3** | Screenshots from the reflection phase. **(A)** Shows the two ratings that students have to fill out. **(B)** Shows the log for a single session. **(C)** Shows the log across sessions [adapted from Baars et al., submitted (see footnote 1)].

controlled motivation experience a low degree of autonomy and experience pressure. This pressure can come from within the student (i.e., introjected motivation) when, for example, students feel pressure to avoid feelings of shame. This pressure can also come from an external source, such as demands from a parent or teacher (i.e., external motivation). It is important to note here that research has shown that intrinsic motives can coexist with extrinsic motives (e.g., Covington and Müeller, 2001). Moreover, these different types of motivation can operate at different levels (Vallerand, 1997), such as trait, contextual (e.g., school level), and the situational level (e.g., for a specific subject or moment). In the current study, we investigated specific motivation for self-studying the learning materials of the course. The type of motivation on the continuum of experienced autonomy students possess is relevant in terms of persistence, well-being, and learning outcomes. Specifically, more autonomously motivated students were found to have better text comprehension (e.g., Vansteenkiste et al., 2004) and (self-reported) academic achievement (e.g., Vansteenkiste et al., 2009; Taylor et al., 2014). Furthermore, autonomous motivation in terms of having interest for a subject, has been associated with better problem-solving performance (for a review, see Mayer, 1998) and better SRL abilities such as effort regulation (i.e., controlling effort and attention) and metacognitive strategy use (i.e., checking and correcting one's own learning behavior; Vansteenkiste et al., 2009; León et al., 2015). The relation between autonomous motivation and SRL skills was also shown in work by Pintrich (1999) who found that students who indicated higher levels of interest for a course (i.e., an autonomous reason for studying), were more likely to use strategies to monitor and regulate their learning. More recently, Baars and Wijnia (2018) and Wijnia and Baars (2021) have shown that secondary education students who were more autonomously motivated improved more in their monitoring skills after a SRL training.

To conclude, the role of motivation in using SRL skills cannot be underestimated. It is likely that students who would be more autonomously motivated will engage in SRL behaviors more often in general but will probably also be more inclined to make use of SRL supports such as the Study app.

## The Current Study

The current study consisted of two parts, Study 1a and Study 1b. First, in Study 1a, SRL activities by first year students as measured in the Ace your self-study app were investigated in relation to SRL skills, motivation, self-efficacy, satisfaction (with study strategy and learning), and performance across a 5-week

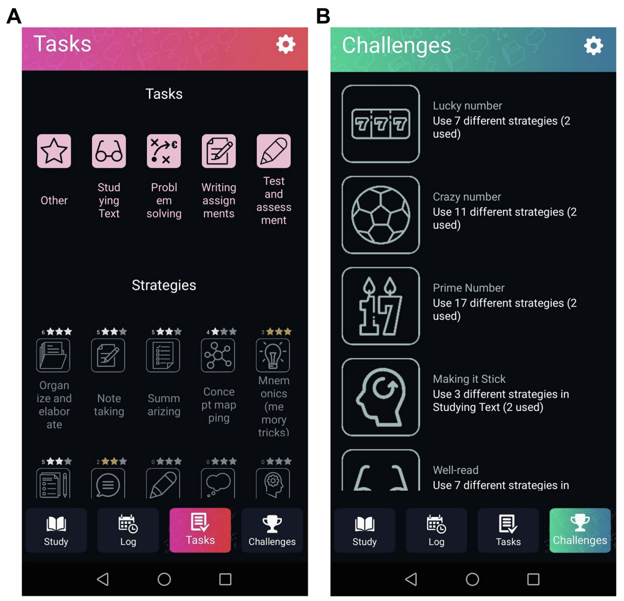


**FIGURE 4 |** Screenshots of gamifzcation elements in app. **(A)** Shows the overview of the strategies with the level of use depicted in stars. **(B)** Shows the challenges students can take when using the app [adapted from Baars et al., submitted (see footnote 1)].

course. Moreover, the effect of using the study app with or without gamification elements on students' app usage (i.e., frequency and duration) and students' motivation (autonomous and controlled), self-efficacy, satisfaction (with study strategy and learning), SRL skills, and course performance was investigated. In study 1b, using a qualitative approach, students' experiences using the app during Study 1a were investigated *via* focus groups interviews.

## STUDY 1A: USING THE ACE YOUR SELF-STUDY APP

In this study, the usage of the Ace Your Self-study app, from here on called the Study app, was investigated by the following research questions. The first research question is:

What is the relation between Study app usage (i.e., frequency and duration) and students' motivation (autonomous and controlled), self-efficacy, satisfaction (with strategy and learning), SRL skills, and course performance?

As SRL and motivation are related to each other (Pintrich, 1999; Baars and Wijnia, 2018; Wijnia and Baars, 2021), we have measured the SRL activities in the app as indication of students' engagement in SRL. We expect the frequency (i.e., number of sessions) and the duration of using the Study app (i.e., total time) will be positively related to pretest autonomous motivation (H1.1), pretest self-efficacy (H 1.2), satisfaction ratings of study strategy and learning in the app (H1.3), pretest SRL skills (H1.4), and course performance (H1.5).

In addition, the effect of the Study app with or without gamification elements (i.e., levels and challenges) was investigated by randomly assigning half of the students to a second version of the Study app in which gamification elements are added to the original version. Therefore, the second research question is: What is the effect of gamification elements in the Study app on students' app usage (i.e., frequency and duration) and students' motivation (autonomous and controlled), self-efficacy, satisfaction (with study strategy and learning), SRL skills across the course (from pre- to posttest), and course performance?

We expect that students in the Study app with gamification elements (Study game app) condition will show higher app usage (both duration and frequency; H2.1), higher autonomous motivation (H2.2), higher satisfaction ratings of study strategy and learning in the app (H2.3), higher self-efficacy, more SRL skills (H2.4), and higher performance (H2.5) compared to students in the non-gamified (Study app) condition.

## Method

We created an Open Science Framework (OSF) page for this project, where all materials, and a detailed description of the procedure are provided (DOI 10.17605/OSF.IO/98NYH). Data are available upon request.

### Participants and Procedure

We offered the Study app in the first-year practical on Problem-Based Learning (PBL) and study skills. Out of 912 students who were enrolled in the practical, 505 students downloaded the Ace your Self-Study app. If students could not or would not use the mobile application, they were invited to use a document containing the same content information as available in the mobile application, which was provided as an appendix to their practical guide. One hundred and ninety first year students ($M_{age} = 20.22$, $SD = 4.05$, 139 females, 49 males, and two other) filled out both the pre and post survey. From this sample, 99 students ($M_{age} = 20.43$, $SD = 4.58$, 70 females, 28 males, and one other) used the app, which allowed us to retrieve their backend data logged by the mobile application showing their activities using the app. From the sample with both completed surveys and app data, 52 ($M_{age} = 19.98$, $SD = 2.92$, 35 females, and 17 males) participants had been randomly assigned to the Study app and 47 ($M_{age} = 20.85$, $SD = 5.67$, 35 females, 11 males, and one other) to the Study Game app.

During the first practical meeting (small-group, tutorial meeting), students were invited to take part in this study. Using a Qualtrics survey,[2] students were provided with information on the current study and asked for their consent regarding using their data from the survey, the practical (i.e., performance), and the Study app for the purposes of the current study only. If students choose to participate in the study, they were presented with a survey about their motivation, self-efficacy, and SRL skills (i.e., pretest). During the practical, students received a homework assignment in meeting 1 (week 1)

[2]www.qualtrics.com

in which they were instructed to use the Study app for their self-study sessions during the whole course of the practical (**Appendix C**). In week 4 of the practical, students took part in a reflection exercise during a meeting to reflect on and evaluate their study behaviors using the Study app (**Appendix C**). This exercise was guided by their tutor. At the end of the practical during the last meeting, a survey on motivation, self-efficacy, SRL skills, and satisfaction with the Study app features was administered (i.e., posttest).

## Materials and Measurements

### *SRL Skills*

Two scales of the MSLQ, the metacognitive self-regulation (MSR) and the time and study environment (TSE) scales were filled in by the participants *via* a Qualtrics questionnaire. The MSLQ consists of 15 subscales with 81 items, which measure motivation, learning strategies, and management of resources with a Likert scale from 1 (*not at all true for me*) to 7 (*very true of me*; Pintrich, 1991, 2004). For this study, we used the adjusted scale "MSR revised" (i.e., MSR-R; Tock and Moxley, 2017) which comprises of nine items with an average weighted reliability of 0.78, and the "time and study environment scale" (i.e., TSE) from the MSLQ which comprises of eight items with a Cronbach's alpha of 0.76 (Pintrich, 1991). The scales were scored by taking the average of the items per scale. In this study, the MSR-R demonstrated a low reliability of 0.57 in the pretest and 0.64 in the posttest. Similarly, the TSE showed a reliability of 0.68 in the pretest and 0.66 in the posttest.

### *Motivation*

Students filled out a 16-item task-specific version of the academic self-regulation scale (Vansteenkiste et al., 2004), for which students had to indicate why they engaged in self-studying the learning materials in the course (i.e., "I engaged in self-study for this course because…"). The scale consisted of four subscales: external (e.g., "… because I am supposed to do so"), introjected (e.g., "… because I would feel guilty if I did not do it"), identified (e.g., "… because I could learn something from it"), and intrinsic motivation (e.g., "… because I found it interesting"). Items were measured on a five-point Likert-type scale ranging from 1 (not at all true) to 5 (totally true). The scales were scored by taking the average of the items per scale. The four subscales were combined into an autonomous motivation composite (intrinsic and identified motivation) and a controlled motivation composite (introjected and external motivation; *cf.* Vansteenkiste et al., 2004). Both composite scales showed good reliability in the pretest (0.85 for autonomous and 0.83 for controlled motivation) as well as in the posttest (0.88 for autonomous and 0.84 for controlled motivation).

### *Self-Efficacy*

Students were asked to indicate their degree of confidence in their ability to be successful in self-studying the learning materials offered in this course by recording a number from 0 to 100 (Bandura, 2006).

### *Learning Performance*

Learning performance was measured by collecting the exam grades for the practicum.

### *Ace Your Self-Study App Log Data*

From the Ace your self-study app, log data were collected per session that was initiated using the app, on the type of task, strategy choice, estimated and elapsed time, goals, and satisfaction ratings about learning and about the strategy that was used. For the purpose of this study, for each participant, the number of sessions and the duration of those sessions during the 5-week course were calculated. We defined a study session using the mobile application as any session that lasted between 1 min and 12 h. Sessions that were shorter or longer were discarded from the analyses for the current study.

### *Evaluation of User-Friendliness Study App*

In the posttest students received seven items on navigating the app, content of the app, errors, bias, and whether one would recommend the app to others, in order to evaluate the user-friendliness of the app (**Appendix D**).

# Results

Descriptive data of study app usage (frequency and duration), study app ratings (average strategy rating and satisfaction with learning), pre-and posttest measures (motivation, self-efficacy, and SRL skills), and course grades are displayed in **Table 1**.

**Figure 5** provides an overview of the percentage of sessions during which one of the types of learning strategies was used by the participants in the study app. The most commonly used strategy was note taking (37%), followed by summarizing (26%), organize and elaborate (15%), and self-explaining (6%). The other strategies only made up 2 or 1% of the total of strategies that were chosen during the study sessions registered by the app. These data show the limited number of strategies students were using in the app during this study.

In order to check for random assignment to the standard and gamified conditions, pretest motivation (autonomous and controlled), self-efficacy, and SRL skills (MSR-R and TSE) were compared between the two conditions. An independent-samples $t$ test revealed no significant differences between the conditions in pre-survey autonomous motivation, $t(97) = -1.59$, $p = 0.116$, controlled motivation, $t(97) = -0.93$, $p = 0.354$, self-efficacy, $t(97) = -1.53$, $p = 0.128$, MSR-R scores, $t(97) = -1.39$, $p = 0.169$, and TSE scores, $t(97) = -1.37$, $p = 0.174$.

## Correlations: Pretest Variables, App Usage, and App Ratings, and Course Performance

**Table 2** displays Pearson's correlations between the pretest variables (motivation, self-efficacy, and SRL skills), Study app usage variables (number of sessions and session duration), Study app rating variables (strategy rating and satisfaction with learning), and course performance (exam grade). Two-tailed tests of significance were conducted. At the 0.01 level, the

**TABLE 1** | Means and SDs for Study App usage, Study App rating, motivation, self-efficacy, self-regulated learning (SRL) skills variables, and final practical grade.

| Variable (Range) | Overall | Gamified | Standard |
|---|---|---|---|
| *Study App Usage* | | | |
| Number of sessions | 4.11 (4.07) | 4.06 (3.79) | 4.17 (4.40) |
| Session Duration in Minutes | 112.58 (80.52) | 108.52 (80.94) | 117.08 (80.69) |
| *Study App Rating* | | | |
| Strategy Rating (1–5) | 3.94 (0.80) | 3.98 (0.70) | 3.89 (0.90) |
| Satisfaction with Learning (1–5) | 3.69 (0.71) | 3.73 (0.65) | 3.65 (0.77) |
| *Motivation* | | | |
| Pre-test Autonomous Motivation (1–5) | 4.03 (0.59) | 4.12 (0.55) | 3.93 (0.62) |
| Post-test Autonomous Motivation (1–5) | 4.15 (0.58) | 4.30 (0.54) | 3.98 (0.58) |
| Pre-test Controlled Motivation (1–5) | 2.18 (0.73) | 2.24 (0.74) | 2.11 (0.71) |
| Post-test Controlled Motivation (1–5) | 2.28 (0.77) | 2.35 (0.80) | 2.21 (0.72) |
| *Self-efficacy* | | | |
| Pre-test Self-efficacy (0–100) | 72.20 (13.14) | 74.12 (12.43) | 70.09 (13.70) |
| Post-test Self-efficacy (0–100) | 72.01 (13.24) | 74.60 (13.17) | 69.15 (12.86) |
| *SRL Skills* | | | |
| Pre-test MSR-R (1–5) | 3.55 (0.47) | 3.61 (0.47) | 3.48 (0.45) |
| Post-test MSR-R (1–5) | 3.65 (0.46) | 3.67 (0.48) | 3.63 (0.45) |
| Pre-test TSE (1–5) | 4.05 (0.47) | 4.11 (0.47) | 3.98 (0.47) |
| Post-test TSE (1–5) | 3.98 (0.49) | 4.05 (0.47) | 3.89 (0.51) |
| *Final Course Grade* | | | |
| Grade (0–100) | 63.16 (13.48) | 65.20 (12.67) | 60.91 (14.13) |

following pairs of variables were significantly positively correlated: average strategy rating and satisfaction with learning ($r = 0.698$), TSE scores and satisfaction with learning ($r = 0.358$), TSE and MSR-R scores ($r = 0.478$), MSR-R scores and autonomous motivation ($r = 0.419$), and autonomous motivation and TSE scores ($r = 0.404$). At the 0.05 level, the following pairs of variables were significantly positively correlated: TSE scores and strategy rating ($r = 0.230$), autonomous motivation and satisfaction with learning ($r = 0.236$), autonomous motivation and self-efficacy ($r = 0.254$) MSR-R scores and self-efficacy ($r = 0.211$), and TSE scores and exam grade ($r = 0.212$). Furthermore, autonomous motivation and average session duration were significantly negatively correlated at the 0.01 level ($r = -0.251$).

## Motivation, Self-Efficacy, SRL Skills, Study App Usage, and Study App Rating as Predictors of Grades

We performed a multiple hierarchical regression to test the predictors of final course grade. For motivation, self-efficacy, and SRL skills, pretest scores were used. Step 1 consisted of autonomous and controlled motivation, to which self-efficacy was added in step 2. In step 3, MSR-R and TSE scores (measures of SRL skills) were added. Study app duration and usage were added in step 4. Regarding the study app rating variables, average satisfaction with learning was added in step 5 and average strategy rating was added in step 6. This order of entering the variables was based on existing theory supporting motivation (e.g., Vansteenkiste et al., 2009), self-efficacy (e.g., Pajares, 1996), and SRL skills (e.g., Broadbent and Poon, 2015; Dent and Koenka, 2015) as predictors of performance. Accordingly, the novel variables specific to this study (i.e., app usage and ratings) were added in later steps.

As can be seen in **Table 3**, the results revealed only model 3 (motivation, self-efficacy, and SRL skills variables) to be significant, $F(5, 96) = 2.61$, $p = 0.030$, $R^2 = 0.125$. Within this model, only controlled motivation ($\beta = 0.21$, $p = 0.042$) and TSE scores ($\beta = 0.30$, $p = 0.012$) significantly predicted final course grades. Higher controlled motivation and TSE scores led to higher grades on the course exam.

## Effects of App Gamification Elements

A series of one-way between-subject ANOVAs were performed to compare the two app conditions (gamification vs. standard) regarding students' app usage, satisfaction ratings of study strategy and learning, and performance (i.e., final grades). Although the Shapiro–Wilk's test revealed violations of the normality assumption for both conditions on all of these variables ($p < 0.05$) except grades, we carried on with using ANOVA given that it is rather robust to deviations from normality (Field, 2018).

There were no significant differences between participants in the two app conditions on the duration of the sessions, $F(1, 97) = 0.28$, $p = 0.600$, partial $\eta^2 = 0.003$, or the number of sessions $F(1, 97) = 0.02$, $p = 0.892$, partial $\eta^2 < 0.001$. Also, no differences between the two conditions were found for satisfaction ratings for the strategies used, $F(1, 97) = 0.33$, $p = 0.568$, partial $\eta^2 = 0.003$, and for learning, $F(1, 97) = 0.30$, $p = 0.583$, partial $\eta^2 = 0.003$. Not surprisingly, no difference in performance between the two conditions was found, $F(1, 97) = 2.48$, $p = 0.119$, partial $\eta^2 = 0.025$.

In order to compare participants of the two app conditions on changes in motivation, self-efficacy, and SRL skills (i.e., MSR-R and TSE) from the start to the end of the course, two-way mixed ANOVAs were utilized. App condition served as the between-subjects independent variable, while time of measurement (pre-test versus post-test) served as the within-subjects independent variable. The Shapiro–Wilk's test demonstrated that the assumption of normality was violated for both app conditions on the pre-test measure of self-efficacy, for the standard condition on the post-test measure of self-efficacy, and for the gamified condition on post-test measures of both autonomous and controlled motivation ($p < 0.05$). Nevertheless, we continued with interpreting the ANOVAs given their robustness to non-normality (Field, 2018).

Regarding main effects, the main effect of condition showed a significant difference in autonomous motivation between the gamified and standard conditions, $F(1, 97) = 5.67$, $p = 0.019$, partial $\eta^2 = 0.055$. In particular, participants in the gamified condition had a significantly higher autonomous motivation score (regardless of time point of measurement; $M = 4.21$,

$SE = 0.073$) than participants in the standard condition ($M = 3.96$, $SE = 0.077$). Differences in self-efficacy scores between participants in the gamified ($M = 74.36$, $SE = 1.70$) and standard condition ($M = 69.62$, $SE = 1.79$) did not reach significance, $F(1, 97) = 3.68$, $p = 0.058$, partial $\eta^2 = 0.037$. Also, we found no main effects of condition for SRL skills measured by MSR-R, $F(1, 97) = 0.95$, $p = 0.332$, partial $\eta^2 = 0.010$, or TSE, $F(1, 97) = 2.71$, $p = 0.103$, partial $\eta^2 = 0.027$. And no main effect of condition was found

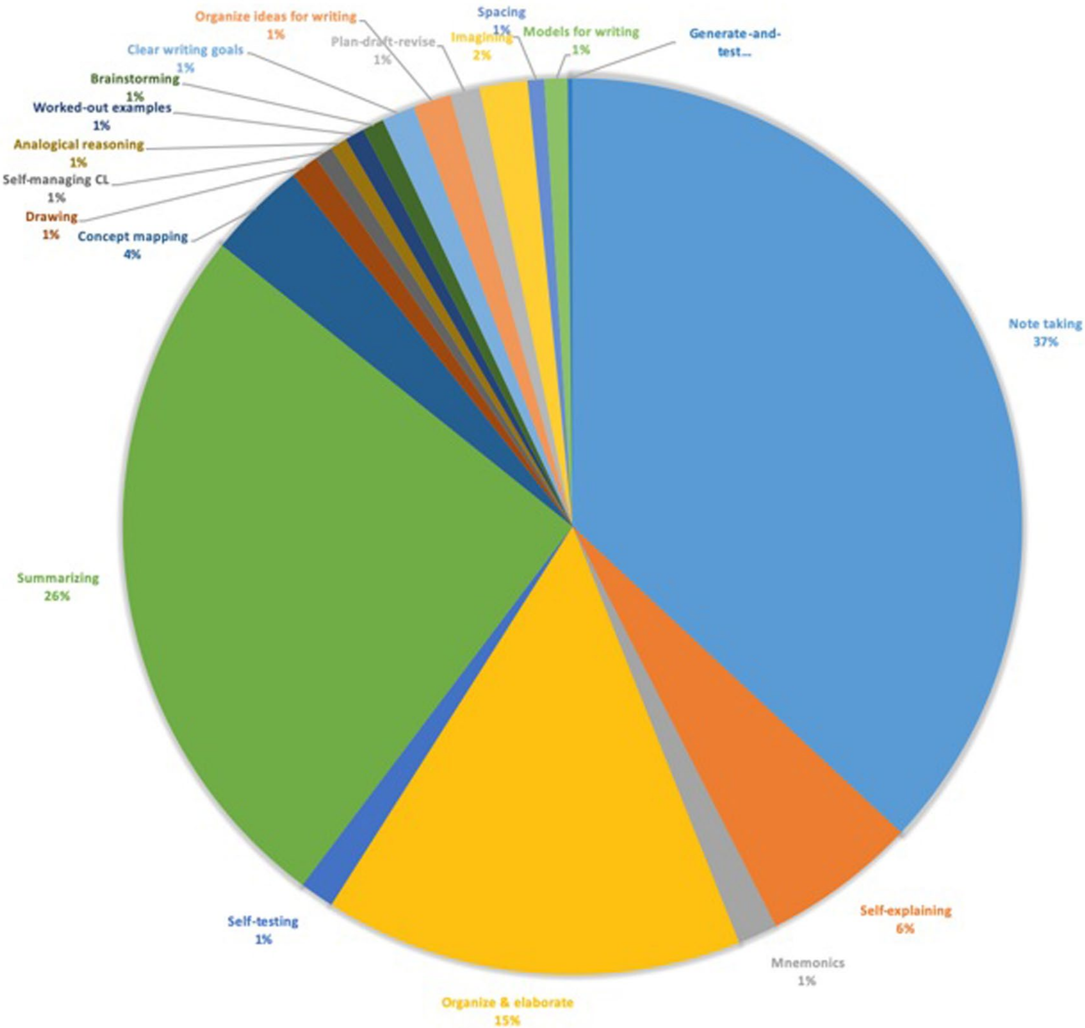


**FIGURE 5 |** Percentage of learning strategies used in study app.

**TABLE 2 |** Pearson's correlations between pre-test variables, Study App usage variables, and Study App rating variables and grades.

| | Number of sessions | Session duration | Strategy rating | Satisfaction with learning | MSR-R score | TSE score | Self-efficacy | Autonomous motivation | Controlled motivation |
|---|---|---|---|---|---|---|---|---|---|
| Session duration | 0.042 | | | | | | | | |
| Strategy rating | −0.070 | −0.022 | | | | | | | |
| Satisfaction with learning | 0.014 | −0.052 | 0.698** | | | | | | |
| MSR-R score | 0.060 | −0.049 | 0.091 | 0.196 | | | | | |
| TSE score | 0.052 | −0.051 | 0.230* | 0.358** | 0.478** | | | | |
| Self-efficacy | −0.108 | −0.092 | −0.034 | 0.073 | 0.211* | 0.184 | | | |
| Autonomous motivation | −0.045 | −0.251* | 0.185 | 0.236* | 0.419** | 0.404** | 0.254* | | |
| Controlled motivation | 0.068 | −0.056 | 0.120 | 0.076 | 0.054 | 0.019 | −0.179 | 0.131 | |
| Grade | 0.111 | −0.001 | 0.164 | 0.199 | 0.013 | 0.212* | 0.145 | −0.020 | 0.153 |

*$p < 0.05$ and **$p < 0.01$.*

**TABLE 3 |** Multiple hierarchical regression: predictors of final course grade.

| | *B* | *SE* | Beta | *p* | $R^2\Delta$ |
|---|---|---|---|---|---|
| **Step 1** | | | | | 0.025 |
| Constant | 60.57 | 9.90 | | < 0.001 | |
| Pre-Autonomous Motivation | −0.928 | 2.34 | −0.04 | 0.693 | |
| Pre-Controlled Motivation | 2.91 | 1.89 | 0.16 | 0.126 | |
| **Step 1** | | | | | 0.038 |
| Constant | 48.83 | 11.49 | | <0.001 | |
| Pre-Autonomous Motivation | −2.21 | 2.40 | −0.10 | 0.359 | |
| Pre-Controlled Motivation | 3.73 | 1.91 | 0.20 | 0.054 | |
| Pre-Self-Efficacy | 0.21 | 0.11 | 0.21 | 0.056 | |
| **Step 3** | | | | | 0.063 |
| Constant | 33.62 | 14.26 | | 0.021 | |
| Pre-Autonomous Motivation | −3.91 | 2.61 | −0.17 | 0.137 | |
| Pre-Controlled Motivation | 3.85 | 1.86 | 0.21 | 0.042 | |
| Pre-Self-Efficacy | 0.20 | 0.11 | 0.19 | 0.070 | |
| Pre-MSR-R | −3.31 | 3.41 | −0.11 | 0.335 | |
| Pre-TSE | 8.54 | 3.35 | 0.30 | 0.012 | |
| **Step 4** | | | | | 0.011 |
| Constant | 33.01 | 15.02 | | 0.031 | |
| Pre-Autonomous Motivation | −3.75 | 2.71 | −0.16 | 0.170 | |
| Pre-Controlled Motivation | 3.74 | 1.88 | 0.20 | 0.049 | |
| Pre-Self-Efficacy | 0.21 | 0.11 | 0.20 | 0.059 | |
| Pre-MSR-R | −3.67 | 3.45 | −0.13 | 0.291 | |
| Pre-TSE | 8.38 | 3.37 | 0.29 | 0.015 | |
| Number of sessions | 0.35 | 0.33 | 0.11 | 0.29 | |
| Session duration | −0.001 | 0.02 | −0.01 | 0.961 | |
| **Step 5** | | | | | 0.018 |
| Constant | 29.95 | 15.12 | | 0.051 | |
| Pre-Autonomous Motivation | −4.08 | 2.70 | −0.18 | 0.135 | |
| Pre-Controlled Motivation | 3.59 | 1.87 | 0.20 | 0.058 | |
| Pre-Self-Efficacy | 0.21 | 0.11 | 0.20 | 0.058 | |
| Pre-MSR-R | −3.66 | 3.43 | −0.13 | 0.289 | |
| Pre-TSE | 7.03 | 3.49 | 0.25 | 0.047 | |
| Number of sessions | 0.36 | 0.33 | 0.11 | 0.285 | |
| Session duration | −0.001 | 0.02 | −0.01 | 0.946 | |
| Satisfaction with learning | 2.75 | 2.01 | 0.15 | 0.174 | |
| **Step 6** | | | | | 0.003 |
| Constant | 28.22 | 15.44 | | 0.071 | |
| Pre-Autonomous Motivation | −4.19 | 2.72 | −0.18 | 0.127 | |
| Pre-Controlled Motivation | 3.51 | 1.88 | 0.19 | 0.065 | |
| Pre-Self-Efficacy | 0.21 | 0.11 | 0.21 | 0.052 | |
| Pre-MSR-R | −3.55 | 3.45 | −0.12 | 0.307 | |
| Pre-TSE | 7.02 | 3.51 | 0.25 | 0.049 | |
| Number of sessions | 0.38 | 0.34 | 0.12 | 0.257 | |
| Session duration | −0.002 | 0.02 | −0.01 | 0.921 | |
| Satisfaction with learning | 1.64 | 2.73 | 0.087 | 0.549 | |
| Strategy rating | 1.41 | 2.35 | 0.084 | 0.551 | |

for controlled motivation, $F(1, 97) = 0.97$, $p = 0.326$, partial $\eta^2 = 0.010$, and self-efficacy, $F(1, 97) = 3.68$, $p = 0.058$, partial $\eta^2 = 0.037$.

Regarding the main effects of time, there was a significant increase in SRL skills measured by the MSR-R subscale from pre-test ($M = 3.55$) to post-test ($M = 3.65$), $F(1, 97) = 7.30$, $p = 0.008$, partial $\eta^2 = 0.07$. On the other hand, SRL skills measured by the TSE subscale significantly decreased from pre-test ($M = 4.05$) to post-test ($M = 3.98$), $F(1, 97) = 4.04$, $p = 0.047$, partial $\eta^2 = 0.07$. Concerning motivation, there was a significant increase in autonomous motivation from the pre-test ($M = 4.03$) to the post-test ($M = 4.15$), $F(1, 97) = 6.41$, $p = 0.013$, partial $\eta^2 = 0.06$. However, the change in controlled motivation from pre-test ($M = 2.18$) to post-test ($M = 2.28$) did not reach significance, $F(1, 97) = 3.90$, $p = 0.051$, partial $\eta^2 = 0.04$. Lastly, the slight decrease in self-efficacy from pre-test ($M = 72.20$) to post-test ($M = 72.01$) was also not significant, $F(1, 97) = 0.07$, $p = 0.796$, partial $\eta^2 = 0.001$.

The interaction between condition and time of measurement was not significant for SRL skills measured by MSR-R, $F(1, 97) = 1.36$, $p = 0.246$, partial $\eta^2 = 0.014$, or TSE scores, $F(1, 97) = 0.19$, $p = 0.666$, partial $\eta^2 = 0.002$. Also, we did not find an interaction between condition and time for self-efficacy, $F(1, 97) = 0.65$, $p = 0.422$, partial $\eta^2 = 0.007$, autonomous motivation, $F(1, 97) = 2.03$, $p = 0.158$, partial $\eta^2 = 0.020$, or controlled motivation, $F(1, 97) = 0.02$, $p = 0.967$, partial $\eta^2 < 0.001$.

### User Friendliness

A five-item scale with a seven-point answer scale was used to measure user friendliness. It was found that students ($N=98$) agreed to a moderate extend with the navigation in the Study app ($M=4.62$, $SD=1.73$), and the flexibility in changing the content in the app ($M=4.06$, $SD=1.59$). The quality of the app measured as the app being "free from errors"($M=4.94$, $SD=1.55$), "up to date" ($M=4.99$, $SD=1.60$), and "free from bias" ($M=6.05$, $SD=1.06$) was also agreed to by student to a moderate or high extend.

Furthermore, using a five-point scale, it was measured whether students would recommend the Study app to others. The probability that students would recommend the app the fellow students ($M=2.78$, $SD=1.06$) or other professional in education ($M=2.67$, $SD=0.95$) was moderate.

## Discussion Study 1a

To conclude, although all participants in this study showed an increase in their self-reported motivation and SRL skills, using the Study app did not seem to play a role in this. The results found in Study 1a did not show a positive relation between Study app use (i.e., frequency of sessions or duration) and pretest SRL, motivation, self-efficacy, or course performance measures and therefore do not confirm our hypotheses (H1.1–H1.5). Yet, there was a negative correlation between autonomous motivation and the durations of sessions. It seems that students who were more autonomously motivated for the practical had shorter sessions in the Study app. Possibly, these students just browsed through the app, got the information they were looking for (e.g., on study strategies), then stopped their session but not their self-study activities outside the app and therefore end up with shorter sessions in the app. In addition, it was found that autonomous motivation was positively related to both SRL measures and self-efficacy which is in line with earlier studies (e.g., Baars and Wijnia, 2018; Girelli et al., 2018; Wijnia and Baars, 2021). Interestingly, the TSE scores were found to be related to satisfaction with learning and the learning strategy as rated in the Study app, as well as with the grade for the practical. This seems to suggest that being able to organize learning sessions in terms of time and study environment, is associated with more satisfaction about the learning process and higher performance. As this is a correlation, there is no evidence for the direction of such a relation. Hence, it could very well be the case that higher performing students were also better able to organize their learning sessions in terms of time and environment. From the hierarchical regression analysis, it follows that only controlled motivation and TSE are significant predictors of performance if autonomous motivation, metacognitive SRL, and self-efficacy are included in the model.

The participants in the gamified Study app and the standard Study app both showed similar changes in MSR-R, TSE, self-efficacy, and autonomous and controlled motivation scores from pre- to post-measures and therefore do not confirm our hypotheses (H2.1–2.5). That is, for all students, autonomous and controlled motivation and metacognitive SRL skills increased over the course of 5 weeks. Yet, all students were found to score lower on the TSE indicating that these SRL skills did not improve. However, participants in the gamified Study app conditions showed higher autonomous motivation during the study compared to the participants in the standard Study app without gamification elements. As there were no significant differences in autonomous motivation at the start of the study, these results seem to indicate that having gamification elements in a mobile application to support SRL can help students to sustain autonomous motivation over time which partially confirms Hypothesis 2.2. Interestingly, sustained autonomous motivation could be beneficial for SRL (Baars and Wijnia, 2018; Girelli et al., 2018; Wijnia and Baars, 2021) and performance (e.g., Vansteenkiste et al., 2009).

There are some limitations to this which should be taken into account when interpreting the results. First, the participants in the sample chose to participate in this study, which might have created a selection bias in our sample. Second, there is a gender imbalance in our sample as we have more women than men. Also, the scales used to measure SRL skills (i.e., MSLQ, MSR, metacognitive self-regulation and TSE, and time and study environment) turned out to have a low reliability, which means they should be interpreted with caution. Furthermore, from the trace data collected in the application, it is unclear how long a participant was actually active during a session which made it difficult to pinpoint duration of sessions. That is, participants could have been doing something else while the application was still running. Future work on this type of applications could look into more detailed ways of measuring engagement with the application to get a better estimate of the session duration. Finally, although we did not have specific hypotheses about the exact number of sessions that participants should have used the study app, from the descriptive statistics in **Table 1** it is clear the number of sessions is quite low (i.e., on average four sessions across 5 weeks). Also, the variety in strategies that were chosen is quite low. That leaves us with the open question as to why this number of sessions and the variety of strategies is low. In Study 1b, these issues were investigated by means of focus group interviews that were taken after the practical and Study 1a had ended.

## STUDY 1B: STUDENTS' EXPERIENCES REGARDING THE ACE YOUR SELF-STUDY APP

Based on the literature, it is clear that people generally overestimate their learning performance (e.g., Dunlosky and Lipko, 2007; Bjork et al., 2013), which could potentially harm subsequent study processes (e.g., Dunlosky and Rawson, 2012). In addition, students are often not aware of effective study strategies (McCabe, 2011; Dirkx et al., 2019) or how to use them effectively (Bjork et al., 2013). Therefore, we assumed that providing support *via* a mobile application offering students guidance and support throughout the different phases of SRL (i.e., forethought, performance, and reflection, Zimmerman, 2008), would benefit their SRL skills, self-efficacy, motivation, and lead to better performance (i.e., course grades) at the end of a 5-week course (Study 1a). However, although students improved their SRL skills and motivation across the course, students' usage of the Study app was relatively low, the variety of strategies that were chosen during study sessions was low and, the usage of the Study app did not significantly predict performance. This result is possibly related to the fact that students had to decide how to study and whether they would use the app (apart from two assignments in which they were explicitly invited to use the Study app). This required students to be able to accurately reflect on their learning processes and decide whether they would need and how they would use the offered guidance and support.

Nevertheless, the precise reasoning behind students' self-study decisions was not captured in Study 1a. Therefore, in Study 1b, the experiences of a subset of students participating in Study 1a were investigated. That is, using a qualitative approach, students' experiences with their self-study activities were investigated retrospectively *via* focus group interviews to gain more insight in student's experiences and reflections on their self-study sessions in the context of Study 1a.

In order to understand students' self-study activities and how students used the Study app during self-study sessions in Study 1a, we investigated (a) students' study behaviors during self-study sessions in general and (b) students' experiences with the Study app during their self-study sessions. Three main research questions were formulated accordingly:

1. How much time did participants spend studying for the course (in terms of both duration and quantity of study sessions) with the Study app compared to without the Study app, and why?
2. Does participants' choice of study strategies differ when studying with and without the Study app, and why?
3. What would motivate participants to try new or unfamiliar study strategies?

# Method

We created an OSF page for this project, where all materials and a detailed description of the procedure are provided (DOI 10.17605/OSF.IO/98NYH).

## Participants

Eleven first-year Psychology bachelor students (eight females, three males) aged between 17 and 36 ($M = 20.91$, $SD = 5.54$) who had participated in study 1a voluntarily participated in the focus group interviews. Specifically, out of the five invited students per focus group, three students participated in focus group 1, four in focus group 2, two in focus group 3, and two in focus group 4. Which focus group a student participated in depended on the student's availability regarding date and time. In return for their participation, the students received research credit of 30 min, which contributes to completing mandatory research hours as per the requirements of the bachelor program. Although all participants had been introduced to the self-study app in practical 1.1 (study skills), not everyone tried using the app or made use of it throughout the course as instructed.

## Design and Instrument

Semi-structured focus group interviews with students who participated in Study 1a took place after the 5-week course during which Study 1a was performed. An interview guide was created and used during the focus group meetings. This guide consisted of a list of questions to be covered during the interviews, divided into topics according to the research questions. Following a deductive approach (Crabtree and Miller, 1999), the interview topics were based on a set of *a priori* themes established from a review of the literature, the research questions and our professional experience in teaching first-year university students. Each section in the interview was allocated a time duration, which was estimated based on the complexity of the questions and a pilot study (i.e., focus group 1). Furthermore, we created slides containing the interview questions and some relevant data obtained from study 1a that helped to support or elaborate on these questions (see **Appendix E**). For topic 3 on study strategies and topic 4 on motivation to use study strategies, we added **Figure 5** showing an overview of the percentage of sessions during which one of the types of learning strategies was used, on the slide to help students reflect on the questions concerning the topic. The slides were printed out on A4 paper to be distributed to the participants and interviewers during the focus groups. Each focus group was audio recorded. Additionally, one or more of the interviewers used a notepad and pen or laptop for note-taking.

## Procedure

Four focus group sessions were organized in total. Students who had provided their email addresses to be invited for a focus group interview at the end of the first survey in Study 1a were invited to participate in a focus group *via* email. After the fourth focus group session, no further sessions were planned as we noticed saturation in terms of the information provided by the participants. For each focus group, one of the two researchers present had the role of the main interviewer, and the other made an audio recording and notes. The interviewer obtained consent from the participants for recording the conversation and informed the participants that the recordings would be treated confidentially and used for research purposes only. The interviewer went through the questions, giving each participant a chance to answer and respond to each other's input.

## Analysis

All focus group audio recordings were transcribed verbatim and then coded, organized, and analyzed. Consistent with a data-driven, inductive approach (Boyatzis, 1998), no predetermined structure was used to analyze the data. This exploratory approach allowed themes to surface directly from the interview data. As some focus groups were quite small (i.e., only two persons), we chose the individual as the unit of our analysis and performed a content analysis. First, two of the researchers carefully read all transcripts, and key topics were identified per transcript (i.e., coding). Then, they summarized the raw data of each participant according to the topics that emerged. Additionally, quotes were extracted per topic. Subsequently, the summaries and quotes across all transcripts were combined according to the recurring topics, from which the following higher-order topics were derived: Self-Study Sessions, Choice of Study Strategies, and Motivators to Use New and Unfamiliar Study Strategies.

# Results

## Self-Study Sessions

It was quite common for students to not keep track of their study sessions in terms of duration and amount. Nevertheless, some estimations were given, supported by explanations. The average duration of self-study sessions for tutorials (course work) reported by the students had much variation. Some students reported shorter durations, such as 2–3 h, while others reported long durations of up to 8 h. A few students indicated that their study schedule is more tentative than planned; they study when they feel like it and stop studying when they do not feel like studying anymore, or when they have lost focus.

> *"If I want to study then I can just focus for a couple of hours straight, and then if I do not feel like studying then I just stop."*

Some commented that the length of the study session depends on external factors such as how busy a given day or week is and the difficulty level of the learning material. More time is spent studying when the study material is of a higher difficulty level. Not all students mentioned whether they take breaks, but those who did, reported longer study sessions said they take lots of breaks in between, whereas those who reported shorter study sessions reported a short break of around 10 min per session.

When it comes to studying length for app users, students tended to forget about the app during a study session. Hence, they forgot to switch it off; the app kept running long after their actual study session was over. As a result, students estimated the length of their study sessions with the app to be around 2 h when they did use it.

> *"One of the things that was very challenging in the app is that I cannot pause it and come back to it."*

Answers regarding how often the students studied per week varied from studying every day to studying 2–3 times a week (mainly as preparation for the tutorial groups that take place twice a week). Some students reported having a fixed routine, for instance: studying 5 days and having 2 days completely off. Others reported a more variable study routine, depending on what other activities there are to do in a given week and how efficient one's studying is on a given day. If inefficiency is high, students would instead stop studying and rest. One student mentioned the tendency to do things last minute due to procrastination and not feeling like studying, which results in mass studying the day before the tutorial meeting. Some students adjusted their amount of study sessions over time as they progressed with the course; for instance, one student increased his/her number of study sessions, whereas another student reduced the number of study sessions due to burnout.

The purpose of using the Study app for self-study sessions differed among students; some only utilized it around the exam period, while others used it only for preparing for the practical.

> *"Only used the study app around exam period, did not use it that much."*

Only one student used the app quite often, and the given reason for this was that the app was assigned for class, and the student was self-disciplined. On the other hand, a few students would have liked to use the app more than they did for the following reasons: it may have helped attain higher grades, added structure, and lower procrastination and stress levels.

Most students did not use the study app much; they tried it once or twice. A common reason for this was that most students did not think they needed it to study better. One explanation for the overall low frequency of app usage was that one would only be motivated to use the app if his or her study method is not working, or he or she is getting bad grades.

> *"I would've liked to use it more, maybe to add more structure, because I also procrastinate and just do it the day before."*

> *"I could try* [using the app] *maybe more because I want higher grades."*

Another explanation for the low app usage frequency was that the students did not receive an adequate explanation of its purpose and how it works beforehand, so they did not find it very useful. They downloaded it because they were asked to, but they did not end up genuinely understanding it and how it can help to study. Some students would not have used the app more than they did for various reasons. Some explanations were more linked to personal study habits and preferences, such as not spending much time preparing for tutorials, and therefore only needing the app to prepare for the exams.

> *"If it's like you always have to set goals, set time for studying, set study materials, and set when you are supposed to be finished, I find that very restricting and very boring and very stressful."*

Another reason was that the student already plans everything and works ahead of time, so the app is redundant for this purpose. Other explanations for not using the study app more pertained to the app itself. Some students found the app distracting and not helpful. They mentioned that the app does not take variability across individuals into account; what method is effective varies across people. This app was said to be more suitable for students who are completely lost about their work method.

To summarize, there was quite some variation in the length of study sessions and the number of sessions per week. Concerning using the Study app for self-study sessions, students' responses seem to show a difference in how the app was perceived across students, and one's perception about their study situation plays a role herein. In general, those who think they know what they are doing in terms of self-study will think they do not need to use a self-study app.

### Choice of Study Strategies

Study strategies commonly used by students were summarizing (including altering/revising summaries after tutorial groups), note-taking (e.g., of keywords and definitions), self-explaining (or explaining to someone else), organize and elaborating, and relating concepts and theories (e.g., through a chart). Highlighting relevant parts from the literature, brainstorming, and using flashcards were also mentioned. Generally, the strategies reported were relatively homogeneous across the students. The reason given by the students for using these strategies is that they are familiar and effective.

> *"Well, I already sort of do these already, so I just inputted the ones I already [use]."*

> *"I always summarize. It's just easy for me and I'll have like a whole picture off what's, how do you say that, yeah, what I need to study."*

Students reported that, especially under time pressure, one needs to be efficient by sticking to the known-to-work strategy. A noteworthy observation is that sometimes students incorrectly labeled a strategy, such as referring to highlighting as summarizing.

> *"That's considered summarizing, and sometimes I use if I have time or if I'm not lazy, too lazy, I sometimes write it down instead of just highlighting it."*

Following the strategies students utilized when studying in general, students commonly used summarizing, note-taking, organize and elaborating, and self-explaining in the self-study app (i.e., familiar strategies). Additionally, some students tried concept mapping. This strategy suited a student with visual memory but did not suit another student's style, who used clear writing goals instead. However, once students learned how to use a strategy provided by the study app, they no longer found it necessary to use the app to continue utilizing that strategy. This indicates reduced benefit of the app once the desired strategy is learned.

Furthermore, students never attempted to use some of the strategies due to a lack of fit to one's personal preferences (e.g., drawing), while others were perceived to be too specific and not necessarily suited to self-study (e.g., brainstorming). Importantly, students mentioned that not all of the strategies offered in the app were familiar to them, which made them less likely to use the app, especially under time pressure. In such situations (e.g., exam week), students are more likely to use strategies that have worked for them in the past and avoid taking risks with unknown strategies.

> *"Uh I have a question because organize and elaborate is little bit same like summarizing right? Or not."*

> *"Um, really it's because when time becomes when you are under pressure, you are going to just switch to what you know, and what you know will get you the result you are looking for, so everything else gets thrown out, and until I know until I have enough practice with these."*

Overall, participants' study strategies did not largely differ when studying with and without the study app. The reason is that students are likely to stick with what is already familiar to them. Students avoid taking risks with new study strategies, especially under time pressure, which is tied to their perception that unfamiliarity decreases studying efficiency, as more effort is required to understand the strategy and utilize it properly. Students' general unwillingness to learn new, unfamiliar study strategies may have contributed to the low amount of app usage observed in this study. In other words, students may not feel an added value of the app if they decide to stick to known strategies that they perceive to be effective and efficient, especially when there is time pressure (which may often be the case due to a high workload, procrastination tendencies, or both).

### Motivators to Use New and Unfamiliar Study Strategies

A commonly-mentioned factor that would motivate students to attempt new strategies was low grades. Students would take this as an indicator that one's current strategy is not working.

> *"Bad grades; if my strategy is not working, then I have to change my strategy."*

More specifically, studying very hard but not getting the grades one desires would indicate a problem with one's current strategy. There was agreement that low grades lead to consideration of what can be done differently when studying. However, so far, this had not happened for the students we interviewed, and therefore they found no need for learning new strategies.

Another mentioned motivator to try a new strategy would be if the topic of study changes, which requires a different approach.

> *"Yeah if the topic changes, so like for statistics it's a different approach to just reading stuff, so I'm gonna do different things."*

For example, mathematics is studied in a completely different way than biology. In addition, the absence of time pressure would also motivate students to attempt new strategies. Regarding the strategies provided by the app, students often found them too time-consuming to learn. Taken together with the time pressure that most students felt, the strategies provided in the app were perceived as inefficient. Furthermore, according to the students, a thorough explanation of the strategies provided by the course instructors would have contributed to efficiently learning the study app strategies. Other suggested motivators include discussing study strategies with peers to understand what works for others.

> *"no inner drives would motivate me to seek a new strategy, but if someone from outside delivers something that I find very interesting and very unorthodox, I might try using it and if it's good for me I might do it again."*

Taken together, the answers given by the students point to external factors as motivators to try new study strategies.

## Discussion

In general, when it comes to self-study experiences and reasons for using the app, it seems that as long as students feel comfortable with their study habits, they are not inclined to seek help or change their strategies. Students tend to avoid the effort or risks they perceive to be involved in changing study strategies. In line with the findings by Biwer et al. (2020), it seems that perceived time and effort play an essential role in making changes in SRL during self-study. Possibly time management could be a prerequisite for students to engage in SRL and using effective study strategies. Furthermore, students' general unwillingness to start using unfamiliar study strategies might have prevented them from using the Study app to support their self-study sessions to some extent. Overall, participants' study strategies did not differ much between studying with or without the study app. In line with earlier studies (McCabe, 2011; Bjork et al., 2013; Dirkx et al., 2019), the current study showed that students primarily used strategies that were already familiar to them, did not use other strategies that were offered, and sometimes mislabeled strategies during the focus group interviews. These findings seem to indicate a lack of knowledge and expertise about using study strategies in general. Moreover, from a motivational perspective, it seems students are not very interested (i.e., intrinsically motivated) in how to regulate their learning during self-study and what study strategies are useful nor find it very relevant (i.e., identified motivation). That is, as long as their grades are fine, most students do not seem to give their SRL activities much thought. Some students do indicate that they might be more willing to think about their self-study habits and study strategies if someone would explain the relevance of it. Hence in line with the SDT (Deci and Ryan, 2000; Ryan and Deci, 2000a,b, 2020; Pelletier et al., 2001), it seems promising to explain to students more about the relevance of SRL activities and using effective study strategies to support their motivation for engaging with them. Indeed, several studies have shown that informing students about the relevance of specific aspects of SRL (e.g., training in applied memory and learning topics, McCabe, 2011; informing about making overconfident judgments, Roelle et al., 2017b), can benefit actual SRL.

These results do need to be interpreted with caution. That is, the slides used to present the questions on study strategies and motivation to use study strategies in the focus groups also contained data on the study strategies that were used in Study 1a. This might have influenced students' responses. Moreover, as a consequence of using semi-structured focus group interviews with preselected topics and questions, our analysis cannot be classified as truly inductive. Furthermore, some of the focus groups were quite small and this might have prevented students from having a discussion about the topics and questions that were presented. Future research could use in-depth interviews as a method to investigate students' experiences with self-study sessions and SRL support such as the Study app.

# GENERAL DISCUSSION

All first-year students in our sample improved their self-reported motivation and SRL skills over the course of 5 weeks, during which they followed a practical on how to study (i.e., Study 1a). Yet, having the Study app to support the phases of SRL and using a variety of study strategies was not related to this increase. Students only used the app for a few sessions and largely stayed with the study strategies they most likely already knew (e.g., note-taking or summarizing). From focus group interviews (i.e., Study 1b) about self-study, study strategy use and using the Study app, it seems students believe the support offered in the form of the Study app was not always what they needed. Results from Study 1b showed that motivators to seek support or try out new study strategies were often external, such as grades students receive.

Based on findings from earlier studies, supporting all three phases of SRL (e.g., Dignath and Büttner, 2008; Wong et al., 2019) and offering guidance on how to use study strategies (e.g., McCabe, 2011; Bjork et al., 2013) was hypothesized to help students employ SRL strategies and thereby improve their SRL, motivation, self-efficacy, and performance across a first-year course. We found SRL skills to be related to autonomous motivation and self-efficacy as expected (Baars and Wijnia, 2018; Girelli et al., 2018; Wijnia and Baars, 2021). However, our findings showed that using the Study app does not affect these relations significantly. In other words, students improved their SRL skills and motivation across the course regardless of their usage of the Study app. Furthermore, we found most students used the app only for a limited number of sessions. For many students, the support offered *via* the Study app was not perceived as fitting to their needs.

As witnessed in Study1b, students have their personal reasons for seeking and using support for SRL and study strategies. Some said the app was useful for preparing for the exams, but others said it was useful for preparing meetings. Moreover, some students indicated the app was not helpful to support their self-study at all. There might be a fundamental issue with the idea of having learners decide how they would like to go about their learning and what support they might need. Although we would like learners to become effective self-regulated learners, they might not be able or equipped to do this. Learners who might need help or support are not always the ones who ask for help or use the support offered (e.g., Ryan et al., 2001; Karabenick, 2003). Our results resonate with these findings and underline that there are several different factors, such as personal motivational characteristics (e.g., Ryan et al., 2001) or the social context of learners (e.g., Won et al., 2021), that play a role in seeking help or using support during self-study. For example, students in our study explained that as long as they were convinced that they did all right (e.g., obtained good grades); they did not see the need to use support during self-study. Possibly, this points toward an "experienced-learning-versus-actual-learning-paradox" in which student are overconfident about the effects of their self-chosen strategies.

As mentioned earlier, some students explained that the app did not suit the individual needs of students. The application might have been too general or not in line with students SRL knowledge or skills to be useful for all. Another possibility would be that the app's implementation could have been more successful when combined with instruction on what SRL is and why it is important. Findings by Broadbent et al. (2020) have shown that combining a mobile application to monitor learning with online SRL training helped students improve their resource management, cognitive, and metacognitive strategies. Future research could investigate the combination of SRL training with the Study app to improve SRL.

Moreover, from the focus group interviews in Study 1b, it also became clear that after students learned about a strategy *via* the app, they sometimes decided not to use the app any longer as they already mastered a new strategy and were no longer in need of other or more support. These findings suggest that the application was not adaptive to the needs of the students. By using adaptive technologies (e.g., Molenaar et al., 2019; Peng et al., 2019), applications such as the Study app could potentially create a more personalized way of SRL support to ameliorate these issues. Future research could investigate how more adaptive applications can be developed for supporting SRL during self-study.

If students used the Study app, results showed that satisfaction with the chosen strategy and satisfaction with learning during that session in general were significantly correlated. Although this result does not show the direction of the relation, it does underline the importance of study strategies for self-study. In line with other studies (Dignath and Büttner, 2008; McCabe, 2011; Biwer et al., 2020), our results suggest that it is promising to support students' strategy knowledge and use to improve their learning processes.

As SRL skills were related to motivation (Vansteenkiste et al., 2009; Baars and Wijnia, 2018; Wijnia and Baars, 2021), it is important to take a look at the results of the current study in terms of motivation. Autonomous motivation increased from pre- to post-test but controlled motivation did not. Interestingly, as motivation can be placed on a continuum (Deci and Ryan, 2000), perhaps participants' motivation moved along the continuum during the 5 weeks of the course. Amongst the students who used the app, half of them got to use a gamified Study app, and the other half got to use the standard Study app. We expected that the gamification elements would keep students more engaged and motivated (*cf.* Su and Cheng, 2015; Mekler et al., 2017) to use the Study app compared to the standard Study app. As motivation increased for all participants regardless of whether they had used the gamified or standard app, this hypothesis was not confirmed. Interestingly, we did find a main effect of condition on autonomous motivation. That is, participants in the gamified Study app conditions showed higher autonomous motivation during the study compared to the participants in the standard Study app without gamification elements. As there were no significant differences in autonomous motivation at the start of the study, these results seem to indicate that having gamification elements in a mobile application to support SRL can help students to sustain autonomous motivation over time. Whether this result can be explained by using the gamified Study app or whether the participants in the gamified condition had slightly more autonomous motivation overall independently from the app seems to be unclear. Future research could look into these possible changes in motivation across weeks at an individual level to gain a better understanding of motivation in relation to SRL. Furthermore, no differences in the use of the Study app, SRL skills or self-efficacy were found. Future research could look into what type of gamification element are attractive to students when using mobile technology for SRL and how it affects motivation, SRL, and self-efficacy.

To conclude, first-year students were offered a mobile-application to support their SRL during self-study sessions across a 5-week course. Moreover, a subset of these students participated in focus group interviews about their experiences with the self-study sessions, the mobile application, and strategy use. Although all participants in this study showed an increase in their self-reported motivation and SRL skills, using the Study app did not seem to play a role in this. Based on the focus group interviews, it seems that students did not always see the need for using the app as support for their self-study sessions. Yet, it was also shown that students mostly used the same, already familiar, study strategies and would only change this if external motivators such as low grades would force them too. Possibly, it is too difficult for students to understand when or why they would benefit from SRL support or how this type of SRL support could help them regulate their learning during self-study sessions more efficiently. Possibly a more firm connection to the curriculum, with an increased involvement of teachers and tutors in the process, or a training for students to understand why SRL is important, could ameliorate these issues. An important takeaway here is that just offering support for SRL in an easy to use and attractive way does not mean that students will use the support and benefit from it.

## DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Research Ethics Review Committee of the

Department of Psychology, Education & Child Studies. The patients/participants provided their written informed consent to participate in this study.

## AUTHOR CONTRIBUTIONS

MB, SK, and LR contributed to conception and design of the study, organized the data files, and wrote sections of the manuscript. SK and MB performed the statistical analysis. MB wrote the first draft of the manuscript. All authors contributed to the article and approved the submitted version.

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## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2022.793002/full#supplementary-material

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# Do Self-Regulated Learning Practices and Intervention Mitigate the Impact of Academic Challenges and COVID-19 Distress on Academic Performance During Online Learning?

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The COVID-19 pandemic introduced significant disruptions and challenges to the learning environment for many post-secondary students with many shifting entirely to remote online learning. Barriers to academic success already experienced in traditional face-to-face classes may be compounded in the online environment and exacerbated by stressors related to the pandemic. In 2020–2021, post-secondary institutions were faced with the reality of rolling out fully online instruction with limited access to resources for assisting students in this transition. Instructional interventions that target students' ability to self-regulate their learning have been shown to improve academic performance and self-regulated learning (SRL) competencies have also been found to mediate the effect of SRL interventions on higher education. However, few studies have examined the efficacy of fully online SRL intervention on mitigating the impact of psychological distress and academic challenges on academic success. This study examined the moderating roles of self-regulatory practices and SRL intervention in buffering the influence of COVID-related psychological distress and academic challenges on academic outcomes (self-reported grade point average (GPA) and academic challenges) in a Canadian sample of undergraduate students ($n$ = 496). We found (a) levels of metacognitive and motivational challenges fully mediated the impact of COVID distress on GPA, (b) SRL adapting practices moderated the impact of metacognitive challenges on GPA, and (c) semester-long SRL intervention buffered the impact of COVID distress on academic challenges and resulted in lower levels of social-emotional, cognitive, and metacognitive challenges for first year undergraduate students.

**Keywords: self-regulated learning (SRL), online learning, COVID-19, post-secondary academic performance, academic challenges, student success**

# INTRODUCTION

During the start of the COVID-19 pandemic in 2020, many students faced the additional challenge of transitioning to undergraduate studies delivered fully online by instructors and institutions with limited pedagogical or technological experience delivering fully online instruction. Learning to adapt and respond productively to challenges as they arise during studying is the hallmark of self-regulated learning (SRL). Self-regulating learners are goal directed, optimizing strategy selection and deployment to progress toward goals and adaptively respond to new situations and challenges (Zimmerman, 1989; Winne and Hadwin, 1998; Pintrich and Zusho, 2007). Theory predicts these students should be well poised to respond to challenges in productive ways that reduce the impact of academic challenges on academic success outcomes such as grade point average (GPA). Extant research examining the academic outcomes and experiences of students who receive SRL support indicates SRL skills and competencies can be taught and developed (Jansen et al., 2019; Theobald, 2021). However, a limited body of research to date points to the importance of SRL during online learning (e.g., Broadbent and Poon, 2015). The aim of this study is to examine (a) the role SRL competencies play in mitigating the impact of COVID-19-related psychological distress on academic outcomes, and (b) how SRL competencies and academic challenges differ between students who do and do not receive explicit SRL intervention during a global pandemic where all learning occurred online.

## Factors Contributing to Academic Success

Many factors contribute to academic success. From a self-regulatory perspective, Weinstein and colleagues conceptualized academic success as comprising skill, will and self-regulation (Weinstein, 1994; Weinstein and McCombs, 1998; Weinstein et al., 2000). *Skill* refers to having the metacognitive and conditional knowledge about strategies that is necessary to choose and deploy strategies well-suited to the task, context, and learner characteristics. *Will* focuses on a broad range of motivational and affective constructs involved in directing and sustaining effort and persistence. *Self-regulation* refers to strategic self-management of cognition and learning, behaviors such as time management and help-seeking, motivational and emotional beliefs and experiences, and metacognitive monitoring and control of strategies themselves (Weinstein et al., 2011). Numerous meta-analyses and systematic reviews have collated findings across studies to identify specific psychosocial predictors of academic success and retention (e.g., Robbins et al., 2004; Richardson et al., 2012; Schneider and Preckel, 2017; Saunders-Scott et al., 2018). Extending the skill, will and self-regulation framework, we posit that psychological predictors of academic success can be loosely organized into five categories: cognitive, motivational, metacognitive, behavioral, and social/emotional factors.

*Motivational factors* comprise aspects of will, desire and confidence to exert effort and persist in academic tasks, particularly when they are difficult or challenging. Motivation factors associated with academic success and performance include effort regulation and self-efficacy beliefs. Meta-analyses and systematic reviews consistently identify motivational factors, particularly self-efficacy, as strong predictors of academic outcomes such as GPA and retention (e.g., Robbins et al., 2004; Richardson et al., 2012; Fong et al., 2017; van der Zanden et al., 2018).

*Metacognitive factors* have been described as the awareness and control of mental thoughts (Flavell, 1979). Self-monitoring, planning, and building self-awareness about beliefs and practices related to learning and success have most often been examined as predictors of academic outcomes. Two systematic reviews indicate that metacognition, often conflated with SRL, correlate with GPA in post-secondary settings (Richardson et al., 2012) including online environments (Broadbent and Poon, 2015).

*Cognitive factors* include learning, remembering, communicating and expressing ideas, and comprehending course concepts regardless of the mode of presentation. Typically referred to as academic study skills, these factors include directing and sustaining attention, selecting, and encoding new information, and being able to access or recall that information from memory. Meta-analyses reveal that cognitive factors and academic study skills, contribute to academic outcomes such as GPA (Richardson et al., 2012), and retention (Robbins et al., 2004).

*Behavioral factors* involve structuring the learning environment, tasks, and studying to optimize engagement. Behavioral factors such as time management, environment management, attendance, task structuring and distribution, and procrastination have been found to have both direct and indirect effects on academic performance (Broadbent and Poon, 2015; Schneider and Preckel, 2017; van der Zanden et al., 2018).

*Social and emotional factors* refer to one's overall psychological, social, and physical well-being including managing emotions such as test anxiety, social belongingness and connectedness with campus life and community, and physical health and wellness such as nutrition, sleep, and physical activity. Aspects of social and emotional well-being have been found to be associated with academic performance (van der Zanden et al., 2018), persistence (You, 2018), and retention (Saunders-Scott et al., 2018).

## Self-Regulated Learning Practices Have Been Associated With Academic Success

Self-regulated learning is a goal-directed process through which students take active and strategic control of their learning. Models of SRL share four fundamental features (c.f, Zimmerman and Schunk, 2011; Schunk and Greene, 2018): (1) Striving toward self-set goals and standards is central to SRL; (2) Metacognitive monitoring and awareness direct learners to when and how to exercise strategic control over learning; (3) Multiple facets of learning are implicated (e.g., motivation, emotions, cognition, and behaviors); (4) Presence of recursive cycles of forethought and planning, strategic engagement, reflection and adaptation.

Numerous self-regulatory practices have been found to contribute to academic success in conventional (Jansen et al., 2019) and online (Broadbent and Poon, 2015) post-secondary contexts. *Task perceptions* (forethought and planning) have been associated with (a) academic success (Callan and Cleary, 2019), task success, and overall GPA (Oshige et al., 2007; Hadwin et al., 2008; Miller, 2009), (b) goal and planning quality (Greene et al., 2012; Beckman et al., 2021), (c) self-efficacy (Miller, 2009), and (d) procrastination and disorganization (Cosnefroy et al., 2018). *Goal setting and planning practices* have been found to contribute to post-secondary academic achievement (Jansen et al., 2019). *Regulation of motivational beliefs and behaviors* has been associated with academic achievement (Kim et al., 2020). Practices for *allocating and controlling time* have been empirically linked to academic outcomes such as GPA (Thibodeaux et al., 2017; Adams and Blair, 2019; Wolters and Brady, 2020).

Theoretically, regulation engages learners in a series of contingent events driving strategic adaptation (Winne and Hadwin, 1998). When learners detect misalignment between goals and progress, they are faced with one of a limited set of options including (a) persist with whatever they were doing and hope it will work better in the future, (b) try a new strategy or approach, (c) adjust or fine tune the strategy, (d) update or change planning in the form of task understanding or goals, or (e) reduce effort or withdraw from the task altogether. Acting in response to detected problems invites a new round of monitoring and evaluating which may in turn lead to continued refinement in approaches. This cyclical process is the essence of strategic and adaptive regulation. Despite the theoretical importance of adaptation and metacognitive control in SRL, student success research has virtually ignored this construct. While metacognitive practices including monitoring, self-evaluation and metacognitive awareness have been found to contribute to academic achievement (e.g., Callan and Cleary, 2019; Colthorpe et al., 2019), practices associated with adapting learning and strategy choices as the result of monitoring and evaluation have been under-examined (Craig et al., 2020). Theoretically adaptation practices deployed when strategies and approaches do not work are essential to SRL (Butler and Winne, 1995; Hadwin and Winne, 2012).

## Navigating the Challenges of Learning Online During a Pandemic

Adjusting to university is not easy for many students. Students are expected to learn and work quite independently with minimal formal instruction about when, how, or what to study (Hadwin and Winne, 2012). Even the most successful high school students report facing new kinds of academic challenges at university. Despite extensive research about the factors contributing to student success, there is extant research examining the specific challenges students report during studying. Koivuniemi et al. (2017) used an open-ended questionnaire to collect data about the types of learning challenges and regulatory skills students deploy across different learning situations. The challenges most frequently reported by students included time management, cognitive strategies, concentration, and tiredness. Student with high SRL skills (as measured by the MSLQ) reported a higher frequency of cognitive challenges during individual learning that students ranking low on SRL skills (Pintrich et al., 1993).

Hadwin et al. (2019a,b) examined challenges reported in a weekly study diary over nine consecutive weeks. Students selected from 12 specific challenges including: motivation/procrastination confidence, goal, and time management, choosing or using strategies, learning and remembering, optimizing conditions for studying, language and communication, adjusting to a new culture, emotions, mental health and well-being and life and self-management, or something else. The most frequently reported challenges were motivation and emotion, goal setting and planning, and cognitive challenges. Motivation and emotional challenges were consistently high, regardless of level of goal attainment. Consistent with findings reported by Koivuniemi et al. (2017), cognitive challenges tended to be more frequently reported among students who were academically successful in terms of attaining goals they set for studying that week.

The abrupt move to fully online instruction introduced new challenges. Many students had limited experience with online learning and were living and learning under new stressors associated with pandemic. In addition to academic challenges, the pandemic also introduces significant social and emotional challenges that can indirectly impact students' academic performance. Pandemic-specific stressors related to economic hardship, social isolation, and health uncertainties can compound academic challenges associated with the transition to remote learning. Since transitioning to online learning, post-secondary students have reported increases in depressive and anxious symptoms (Fruehwirth et al., 2021) and lower psychological well-being (Dodd et al., 2021).

Emerging research has focused on academic challenges experienced by undergraduate students during COVID-19 pandemic. In a study of 114 undergraduate students, Giusti et al. (2021), found that experiences of challenges were mixed with 55% reported cognitive challenges related to concentration and learning abilities in attending online lessons, while 25% reported better concentration and learning abilities. Similarly, 60% of the students reported the lack of "face-to-face" contact with teachers as the main negative aspect, with 40% reporting difficulty interacting with teachers during the online lessons on the platform. Changes in study context and habits during the shift to online distance education increased the likelihood of poor perceived academic performance by almost four times. However, when attention and memory impairment, COVID anxiety and depression, and satisfaction with distance education were added to the model, changes in the study context and habits was no longer significant. Instead, reporting impairments in attention and concentration during distance education increased the likelihood of perceived poor academic performance by more than 8 times, and high COVID anxiety increased the perception of poor academic performance more than three times. Overall, satisfaction with distance education seemed to serve as a protective factor against perceptions of poor academic performance. Findings from this study were based on a small cross-sectional online convenience sample of university students at one university in Italy.

Negative associations between online learning and academic engagement during the pandemic have been reported in a sample of Canadian undergraduate students. Daniels et al. (2021) found online learning during the pandemic was associated with lower achievement goals, school engagement, and perceptions of success. While, diminished school engagement can indirectly impact academic performance, further research is needed to contribute to a more nuanced explanation of the underlying mechanisms that impact student success to further support students faced with the challenges of learning fully online during the pandemic.

Theoretically, challenges create opportunities for students to exercise self-regulatory control by deploying and adapting strategies and practices for the academic challenges they face. In other words, SRL practices provide mechanisms for productively responding to academic challenges and potentially buffering the effect of increased COVID-related stress that occurred after the shift to fully online undergraduate instruction. Further research is needed to understand (a) the kinds of challenges impacting student success and perceptions of success during the pandemic, (b) the impact of pandemic related distress on academic performance, and (c) the role of SRL practices in mitigating the impact of those challenges on academic performance. In this study, we focus specifically on academic challenges that impede students' metacognitive and motivational abilities.

## Impact of Self-Regulated Learning Instruction/Intervention for Academic Success

Providing instruction about SRL through SRL interventions and courses has been found to improve academic performance, strategy engagement, and motivation (Jansen et al., 2019; Theobald, 2021), even when instructional prompts are provided without direct strategy instruction (Bannert and Reimann, 2012). Meta-analysis results indicate the effect of SRL interventions on academic achievement is partially mediated by SRL practices (Jansen et al., 2019). SRL instruction has been found to influence metacognitive and resource management strategy use, with smaller effects on cognitive strategy use (Theobald, 2021). Evidence suggests SRL interventions improve goal setting and planning strategies before learning as well as self-monitoring during studying, therefore Theobald (2021) recommended that future SRL training and research emphasize the role of metacognitive processes in improving strategy deployment and influences on academic achievement. In addition, Theobald's (2021) meta-analysis revealed limitations in both the range and scope of self-report measured used to examine SRL practices.

Despite evidence that SRL strategy use is associated with higher academic achievement in online learning courses (Broadbent and Poon, 2015), research has rarely examined the influence of semester long SRL instruction/intervention on online academic achievement. Specifically, can online SRL training/instruction mitigate some of the impacts of pandemic-related distress on academic challenges and outcomes experienced by undergraduate students?

There is little question that the global pandemic dramatically changed the learning modes and experiences of undergraduate students. A rapid and unexpected shift to online learning can potentially introduce mounting new challenges and stressors for learners. Research is needed to understand the impact of pandemic-related stressors and academic challenges on academic performance. Furthermore, research is needed to examine the role of SRL intervention and practices in ameliorating the impact of these challenges on academic performance.

## Purpose and Hypotheses

The purpose of this study was to examine the role of SRL practices and SRL intervention in mitigating the impact of COVID-related psychological distress on academic success during fully online pandemic teaching. First, we tested our hypothesis that SRL practices would moderate the impact of COVID-related psychological distress and academic challenges (metacognitive and motivational) on academic performance for undergraduate students learning fully online during the pandemic ($N$ = 496). Second, we tested our hypothesis that SRL training would moderate the impact of COVID distress on academic performance for first year undergraduate students. Finally, we examined differences in academic challenges and SRL practices reported by first year undergraduate students who did or did not receive online SRL intervention throughout their first semester of university to better understand some of the specific ways study practices and challenges may be experienced by students who receive SRL training ($n$ = 157, SRL training group = 71; without training group = 86).

# MATERIALS AND METHODS

## Sample

Participants ($N$ = 463) were enrolled in a Western Canadian university and recruited from: (a) an elective learning-to-learn course in educational psychology designed to teach and promote strategic SRL processes and strategies ($n$ = 82), and (b) a psychology research participation pool open to students from all faculties who enrolled in at least one undergraduate psychology course ($n$ = 381). Most students (45%) were registered with the Faculty of Social Sciences with most (41%) majoring in psychology. Introduction to Psychology (PSYC 100A) is a required or recommended course across several faculties and programs at this university. Students enrolled in the elective course completed questionnaires as part of course activity requirements. Students from the SONA psychology research participation pool received one course credit that could be allocated to any of their psychology courses for participating in the research. All participants gave consent to participate in research and received debriefing about their SRL practices and challenges. All students attended university fully online for that academic year. Prior to the pandemic, online learning was not a typical mode of instruction at this university. While students may have had experience with one distance course during high school, few students had pre-pandemic experience with fully online instruction across all courses.

## Self-Regulated Learning Instruction

Self-regulated learning instruction was provided in a credit-bearing first year undergraduate educational psychology course (*ED-D101: Learning strategies for University Success)* introducing the science behind learning and motivation from an SRL perspective. The course consisted of a series of eleven online learning modules delivered over one academic semester (13 weeks).

Content for each weekly learning module was delivered asynchronously online through D2L Brightspace, 2020[1]. Students started by reading an interactive chapter that included text, video, images, and examples. Every topic was introduced with a link to the process of self-regulating learning to manage day-to-day academic challenges. Weekly topics included: (1) Introduction to online learning, (2) Introduction to SRL and academic success, (3) Understanding academic tasks and expectations, (4) Setting goals and monitoring learning during study sessions, (5) Information processing and active cognitive processes (e.g., activating prior knowledge, generative processing, etc.), (6) Understanding and regulating motivation, (7) Regulating time and procrastination, (8) Reading, notetaking, and learning in reading the social sciences, (9) Reading, notetaking and learning computational and STEM related concepts and procedures, (10) Regulating emotions, mental health, and well-being, (11) Active rehearsal and exam preparation.

The asynchronous modules were coupled with weekly synchronous online small-group lab sessions delivered through *Zoom* (Zoom Video Communications Inc, 2016) and coupled with *Microsoft-365 Teams* channels for communicating and sharing resources and examples. Each online lab engaged 20 students and a teaching assistant in guided activities and discussions designed to build on the content module by applying strategies to students undergraduate courses and respective disciplinary areas.

Students also accessed an online Strategy Library stocked with over 100 strategies organized by factors contributing to student success (Hadwin, 2020). Each strategy included a description, introduction to the science about why it works, instructions about how to use the strategy and examples of that strategy in use. The strategy library was created and deployed through D2L Brightspace for all students at the University.

A key component of this course was developing metacognitive awareness of studying approaches, strategies, and outcomes. Students completed a weekly study diary activity (McCardle and Hadwin, 2015) requiring them to (a) plan a 1-to-2-hour study session for one core academic course by setting a specific learning goal, (b) completing that study session, and (c) reflecting on the outcomes, experiences and challenges encountered during that study session. This weekly activity intentionally engaged students in cycles of SRL with the goal of helping them leverage past experiences to optimize subsequent study sessions.

[1]https://bright.uvic.ca/d2l/home/73882

## Procedure

Surveys were administered in week 11 of a 13-week academic semester in the Fall of 2020 during the COVID-19 pandemic. Immediately after completing the questionnaire, students were provided with individualized profile reports and provided with instruction about how to use those reports to self-diagnose strengths and weaknesses in studying and identify strategies for improving SRL based on their individualized data. Students were provided links to specific evidence-based study strategies based on those individualized reports.

## Measures

***The self-regulated learning profile and self-diagnostic instrument*** (SRL-PSD; Hadwin et al., 2021) examines self-reported SRL practices and SRL challenges (see Appendix 1 for items in the scales). The scale was developed to incorporate practices associated with forethought (task understanding, goal setting, and planning), performance, and reflection during studying. Importantly, the scale includes practices associated with metacognitive adaptation during studying that are often under-examined in SRL research.

***The SRL- Practices Scale*** (SRL-P; Hadwin et al., 2021) measures students' perceptions about their engagement in practices that foster SRL. The SRL-P comprises 31 items yielding 8 subscales related to (1) task understanding (e.g., "*Asked myself if I know what is important to learn*"), (2) goal management (e.g., "*Set goals for my work*"), (3) motivation: task value (e.g., "*Reflected on why this work is important*"), (4) motivation: appraisal (e.g., "*Assessed if think I can do it*"), (5) time management (e.g., "*Created a timeline or schedule*), (6) metacognitive monitoring (e.g., "*Asked myself if I am understanding the material*"), (7) metacognitive adaptation (e.g., "*Modified my plans for the task*"), and (8) social engagement (e.g., "*Got to know people in the class*"). Participants were required to rate their level of agreement for each statement in a five-point Likert scale ranging from (1) Strongly disagree to (5) Strongly agree.

***Self-regulated learning challenges scale*** (SRL-C; Hadwin et al., 2021) is comprised of 43 items (5 subscales) assessing the degree to which students encountered a range of challenges in their studying. Responses were reported on a 5-point Likert scale from (1) *Strongly disagree* to (5) *Strongly agree*. Higher scores indicate a student is struggling to manage aspects of studying theoretically and empirically associated with student success and performance. The *Motivation challenge* subscale was comprised of six-items related to motivational beliefs, interest, and persistence. The *Metacognitive challenge* subscale was comprised of 10-items related to task understanding, goal setting, planning, and monitoring. The *Cognitive challenge* subscale was comprised of eight-items related to attending, encoding, and remembering. The *Behavioral challenge* subscale was comprised of eight-items related to managing time, tasks, and procrastination. The *Socio-emotional challenge* subscale was comprised of 11-items related to emotional, social, and relational aspects of academic success.

***Academic Performance*** was measured using two distinct but correlated variables: self-reported *perceptions of academic performance* where students were asked to report on what

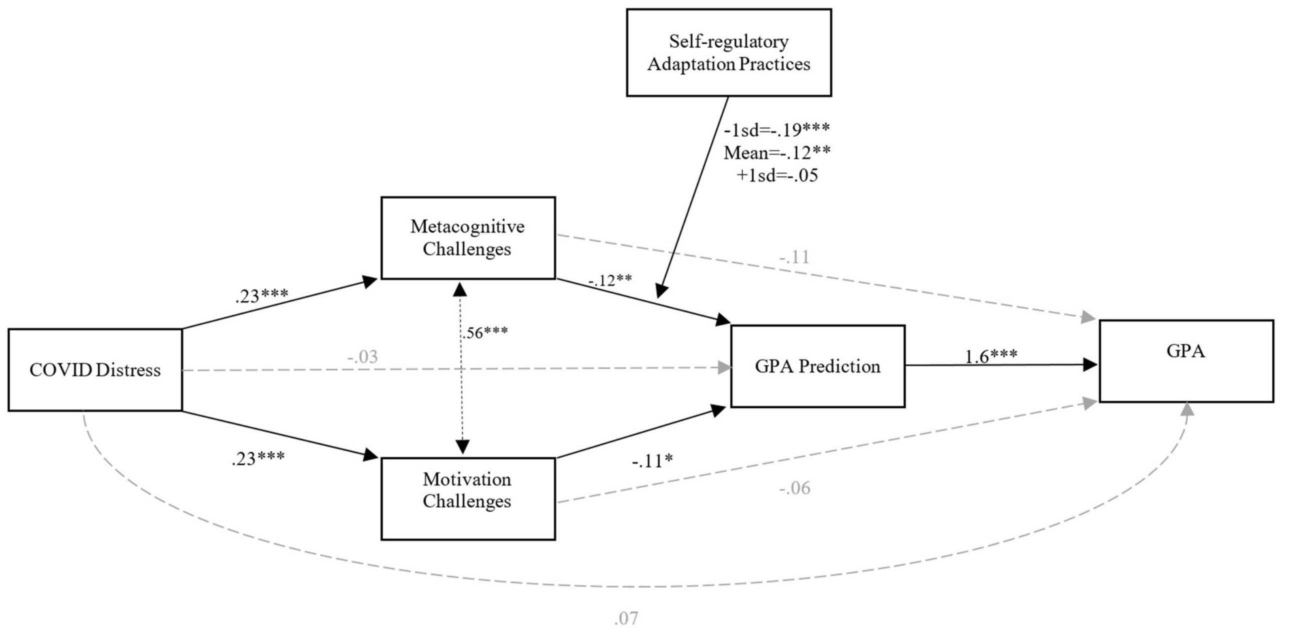


**FIGURE 1 |** Structural relationship between COVID-D (predictor), metacognitive and motivation challenges (parallel mediators), GPA-P (serial mediator), adaptation practices (moderator), and GPA (outcome): a conditional process path analysis ($N$ = 463).

overall GPA (average grade) they expected to get this year and objective measures of academic performance obtained through institutional reports (i.e., GPA on a 9-point scale).

***COVID-19 Distress*** was adapted from the COVID Stress Scales (Taylor et al., 2020) which comprised of 23 items related to (1) danger and contamination fears (e.g., I am worried about catching the virus from handling money or using a debit machine), (2) fears about economic consequences (e.g., "I am worried my financial situation will be affected by COVID-19"), (3) compulsive checking and reassurance seeking (e.g., "I sought reassurance from friends and family about COVID-19"), and (4) traumatic stress symptoms related to the pandemic (e.g., "Disturbing mental images about the virus popped into my head against my will"). In addition, two items related to feelings of guilt and shame about the pandemic ("I feel guilty for not doing more to prevent COVID-19"; "I feel ashamed of my emotional reactions to COVID-19") were also added from the COVID-19 Peritraumatic Distress Index (CPDI; Qiu et al., 2020). The items were rated on a 5-point scale ranging from 0 (not at all) to 4 (extremely) and were summed to create a composite for COVID-19 rumination.

## Data Analytic Strategy

Conditional process analysis was used to test the hypotheses (Hayes, 2015, 2017) using Process syntax version 3.5.3. As shown in **Figure 1**, COVID-D was regressed on the GPA (the outcome variable) with two parallel mediators (metacognitive and motivation challenges) and one serial mediator (perceptions of GPA; GPA-P). Adaptation practices was added to the model to test if the magnitude of COVID-D's indirect effect on GPA-P through metacognitive challenges depends on variation in adaptation practices scores. It was hypothesized that experiencing higher COVID-D would increase students' metacognitive and motivational challenges. These challenges, in turn, would have an inverse effect on students' perception of academic performance which in turn diminishes their actual academic performance. This model is regarded as an inconsistent mediation model (MacKinnon et al., 2007) because it includes mediated effects with different signs.

# RESULTS

## The Role of Self-Regulated Learning Practices in Moderating the Impact of COVID Distress on GPA

Descriptive statistics and intercorrelations for the main study variables for the entire sample are provided in **Tables 1**, **2**. As shown in **Table 2**, academic challenges negatively associated with GPA prediction and GPA. While COVID distress was not associated with GPA, it was found to be negatively related to GPA predictions (GPA-P). Results from the model represented in **Figure 1** indicate COVID distress positively predicts metacognitive challenges [$B = 0.23$, $t(461) = 4.96$, $p < 0.001$] as well as motivation challenges [$B = 0.23$, $t(461) = 5$, $p < 0.001$]. These challenges both have inverse effects on GPA prediction. The inverse effect indicates higher levels of challenge were associated with lower GPA prediction [$B_{\text{Metacognition}} = -0.12$, $t(457) = -2.61$, $p = 0.009$ | $B_{\text{Motivation}} = -0.11$, $t(457) = -2.47$, $p = 0.014$]. Adaptation was added as a moderator to test if the indirect effect of COVID-D on GPA prediction (GPA-P) through metacognitive challenges is contingent on adaptation practices.

**TABLE 1 |** Descriptive statistics for the whole sample.

| Scale variable (sub-scale) | | Mean | *SD* |
|---|---|---|---|
| – | High School GPA | 87.74 | 6.05 |
| – | Term GPA | 6.68 | 1.82 |
| – | GPA-P | 3.45 | 0.78 |
| – | COVID-D | –0.04 | 0.99 |
| SRL-P | Goal management | 0.09 | 1.00 |
| SRL-P | Task understanding | 0.03 | 0.99 |
| SRL-P | Task value | –0.05 | 1.00 |
| SRL-P | Motivation appraisal | 0.04 | 0.98 |
| SRL-P | Adaptation | 0.00 | 1.01 |
| SRL-P | Monitoring | 0.07 | 0.94 |
| SRL-P | Social engagement | 0.00 | 1.01 |
| SRL-P | Time management | 0.08 | 1.00 |
| SRL-C | Metacognition challenges | –0.09 | 0.98 |
| SRL-C | Socio-emotional challenges | –0.01 | 0.98 |
| SRL-C | Cognitive challenges | –0.08 | 1.01 |
| SRL-C | Initiating and sustaining engagement challenges | –0.01 | 0.98 |
| SRL-C | Goal and time management challenges | –0.10 | 1.00 |
| SRL-C | Motivation challenges | –0.05 | 1.00 |

*SRL, self-regulated learning; P, SRL practices; C, SRL challenges.*

The interaction of metacognitive challenges and adaptation practices was a significant predictor of students' GPA prediction [$B = 0.72$, $t(457) = 2.3$, $p = 0.020$]. Further analysis of conditional effects of the metacognitive challenges at values of the adaptation practices showed that the inverse indirect impact of COVID-D on GPA-P is stronger for students who practiced less adaptation. To elaborate, while this effect is significant at 1 standard deviation below adaptation average [$B = -0.19$, $t(457) = -3.53$, $p = 0.0005$], it is less strong at the adaption average value [$B = -0.12$, $t(457) = -2.6$, $p = 0.009$], and less strong and non-significant at 1 standard deviation above the adaptation average [$B = -0.05$, $t(457) = -0.89$, $p = 0.37$]. The index of moderated mediation (difference between conditional indirect effects, see Hayes, 2015) was also significant (Index = 0.026, Boot*SE* = 012, 95% Boot*CI* [0.003, 0.52]) indicating higher versus lower levels of adaptation practices produce a differential effect on the indirect effect of COVID-D on GPA-P through metacognitive challenges. Follow up Johnson–Neyman significance region(s) analysis showed that the effect is significant for adaptation values falling above 61 percentiles. Finally, GPA-P was shown to have a strong direct influence on GPA [$B = 1.6$, $t(458) = 19.23$, $p < 0.001$].

COVID-D was found to have no significant direct effect ($c'$) on GPA [$B = 0.07$, $t(458) = 0.104$, $p = 0.30$]. Analysis of indirect effects showed that motivation and metacognitive challenges fully mediated the effect of COVID-D on GPA-P, making the direct link between COVID-D and GPA-P insignificant [$B = -0.03$, $t(457) = -0.75$, $p = 0.45$]. Also, COVID-D was found to have no significant indirect effect on GPA through motivation challenges ($B = -0.026$, Boot*SE* = 0.019, 95% BootCI [−0.065,0.01]), metacognition challenges ($B = -0.01$, *BootSE* = 0.02, 95% Boot*CI*

**TABLE 2 |** Intercorrelations for study variables (*N* = 463).

| Sub-scales | GPA TERM | GPA-P | COVID-D | Adaptation (SRL-P) | Metacognition (SRL-C) | Social and emotional (SRL-P) | Cognitive (SRL-C) | Initiating and Sustaining engagement (SRL-C) | Goal and time management (SRL-C) | Motivation (SRL-C) |
|---|---|---|---|---|---|---|---|---|---|---|
| Term GPA | 1 | | | | | | | | | |
| GPA-P | 0.691** | 1 | | | | | | | | |
| COVID-D | −0.054 | −0.104* | 1 | | | | | | | |
| Adaptation (SRL-P) | −0.090 | −0.029 | 0.048 | 1 | | | | | | |
| Metacognition challenges | −0.226** | −0.248** | 0.225** | 0.020 | 1 | | | | | |
| Social and emotional challenges | 0.046 | −0.033 | 0.299** | 0.003 | 0.514** | 1 | | | | |
| Cognitive challenges | −0.255** | −0.236** | 0.148** | 0.031 | 0.639** | 0.354** | 1 | | | |
| Initiating and sustaining engagement | −0.073 | −0.121** | 0.116* | −0.040 | 0.429** | 0.353** | 0.340** | 1 | | |
| Goal and time management | −0.148** | −0.105* | 0.058 | 0.064 | 0.571** | 0.344** | 0.464** | 0.546** | 1 | |
| Motivation challenges | −0.235** | −0.245** | 0.226** | 0.033 | 0.613** | 0.489** | 0.594** | 0.472** | 0.536** | 1 |

*SRL-P, SRL Practices; SRL-C, SRL Challenges.*
*$^{*}p \leq 0.05$, $^{**}p \leq 0.01$.*

**TABLE 3 |** Unconditional and conditional indirect effects of COVID-D on GPA.

| | | | | | | | | | | Bootstrap | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | **Effect** | ***SE*** | **LLCI** | **ULCI** |
| 1 | COVID-D | → | MOT CH | → | GPA | | | | –0.026 | 0.019 | –0.065 | 0.01 |
| 2 | COVID-D | → | META CH | → | GPA | | | | –0.014 | 0.02 | –0.055 | 0.024 |
| 3 | COVID-D | → | GPAP | → | GPA | | | | –0.045 | 0.068 | –0.17 | 0.09 |
| 4 | COVID-D | → | MOT CH | → | GPAP | → | GPA | | –0.04 | 0.02 | –0.086 | –0.007 |
| 5 | | | | | | | | ADAPT SD-1 | –0.07 | 0.024 | –0.12 | –0.026 |
| | COVID-D | → | META CH | → → ADAPT | GPAP | → | GPA | ADAPT Average | –0.043 | 0.019 | –0.085 | –0.009 |
| | | | | | | | | ADAPT SD+1 | –0.018 | 0.022 | –0.064 | 0.023 |

*COVID-D, COVID distress; MOT CH, motivational challenges; META CH, metacognitive challenges; GPAP, GPA prediction; ADAPT, adaptation practices.*

[–0.05,0.02]), and GPA-P ($B$ = –0.045, Boot$SE$ = 0.068, 95% Boot$CI$ [–0.17,0.09]).

**Table 3** contains the indirect effects tested in model 1. Rows 4 and 5 in the table represent two statistically significant processes by which COVID distress indirectly influences academic performance, i.e., through enhancing academic challenges, which in turn decreases GPA prediction and GPA itself [$F(4,458) = 107.14$, $p < 001$, $R^2 = 0.48$]. The indirect effect through metacognitive challenges (**Table 3**, row 5) is presented at three levels of adaptation practices to reflect its moderating role in the model.

## Self-Regulated Learning Training as a Moderator of the Impact of COVID Distress on GPA for 1st Year Students

A mediated moderation model was used to test if SRL training moderates the impact of COVID distress on academic performance. Analysis was conducted on a subset of the sample comprised of 1st year students as only first-year students participated in the SRL intervention ($n$ = 157, SRL training group = 71; without training group = 86; means and standard deviations are provided in **Table 4**). Parameters were estimated with a robust standard error (HC3 method; Davidson and MacKinnon, 1993) to obtain unbiased standard errors under heteroscedasticity. As depicted in **Figure 2**, results show that COVID-D had no significant influence on GPA-P [$B = 0.20$, $t(152) = 1.08$, $p = 0.28$] but the interaction of training (0, 1) and COVID-D negatively impacted GPA-P [$B = 0.26$, $t(152) = –2.15$, $p = 0.03$]. Conditional effects of the COVID-D across two groups indicate that COVID-D negatively affected students' GPA predictions in the group with no SRL training [$B = –0.32$, $t(152) = –3.6$, $p < 0.001$] but such an effect was not observed in the group that had received SRL training [$B = –0.06$, $t(52) = –0.69$, $p = 0.5$]. Consistent with the results of the previous model, GPA-P had a strong positive influence on GPA [$B = 1.26$, $t(153) = 7.6$, $p < 0.001$]. The direct path in the model ($C$') is not significant [$B = 0.05$, $t(153) = 0.33$, $p = 0.74$] meaning that COVID-D impacts GPA only indirectly through mediation of GPA-P in the model [$F(2,153) = 37.13$, $p < 0.001$, $R^2 = 0.27$].

The index of moderated mediation was found to be significant (Index = –0.33, Boot$SE$ = 0.16, 95% Boot$CI$ [–0.65, –0.006]) showing that the full mediated effect between COVID-D and GPA through GPA-P significantly differs across the two groups. Investigating the indirect effects in the model shows that among those who did not receive SRL training, COVID-D had a significant negative indirect effect on GPA through GPA-P ($B$ = –0.4, Boot$SE$ = 0.13, 95% Boot$CI$ [–0.64, –0.13]). In contrast, this indirect effect was weaker and non-significant in the SRL training group ($B$ = –0.07, Boot$SE$ = 0.11, 95% Boot$CI$ [–0.29,0.14]). In sum, findings support that SRL training moderated the impact of COVID distress on academic performance such that the effect of COVID distress on academic performance through GPA prediction was mollified for students who were enrolled in ED-D101 compared to students who were not enrolled in ED-D101.

## Mean Differences in Self-Reported Academic Challenges and Self-Regulated Learning Practices Between 1st Year Students With and Without Self-Regulated Learning Training

Two multivariate analyses of covariance (MANCOVA) were conducted to better understand how first-year students with and without SRL training differed in terms of academic challenges and SRL practices after controlling for their incoming GPA. Box's test of equality of covariance matrices was insignificant for both academic challenges and SRL practices [for Academic Challenges: $M = 32.7$, $F = (21,81859) = 1.5$, $p = 0.07$; for SRL practices: $M = 28.9$, $F(36,75006) = 0.76$, $p = 0.85$] indicating that the observed covariance matrices of the dependent variables are equal across groups. Homogeneity of regression slopes was tested by adding interaction terms between the covariate and independent variable into analyses and making sure the term is insignificant.

Results summarized in **Table 5** showed that while there was a statistically significant difference between the groups with and without SRL training on the combined academic challenges after controlling for incoming GPA [$F(6,148) = 3.2$, $p = 0.005$, Wilks' $\Lambda = 0.885, \eta_p^2 = 0.115$], there was no statistically significant difference between the groups on the combined SRL practices

**TABLE 4 |** Descriptive statistics for the "first-year students" sub-sample (Model 2).

| Scale Variable (Sub-scale) | | | Mean | *SD* |
|---|---|---|---|---|
| – | High School GPA | G1 | 88.05 | 5.28 |
| | | G2 | 90.88 | 4.97 |
| – | Term GPA | G1 | 5.92 | 1.63 |
| | | G2 | 6.69 | 1.85 |
| – | GPA-P | G1 | 3.10 | 0.62 |
| | | G2 | 3.51 | 0.81 |
| – | COVID-D | G1 | – 0.19 | 0.98 |
| | | G2 | – 0.11 | 0.95 |
| SRL-P | Goal management | G1 | 0.18 | 0.76 |
| | | G2 | 0.15 | 1.06 |
| SRL-P | Task understanding | G1 | 0.00 | 0.85 |
| | | G2 | 0.21 | 0.95 |
| SRL-P | Task value | G1 | 0.09 | 0.93 |
| | | G2 | – 0.04 | 1.05 |
| SRL-P | Motivation Appraisal | G1 | – 0.14 | 0.99 |
| | | G2 | 0.19 | 0.96 |
| SRL-P | Adaptation | G1 | 0.27 | 0.92 |
| | | G2 | 0.07 | 0.95 |
| SRL-P | Monitoring | G1 | 0.20 | 0.83 |
| | | G2 | 0.19 | 0.86 |
| SRL-P | Social engagement | G1 | 0.15 | 0.98 |
| | | G2 | – 0.05 | 1.06 |
| SRL-P | Time management | G1 | 0.09 | 1.00 |
| | | G2 | 0.15 | 1.02 |
| SRL-C | Metacognition Challenges | G1 | – 0.39 | 0.75 |
| | | G2 | – 0.02 | 1.04 |
| SRL-C | Socio-emotional Challenges | G1 | – 0.44 | 0.90 |
| | | G2 | 0.02 | 1.02 |
| SRL-C | Cognitive Challenges | G1 | – 0.33 | 0.83 |
| | | G2 | – 0.03 | 1.06 |
| SRL-C | Initiating and Sustaining engagement Challenges | G1 | – 0.15 | 0.87 |
| | | G2 | – 0.15 | 1.13 |
| SRL-C | Goal and Time Management Challenges | G1 | – 0.20 | 0.83 |
| | | G2 | – 0.24 | 1.11 |
| SRL-C | Motivation Challenges | G1 | – 0.27 | 0.85 |
| | | G2 | 0.01 | 1.09 |

*Training Group = (G1, n = 71); Without Training = (G2, n = 86); COVID- Distress, and all SRL-P and SRL-C dimensions are Croon's Bias-Corrected Bartlett factor scores. GPA-P, GPA perception; COVID-D, COVID distress; SRL-P, SRL practices; SRL-C, SRL challenges.*

scales after controlling for incoming GPA [$F(8{,}147) = 1.55$, $p = 0.144$, Wilks' $\Lambda = 0.92$, $\eta_p^2 = 0.078$].

Follow-up univariate analyses were carried out to elaborate more on adjusted mean differences between the groups in terms of each dependent variable after controlling for the effect of incoming GPA. As we had unequal variances particularly for SRL practices scales, we used HC3 robust standard error estimator to handle the heteroscedasticity problem that might have caused by heterogeneity of error variances across the two groups. However, research indicates that univariate group analyses are robust to moderate violations of homogeneity of variances if group sample sizes are approximately equal (Nimon, 2012). This analyses revealed that after controlling for the effect of incoming GPA, students without SRL training had a significantly higher average adjusted mean for the SRL practice – motivation appraisal scale [Mean Difference = 0.33, $t(154) = -1.99$, $p = 0.049$, $\eta_p^2 = 0.025$], metacognitive challenges [Mean Difference = 0.42, $t(154) = -2.86$, $p = 0.005$, $\eta_p^2 = 0.05$], cognitive challenges [Mean Difference = 0.47, $t(154) = -2.96$, $p = 0.004$, $\eta_p^2 = 0.054$], motivation challenges [Mean Difference = 0.37, $t(154) = -2.23$, $p = 0.027$, $\eta_p^2 = 0.031$], and socio-emotional challenges [Mean Difference = 0.43, $t(154) = -2.6$, $p = 0.01$, $\eta_p^2 = 0.042$].

To summarize, students without SRL training reported higher levels of social-emotional, cognitive, metacognitive, and motivation challenges than students with SRL training. Furthermore, students with SRL training reported fewer motivation appraisal practices such as thinking about why they are being asked to know a concept, reflecting on why it is important, and making judgments about the usefulness or value of the content.

## DISCUSSION

The current study examined how pandemic-related stressors affect students' academic performance and the role of SRL practices in ameliorating the impact of academic challenges on performance. Findings show that COVID stressors impaired students' academic performance through introducing more metacognitive and motivational academic challenges. However, for individuals who are highly skilled in SRL practices, specifically around adaptation (i.e., scoring in the top third of the sample on the SRL adaptation measure), academic challenges did not mediate the relationship between COVID stressors and academic performance. This finding is consistent with SRL theory which posits that self-regulated learners who are more adaptive fare better in the face of ongoing academic adversities because they can recognize that the acquisition of learning skills requires systematic variations in approaches that will help them overcome learning difficulties (Winne and Hadwin, 2008; Zimmerman, 2008). Moreover, students with a more adaptive profile of SRL strategy usage tend to report higher academic achievement (Liu et al., 2014).

While academic challenges are normative for students, the abrupt shift to remote learning coupled with impeding psychological distress about the pandemic can further tax already compromised SRL abilities. Pandemic-related stressors can exacerbate existing academic challenges particularly among those who struggle to monitor and adapt their learning strategies effectively to changing demands. The enhanced process of self-reflection and adaptive decision-making among self-regulated learners requires a greater understanding and awareness of one's own learning processes, or meta-cognitive ability. While few studies have directly examined SRL practices specifically

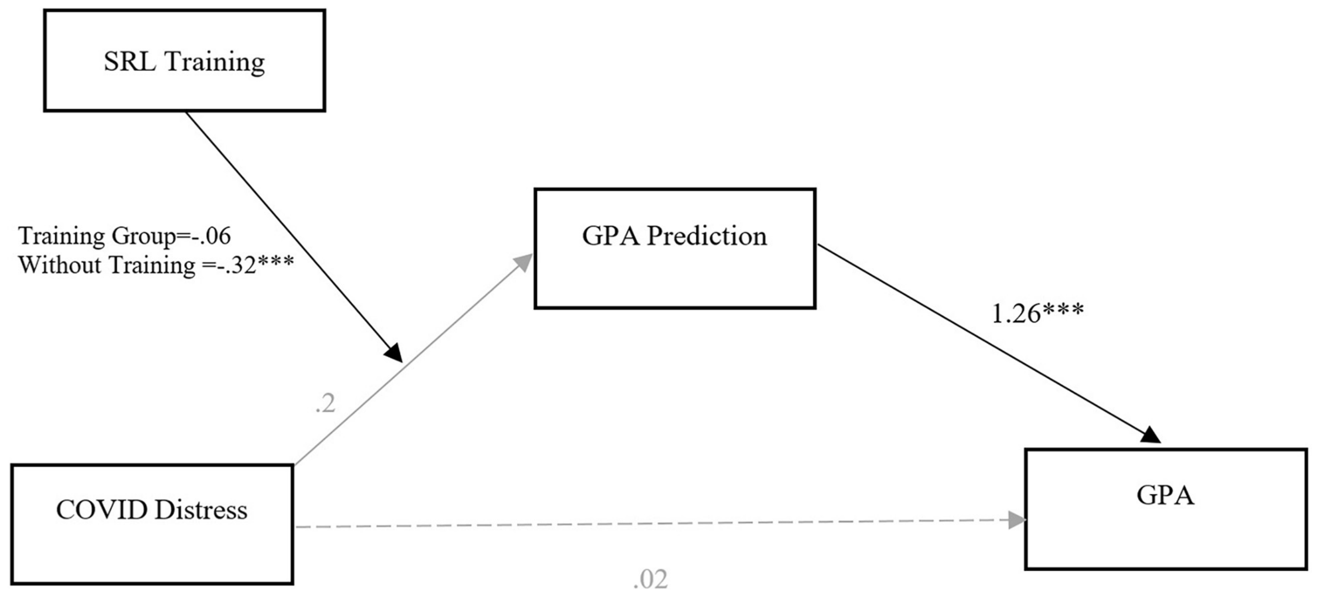


**FIGURE 2 |** SRL training as a moderator of the impact of COVID distress on GPA for 1st year students: a moderated mediation path analysis ($N$ = 169).

**TABLE 5 |** Pairwise comparisons of SRL-P and SRL-C based on estimated marginal means (SRL Training = I, Without Training = J).

| Scale | Sub-scale | Mean difference (I-J) | Robust standard error (HC3) | *t* | Sig. | 95% CI for difference LL | 95% CI for difference UL | $\eta_p^2$ | Levene's test *F*(1,155) |
|---|---|---|---|---|---|---|---|---|---|
| SRL-C | Metacognition challenges | – 0.42 | 0.149 | – 2.86 | 0.005 | – 0.72 | – 0.13 | 0.050 | 12.66*** |
| SRL-C | Cognitive challenges | – 0.47 | 0.158 | – 2.96 | 0.004 | – 0.72 | – 0.16 | 0.054 | 3.93* |
| SRL-C | Motivation challenges | – 0.37 | 0.167 | – 2.23 | 0.027 | – 0.70 | – 0.04 | 0.031 | 5.64* |
| SRL-C | Social and emotional challenges | – 0.43 | 0.165 | – 2.6 | 0.010 | – 0.76 | – 0.10 | 0.042 | 0.25 |
| SRL-C | Initiating and sustaining engagement challenges | – 0.05 | 0.174 | – 0.27 | 0.789 | – 0.39 | 0.3 | 0.000 | 6.3* |
| SRL-C | Goal and time management challenges | 0.00 | 0.166 | 0.02 | 0.983 | – 0.32 | 0.33 | 0.000 | 7.16** |
| SRL-P | Goal management | – 0.002 | 0.146 | – 0.014 | 0.989 | – 0.291 | 0.287 | 0.000 | 9.4** |
| SRL-P | Task understanding | – 0.121 | 0.148 | – 0.822 | 0.412 | – 0.413 | 0.170 | 0.004 | 0.16 |
| SRL-P | Task value | 0.181 | 0.165 | 1.101 | 0.273 | – 0.144 | 0.506 | 0.008 | 2.26 |
| SRL-P | Motivation appraisal | – 0.333 | 0.167 | – 1.987 | 0.049 | – 0.663 | – 0.002 | 0.025 | 0.09 |
| SRL-P | Adaptation | 0.160 | 0.159 | 1.009 | 0.315 | – 0.154 | 0.474 | 0.007 | 0.14 |
| SRL-P | Monitoring | 0.047 | 0.148 | 0.317 | 0.751 | – 0.245 | 0.339 | 0.001 | 0.71 |
| SRL-P | Social engagement | 0.194 | 0.163 | 1.186 | 0.237 | – 0.129 | 0.516 | 0.009 | 0.37 |
| SRL-P | Time management | – 0.053 | 0.174 | – 0.306 | 0.760 | – 0.397 | 0.291 | 0.001 | 0.03 |

*SRL-P, SRL practices; SRL-C, SRL challenges.*
*$^*p \leq 0.05$, $^{**}p \leq 0.01$, $^{***}p \leq 0.001$.*

in the context of adaption, meta-cognitive awareness has been linked to academic performance (e.g., Ward and Butler, 2019). Consistent with the SRL process model (Zimmerman, 2000), regular use of forethought (e.g., strategic planning, goal setting) and self-reflection seems to distinguish high achieving from poor achieving students, enabling them to adapt more effectively to shifting contextual changes. Indeed, high-achieving students tend to use higher-quality learning strategies related to forethought and self-reflection (Colthorpe et al., 2019).

Our findings also show that students' SRL practices can be supported through a course-based intervention that help students navigate academic challenges associated with online learning. Specifically, first year students who received SRL training in the course *ED-D101: Learning Strategies for University Success* reported fewer metacognitive, cognitive, motivational, and socio-emotional challenges compared to their counterparts who were not enrolled in the SRL course. Moreover, the intervention moderated the impact of pandemic-related stressors on academic performance since the negative impact of COVID stressors on academic performance was stronger among students who were not enrolled in the SRL course. This finding suggests that students who are taught strategic ways to enhance their SRL through understanding tasks, setting goals, monitoring their studying approaches, and managing their time, and mental-health and well-being are better able to overcome academic challenges compared to students without this SRL-focused training.

Leveraging SRL instructional tools and resources can promote metacognitive monitoring processes. SRL interventions have shown efficacy in improving academic performance, in part, through enhancing their knowledge of SRL and engagement in SRL activities (de Bruijn-Smolders et al., 2016; Jansen et al., 2019). Guiding students to better assess their learning gains, attributing those gains to a specific effective strategy, and systemically applying that strategy to appropriate tasks, optimizes their learning. Moreover, encouraging students to identify and modify strategies that are not working enhances their adaptive ability. The iterative cycle of monitoring tasks and recalibrating strategies is not intuitive for all students particularly under competing demands of academic and social post-secondary life. Compounding such demands with unique circumstances surrounding a global pandemic can further impede students' ability to transfer their self-regulatory abilities across multiple contexts. For example, studying habits that were effective for an in-person learning may not be optimal in a online learning. SRL is contextual and dynamic, requiring learners to regulate their cognition, motivation and emotions during learning tasks that change across different situations (Winne and Hadwin, 2008; Zimmerman, 2008). Changing tasks and demands introduce new challenges overcomeing these challenges requires learners to successfully adapt and adjust previously learned strategies. During the pandemic, post-secondary students encountered new academic challenges necessitating SRL capacities (e.g., metacognitive awareness); students with fewer SRL skills are less equipped to handle pandemic-related stressors that diminish academic performance. However, our findings suggest that students provided with SRL training were able to moderate the impact of COVID distress on academic performance, mollifying its effect. Providing students with the opportunity to reassess learning approaches and identify specific challenge areas through SRL interventions enables them to strategically direct studying efforts. For example, learning task understanding skills for deciphering specific course content and assigned tasks more accurately is an important predictor of academic performance (Oshige et al., 2007; Hadwin et al., 2008). Promoting students' awareness of their own learning and guiding them to use higher-quality strategies related to goal setting, strategic planning and self-evaluation can improve student learning outcomes (Colthorpe et al., 2019). However, it is worth noting that while the SRL intervention group reported fewer academic challenges compared to the non-intervention group, they did not differ significantly in their levels of SRL practices after controlling for incoming GPA (except for motivation appraisal). It may be that the SRL intervention operates through enhancing students' pre-existing SRL skills by helping students apply learning strategies more efficiently and adaptively, thereby mitigating academic challenges.

### Limitations and Future Direction

While the current study offers a more nuanced understanding of how SRL processes mitigate academic challenges in the face of a contextual stressor, such effects are limited to the specific context of the 2020 COVID-19 pandemic. Nevertheless, the pandemic provides a unique examination of the unprecedented changes to students' educational environments that are not typical of everyday academic challenges. Individual differences in the SRL skills students' use to overcome these academic challenges can help educators support the transition from varying modes of instruction (e.g., online/blended/in-person settings). Another limitation of the study surrounds the use of self-reports of SRL practices which can be subjected to respondent and recall biases. Moreover, as SRL is a context-dependent process, SRL practices can change depending on that task and goal at hand which may not be accurately captured in traditional self-reported inventories. Nonetheless, self-report still provides valuable insights into learner's motivation processes and perceptions of how they monitor, set goals, and adapt effectively particularly if measures are sensitive to time and task (McCardle and Hadwin, 2015). More research may benefit from using objective measures of SRL practices to discern the frequency and quality of these skills (e.g., Winne, 2010). Lastly, it is important to acknowledge limits to the design of the study. Specifically, participants were not randomly assigned to the intervention condition, which limits the comparability across groups. As group comparisons were only permitted among first year students in the analysis (i.e., to match the samples), such truncation significantly reduced the sample size. Without a true randomized control trial (RCT) design with pre-test and post-test differences in both groups, findings regarding the effectiveness of the intervention should be viewed with caution. RCTs of SRL interventions are needed to systematically evaluate its impact on student success.

## CONCLUSION

The prolonged COVID-19 pandemic continues to impact post-secondary institutions across the globe. Shifts to online instruction in the Fall of 2020 combined with the ongoing demand for instructional approaches that flexibly blend online options with on-campus delivery amplifies the need for students to develop and deploy SRL practices. Findings from this study demonstrate that psychological stressors related to the pandemic can impair students' academic performance by introducing more metacognitive and motivational challenges during online learning. However, self-regulatory learning practices that promote adaption to new learning contexts, tasks and situations can help alleviate the impact of COVID stressors on academic performance. Moreover, students SRL skills can be bolstered by a 13-week on online academic course that explicitly supports students to diagnose and overcome a range of academic difficulties associated with online learning.

While the COVID-19 pandemic will end, it has illuminated the effect that additional stressors have on post-secondary students particularly when they are transitioning to first year studies and new modes of delivery such as online learning. Findings from this study point to the critical importance of equipping students with a toolbox of self-regulatory practices and strategies that help them to adaptively respond to new live and school stressors. Findings from this study indicate that learning to manage stressors and remediate academic challenges using self-regulatory strategies and practices is something that can (a) be taught over an academic semester, and (b) contribute to better academic outcomes such as GPA. Proactively investing in these types of courses may have potential to improve online learning outcomes and position institutions and students to adapt to future life stressors and global events more proactively.

## DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## ETHICS STATEMENT

The studies involving human participants were reviewed and approved by University of Victoria Human Research Ethics Board. The patients/participants provided their written informed consent to participate in this study.

## AUTHOR CONTRIBUTIONS

AH is the grant holder and contributed to the funding, theory, development and delivery of the SRL online intervention, formulation of study design and is the main writer of the submitted manuscript (i.e., the section "Introduction"). PS contributed to the evaluation funding, formulation of study design, theory, and manuscript preparations (e.g., writing of discussion). RR contributed to the study design, programming and coordination of the online evaluation, facilitated the SRL intervention, and conducted the statistical analyses. LB-O facilitated the SRL intervention, conducted the evaluation of the intervention, and made editorial contributions to the manuscript. All authors contributed to the article and approved the submitted version.

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## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2022.813529/full#supplementary-material

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# Tracking Changes in Students' Online Self-Regulated Learning Behaviors and Achievement Goals Using Trace Clustering and Process Mining

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Success in online and blended courses requires engaging in self-regulated learning (SRL), especially for challenging STEM disciplines, such as physics. This involves students planning how they will navigate course assignments and activities, setting goals for completion, monitoring their progress and content understanding, and reflecting on how they completed each assignment. Based on Winne & Hadwin's COPES model, SRL is a series of events that temporally unfold during learning, impacted by changing internal and external factors, such as goal orientation and content difficulty. Thus, as goal orientation and content difficulty change throughout a course, so might students' use of SRL processes. This paper studies how students' SRL behavior and achievement goal orientation change over time in a large ($N = 250$) college introductory level physics course taught online. Students' achievement goal orientation was measured by repeated administration of the achievement goals questionnaire-revised (AGQ-R). Students' SRL behavior was measured by analyzing their clickstream event traces interacting with online learning modules *via* a combination of trace clustering and process mining. Event traces were first divided into groups similar in nature using agglomerative clustering, with similarity between traces determined based on a set of derived characteristics most reflective of students' SRL processes. We then generated causal nets for each cluster of traces *via* process mining and interpreted the underlying behavior and strategy of each causal net according to the COPES SRL framework. We then measured the frequency at which students adopted each causal net and assessed whether the adoption of different causal nets was associated with responses to the AGQ-R. By repeating the analysis for three sets of online learning modules assigned at the beginning, middle, and end of the semester, we examined how the frequency of each causal net changed over time, and how the change correlated with changes to the AGQ-R responses. Results have implications for measuring the temporal nature of SRL during online learning, as well as the factors impacting the use of SRL processes in an online physics course. Results also provide guidance for developing online instructional materials that foster effective SRL for students with different motivational profiles.

**Keywords: achievement goal orientation, online learning modules, process mining, self-regulated learning, trace clustering**

## INTRODUCTION

Self-regulated learning (SRL) behaviors are an essential component of post-secondary students' academic success, especially in courses covering complex topics like physics and calculus. Incoming undergraduates often transition from high school into large, blended learning environments that may provide reduced direct instruction and fewer opportunities for students to engage with instructors. These differences require learners to navigate their course work with increased independence, taking a more active role in their own instruction (Schunk and Zimmerman, 2011). Without the external supports traditionally provided in high school classrooms, post-secondary learners must independently self-regulate throughout their coursework by planning how they will complete assignments, setting goals for their learning within the course, metacognitively monitoring their performance, and reflecting on their academic outcomes (Winne and Hadwin, 1998, 2008; Zimmerman, 2013; Winne, 2018). Learners must continually repeat these processes throughout the semester, adapting their SRL behaviors in response to changing internal (e.g., motivation) and external (e.g., increased use of technology-driven instructional tools) factors as they navigate required academic tasks (Winne and Hadwin, 1998, 2008). Students who engage in these behaviors generally exhibit positive academic outcomes; however, many students do not inherently possess effective SRL skills (Winne and Hadwin, 2008; Winne and Azevedo, 2014), which may negatively impact their ability to master the required academic content. For this reason, it is important to investigate students' SRL behaviors and how they unfold over time, as well as how those behaviors are impacted by shifting factors like course difficulty and students' own motivation.

There are several data channels that can be used to measure SRL during learning. This includes (but is not limited to): (1) log files of students' clickstream actions implemented during learning (e.g., mouse clicks to make metacognitive judgments, keyboard entries demonstrating note taking, or student learning analytics of course navigation behaviors; Ochoa and Wise, 2021; Taub et al., 2021), (2) self-reports gauging students' perceived use of strategies (e.g., MSLQ; Pintrich et al., 1991, SRSI-TRS (Self-Regulation Strategy Inventory-Teacher Rating Scale); Cleary and Kitsantas, 2017), (3) eye tracking to capture visual attention on different elements of a user interface (e.g., inspecting texts and diagrams or other areas of interest; Catrysse et al., 2018; Taub and Azevedo, 2019; Lallé et al., 2021), (4) concurrent think-aloud protocols to record students' verbalizations (e.g., utterances of a judgment of learning or feeling of confusion; Greene and Azevedo, 2009; Greene et al., 2018; Engelmann et al., 2021), or (5) videos of facial expressions of emotional states to capture the impact of emotions on learning processes (e.g., emotion variability during phases of SRL or impact of emotions on the use of cognitive and metacognitive processes; Li et al., 2021; Taub et al., 2021).

As outlined in Azevedo and Taub (2020), there are advantages and disadvantages for collecting each type of data to examine SRL (see Azevedo and Taub, 2020). Since our paper focuses on trace data, our remaining review will focus on considerations related to using both clickstream data and self-report measures to investigate learners' SRL behaviors and related contextual factors in online learning settings. There are several strengths for log files; these data are a record of all student actions during learning that are automatically collected *and* timestamped by a system (such as an online learning environment). We can also determine sequences of actions that are time- or event-based. Finally, and arguably most importantly, they are easy to understand and analyze. However, log files require a level of researcher inference making to interpret what behaviors students are engaging in (e.g., are actions indicative of making a plan or metacognitive judgment?) when using these data. Therefore, including screen recordings would provide more contextual information of what elements were on screen during these actions. In contrast, self-reports are a direct measure of student perceptions, thereby not requiring researchers to make inferences of students' intentions when filling out surveys. However, using self-reports relies on student perceptions as opposed to their behaviors, leaving researchers unaware if students are accurately reporting their actions or beliefs due to possible experimenter bias or a lack of student awareness of behaviors. By utilizing the two data channels (e.g., trace data and self-report measures), researchers interested in investigating SRL behaviors can generate a richer picture of learners' behaviors within online environments, merging learners' perceptions and their recorded actions in a complementary manner that stands to mitigate some of these issues.

Recent attention to SRL processes within the learning analytics (LA) community has provided new methods with which to identify real-time SRL behaviors using the aforementioned data channels. Clickstream data (i.e., log files) generated from students' interactions within blended and online learning environments have gained popularity in this area as a non-intrusive way to capture extensive amounts of granular data, providing the means with which to investigate learners' behaviors as they unfold across a learning task (Siadaty et al., 2016; Winne, 2017; Saint et al., 2020a). Emerging methods like process mining, sequence mining, and temporal analytics offer new ways to utilize this data channel to capture and analyze students' SRL behaviors while highlighting the dynamic, contextualized nature of these processes. These methods allow for the interpretation of learners' real-time behaviors with increased granularity (Azevedo, 2014), tracking changes in self-regulatory behaviors more objectively than traditional self-report measures alone. Despite these benefits and the increased use of log-file data to capture and interpret learners' SRL behaviors, it is important to note limitations related to the use of this data channel in SRL research. Ongoing challenges in interpreting trace data include inconsistencies in the data produced across different learning management systems, a lack of consensus on what constitutes the optimal levels of data granularity to accurately interpret SRL behaviors, and the absence of a unified SRL theory or framework for this line of research (Winne, 2017). These challenges can be addressed through continued investigations that utilize theoretically grounded interpretations of trace data alongside additional data channels, such as self-report measures or concurrent think-aloud protocols.

As an unprecedented number of higher education students continue to be impacted by the COVID-19 pandemic and related shifts to online learning, researchers now have increased access to large amounts of clickstream data generated within online learning environments and a concurrent need to better understand the factors impacting learners' success in online course work (Zhang et al., 2021). Continued analysis of learners' clickstream data, in combination with additional data streams, such as self-report measures, can provide SRL and LA researchers with a deeper understanding of learners' behaviors when engaging with online content, the contextual factors that may impact those behaviors throughout the course, how those elements work to change students' SRL processes over time, and the resulting academic outcomes, providing needed guidance for the ongoing development of online and blended learning environments (Marzouk et al., 2016; Winne, 2017).

While existing studies have analyzed the occurrence of micro and macro SRL processes in online learning environments (Siadaty et al., 2016; Saint et al., 2020b; Fan et al., 2021), more research is needed to highlight the dynamic nature of these behaviors, including how learners' SRL strategies are impacted by temporal changes in internal and external conditions, such as course content difficulty and individual motivation. It can be assumed that successful SRL in online courses requires students to continuously (and often independently) judge and adapt their cognition and metacognition in accordance with shifting internal and external conditions (Winne and Hadwin, 2008), an added component of SRL that makes these processes particularly challenging for post-secondary students who do not possess effective self-regulation skills. By revealing the temporal changes in learners' SRL behaviors through analysis of clickstream data through lenses provided by theories, such as COPES model of Winne and Hadwin (1998, 2008) and the 2×2 achievement goal framework (Elliot and McGregor, 2001), researchers can gain significant insight into how students dynamically adapt their SRL strategies in response to changing contextual conditions, and how their processes unfold across an entire semester.

Building upon existing LA SRL research, this study utilized a combination of hierarchical clustering, process mining, and sequence mining techniques to analyze students' clickstream data and investigate how learners' SRL behaviors temporally unfolded throughout a semester-long blended learning physics course. Furthermore, this study interprets these behaviors through the lens provided by COPES model of Winne and Hadwin (1998, 2008), which allows for the examination of relationships between learners' SRL behaviors and changes in external and internal conditions, highlighting the multifaceted nature of learners' strategy use within a large post-secondary STEM course. The results of this study provide insight into the measurement and analysis of temporal SRL behaviors, as well as the relationship between those behaviors and additional relevant conditions, such as learners' achievement motivation profiles and academic outcomes.

## Theoretical Frameworks

Given the many factors (both internal and external) that stand to impact learners' behaviors in online and blended learning environments over time, it is important to consider SRL behaviors as they relate to additional conditions, such as affective, metacognitive, and motivational processes (Azevedo and Taub, 2020). For this reason, we utilize the COPES model of SRL which considers both the multifaceted and temporal nature of SRL behaviors (Winne and Hadwin, 2008). In addition, we investigated the impact of learners' reported motivation on SRL behaviors (Cleary and Kitsantas, 2017) through the lens of 2×2 achievement goal orientation framework of Elliot and McGregor (2001). In combining these frameworks, we aim to highlight the dynamic, interwoven nature of SRL behaviors and motivation.

### Winne and Hadwin COPES Model

In this study, COPES model of Winne and Hadwin (1998, 2008) was used to interpret student clickstream data due to the model's focus on the impact additional factors, such as motivation, have on learners' SRL behaviors over time. The COPES model (Winne and Hadwin, 2008) describes SRL as a series of events that unfold over time, an important distinction for the temporal analysis of students' clickstream event traces produced while learning within dynamic contexts like online learning environments. The COPES model posits four phases of SRL in which self-regulating students are actively and repeatedly generating perceptions of an academic task (Phase 1), defining goals and plans related to the completion of that task (Phase 2), enacting planned study tactics (Phase 3), and adapting their plans and future goals based on metacognitive judgments of how well their operations and products aligned with their goals (Phase 4). Within each of these phases, the researchers further describe features related to how a student COPES with a task, an acronym that illustrates how the *Conditions* (e.g., internal and external contexts for students' work), *Operations* (e.g., cognitive processes enacted by students), *Products* (results of the enacted operations), *Evaluations* (e.g., information based on the created products), and *Standards* (e.g., criteria used to monitor products) of a given task further influence students' learning and enacted SRL behaviors. Within the context of self-paced blended and online learning environments, this means that a student's SRL behaviors are continually impacted by a range of internal and external factors, including task conditions like low prior content knowledge or evaluations of products like quiz scores (Winne and Hadwin, 2008). As learners in self-paced blended and online learning environments independently navigate these recursive phases and related judgments of their learning over time, it is important to consider how the additional impact of changing internal and external factors, such as motivation, work to shape students' SRL behaviors.

### Achievement Goal Orientation

The COPES model further emphasizes the impact of internal and external factors, such as content difficulty and motivation, on students' behaviors during each of the four phases of SRL (Winne and Hadwin, 2008). Through this lens, contextual factors like achievement motivation can provide added insight when investigating learners' SRL behaviors. The 2×2 achievement goal orientation framework has been widely used to examine learners' motivation across academic contexts and provides a complementary theoretical perspective with which to further consider the relationship between learners' motivation and their enacted SRL behaviors (Kaplan and Maehr, 2007; Elliot et al., 2011; Cleary and Kitsantas, 2017). The framework defines four distinct achievement goal orientations that differ in definition (mastery and performance) and valence (approach and avoidance), each with a unique set of antecedents and outcomes (Elliot and McGregor, 2001). In this framework, learners who are mastery oriented are motivated by content mastery while performance-oriented learners are driven by peers' perceptions of their academic competence, with the added valence component of approach (positive) and avoidance (negative) further delineating differences in goal orientation (e.g., a student with a performance approach orientation is believed to be motivated by a desire to appear competent while someone with a performance avoidance orientation wants to avoid appearing incompetent). The resulting goal profiles [i.e., mastery approach (MAP), mastery avoidance (MAV), performance approach (PAP), and performance avoidance (PAV)] have been widely researched in a variety of academic settings, with approach-based goal orientations frequently linked to desired academic outcomes (Linnenbrink and Pintrich, 2002; Van Yperen et al., 2014) and focus on success (Elliot et al., 2011). The Achievement Goal Questionnaire-Revised (AGQ-R) is still frequently used to determine learners' self-reported goal orientations (Elliot and Murayama, 2008). The AGQ framework and its associated goal orientations have been used to examine relationships between learners' achievement motivation, SRL behaviors, and academic outcomes, but only recently have researchers begun to explore the temporal dynamics of these relationships.

In combining these two theoretical perspectives, we aim to examine how students' SRL behaviors unfolded throughout the online learning course as well as how those behaviors were impacted by external factors, such as learner motivation.

## Literature Review

There is a lot of research using multichannel multimodal data to examine SRL (Azevedo et al., 2018; Azevedo and Taub, 2020), despite some potential limitations (discussed above), that affords us the opportunity to investigate SRL processes and behaviors in a more dynamic way. Specifically, trace data or learning analytics can be used to capture student behavior throughout a semester during online learning (Winne, 2017). We focus the literature review of this paper on data and analyses investigating the changing nature of SRL as the goal of the current study was to contribute to this field of emerging research by using some established LAs methods, such as process mining. In addition, our paper also contributes to the field of SRL by examining the temporal nature of factors that impact SRL (Cleary and Kitsantas, 2017), as motivation (AGQ) is not typically examined more than once during a learning session.

### Temporality of SRL and AGQ

Historically, SRL research has relied on self-report measures to identify and examine learners' use of SRL processes within academic contexts, viewing SRL as a trait rather than an event that unfolds during learning (Azevedo, 2014; Winne, 2017). These measures are inherently subjective (respondents may not be conscious of the SRL strategies they use) and are often administered at a single time point within a study (e.g., after a student completes an academic activity), which may fail to capture the dynamic nature of learners' SRL processes. Recent shifts toward the use of multimodal data in SRL research have allowed for more detailed investigations of SRL, with current works using advanced data channels and analyses like multilevel modeling to highlight the dynamic, interrelated nature of learners' SRL behaviors (Taub et al., 2017; Winne, 2019; Li et al., 2020). The influence of these advances can be seen within current LA research using large-scale data sets to analyze SRL behaviors, with recent work considering the temporal dynamics of those students' processes (Saint et al., 2020b). However, continued investigation is needed to establish best practices for using temporal analytics to analyze SRL behaviors (Molenaar and Järvelä, 2014; Chen et al., 2018a).

While SRL research continues to benefit from the inclusion of more fine-grained data channels, investigation of learners' achievement motivation is still largely reliant on data generated from single administration self-report measures (Urdan and Kaplan, 2020). Despite this, the dynamic nature of motivation has prompted researchers to consider the stability of learners' achievement goal orientation, examining if and how learners' achievement motivation changes over time (Senko and Harackiewicz, 2005; Fryer and Elliot, 2007; Muis and Edwards, 2009). Fryer and Elliot (2007) argue the adaptive nature of self-regulation, as well as changing internal and external antecedents (e.g., classroom environment and content difficulty), are equally as likely to result in goal stability or change in learners' achievement goal endorsements, despite the literature's focus on achievement goals as a fixed personal state. Through this lens, recent studies investigating changes in learners' achievement goals have used repeated self-report administrations to investigate longitudinal trends in learners' goal endorsement (Lee et al., 2017; Tuominen et al., 2020). The temporal nature of these studies stands to complement existing analyses of unfolding SRL behaviors, allowing for the incorporation of contextual factors like learner motivation.

### Analyzing Students' SRL Behavior Using Process and Sequence Mining

Multiple recent studies have investigated students' use of SRL strategies by analyzing clickstream data using techniques, such as sequence mining, process mining, and hierarchical clustering. For example, process mining has been used across multiple studies (Siadaty et al., 2016; Maldonado-Mahauad et al., 2018; Matcha et al., 2019; Fan et al., 2021), to identify learners' interaction strategies, learning tactics, indicators of engagement in SRL processes, and to develop SRL process maps from micro-level SRL processes as a means of comparing learners' behaviors in response to varying interventions and course structures. Sonnenberg and Bannert (2019) also utilized conformational checking (a process mining technique) to identify the stability of metacognitive prompts of SRL behavior. Most recently, Saint et al. (2020b) proposed the Trace-SRL framework for analyzing clickstream data by multiple levels of trace clustering and process mining.

Within many of the existing studies, the clickstream data being analyzed were collected from online learning environments that provide a rich variety of event traces, ranging from the number of problem attempts to how frequently learners access dashboards. Students also had relatively high levels of freedom to access different course components in their preferred order. Under those conditions, students' different SRL strategies are likely to produce event traces with distinct event types and event orders, which makes it easier for both the interpretation and the clustering of event traces.

However, clickstream data from other popular online learning systems are often markedly more restrictive, containing fewer event types and less variability in event orders. For example, homework platforms or intelligent tutoring systems may require students to complete assignments in a pre-determined order that is pedagogically beneficial. In addition, certain events, such as checking the dashboard, may not be recorded in the data set or are stored in a different data set that may not be readily available to the researcher.

In those cases, a different analysis scheme is needed to extract information about students' SRL behaviors from clickstream data that contain a much smaller set of event types and possible event orders.

## Current Study

The goal of the current study was to investigate students' SRL behaviors and self-reported achievement goals, as well as how each of them changes throughout the semester in a college-level physics course that has students complete online learning modules (OLM). We argue that based on the COPES model of SRL (Winne and Hadwin, 1998, 2008), SRL is a cyclical process that consists of a series of events that temporally unfold during learning and studying. Therefore, students will demonstrate different self-regulatory events, such as motivational processes, during learning with the online learning modules over a period of time under changing external conditions.

### Research Questions

To address if and how students' SRL and motivational processes changed throughout the semester, we posed the following research questions for our study:

1. What are the different types of SRL processes students employ in a self-paced online learning environment?
2. To what extent do students' SRL behaviors and AGQ responses change over the semester?
3. How do changes in observed SRL behavior and AGQ responses relate to students' learning outcome?

### Mastery-Based Online Learning Modules

The current study examines students' SRL behavior in a mastery-based OLM system, designed based on principles of mastery-learning (Bloom, 1968; Kulik et al., 1974; Gutmann et al., 2018) and deliberate practice (Ericsson et al., 1993, 2009).

An OLM is a standalone online learning unit that combines assessment, instruction, and practice, centered around one or two basic concepts, or developing the skills to solve one kind of problem. Each OLM (see **Figure 1**) is designed to be completed by the average student in about 5–30 min, depending on their incoming knowledge. Each OLM consists of an assessment component (AC), which tests students' content mastery in 1–2 questions, and an instructional component (IC) with instructional text and practice problems on the topic. Upon accessing a module, students are shown the learning objectives of the current module and are required to make an initial attempt on the AC before being allowed to access the IC. If the first attempt fails, students can make additional attempts either immediately after the first or after interacting with the IC. This design is motivated by both the "mastery-learning" format that allows students who are already familiar with the content to proceed quickly to the next assignment, and by the concept of "preparation for future learning" intending to improve students' learning from the IC by exposing them to the questions first. It also provides better interpretability of student log data (Chen et al., 2018b) and allows for measurement knowledge transfer between consecutive modules (Whitcomb et al., 2018, 2021; Chen et al., 2019).

A number of OLM modules form an OLM sequence on a more general topic typically covered over a period of 1 or 2 weeks in the course. Students are required to pass the AC or use up all attempts on one OLM before moving onto the next in the same sequence. A typical OLM sequence consists of 5–12 modules that are assigned as self-study homework for students to complete over a period of 1–2 weeks.

### Multilevel Hierarchical Clustering

In order to observe the changes in students' SRL strategy from log data collected from the OLM platform, we developed a novel analysis scheme involving three consecutive clustering operations on three consecutive levels of data granularity:

#### *Level I*

Clustering of individual events: Prior research on OLMs (Chen et al., 2020; Garrido et al., 2020) has shown that an abnormally

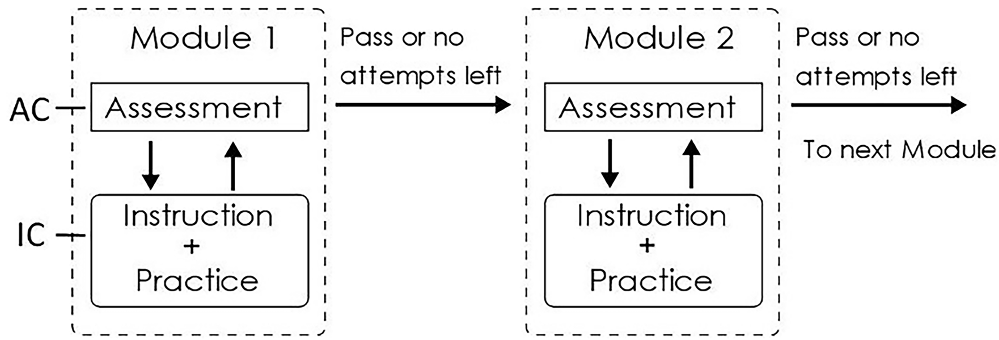


**FIGURE 1** | Overview of online learning modules (OLMs).

short assessment attempt is likely the result of random guessing or answer copying, perhaps indicative of the student adopting a performance avoidance goal. Therefore, the main goal of event-level clustering was to distinguish between abnormally short guessing attempts and normal problem-solving attempts. This was achieved by fitting the log distribution of attempt duration on each AC with finite mixture modeling (FMM), which can be seen as clustering based on a single continuous variable (event duration), following a similar procedure outlined in (Chen et al., 2020). The same method was also applied to identify and exclude very short study events which likely originated from a student clicking through the instructional contents without meaningfully interacting with them.

#### *Level II*

Clustering event traces on a single module: To identify the main strategies that students adopt when interacting with individual OLM modules, we partitioned students' event traces on a single module into multiple "module-level clusters" by hierarchical agglomerative clustering. Different from most existing trace clustering methods that use the "edit distance" as a metric for calculating the dissimilarity between event traces, the current analysis calculates the dissimilarity based on a set of derived features. Those features were selected according to a model of student interaction with OLMs based on the COPES framework of SRL. For each resulting module-level cluster, a causal net was generated using heuristic process mining for 80% of most frequent traces for visual interpretation of the main strategy.

#### *Level III*

Clustering of module-level cluster traces for entire OLM sequences: As a result of module-level clustering, students' interaction with an entire OLM sequence can be captured as a trace of multiple module-level cluster memberships. We can then partition those traces into sequence-level clusters by conducting hierarchical clustering based on the optimal matching distance between each pair of traces. Using the optimal matching distance preserves the information on the temporal order of the module-level cluster memberships, which enabled us to investigate when students change their interaction strategy in response to change in content difficulty or other factors.

## MATERIALS AND METHODS

Data used in this study were collected from a calculus-based university introductory physics course taught in the Fall 2020 semester. A total of 251 students (27% female) were initially enrolled in the class. The course was taught asynchronously using pre-recorded lecture videos as the main method for content delivery during the COVID pandemic. Students and instructors interacted *via* messages, posts, and video conferences (for more information of the course design[1]). Students were required to take a total of seven 20-min quizzes during the semester.

A total of 70 OLMs consisting of nine sequences were assigned as online homework and self-study material. Each OLM sequence was assigned for students to complete over 1–2 weeks. Students could earn extra credits by completing some OLMs earlier than the due date, as explained in more detail in Felker and Chen (2020).

### Data Collection

We collected data from the following channels: (1) self-reported achievement goals *via* the Achievement Goals Questionnaire-Revised, and (2) event data as students interacted with the OLM. Students were given the AGQ survey as an optional activity in the course with no extra credit nor any other incentives associated with completing them. Students enrolled in the course were presented with an informed consent at the beginning of the course, which explained that their interaction with the course, including surveys, will be used for research purposes, and their identity would not be revealed in the research.

#### Achievement Goal Questionnaire-Revised

The AGQ-R was administered at three different points throughout the course. The 12-item questionnaire measures students' achievement goals through four subscales, with each subscale representing one of four achievement goal orientations (see section "Achievement Goal Orientation"; Elliot and McGregor, 2001). Students were asked to rate their agreement (from 1 = "*strongly disagree*" to 5 = "*strongly agree*") to each of the statements as a means of measuring their goals and expectations as they related

[1]https://www.aaas-iuse.org/resource/course-design/

to the course. Confirmatory factor analyses support the continued use of the AGQ-R to measure achievement goal orientation within academic contexts [$\chi^2(1.63) = 78.32$, $p < 0.01$, CFI = 0.99, IFI = 0.99, RMSEA = 0.053; Elliot and Murayama, 2008]. Additionally, all four subscales were found to have high levels of internal consistency [mastery approach (=0.84), mastery avoidance (=0.88), performance approach (=0.92), performance avoidance (=0.94); Elliot and Murayama, 2008].

Each AGQ-R administration coincided with one of the three course sequences, resulting in three sets of questionnaire responses that represented students' achievement goal orientations at roughly the beginning, middle, and end of the term. Student response rates declined slightly from the beginning of the term ($n = 248$) to midterm ($n = 238$) and fell dramatically by the end of the course ($n = 40$). For this reason, only scores from the first and second survey administration were included in the analyses.

### Online Environment and Event Data

The OLM modules were created and hosted on Obojobo Learning Objects Platform, an open-source online learning platform developed by the Center for Distributed Learning at the University of Central Florida. In the current iteration, the assessment component of each OLM contains 1–2 multiple choice problems and permits a maximum of five attempts. The first three attempts are sets of isomorphic problems assessing the same content knowledge with different surface features or numbers. On the fourth and fifth attempts, students are presented with the same problems in the first and second attempts, respectively, and are awarded 90% of credit. The instructional component of each module contains a variety of learning resources including text, figures, videos, and practice problems. Each OLM sequence contains between 3 and 12 OLMs, which students must complete in the order given, with completion defined as either passing the assessment or using up all five attempts. Each OLM sequence is assigned over a period of 1 or 2 weeks depending on the length of the sequence. Readers can access example OLMs at https://canvas.instructure.com/courses/1726856.

For the current study, we extracted student event data from clickstream log files from three OLM sequences: Sequence 1: Motion in 1 Dimension, Sequence 6: Mechanical Energy, and Sequence 9: Angular Momentum. The three sequences were assigned to students during week 2, week 7 and 8, and week 14 of the semester, respectively. They consist of a total of 26 modules, and the resulting data set contains a total of 5,960 traces. In addition, all records after the first passing attempt or after the last attempt were truncated for simplicity of analysis, since there were significantly fewer records after passing or using up all attempts, and most of those events took place before an exam (Chen et al., 2020).

## Data Coding and Scoring

### AGQ Change Scores

Changes in students' aggregate scores for each subscale across the first and second administration of the AGQ-R were calculated using the reliable change index (RCI; Jacobson and Truax, 1991; Fryer and Elliot, 2007). The RCI provides a standardized method for categorizing participants by the amount of change in their scores across two test administrations given at separate time points. The RCI formula below was used to compute an RCI score for each of the four achievement goal profiles, allowing us to examine the level of change in students' AGQ-R scores between the beginning of the semester ($x_1$) and the middle of the semester ($x_2$), resulting in four RCI scores that correspond with the four established achievement goal constructs for each participant (Jacobson and Truax, 1991; Elliot and McGregor, 2001).

$$RC = \frac{x_2 - x_1}{S_{diff}}$$

The standard error of difference between students' AGQ-R responses at the beginning and middle of the term ($S_{\text{diff}}$) was calculated using the method discussed by Jacobson and Truax (1991).

$$S_{diff} = \sqrt{2\left(S_E\right)^2}$$

Resulting RCI scores allowed for the categorization of students' change in goal endorsement over time for each of the four goal orientation profiles [MAP ($M = -0.4$, SD = 0.99), MAV ($M = 0.211$, SD = 0.91), PAP ($M = -0.03$, SD = 1.01), PAV ($M = -0.15$, SD = 0.96)].

### Log File Event Processing

Students' clickstream log data collected from the Obojobo learning platform was first processed into attempt events and study events. An attempt event starts when the student enters the assessment page of the module and ends when the student clicks the submit button on the assessment page. During this period, the student is unable to navigate to any other pages in the current module or to other modules. The duration of the attempt event is defined as the time between those two clicks minus the duration of: (1) when the browser window is either closed or minimized, or when another window is in focus and (2) any non-active duration beyond 10 min. A "Pass" event is added after an attempt event only if the student correctly answers all questions in the assessment on that given attempt. A study event starts when the student clicks on any page in the instructional component of the module and ends when the student clicks on the last record before a new attempt event is initiated. In other words, a study event includes all the interaction with the instructional component between two attempt events. The duration of the study event is calculated as the sum of all the time spent interacting with each instructional page, minus the duration of inactive periods (explained above). In the current analysis, a small fraction of events that took place after the "Pass" event were excluded from the analysis.

### Event-Level Trace Clustering

At this stage, abnormally short attempts on the assessment component (AC) of a given OLM were distinguished from normal AC attempts by fitting the log duration distribution of all attempts on a single module using FMM. FMM is a model-based clustering algorithm that divides a population into subgroups according to one or more observable characteristics by fitting the distribution of characteristics with a finite mixture of normal or skewed probability distributions. When two or more distinct problem-solving behaviors are present, the log attempt duration distribution can be fitted with the sum of two or more distributions, with the shortest distribution corresponding to abnormally short attempts. In the current study, we fit the log duration of each assessment attempt using either normal or skewed distribution models using the R package mixsmsn (Prates and Cabral, 2009), following the fitting procedure described in detail in the appendix of a previous study (Chen et al., 2020). In the case when a single component distributed was the best fit for the duration, the cutoff was set as either 2 standard deviations below the mean duration, or 15 s, whichever was longer (Guthrie et al., 2020).

The main reason for using a different cutoff for different problems, rather than using a single, uniform cutoff is because certain conceptual problems require significantly less time to solve than numerical calculation problems. In one previous study (Chen et al., 2020) it was found that the mean duration for answering certain conceptual problems can be as short as 30 s. Using an individualized cutoff avoids accidentally categorizing half of the class as making a "short" attempt on those conceptual problems. On the other hand, certain numerical problems also have longer and more sophisticated problem text, and students who are making a decision to guess or answer copy after reading the text might also take longer. On those problems, short attempts may also include students who solved the problem using incorrect methods that are significantly faster than the correct method.

We also conducted mixture-model fitting of the combined log duration of all study events from all modules in the data set to determine the cutoff time between normal study events and very short study events that were likely the result of students clicking through the instructional pages. Unlike short assessment attempts, which could include cases in which the students read the problem body, the very short study events identified using this method predominantly consist of students who clicked through the pages without meaningfully interacting with the materials. Since those study events are content-independent, the fitting is conducted on all study events, which could amplify the frequency of content-independent actions. Note that the current analysis methods do not distinguish between short interaction and extensive interaction with learning materials. This is because short interactions could result from students actively searching for information that they need, which reflects high levels of self-regulation.

## Module-Level Clustering

As a result of the event-level clustering, each student's interaction with a given OLM was represented by a trace of either normal or short attempt events and study events that are longer than the minimum duration. Study events shorter than the minimum duration are excluded since the majority of those are "click-through" events with no meaningful interaction with the material.

Each attempt is treated as a separate event and labeled as "Attempt_N" with N being the attempt number. Short attempts are labeled as "Attempt_N_S" to distinguish from normal attempts. For example, a trace of {Attempt_1_S, Study, Attempt_2, Attempt_3} indicates that the student took three attempts on the OLM, with the first attempt being a short attempt, and took a study session (longer than the minimum cutoff) between attempts 1 and 2. Hierarchical agglomerative clustering using Ward's method was performed *via* the R package cluster (Maechler et al., 2021) on traces from all three selected OLM sequences, with each trace treated as a data entry. The distance metric that determines the distance between any two traces, which is central to the clustering algorithm, was determined by a set of features for each trace selected based on the COPES SRL framework of Winne and Hadwin (1998, 2008), explained below.

A student's interaction process with a single OLM can be summarized in the flowchart shown in **Figure 2**. For each OLM, students start with the mandatory first attempt on the assessment. If the attempt fails, then the student can either study the instructional material or immediately make another attempt, until they either successfully pass the assessment or use up all five attempts. During the process, students are presented with two tasks: a required task, which is to answer the problem in the assessment component, and an optional task, which is to study the learning material. Students needed to make two types of decisions: (1) whether to seriously engage in problem-solving on a given attempt (resulting in a normal length attempt) or to make a guess (usually resulting in a short attempt) and (2) whether to engage with the study material if the previous attempt fails.

Using the four recursive phases of SRL presented in COPES model of Winne and Hadwin (1998, 2008) we propose six features that capture students' interactions with the OLMs and their associated SRL processes:

1. Total Number of Assessment Attempts (nA): The total number of assessment attempts reflects the quality of a student's enacted plan of action on both problem-solving tasks and studying tasks. In general, passing on fewer attempts indicated students entered with high subject matter knowledge, engaged in successful self-instruction, or both.
2. Number of Attempts Before Study (nY): When or whether to access study materials can be influenced by learners' planning or adaptation. Students who access study materials are likely generating reflective self-evaluations and continually engaging in planning based on their judgments of conditions like existing content knowledge or previous assessment scores. Continued assessment attempts and subsequent access of study materials may indicate a student has reflected on prior performance and is engaging in setting new goals and planning based upon a reassessment of their strategy use following failed assessment attempts. In the current data, 90% of study events took place after a first attempt.
3. Fraction of Short Attempts Among All Attempts (fS): Since most short attempts likely originate from either guessing

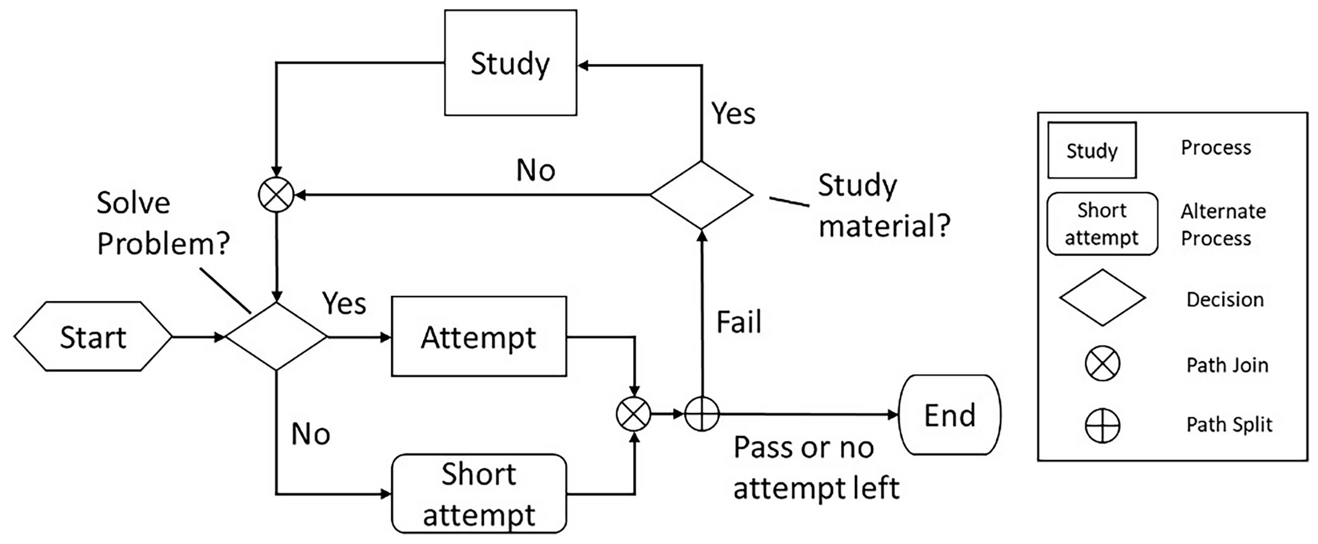


**FIGURE 2** | Interaction process within a single OLM.

or answer copying behaviors, a higher fraction of short attempts signifies limited planning and enacting lower quality study strategies. Many short attempts may indicate low prior knowledge, low self-efficacy, low effort, or limited execution strategies like time management.

4. Is the First Attempt Short (1S): The first attempt is of particular significance as it reflects a strategic choice based upon students' perception of the task, with the outcome of students' task analysis determining the amount of time and effort they will dedicate to the mandatory first attempt before accessing associated learning materials. A short first attempt may signal that a student plans to limit the time and energy they devote to the task by guessing. This strategy enactment could also indicate that a student is adapting their strategy use based on previous modules and their perceived self-efficacy within the course. A student who experienced prior frustrations may experience low content self-efficacy, resulting in limited energy or motivation to engage with the course and a short first attempt for subsequent modules. On the other hand, making a short first attempt may indicate the student is aware of their low prior knowledge and wants to access the material as quickly as possible because they know they need to learn the content before answering any quiz questions.
5. Is the Last Attempt Short (lS): The last attempt is also of particular significance since it is the passing attempt in all event traces, except for those with five failed attempts. A short final passing attempt may signify limited monitoring during the enactment, with students struggling to effectively activate relevant task strategies during content learning and problem-solving tasks. This feature may also indicate adaptation based on learners' negative interactions with prior assessments modules in the course, resulting in limited motivation to devote significant time to the final assessment attempt.
6. Did the Student Abort the Module (Ab): This feature represents a small number (22 out of 5,960) of event traces that ended on a failed attempt prior to assessment attempt 5. Those traces exist either because the student aborted the module, or because of corrupted data logs. This behavior may indicate that a student's deliberation produced a negative self-evaluation in which they saw no means of successfully completing the module, leading them to adapt by discarding the learning task prior to a successful assessment attempt.

Since features 1, 2, and 3 are numeric while features 4, 5, and 6 are binary, the distance metric between two event traces is computed using the Gower dissimilarity coefficient. The Gower dissimilarity coefficient allows for the assignments of different weights to different features. We tested four different sets of feature weights. The first three sets emphasize the task perception, goal setting and planning, enactment, and adaptation phases respectively, while the last set puts equal weight on all features.

The best cluster structure, as judged by the maximum average silhouette value described below, was produced by the set of feature weights emphasizing the task perception and goal setting and planning phases, where the weights for nA and lS are set to 0.5 and all other weights set to 1.0.

### *Selecting the Optimal Number of Clusters*

Since agglomerative clustering produces a tree structure of all possible numbers of clusters, we choose to determine the optimum number of module-level clusters based on the average silhouette value of each cluster. In short, the average silhouette value is a measure of the ratio of intra- and inter-cluster variability which is described by Rousseeuw (1987). A larger silhouette value indicates tighter cluster structure. Theoretically, the optimal number of clusters is chosen to maximize the average silhouette, as it indicates that the variability within clusters is minimized compared to the variability between clusters, thus being well defined.

However, in practice, the current data set of 5,960 traces contains only 53 unique traces. As a result, the average silhouette will always reach the global maximum at or near 53 clusters, as the within cluster variability approaches zero. Therefore, we instead chose the number of clusters according to the local average silhouette maximum under 10 clusters, since more than 10 clusters caused significant difficulties in the interpretation of observed clusters as the differences became trivial. Of all the four feature weights tested, the set that emphasized the forethought phase resulted in a local silhouette value maximum below 10 clusters.

To visualize the main characteristics of each identified module-level cluster, we generated causal nets on the most frequent 80% of traces, by applying the heuristic mining algorithm using the R package heuristicsmineR (Weijters and Ribeiro, 2011).

### Sequence-Level Clustering

Since a student's event trace interacting with a single OLM is classified into one of several module-level clusters (see above), their interaction with an entire OLM sequence of $n$ modules was captured by a sequence-level trace of $n$ elements in the form of $\{m1, m2…mn\}$. Each element $m_1$ is represented by a number indicating the module-level cluster that the student's event trace on module $i$ belongs to. We performed hierarchical agglomerative trace clustering on the sequence-level traces for each of the three OLM sequences separately. The dissimilarity between two traces was calculated using the optimal matching distance *via* the TRATE method, as it takes into account the local ordering of states. Since each student contributes one trace per sequence to the data set, the sequence-level clusters reflect the strategy adopted by each individual student on a given module sequence.

The number of s-clusters for each sequence was determined by maximizing the average silhouette value between 2 and 10 clusters. In the case that the maximum average silhouette is two clusters, but a second maximum exists for a higher number of clusters, then the higher number of clusters is selected to display relatively rare but distinct strategies.

## RESULTS

### Research Question 1: What Are the Different Types of SRL Processes Students Employ in a Self-Paced Online Learning Environment?

For this research question, we first outline the results of event-level finite mixture modeling to distinguish between short and normal assessment attempts, followed by a description of student behavior clusters at the module-level and the sequence-level. Module-level clusters are behaviors students engaged in while completing an individual module within the course. Sequence-level clusters outline behaviors across multiple modules in the same OLM sequence.

### Event-Level FMM Fitting

Of the 26 modules included in this study, the log attempt duration distribution on the assessment component (AC) of eight of the modules was fitted with one component FMM, and the rest are all fitted with 2 or more component FMMs. For four modules, FMM determined the short vs. normal attempt cutoff to be less than 15 s and was adjusted to 15 s. The short vs. normal cutoffs of 16 modules were between 15 and 60 s, four modules were between 60 and 120 s, and two modules had cutoffs beyond 120 s. Of those two modules, visual examination of the distribution profile found one of the modules to be an artifact of overfitting, and the cutoff was adjusted to 35 s based on best estimates from a previous study on OLMs (Chen et al., 2020). In general, ACs of modules involving numerical calculation problems had longer cutoffs compared to those involving conceptual questions, indicating that the short attempts identified likely include "educated guesses" in which students make a guess after reading the problem, or students solve problems using fast, incorrect methods.

Applying the same FMM fitting method to the distribution of all study events determined the cutoff for abnormally short study event to be at 35 s. Therefore, all study events less than 35 s were deemed to be not authentically interacting with the learning materials and removed from the data set.

### Causal Nets for Module-Level Clusters

We applied heuristic miner, a process mining algorithm (Maechler et al., 2021) on 80% of the most frequent traces of each module-level cluster to capture the main patterns in student behavior through causal nets. Seven types of causal nets were generated, with the frequency distribution plotted in **Figure 3** (i.e., the percentage of each causal net represented in the data). As seen in the figure, the most dominant module-level cluster was cluster 1 (*normal first or second pass*), followed by clusters 2 (*attempt, study, attempt, pass*) and 4 (*short attempt and pass*). As such, although we did identify seven different causal nets, in the majority of cases, students' interaction data can be classified into module-level clusters (or causal nets) 1, 2, and 4.

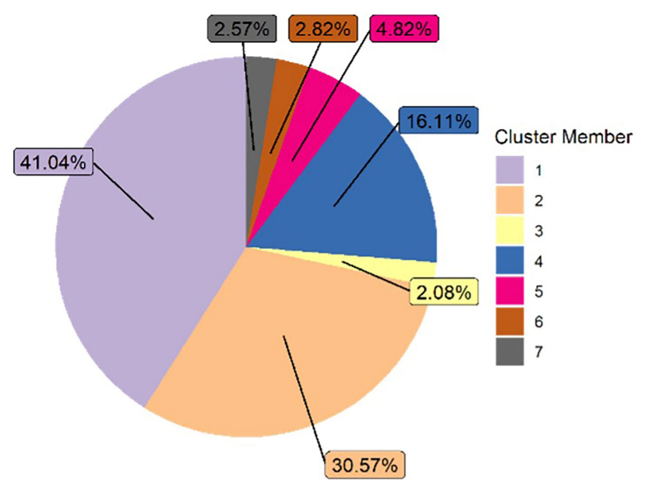


**FIGURE 3** | Distribution of causal nets.

### *Causal Net 1: Normal Attempts and Pass*

In this causal net, students demonstrated beginning the module and passing the quiz on either their first attempt without needing to access the instructional content or on their second attempt. Both types of attempts were normal, indicating students spent an adequate amount of time making these attempts. From a self-regulatory perspective, this can indicate these students were spending time activating their prior knowledge and self-assessing what they already knew about the topic. If they were able to do so effectively and had sufficient prior knowledge of the topic, this could have led to a correct response to the question, as demonstrated by the first successful attempt. If a student needed to make the second attempt, perhaps they did not pay close attention to or misunderstood the question. After spending more time reading through the question and activating more prior knowledge, they ultimately passed. The causal net (see **Figure 4A**) indicates there were at least 1,940 traces of passing on the first attempt and at least 255 traces of passing on the second attempt, with a total of at least 2,195 traces in this cluster.

### *Causal Net 2: Attempt, Study, Attempt, Pass*

In this causal net, most students made a normal failed attempt, followed by studying the course content (at least 1,422 traces), and then either passed the assessment on the second (at least 952 traces), third (at least 346 traces), or fourth (at least 136 traces) attempt. Some students were not able to pass by the fifth attempt. Students who passed on the third or fourth attempt did not return to studying after the failed second attempt; they simply took the quiz again and passed. Regardless of the attempt number, all attempts had "normal" attempt times, meaning students were taking the time to complete the assessment problems, perhaps paying special attention to reading and answering the questions. From an SRL perspective, contrary to the first causal net, these students may have attempted to activate their prior knowledge (as seen in the normal first attempt); however, they did not possess sufficient prior knowledge to pass the assessment, leading them to study the course material. For some students, this study event led to a successful attempt, while others were still unable to pass. Perhaps after reading, students engaged in a judgment of learning (asking if they felt they understood the content) and deemed they now understood the material. Some students made accurate judgments, however other students did not and continued to attempt the assessment without studying the material again. Students who continued to take the quiz might have still felt like they covered enough material, but felt they needed to focus more attention on the question (i.e., continued to make normal, as opposed to short attempts). After three or four attempts, some students did pass the quiz (at least 346 traces after attempt 3 and at least 136 traces after attempt four). There were at least 50 traces of making a fifth attempt, but not passing after this attempt. Therefore, these

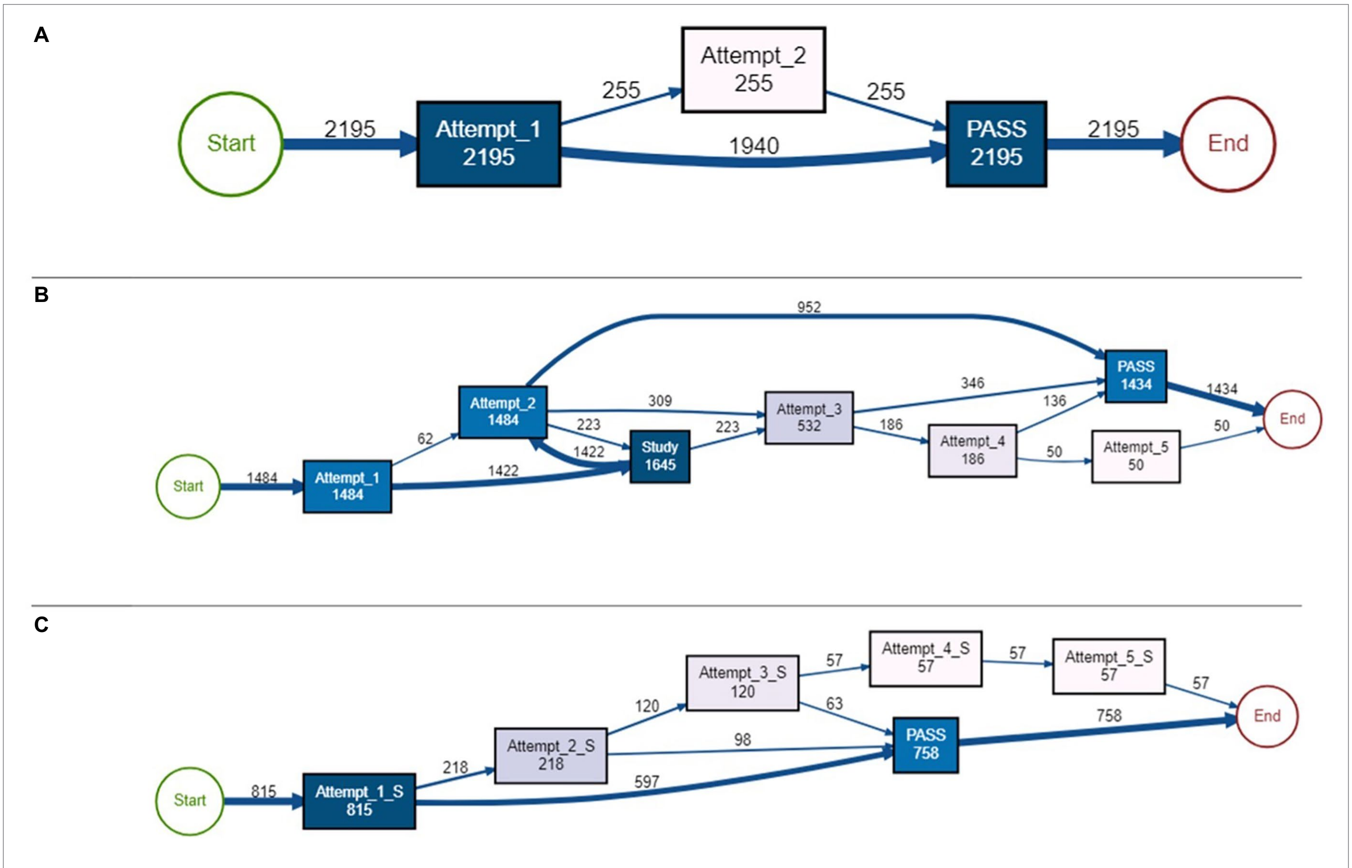


**FIGURE 4 |** Causal nets. **(A)** Normal first or second pass, Causal net 1; **(B)** attempt, study, attempt, pass, Causal net 2; **(C)** short attempt, pass, and Causal net 4.

students were perhaps demonstrating some regulatory behaviors, including planning by activating prior knowledge, making adaptations by accessing the content, then monitoring their performance, even though they did not always pass the assessment. Overall, there were at least 1,434 traces of passing behaviors and 50 traces of non-passing behaviors. See **Figure 4B** for the causal net of this cluster.

#### *Causal Net 4: Short Attempt and Pass*

This causal net can be described by the majority of students (at least 597 traces) passing after a short first attempt. Some students continued to make more attempts, but none of the attempts were normal (i.e., all attempts were short attempts). Traces in this cluster did not include any study attempts, nor did it include any normal attempts. From an SRL perspective, these traces could indicate students started the module with low self-efficacy and therefore planned from the onset to pass the assessment (by possibly guessing) as soon as they could. These traces do not demonstrate students were monitoring or making any adaptations to their plans because failed short attempts were always followed by another short attempt, therefore not demonstrating any change in behavior for the students who did not pass on their first attempt. Since the majority of traces in this cluster passed on the first short attempt, it is likely that a significant fraction of traces in this cluster resulted from students obtaining the answer from another source, rather than making a lucky guess. Out of at least 815 total traces in this causal net, there were at least 597 traces of passing after the first short attempt, 98 from the second short attempt, and 63 from the third short attempt. Students were not able to pass after making a failed fourth or fifth short attempt (at least 57 traces). **Figure 4C** outlines this causal net.

#### *Causal Net 3: Normal, Then Short Attempts*

This causal net demonstrates traces of behaviors with many short attempts after making at least one normal attempt. All students in this cluster (at least 109 traces) began completing the module by making a longer first attempt. Then, some students (at least 28 traces) made a long second attempt, with at least 11 traces followed by a normal third attempt, and at least seven traces followed that by a normal fourth attempt. However, none of these normal attempts led to passing the quiz. In this cluster, the only attempts that did lead to passing the quiz were short attempts. These short attempts were either made after the first failed attempt (at least 81 traces) or after three (at least 20 traces) or four (at least 27 traces) short attempts. There were at least 26 traces of failed fifth attempts as well. It is interesting to note that in this cluster, students did not make any study attempts, regardless of the attempt being normal or short. From an SRL perspective, these students seem to be demonstrating some planning or even monitoring behaviors, and the adaptations they were making were to shift from making normal attempts to short attempts to pass the assessment. Perhaps these students generated low self-efficacy in their ability to pass the assessment after their first failed attempt, and therefore did not feel exerting a substantial amount of effort would help them anyways, leading to more guessing-type behaviors. As such, perhaps these students were demonstrating self-regulation by making plans and adaptations to those plans; however, these might not have been the most desirable self-regulatory strategies needed to master the course material. Out of the at least 109 traces included in this cluster, at least 87 traces led to passing the assessment and at least 26 traces led to ending the module without passing. See **Figure 5A** for the overview of this causal net.

#### *Causal Net 5: Attempt, Study, Multiple Short Attempts*

This causal net can be categorized by students making both normal and short attempts after making study attempts. Out of at least 254 traces in this cluster, no one passed after the first attempt, which was a normal attempt. After this failed first attempt, most students (at least 240 traces) studied the material. Interestingly, traces following studying or making a normal second attempt did not lead to passing the module but making a short second attempt (at least 54 traces) did lead to passing. In fact, the only attempts that did lead to passing were short attempts, which occurred right after studying or after making more attempts (at least 22, 100, or 70 traces of passing after a third, fourth, or fifth short attempt, respectively). Making long attempts never led to passing the module. From an SRL perspective, it seems these students were monitoring their performance and were making adaptations (e.g., switching from normal to short attempts), but it seems like these students were not able to make accurate judgments of their understanding, demonstrated by making several attempts before passing the module, leading to changing to more guessing. Some students seemed to want to master the material, demonstrated by studying, but some students did not study at all, meaning they focused on their performance from the beginning. There were at least 233 traces of passing and only 21 traces of ending after a failed fifth attempt, so these students seemed persistent, and demonstrated self-regulation by adapting, but then possibly gave up and guessed until passing the module. **Figure 5B** demonstrates the traces in this cluster.

#### *Causal Net 6: Short Attempt, Study, Multiple Short Attempts*

This cluster net has similar characteristics as the above (**Figure 5B**), however in this cluster, all students (at least 142 traces) began with a first failed short attempt followed by studying the content. Only short attempts led to passing the module after two (at least 37 traces), three (at least 19 traces), four (at least 41 traces), or five (at least 45 traces) attempts. In this cluster, all students passed the assessment (at least 137 traces). From an SRL perspective, these students appear to be strategic planners. It is possible they quickly evaluated having low prior knowledge and therefore made a short attempt so they could proceed to studying the material they knew they needed to learn. After studying, most students judged their understanding of the material. Some students were accurate and passed the assessment. However, the majority made a third or fourth attempt before passing, demonstrating their content mastery was still not perfect, but instead of going

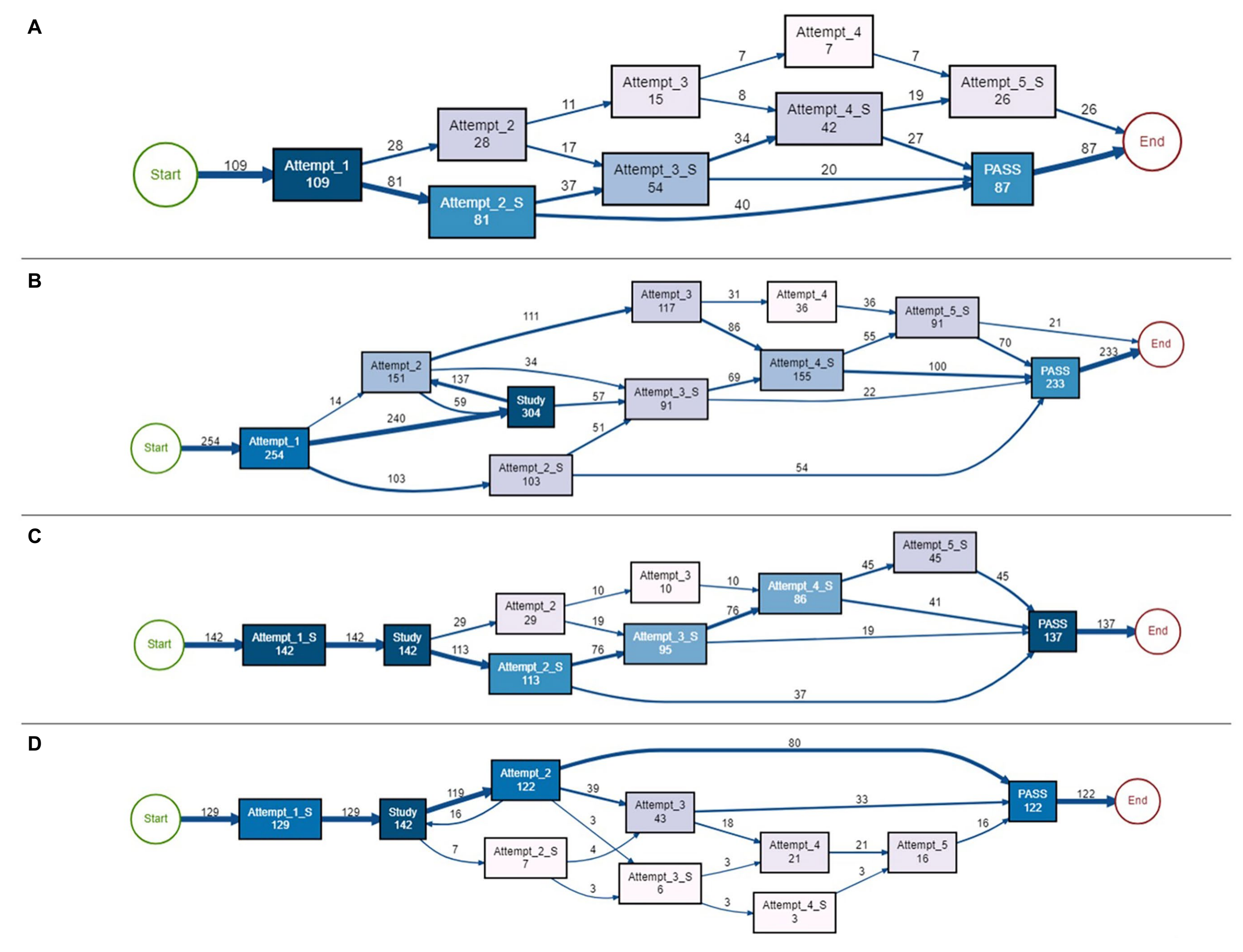


**FIGURE 5 |** Causal nets. **(A)** Normal, then short attempt, Causal net 3; **(B)** attempt, study, many short attempts, Causal net 5; **(C)** short attempt, study, many short attempts, Causal net 6; **(D)** short attempt, study, attempt, pass, and Causal net 7.

back to studying, they continued making short attempts. Perhaps these students started with the strategy to master the content, but after being unsuccessful, most of them adapted to trying to pass the assessment with minimal effort, like previous clusters. The causal net can be seen in **Figure 5C**.

### *Causal Net 7: Short Attempt, Study, Attempt, Pass*

This causal net is similar to the one seen in **Figure 5C** where all students started with a short failed first attempt followed by studying. However, what differentiates this one is that students only passed after making two (at least 80 traces), three (at least 33 traces), or five (at least 16) normal attempts. In addition, this is the only cluster that has some traces of students returning to the instructional materials with an earlier study event (at least 16 traces). The majority of traces in this cluster involve passing after making a second normal attempt, but all students did pass the module. From an SRL perspective, this suggests these students did assess needing to study the material and therefore made a short first attempt to get to the content quickly, and even if not successfully passing after the next attempt, students did spend time reading the question, suggesting they were monitoring their understanding of the question before answering. Even if they still did not pass, they did not give up and resort to guessing, at least before spending more time reading the question. For the few traces of short attempts, perhaps these students did try to guess, but adapted this strategy to spend more time reading the question to ensure they answered it correctly. In comparison to other causal nets, this cluster did not demonstrate successful quick guessing behaviors. See **Figure 5D** for the representation of this causal net.

In the remainder of this paper, we will refer to the seven module-level clusters as Causal Nets 1–7, to better distinguish from sequence-level clusters discussed below.

## Sequence-Level Clusters

After outlining the seven causal nets, we wanted to determine whether students engaged in these behaviors repeatedly and consistently throughout the OLM sequence or were only adopting certain strategies occasionally. We investigated this by hierarchical agglomeration clustering at the sequence level (i.e., sequence-level clusters).

The algorithm detected 5, 4, and 6 sequence-level clusters for sequences 1, 6, and 9 respectively, as visualized in **Figures 6–8**, which show the frequency of observing different module-level clusters (or causal nets) for each OLM using stacked bar charts, with the height of each bar representing the fraction that a given module-level cluster was observed for a given OLM. In all three figures, causal net 0 is used to indicate that the student did not interact with the given module. Based on the s-clusters, we determined that students did demonstrate a shift from engaging in behaviors for some modules at the beginning of the semester, to different behaviors 7 and 15 weeks into the semester. We will describe the dominant sequence-level clusters for each sequence below.

### *Sequence 1*

In the beginning of the semester, we see the majority (but not all) of the traces in the s-clusters contained causal nets 1 and 2. This indicates that most students made normal attempts, and/or also studied the material upon failing their first attempts. Sequence-level cluster 1-1 (see **Figure 6**) is dominated by m-cluster 1 (*normal attempts and passing*); however, there is more observation of causal net 2 (*attempt, study, attempt, pass*) in sequence-level clusters 1-2, 1-3, and 1-4, suggesting many students did engage in study behaviors at the beginning of the semester. Sequence-level cluster 1-5 predominantly contains causal net 4 (*short attempt and pass*), likely a guessing-type behavioral cluster. It is important to make note of this cluster because while it only had two students at the beginning of the semester, similar behavior patterns will become more dominant toward the end of the semester, as detailed later. In general, evidence from these clusters demonstrates the majority of students were engaging in effective self-regulatory processes at the beginning of the semester.

### *Sequence 6*

In the middle of the semester (7 weeks into the semester), we still observed some traces of causal nets 1 and 2; however, there

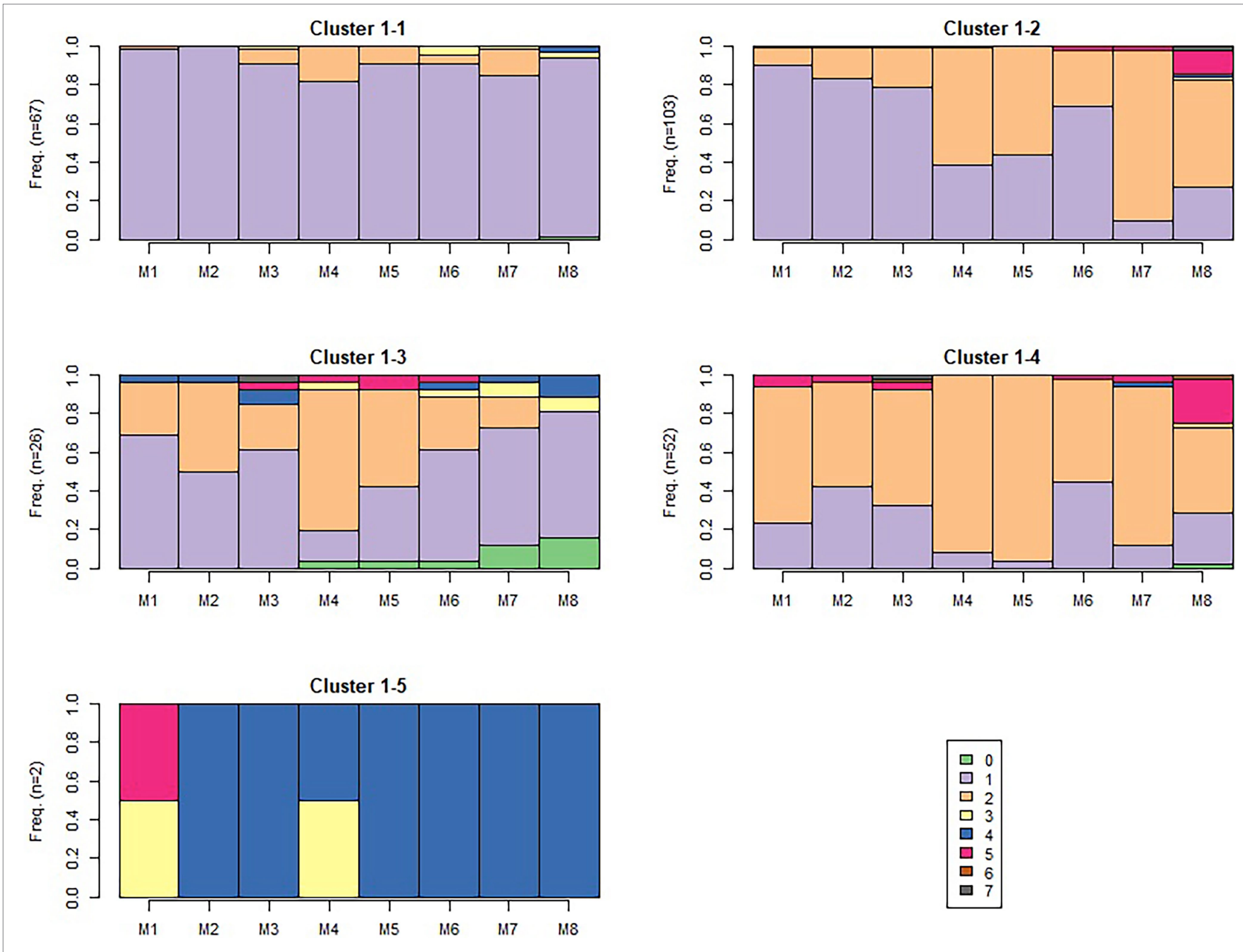


**FIGURE 6** | Sequence 1 sequence-level clusters. The number of students in each s-cluster is shown on the left of each figure.

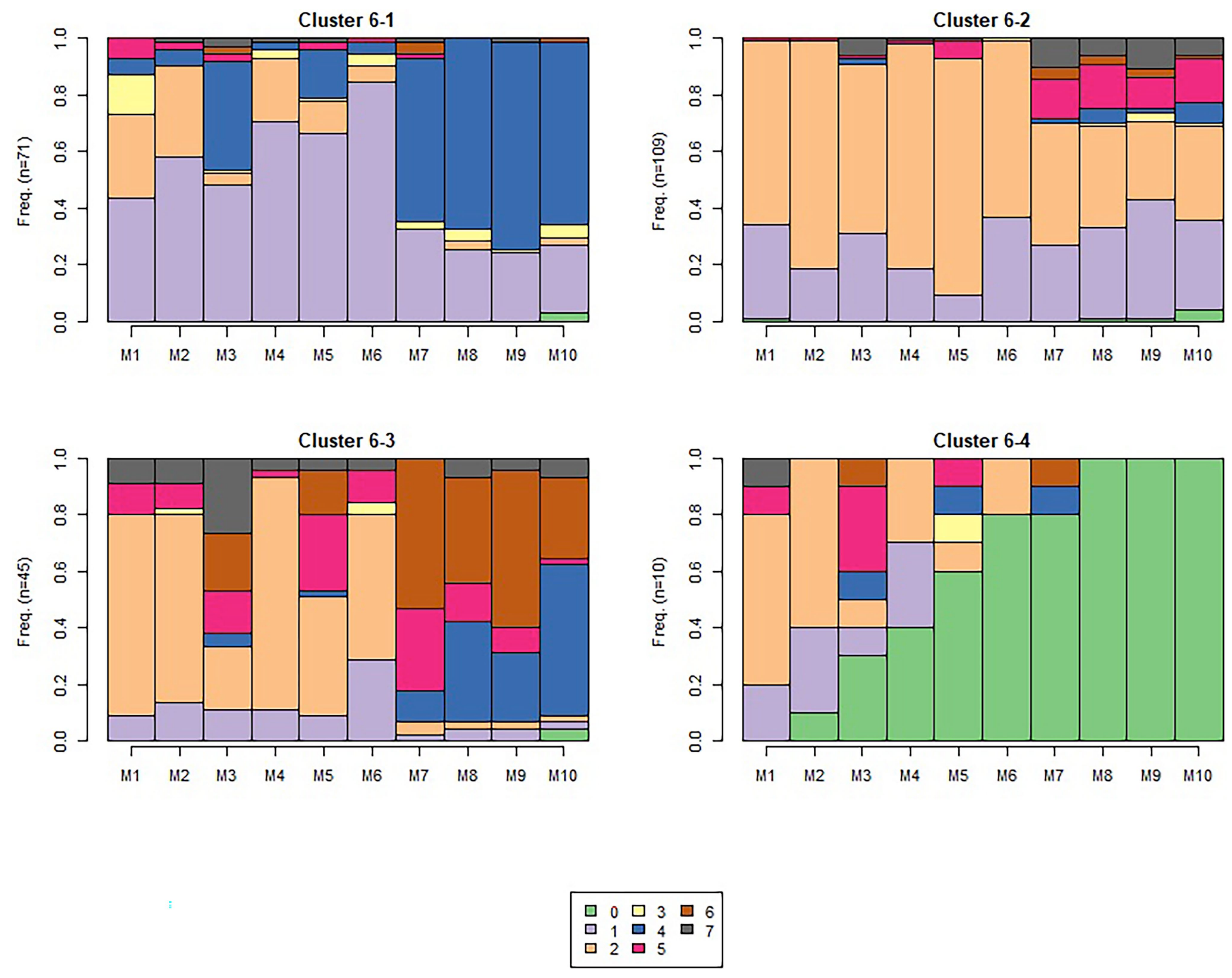


**FIGURE 7** | Sequence 6 sequence-level clusters. The number of students in each s-cluster is shown on the left of each figure.

appears to be more traces of the other m-clusters (see **Figure 7**). Sequence-level cluster 6-1 has many traces of causal net 1 (*normal first or second pass*) with many traces of causal net 4 (*short attempt and pass*) as well, and with some, but fewer traces of causal net 2 (*attempt, study, attempt, pass*) and 3 (*normal, then short attempt*). Sequence-level cluster 6-2 still reveals traces of causal nets 1 and 2, but with some causal net 5 too (*attempt, study, multiple short attempts*). Sequence-level cluster 6-3 demonstrates many more traces of causal nets 4, 5, 6, and 7 (all m-clusters with short attempts), with fewer traces of causal nets 1 and 2. Although s-cluster 6-4 has traces of several causal nets, it has the most traces of causal net 0, which was used to indicate the student did not interact with the module. This is likely due to students dropping the course prior to the add/drop period. Overall, from what we see in these sequence-level clusters, as we monitor traces of student behaviors across the semester, we see a transition to engaging in what seems like some effective self-regulatory behaviors, but also students are starting to engage in more guessing-type behaviors.

### *Sequence 9*

Sequence 9 was administered toward the end of the semester (see **Figure 8**). From these sequence-level clusters, we again see the transition from engaging in more of causal nets 1 and 2 in the beginning of the semester to a shift to other causal nets that include short attempts and fewer study behaviors. This is especially apparent in more traces with a high frequency of causal net 4 (*short attempt and pass*). We do still see some traces of causal nets 1 and 2 (indicative of more effective self-regulatory behaviors), seen in sequence-level cluster 9-1 and sequence-level cluster 9-2. However, sequence-level clusters 9-3 and 9-4 seem to have a broad range of causal nets—specifically, 4, 5, and 6. These clusters all include short attempts, perhaps indicative of students engaging in a combination of study and guessing behaviors to finish the modules. Sequence-level cluster 9-5 is dominated by m-cluster 4 (*short attempt and pass*), which is the most indicative of guessing behaviors. Sequence-level cluster 9-6 is dominated by traces of not completing the modules (causal net 0, see above). In comparison

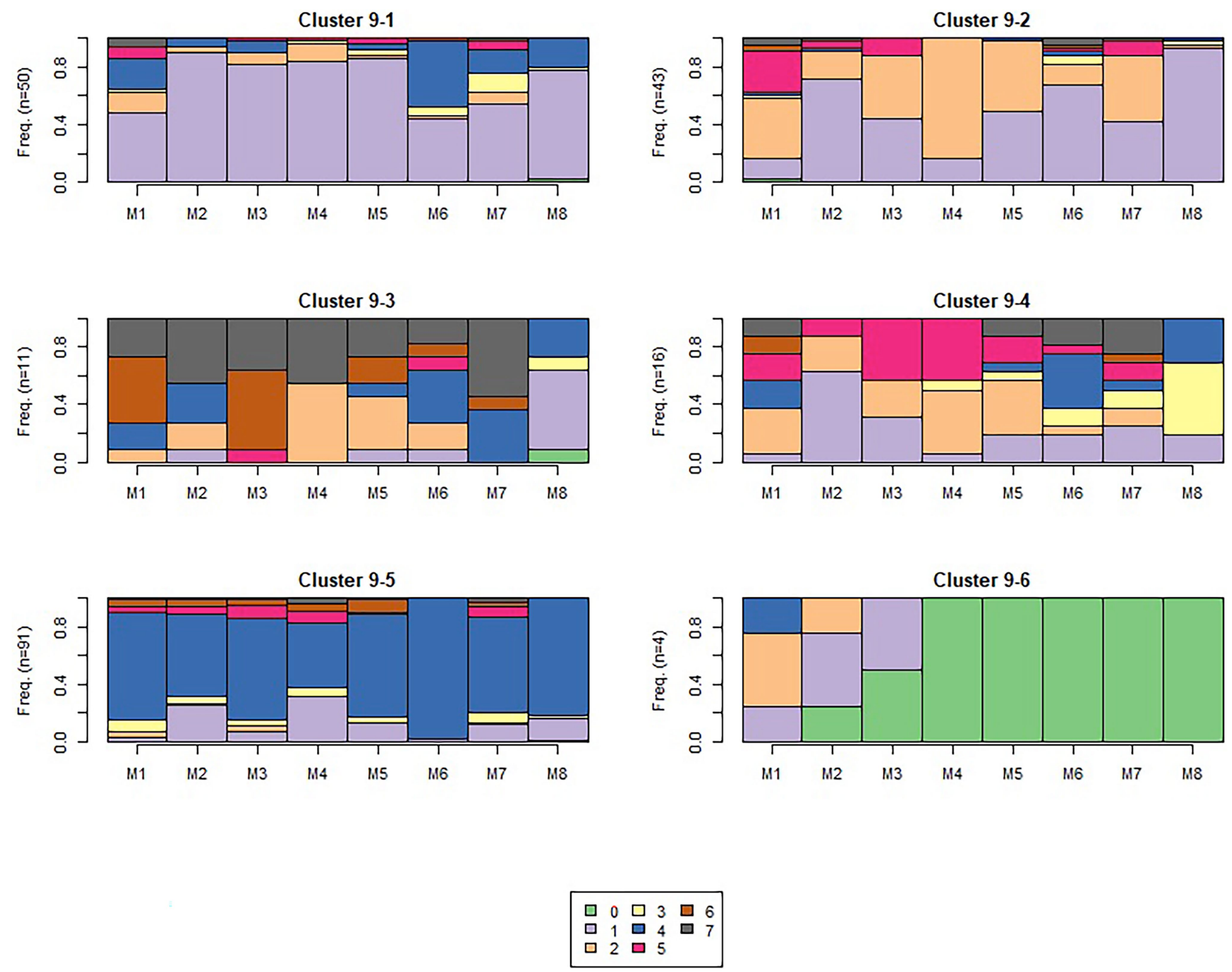


**FIGURE 8 |** Sequence 9 sequence-level clusters. The number of students in each s-cluster is shown on the left of each figure.

to the previous sequences, these traces suggest students were not engaging in effective learning behaviors and were guessing to complete the modules. It is important to note that this behavior was not as prevalent across s-clusters for the two earlier sequences in the semester. This can be indicative that by the end of the semester, students have accumulated a sufficient amount of course credit, and were aiming to ensure they were passing their courses with acceptable scores, but also reserving effort—in alignment with a performance-oriented goal orientation (Elliot and Murayama, 2008).

## Research Question 2: To What Extent Do Students' SRL Behaviors and AGQ Responses Change Over the Semester?

### Change in SRL Behaviors

To describe a student's shift in SRL strategy, we first sorted the sequence-level clusters into five different types, according to the frequency and type of causal nets observed within that sequence-level cluster. We then assigned a score ($S$) to each type, as listed in **Table 1**. **Table 1** outlines which SRL strategy type scores are represented in each sequence-level cluster for each sequence 1, 6, and 9. For example, SRL strategy pass or study (SRL strategy type score 2) can be found in sequence clusters 2, 3, and 4 in sequence 1, sequence cluster 2 in sequence 6, and sequence cluster 2 in sequence 9. SRL strategy varied strategy (SRL strategy type score 3) cannot be found in any sequence clusters in sequence 1, however it can be found in sequence cluster 3 for sequence 6 and sequence clusters 3 and 4 for sequence 9. In **Table 1**, lower score numbers correspond to interactions that closely mirrored effective or desirable course interactions, such as learners passing on the first attempt or studying after the first failed attempt. Higher score numbers correspond to less desirable interactions, such as guessing. We then further described transitions between neighboring SRL strategies ($\Delta S = 1$) as "Moderate" transitions and those between more distant strategies ($\Delta S > 1$) as "Large" transitions. For example, if a student belongs to sequence-level cluster 1-1 (Type score of 1) and 6-3 (Type score of 3), we consider this a "Large" transition. The relative frequencies of same, moderate, and large transitions are listed in **Table 2**.

### Change in AGQ Responses

Based on students' RCI scores (see section "AGQ Change Scores", above) we categorized scores according to Jacobson and Truax (1991) who stated RCI scores beyond |1.96| are statistically unlikely ($p < 0.05$) without the occurrence of real change between the set of test scores in question. Therefore, we define a decrease in goal endorsement as an RCI of −1.96 or less and an increase in goal endorsement as an RCI of 1.96 or larger for any of the four goal orientation profiles (Jacobson and Truax, 1991; Fryer and Elliot, 2007). RCI scores that fell within |1.96| were classified as a non-significant change, as was done in Jacobson and Truax (1991) and Fryer and Elliot (2007). See **Table 3** for the breakdown of scores by goal orientation profile.

### Change in SRL in Relation to Change in AGQ Responses

A Kruskal-Wallis test found a significant relationship between students' performance approach RCI scores (RCI_PAP) and end of term (from seq6 to seq9) behavior transition sequence-level cluster membership, $KW(2, n = 205) = 6.275$, $p = 0.035$. Students who stayed the same in their course behaviors between midterm and end of term (i.e., did not change SRL behaviors, based on shifts in students' sequence-level cluster membership from seq6 to seq9) had larger changes in their performance approach scores ($M_{\text{Rank}} = 118.86$) than students who made moderate shifts in behavior ($M_{\text{Rank}} = 93.34$). Results were not significant for the other RCI scores (MAP, MAV, and PAV).

**TABLE 1** | S-Clusters sorted by dominant SRL strategy type score across the semester.

| SRL strategy type score (*S*) | Sequence (S)–S-Cluster (SC) | | |
|---|---|---|---|
| | Sequence 1 | Sequence 6 | Sequence 9 |
| Initial pass (1) | S1-SC1 | S6-SC1 | S9-SC1 |
| Pass or study (2) | S1-SC2, S1-SC3, S1-SC4 | S6-SC2 | S9-SC2 |
| Varied strategy (3) | – | S6-SC3 | S9-SC3, S9-SC4 |
| Short pass (4) | S1-SC5 | – | S9-SC5 |
| Abort (5) | – | S6-SC4 | S9-SC6 |

*S, sequence; SC, sequence cluster.*

**TABLE 2** | Frequencies of self-regulated learning (SRL) transitions between course module sequences.

| Sequence transition | Large | Moderate | Same | Total |
|---|---|---|---|---|
| 1–6 | 6.4% | 45.1% | 48.5% | 235 |
| 6–9 | 32.1% | 39.1% | 28.8% | 212 |

**TABLE 3** | Reliable change index (RCI) change % [*n*] from AGQ-R 1 to AGQ-R 2.

| | Decrease | Increase | Non-significant change | Total |
|---|---|---|---|---|
| MAP | 5.9% [14] | 2.1% [5] | 92% [219] | 238 |
| MAV | 0.4% [1] | 4.2% [10] | 95.4% [227] | 238 |
| PAP | 3.8% [9] | 2.5% [6] | 93.5% [223] | 238 |
| PAV | 3.8% [9] | 3.4% [8] | 92.9% [221] | 238 |

*MAP, mastery approach; MAV, mastery avoidance; PAP, performance approach; PAV, performance avoidance.*

## Research Question 3: How Do Changes in Observed SRL Behavior and AGQ Responses Relate to Students' Learning Outcome?

For this research question, we sought to compare change in SRL and AGQ with course exam scores by comparing exam scores between sequence clusters and correlating exam scores with AGQ change scores.

### SRL Behavior Changes and Exam Scores

Within each of the three OLM sequences, ANOVA tests reveal that the exam scores between different s-clusters were significantly different (see **Table 4**). *Post-hoc* pairwise comparison using Tukey HSD tests revealed a total of seven pairs of s-clusters that had significantly different exam scores, as listed in **Table 5** [*p*-values were adjusted using the fdr method (Benjamini and Hochberg, 1995)]. In each pair, s-clusters classified as either "initial pass" or "pass or study" had higher exam scores than other types of s-clusters. The only exception is sequence-level cluster 1-4, which is classified as "pass or study," yet had significantly lower exam scores compared to sequence-level clusters 1-1 and 1-2. Sequence-level cluster 1-4 had a higher fraction of study events (causal net 2) than sequence-level clusters 1-1 and 1-2, especially on the first two modules. See **Figure 9** for a breakdown of exam score for each s-cluster at sequences 1, 6, and 9.

**TABLE 4** | ANOVA results for exam scores between sequence-level clusters.

| Sequence | *F*-Statistic | *p*-Value | Partial Eta Squared |
|---|---|---|---|
| 1 | $F_{4,230} = 13.3$ | <0.001 | 0.187 |
| 6 | $F_{3,224} = 13.2$ | <0.001 | 0.150 |
| 9 | $F_{5,209} = 4.07$ | 0.00152 | 0.089 |

**TABLE 5** | *Post-hoc* comparisons for exam scores between s-clusters.

| Sequence | Sequence-level cluster comparison | Estimated difference |
|---|---|---|
| 1 | 1:2*** | 0.71 |
| 1 | 1:4*** | 1.21 |
| 1 | 2:4* | 0.50 |
| 6 | 1:3*** | 0.86 |
| 6 | 2:3*** | 1.00 |
| 9 | 1:5* | 0.51 |
| 9 | 2:5* | 0.57 |

*$p < 0.05$; ***$p < 0.001$.

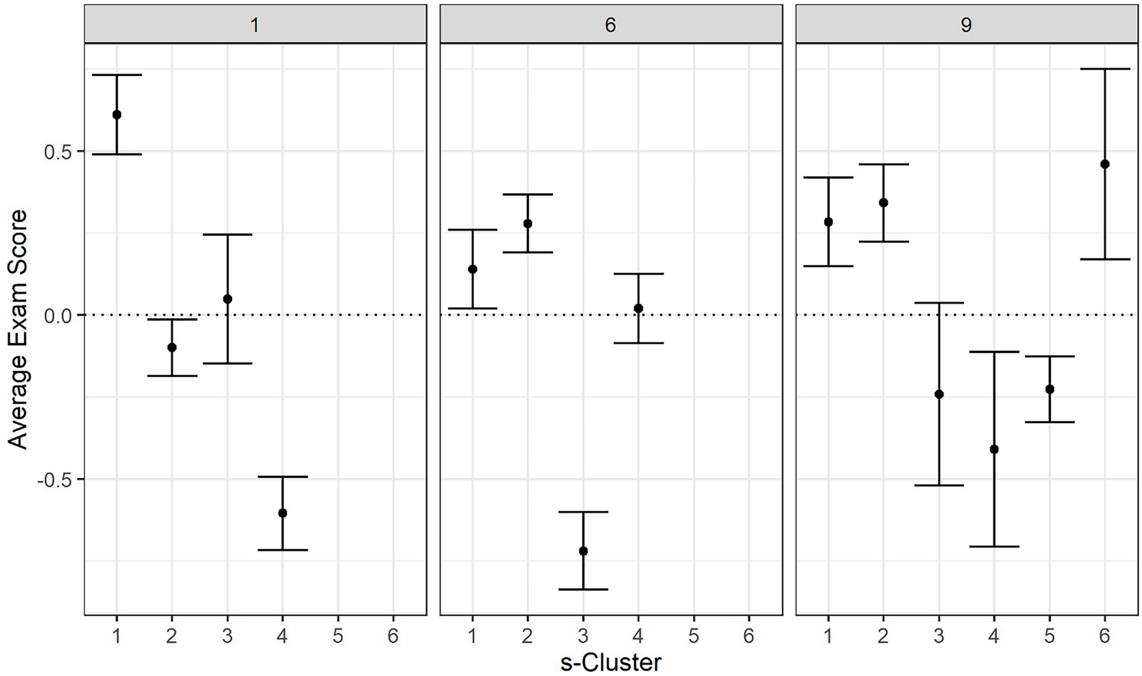


**FIGURE 9** | Average exam scores by sequence-level clusters 1 (left), 6 (middle), and 9 (right).

### AGQ Response Changes and Exam Scores

A Pearson correlation did not find a statistically significant correlation between students' mastery approach AGQ change score and their final exam score [$r(227) = 0.044$, $p = 0.505$], their mastery avoidance AGQ change score and their final exam score [$r(227) = 0.067$, $p = 0.317$], their performance approach AGQ change score and their final exam score [$r(227) = -0.006$, $p = 0.926$], or their performance avoidance AGQ change score and their final exam score [$r(227) = 0.114$, $p = 0.086$].

## DISCUSSION

The goal of this study was to examine how students engaged in self-regulatory actions during physics learning with OLMs, and whether their self-regulatory behaviors changed throughout the semester. We also sought to examine students' self-reported goal orientations and whether those changed over time (i.e., throughout the semester) as well. Finally, we assessed the relationship between SRL and AGQ with exam scores for the course. In the next section, we discuss our overall findings from our research questions, followed by a discussion of the implications of these findings.

### Research Question 1: What Are the Different Types of SRL Processes Students Employ in a Self-Paced Online Learning Environment?

In general, evidence from the seven causal nets demonstrates students took different approaches to trying to complete the assignment, yet similar behavior patterns were found across groups of students. For example, some students took the time to make their first assessment attempt, but others made short attempts, possibly because they were either guessing, had obtained the answer from another source, or wanted to get to reading the study materials right away. Although all demonstrating self-regulation, these behaviors suggest students set different achievement goals within the learning modules. It seems some students engaged with provided learning materials as a means of mastering the content, while others wanted to ensure they could pass the assessment components as quickly, or with as little effort, as possible. It is important to note we cannot confirm each students' established goals, but we believe examining how learners engaged in these modules over time can demonstrate whether these behaviors are spontaneous for one module or are more representative of a student's typical behaviors across the semester. We addressed this by examining sequences of engaging in these m-clusters.

Results from sequence analysis demonstrated a shift in the frequency of various m-clusters among the student population, indicative of a shift in students' SRL behaviors over time. More specifically, some students appeared to shift from more effective to less effective SRL strategies, suggesting they no longer seemed to set the goal of mastering the content. Rather, it seems they were focusing more on their grades and performance in the class. This was especially apparent by the shift in the number of students adopting causal net 4 (short attempt and pass), which was very low in the first sequence of the course but became much higher in sequences 6 and 9 toward the end. By the end of the semester, students often feel overwhelmed with the amount of work they need to complete to pass their courses, requiring motivation regulation (Schunk and Zimmerman, 2012). Therefore, it is possible that we are seeing this shift because students are realizing the work they need to complete not only in this class, but also all of their other courses as well. This does not imply they no longer value the mastery of course content, but rather the letter grade calculation takes priority in this case. As introductory physics is a challenging course, this might have been even more apparent to these students. Future work is needed to confirm what is causing these shifts in student behavior traces throughout the semester.

## Research Question 2: To What Extent Do Students' SRL Behaviors and AGQ Responses Change Over the Semester?

When examining change in SRL behaviors, students did not make large shifts from sequence 1 to sequence 6 (6.4%), especially in comparison to making a moderate shift (45.1%) or making no shift (48.5%). However, this changed from sequence 6 to sequence 9 where we see a much larger percentage of large shifts (32.1%), and still moderate (39.1%) or no shifts (28.8%); however, to a lesser extent than the previous sequence shift. In addition, the results demonstrated that students' SRL strategy can shift abruptly on a shorter timescale, such as a sudden shift in strategy at the middle of sequence 6.

Those strategy shifts may have been caused by students' sense of urgency to increase their course grade. It could be that students suddenly became aware of the fact that they were not achieving a desirable grade in the course and came to conclude that they were spending too much time reading the content with little improvement on assessment performance. Another interpretation could be related to students' reaction to changes in content difficulty. Since the modules in general get progressively more difficult over time, students were having a more difficult time completing the later modules successfully, which eventually lead to more guessing behaviors. Therefore, similar to our earlier interpretation of behaviors for research question 1, it is possible students are making a shift later on in the semester because they are suddenly focusing on ensuring they earn an acceptable grade in the course, so instead of focusing their attention on mastering the content, they are ensuring they are performing well.

For AGQ responses, although some students demonstrated a shift in their responses, it was much less than expected. Specifically, scores for mastery approach changed the most, yet it was only for a 5.9% increase and 2.1% decrease (and 92% no significant change). In general, between 1 and 10 students along different dimensions shifted their responses to the AGQ after completing the questionnaire a second time, which demonstrates *some* students do change their self-reported goal orientation, despite the majority of students being consistent in their response.

It is interesting that students who did not demonstrate a shift in SRL behaviors (i.e., remained in the same cluster from sequence 6 to sequence 9) demonstrated larger changes in performance approach scores compared to students who demonstrated a moderate shift in SRL behavior from sequence 6 to sequence 9. Perhaps these students were better able to re-align their goal orientation with their SRL behaviors at the end of the semester. In other words, their SRL behaviors did not change from sequence 6 to 9, but their reported goal orientation did. Based on this result, now that we know there is a relationship between students who are not changing their SRL behaviors, but are changing their AGQ responses, future work is needed to examine *why* they are making these changes or not.

## Research Question 3: How Do Changes in Observed SRL Behavior and AGQ Responses Relate to Students' Learning Outcome?

Findings from this research question outlined that not only were we able to outline the changes in SRL and AGQ behaviors throughout the semester, changes in SRL behaviors were also associated with performance in the course. As expected, in most cases students who engaged in m causal nets 1 and 2 had higher exam scores compared to their peers. However, sequence-level cluster 1–4, which did contain predominantly causal nets 1 and 2, is an exception for having significantly lower exam scores. It is possible that even though students seemed to be engaging in effective SRL behaviors, this does not always guarantee greater performance (Taub and Azevedo, 2018, 2019). For example, if a student is focusing on mastering the content, perhaps they are not focusing on content that is included in the test. The student, therefore, has high procedural knowledge of engaging in SRL strategies, but might not have high levels of content knowledge (Azevedo and Taub, 2020). Since sequence-level cluster 1–4 contains more causal net 2, it could also be that those students had less incoming knowledge compared to their peers. It would be interesting to investigate students' levels of procedural and conditional knowledge in addition to their content knowledge, as well as their content knowledge prior to instruction.

In addition, findings did not reveal significant correlations between course scores and change in response scores to the AGQ, likely due to the low frequency of students who completed the AGQ at the end of the semester, resulting in an incomplete picture of how students' goal orientation shifted by the end of the course. As such, future work should seek to encourage the completion of the AGQ for all participants at more timepoints throughout the semester.

However, there were significant relationships between AGQ scores taken at different points in the semester (i.e., when using raw scores instead of change scores), which exceeds the scope of this paper given that our research question sought to examine change in both SRL behaviors and AGQ scores, not raw data. However, it is worth noting that perhaps the significance of the relationship between exam score and raw AGQ scores suggests students are focusing on achieving both mastery and performance at the beginning of the semester (approach), followed by a shift to focusing on avoiding failure in mastering the content or performing poorly (avoidance). Put differently, there is a potential shift from *approach to avoidance* raw scores being significant. This aligns with other findings in that students are demonstrating a shift in behavior from the beginning to middle to end of the semester, and future research examining the nature of this change will be important.

## Limitations and Future Directions

It is important to acknowledge that although our research yielded interesting and informative results, we must address the limitations from our study as well. First, although we administered the AGQ-R three times at the beginning, middle, and end of the semesters, there were much fewer responses to the third AGQ administration ($n = 40$) and we were therefore unable to include it in our analyses. In addition, we only performed clustering on sequences 1, 6, and 9 of the semester. In future studies, we will expand our analyses to include all sequences from the course and find methods to improve survey response rate toward the end of the semester. In addition, our method for producing the Gower dissimilarity matrix was not exhaustive—we simply chose between several different weights selected to emphasize certain phases of SRL. In future studies, we plan to use bootstrapping methods to more comprehensively search the space of Gower weights to find the weights for which the cluster membership most closely represents the underlying structure of the data.

Regarding the multilevel clustering analysis scheme, one outstanding limitation is that the current analysis simplified students' interactions with the instructional materials into a single binary variable. Future analysis should incorporate more interaction details, such as the number of practice questions answered or time spent on the materials, to better reflect students' study strategies. A second technical limitation is that the weights of the Gower dissimilarity coefficients were chosen so that it produced well-structured clustering structures for less than 10 clusters. Future studies should explore whether there are other sets of parameters that result in well-structured clusters, which could emphasize a different aspect of the SRL process, such as content knowledge mastery and problem-solving ability.

Our results left a lot of room for interpretation. We used a theoretical framework and based our findings on the information processing theory of SRL; however, these are speculations. In other words, we know which actions students completed, but we do not know *why* they performed these actions. Therefore, in future studies, we will seek to explore this question and investigate why students are changing their behaviors or motivations throughout the semester. Possible studies can include incorporating prompts to foster student reflections throughout the semester. In addition, measuring student achievement goals is not the only factor at play here. Thus, we can administer additional questionnaires to complement the AGQ-R to gauge student motivation (e.g., self-efficacy and task value), emotions (e.g., emotions and values and emotion regulation), and students' perceived use of self-regulatory processes. It might also be helpful to conduct student interviews that ask them to discuss the processes they use while engaging in the learning modules in the course.

These potential future directions pave the way toward developing online learning modules or MOOCs that provide adaptive support based on student behaviors. For example, if the system detects many student-level traces of causal net 4 (i.e., guessing), the system can suggest the student spend more time reading through questions or spending time studying the course material. This can help to ensure all students are successfully learning course materials while also earning acceptable grades to help them pass their courses.

# CONCLUSION

This paper examined college students' SRL behaviors and self-reported AGQ as they completed one semester of college-level introductory physics during the Fall 2020 semester, using OLMs as homework and self-study materials. Based on our findings, we propose it is informative for the study of SRL to examine the changing nature of SRL and AGQ because we did find evidence for that in our results. Our results therefore confirm what is posited in the information processing theory of SRL (Winne and Hadwin, 1998, 2008; Winne, 2018)—that SRL should be viewed as a series of events that unfold during learning. Our results have useful implications for designing future online and blended courses because we are progressing toward fostering the use of effective SRL throughout the entire semester. In future studies, it would be helpful to determine actions at the student-level, which could be used to inform the design of future OLMs or MOOCs that provide adaptive feedback based on individual student behavior. We conclude that there is still significant work ahead in investigating and fostering SRL during online and blended learning settings, but this paper provides a good blueprint for the types of analyses helpful for investigating how students' learning strategies as well as goals and orientations change over the semester.

# DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

# ETHICS STATEMENT

The studies involving human participants were reviewed and approved by University of Central Florida Institutional Review Board (STUDY00000994). Written informed consent for participation was not required for this study in accordance with the national legislation and the institutional requirements.

# AUTHOR CONTRIBUTIONS

All authors contributed to the conception of the work and revised the final manuscript. MT led the conceptualization and writing of the paper. ZC designed and conducted the study and proposed the analysis scheme. ZC, AB, and TZ conducted the statistical analyses. MT, AB, TZ, and ZC all contributed sections to the manuscript. All authors also provided several rounds of edits on the manuscript.

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# Fostering Self-Regulated Learning in Online Environments: Positive Effects of a Web-Based Training With Peer Feedback on Learning Behavior

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Although training in self-regulated learning (SRL) is effective in improving performance, human trainers can reach only a few people at a time. We developed a web-based training for potentially unlimited numbers of participants based on the process model of SRL by Schmitz and Wiese (2006). A prior study (Bellhäuser et al., 2016) observed positive effects on self-reported SRL and self-efficacy. In the present randomized controlled trial, we investigated an improved version of the web-based training, augmented by the application of peer feedback groups. Prospective university students in an online mathematics preparation course were assigned randomly to one of four experimental conditions: Group D (diary), group TD (training + diary), group TDP (training + diary + peer feedback group), and group C (control). Complete data was obtained for 136 participants (78.8% male; *M* = 19.8 years). The learning diary was intended to trigger goal setting, planning, and self-motivation in the morning and reflection in the evening. The web-based training consisted of three lessons (approximately 90 min each) with videos, presentations, self-tests, and exercises. In the peer feedback condition, participants were randomly assigned to groups of five persons each and used a bulletin board to discuss pre-defined topics related to the content of the web-based training. Outcome measures included a test of declarative SRL knowledge, an SRL questionnaire, a general self-efficacy scale, log file data, and a mathematics test. Results showed positive effects for the web-based training, particularly when combined with peer feedback on both SRL knowledge and SRL questionnaires, self-efficacy, and on objective time-investment, but not on the mathematics test. The learning diary did not exhibit positive effects. We conclude that additional peer-feedback seems to be a useful supplement to web-based trainings with comparably low organizational costs.

**Keywords: self-regulated learning, web-based training, peer feedback, training evaluation, learning diary**



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## INTRODUCTION

Self-regulated learning (SRL) has been shown to be highly relevant to academic achievement not only in secondary schools (Dignath and Büttner, 2008) but also in particular at university level (Richardson et al., 2012). University students need to work independently and decide every day what to learn, when and where to learn, and which learning strategies they want to apply. Due to their high workload, students need to plan their learning process based on their personal goals. Further, as setbacks and failures are common experiences, students also have to regulate their motivation. In particular, SRL strategies are a requirement for the success of students in computer-based learning environments (CBLE) (Broadbent and Poon, 2015). However, many students appear to have difficulties regulating their own learning process. Fortunately, researchers have demonstrated that training in SRL strategies is possible and that participants in SRL training substantially increase their academic performance (Theobald, 2021). Most approaches to fostering SRL apply face-to-face training [e.g., Dörrenbächer and Perels (2016)] that inherently limits the number of students who can participate. Therefore, Bellhäuser et al. (2016) developed a web-based training (WBT) to foster SRL strategies online. In their evaluation study, this WBT was demonstrated to have a positive effect on SRL knowledge, SRL behavior, and self-efficacy. However, the training also had a small detrimental effect on mathematics performance in an online mathematics preparation course. In a similar approach, Broadbent et al. (2020) tested the effect of a discipline-independent online training on SRL outcomes and found promising results, particularly when the online training was combined with a mobile-app based learning diary.

Both Bellhäuser et al. (2016) and Broadbent et al. (2020) followed an individual learning approach in which students acquired SRL strategies on their own through participation in the training. Thereby, students learned about the theoretical background of SRL strategies and were instructed to apply those strategies to a given example situation. In order to foster the application of those strategies in their daily lives, students additionally used a learning diary. Such diaries act as a prompt for SRL strategies by reminding students to formulate goals and to reflect on their learning behavior on a daily basis. However, both online trainings and learning diaries target individual students without taking advantage of the beneficial effects of collaborative learning (Johnson et al., 2000; Chen et al., 2018). Contact to fellow students that are also enrolled in the online training might help to keep up the motivation for following the training instructions. Additionally, peer students can provide valuable feedback on the learning process. The aim of the present study is therefore to augment the WBT applied by Bellhäuser et al. (2016) with a new peer feedback intervention that helps participants use the strategies from the WBT to improve their self-regulated learning as well as their performance.

## Process Model of Self-Regulated Learning

Our study is based on the process model of self-regulated learning by Schmitz and Wiese (2006), which is an adaptation of Zimmerman's (2000) conception of self-regulation. According to this model, learning is a process that can be divided into three phases: pre-action, action, and post-action. These phases follow one another cyclically in every learning episode (i.e., one cycle of pre-action, action, and post-action phases such as homework on 1 day) and influencing the next learning episode (i.e., the next cycle of the phases such as homework on the next day) *via* a feedback loop. Every phase is characterized by a different set of tasks and challenges for the learner; therefore, different strategies and different competencies are required to achieve good learning results.

In the pre-action phase, learners establish goals according to the situation in which these students find themselves and the task with which the students are confronted. The next step is to deduce a plan to achieve these goals. If intrinsic and extrinsic motivation is not sufficient to initiate learning, self-motivation strategies serve as a further resource. In the action phase, learners operate with the actual learning content. Here, cognitive learning strategies (such as elaboration) and meta-cognitive learning strategies (such as monitoring) are crucial to learning success. Further, learners must utilize volitional strategies when observing a decrease in motivation to avoid procrastination. In the post-action phase, learners reflect on their learning episode and determine their level of satisfaction with their performance. For this purpose, learning goals are compared to actual achievement. The result of this comparison triggers the next pre-action phase in which learners establish new learning goals or modify unfinished goals.

## Fostering Self-Regulated Learning With Web-Based Training

The process model of SRL (Schmitz and Wiese, 2006) has been the foundation for many training interventions intended to foster SRL (Perels et al., 2005, 2009; Schmitz and Wiese, 2006; Leidinger and Perels, 2012; Werth et al., 2012; Dörrenbächer and Perels, 2016; Beek et al., 2020). Although those trainings differ in terms of the target groups, focus, and success, in all trainings, a human trainer conducts three or more face-to-face training sessions of approximately 2 h with a group of up to 30 participants. The effects of such trainings have been shown to be substantial not only in terms of improved self-reported learning behavior but also in increased performance (Dignath and Büttner, 2008; Benz, 2010). The disadvantages of face-to-face training, however, are that participants cannot flexibly choose when and where to attend training sessions and that trainers must restrict the number of participants in each training. For research purposes, another disadvantage is that sessions of face-to-face training are never absolutely identical on different occasions. Often because of time constraints, different persons conduct the trainings, leading to different effects. Even in studies in which only one person was the trainer, that person may have varied the exact wording of explanations from one training group to the next. Finally, with different participants in every training group, the quantity and quality of contributions by participants may also vary greatly.

Bellhäuser et al. (2016) therefore developed a web-based training that can be attended by virtually unlimited numbers of participants who are free to choose the time and location for their training. The WBT comprises three lessons of approximately 90 min each. The first lesson ("Before Learning") focuses on the pre-action phase and covers goal-setting and time management. Lesson 2 ("During Learning") addresses the action phase and covers volition, cognitive learning strategies and metacognitive learning strategies. The third lesson ("After Learning") highlights the post-action phase and covers attribution and reflection. Each lesson utilizes videos, presentations, tests, exercises, and group discussions in an online forum.

The WBT was evaluated in the context of an online mathematics preparation course in which prospective students prepared themselves for their first university term in mathematically oriented fields of study (computer science, civil engineering, mechanical engineering, or mathematics). The preparation course occurred during the last four weeks before the university term began; covered mathematical knowledge from all school grades; and provided learners with definitions, arguments, examples, assignments, and visualizations. Because the preparation course was conducted completely online (created with the learning management system *Moodle*), no face-to-face instruction occurred. The preparation course took four weeks, during which all participants had the freedom to decide for themselves what to learn, when to learn, and how to learn.

In a randomized experimental design, Bellhäuser et al. (2016) investigated the effects of the WBT on SRL knowledge, self-regulated learning, self-efficacy, and mathematics performance. The intervention was deemed successful in conveying declarative knowledge regarding SRL, increasing self-efficacy, and improving self-reported SRL behavior. However, the results indicated a detrimental effect on participants' mathematics performance. The authors discussed several possible explanations for this undesirable finding. The WBT required a certain amount of time that participants did not invest in the actual learning task (i.e., the preparation course). Furthermore, according to Siegler's (2007) overlapping waves model, the acquisition of new strategies can impair performance in the short term, with beneficial effects appearing only in the long term. Finally, flaws in the mathematics test may have contributed to the decrease in mathematics performance. No matter how convincing these arguments may appear, an intervention with negative effects on performance is not satisfactory for practical use, and improvements in the training are therefore highly desirable.

Beek et al. (2019) applied the same WBT and compared its effects to a regular face-to-face training. They found equally high satisfaction with the two approaches and positive effects on subjective and objective learning outcomes for both presentation modes, thereby showing that web-based trainings can be feasible SRL interventions.

In a recent replication study, Broadbent et al. (2020) followed a similar approach, with the main differences that they implemented a discipline-independent online training [compared to the discipline-specific training from Bellhäuser et al. (2016)] and that they used mobile-app based diaries [compared to the browser-based application by Bellhäuser et al. (2016)]. The results confirmed that the online training had a positive effect on SRL and that a pure diary condition (without access to the online training) did not improve students' SRL. The combined intervention condition outperformed both the pure training and the pure diary condition. However, no measures of actual performance were assessed in the study.

## Learning Diary Interventions

Learning diaries are a different approach for fostering SRL. Here, students are not instructed explicitly on SRL strategies; instead, they report their learning behavior in a short systematic collection of both open and closed questionnaire items. There are several mechanisms through which learning diaries are supposed to improve learning behavior. First, they are used to prompt SRL behavior daily (e.g., by asking questions such as "What are your learning goals for today?" in the morning or "How successful was your learning day?" in the evening), thereby acting as an external cue or reminder (Fabriz et al., 2014). This is particularly helpful because diaries are a method to reach students in their actual learning environment and not in an artificial situation. Second, learning diaries foster self-monitoring, drawing students' attention to their own learning behavior (Schmitz and Perels, 2011). This is a necessary step toward critically reflecting whether one's learning strategies are successful or need to be adjusted. Third, digital learning diaries can provide feedback on the learning process. By integrating interactive elements, students can be supported with graphical feedback about their learning behavior [e.g., the trajectory of procrastination: Wäschle et al. (2014)], about the status of their learning tasks (Neitzel et al., 2017), or even provide direct strategy instructions (Loeffler et al., 2019).

Multiple studies have shown that keeping such a diary over a certain time span (in many cases several weeks) can lead to improvements in SRL (Ewijk et al., 2015; Dörrenbächer and Perels, 2016; Loeffler et al., 2019). However, as there are also unsuccessful examples in the literature (Bellhäuser et al., 2016; Broadbent et al., 2020), it still remains unclear which circumstances are necessary for learning diaries to exhibit positive effects.

## Peer Feedback Interventions

In the evaluation forms, participants in the study by Bellhäuser et al. (2016) described bulletin boards in the WBT to be less helpful than elements of instruction such as videos and presentations. This response was surprising because as Davies and Graff (2005) stated, online discussions are expected to promote learning and performance. One possible explanation may be that participants did not know their peers on the bulletin boards and therefore did not have sufficient trust in their peers to share the details of their learning difficulties. Trust among members of virtual communities has been shown to be essential in the exchange of information (Ridings et al., 2002). Grouping participants into smaller peer groups (Wheelan, 2009) with a common interest such as a certain field of study (Ziegler and Golbeck, 2007) and the personal introduction of each participant (Rusman et al., 2009) can reduce anonymity and increase trust.

Peer feedback refers to "a communication process through which learners enter into dialogues related to performance and standards" (Liu and Carless, 2006). It involves at least two students that act as feedback giver and feedback receiver, with the feedback typically including both an assessment of the peer's competency (feed-back) and a recommendation on how to proceed (feed-forward) (Hattie and Timperley, 2007). A recent meta-analysis (Huisman et al., 2019) demonstrated a rather large positive effect of receiving peer feedback on performance in academic writing tasks. Beneficial effects have further been shown for academic self-concept (Simonsmeier et al., 2020) and in other domains, such as language teaching, peer feedback has been shown to be successful in fostering affect and performance (Nelson and Schunn, 2009; Gielen et al., 2010). But not only the feedback receiver can profit from peer feedback: Zong et al. (2021) showed that feedback givers benefit even more than receivers. This might be the case because feedback givers need to reflect on the learning goals and the evaluation criteria as well as consider alternative solutions to a given task, all of which are learning strategies toward a deeper understanding of the topic (Bürgermeister et al., 2021). While peer feedback is often applied in situations where teachers cannot provide feedback themselves (e.g., in large courses), it should not necessarily be regarded as the second best solution. Huisman et al. (2019) found that peer feedback and teacher feedback lead to comparable achievements.

However, prior research has applied peer feedback only in the context of subject-specific academic tasks. To the best of our knowledge, there have been no attempts to foster non-specific SRL strategies by means of peer feedback. Given the known positive effects of teacher feedback on students' self-regulated learning strategies (Azevedo et al., 2007), we expect peer feedback to be beneficial for both feedback receivers as well as feedback givers. Particularly in the context of a web-based SRL training that students work through individually, peer feedback groups might also help by reducing the feeling of loneliness, thereby increasing the motivation to complete the training.

## Research Questions

In the present study, we examined the effects of three different interventions designed to foster self-regulated learning. Prospective university students in an online mathematics preparation course were assigned to one of four experimental conditions: Group D (diary), Group TD (training + diary), Group TDP (training + diary + peer feedback group), and Group C (control). We expected each of the interventions to have positive effects on SRL knowledge, self-reported SRL behavior, self-efficacy, learning behavior (as measured by log file data) and mathematics performance.

Hypothesis 1 covered the positive effects of the learning diary. Because of the reactivity effect (Korotitsch and Nelson-Gray, 1999), we expected the diary to have a positive effect on SRL behavior (H1a), self-efficacy (H1b), mathematics performance (H1c), and time investment (H1d). These effects should result in greater gains for Group D than for Group C. However, we expected no effect on SRL knowledge because SRL strategies were not taught explicitly in the diary.

Hypothesis 2 covered the positive effects of the web-based training. By explicitly explaining SRL strategies and helping participants test the strategies personally (Bellhäuser et al., 2016), we expected the training to increase knowledge regarding SRL (H2a), thereby improving SRL behavior (H2b) and self-efficacy (H2c), which should result in increased mathematics performance (H2d). We also expected an increased time investment in the preparation course (H2e). The effects should be visible in the comparison between Group D and Group TD, with the latter achieving higher gains.

Hypothesis 3 covered the positive effects of the peer group interventions. Because students were deepening the content of the training and affiliating with peers, we expected statistically significant gains in SRL behavior (H3a), self-efficacy (H3b), mathematics performance (H3c), and time investment (H3d). These effects should exceed the gains of Group TD. No effect on SRL knowledge was expected.

# MATERIALS AND METHODS

## Participants

We recruited 289 prospective students from an online mathematics preparation course at a technical university in Germany. The mean age was 19.8 years (SD = 1.48). Because participants were enrolled in mathematically oriented fields of study (computer science, civil engineering, mechanical engineering, or mathematics), the sample was predominantly male, comprising 233 male and 56 female students. We assigned participants randomly to one of four experimental conditions: Group D (Diary) kept a learning diary throughout the preparation course. Group TD (Training + Diary) had access to web-based SRL training and kept a learning diary. Participants in Group TDP (Training + Diary + Peer feedback group) also kept a diary and attended the web-based SRL training. In addition, members of Group TDP were placed in groups of five students each; these groups worked on additional SRL tasks that included peer feedback. Participants in control Group C did not have access to the training or the diary, nor were they placed into peer feedback groups. The randomized assignment controlled for gender and field of study by dividing the sample into eight subpopulations (2 gender × 4 fields of study, e.g., female mechanical engineers) and randomizing within each subpopulation separately. We expected more dropouts in Groups TD and TDC because of the higher workload and therefore assigned disproportionally more participants to these groups.

Complete data were obtained for 170 participants (134 male): 45 in group TDP (34 male), 45 in Group TD (37 male), 36 in Group D (29 male), and 44 in Group C (34 male). Because of the high dropout rate (41.2%), we investigated differences between participants and dropouts. Analyses revealed significantly lower scores in conscientiousness and the mathematics test for dropouts but no significant differences in demographic data (gender, age, school grades), SRL (including subscales), self-efficacy, extraversion, openness, agreeableness, or neuroticism.

## Procedure

The online mathematics preparation course is an e-learning course that covers the last 4 weeks before participants begin university lectures. The course is a voluntary option for students enrolled in mathematically oriented fields to prepare for course work, deepen school knowledge, and establish a common knowledge base among students (Bausch et al., 2014). The preparation course included six chapters ("Arithmetic," "Powers," "Functions," "Higher Functions," "Analysis," and "Vectors") with 52 mathematical topics, each of which comprised the following elements: diagnostic pre-test, overview, introduction to the domain, information, interpretation, application, typical mistakes, exercises, and diagnostic post-test. The preparation course was delivered in an online learning management system that involved no classroom instruction by tutors or teachers.

We chose this particular course because of its unique challenges regarding the self-regulation of the participants. The preparation course covers all topics that students are expected to be familiar with from school, resulting in a very large collection of instructions, examples, and self-tests. Working through this amount of material within 4 weeks therefore requires good time management skills. Further, there are no extrinsic factors to reinforce participation. The course was neither compulsory, nor were there grades or credit points for students to achieve. Finally, participants in this course were typically not well-prepared for such a learning environment. Most students came directly from school where they had little experience with self-regulated learning over long periods of several weeks, let alone on online learning platforms. Consequently, the mathematics preparation course was known for high dropout rates and low performance before we conducted our study.

After the mathematics course started, participants completed the online pre-test in the learning management system within the first three days, which comprised a demographic survey, an SRL knowledge test, a mathematics test, and several questionnaires that are discussed later. Depending on their experimental condition, participants had access to up to three separate interventions during the preparation course that were intended to foster SRL by different processes: a learning diary (prompting SRL strategies daily), a WBT on SRL (conveying SRL knowledge), and peer feedback groups (providing social support). The post-test was accessible online for three days after the end of the preparation course and comprised the SRL knowledge test, an SRL questionnaire, the mathematics test, and an evaluation sheet. As an incentive, all participants who completed both the pre- and post-tests were included in a lottery drawing (an electronic device and several monetary prizes).

## Interventions

### Learning Diary

Groups D, TD, and TDP were requested to keep a learning diary throughout the preparation course. When filling in the diary, participants first decided whether they planned to learn on that day. If the students chose not to learn, the diary requested reasons and whether they planned to learn on the following day. Participants were further asked for their learning goals for the next learning day.

When participants chose to learn on a particular day, the students filled in two sections of the learning diary: one section to be completed before learning and one section to be completed after learning. Before learning, open-ended questions triggered goal-setting, planning, and self-motivation. Participants were requested to choose chapters from the preparation course to study on that day and set individual goals for those chapters (e.g., to solve all the problems and to get at least 70% of the problems correct). Learners were further asked which learning strategies they intended to apply and how much time they planned to invest. Closed questions were applied primarily for measuring purposes (e.g., motivation and well-being). Because this paper investigates the learning diary only as an intervention and not as a measurement instrument, the closed questions are not described in detail here.

The second section of the learning diary triggered reflection and goal-setting for the following day. Participants were asked which chapters they truly worked on and how much time they had invested in learning. By explicitly separating general time investment from effective learning time, participants critically reflected on their use of time. Learners were then requested to review the learning goals established in the first portion of the learning diary and judge the degree to which they had reached each goal. Further, students described which obstacles they had encountered during the day and how they planned to overcome such obstacles on the next learning day. For measuring purposes, participants rated their learning behavior on that day in closed questions (e.g., concentration, effort, and satisfaction). Participants made an average of $M = 12.58$ ($SD = 4.92$) learning diary entries over the course of the study.

### Web-Based Training on Self-Regulated Learning

Groups TD and TDP had access to three lessons on self-regulated learning that were unlocked consecutively in 1-week intervals. Participants were asked to work through each lesson within a time frame of three days. Lessons were designed to take approximately 90 min. As described by Bellhäuser et al. (2016), the WBT imparts knowledge of the process model of self-regulated learning (Schmitz and Wiese, 2006) and utilizes videos, presentations, self-tests, exercises, and online bulletin boards to help participants transfer the knowledge to their daily learning routines.

Unlike Bellhäuser et al. (2016), we did not include animated videos. Instead, real-life videos were created by two amateur actors in a real classroom scenario, one actor acting as the trainer, the other actor acting as a participant in the training. Choosing human actors was intended to increase credibility and personalize the experience for the audience, thereby improving satisfaction with the WBT.

The first lesson, "Before Learning," covered the pre-action phase, including chapters on goal-setting, planning, and time-management. Participants were advised to establish learning goals for the preparation course according to the SMART technique (Doran, 1981). After a presentation regarding time-management, participants reflected on their own time-management and discussed individual problems on a bulletin board. The last step was developing a learning plan for the entire four weeks of the preparation course, considering personal learning goals and time restrictions such as chores or hobbies.

The second lesson, "During Learning," focused on the action phase, the chapters including volitional learning strategies (such as addressing distractions and avoiding procrastination) and cognitive and metacognitive learning strategies. A video introduced the concept of procrastination, and participants analyzed whether they were prone to delaying tasks. To avoid distractions in the future, participants were advised to switch off mobile phones and communication software on their computers before entering the preparation course. Self-motivation strategies (e.g., self-reward) were presented, and participants developed a personal motto for situations in which they may lack motivation to learn. Referring to examples from the preparation course, presentations explained how to use cognitive learning strategies (e.g., structuring, elaborating, and summarizing) and metacognitive learning strategies (particularly monitoring).

The third lesson, "After Learning," addressed the post-action phase, including chapters on attribution, frame of reference, reflection, and motivation. A video exemplified different attribution styles in the face of failure. Participants were encouraged to identify personal but changeable causes to alter motivation. Similarly, an individual frame of reference was promoted: Instead of comparing oneself to other students, participants were instructed to focus on improving their own performance. In the chapter on reflection, a presentation explained how reflection can be applied on a short-term basis (e.g., whether one successfully solved a particular mathematical problem), on a medium-term basis (e.g., whether one was satisfied with today's learning progress), and on a long-term basis (e.g., whether one would approach future examinations in a different manner). Participants were instructed to review their learning goals from Lesson 1 and to reflect on necessary adjustments for the remaining days of the preparation course. In the last chapter on motivation, implementation intentions (Gollwitzer, 1999) were presented as a strategy to increase motivation. After a summary of the process model of self-regulated learning, the training ended with participants writing a letter to their future selves regarding what they planned to change in their learning behavior.

In the final evaluation of the study, we asked participants to which degree they followed the instructions in the web-based training. Mean compliance was $M$ = 82.18% ($SD$ = 15.03%).

### Peer Feedback Intervention

Participants in Group TDP were assigned to peer feedback groups of five persons each. Although group assignments were random, when possible, group members were chosen from the same field of study (e.g., five civil engineers). Peer feedback groups were able to communicate on a separate bulletin board on which discussion topics were suggested. Beginning with a welcome message, participants were encouraged to get to know their peers by creating quiz questions about themselves, posting them on the bulletin board, and guessing the right answers to their peers' quiz questions. After each lesson of the WBT, a group task referring to the current lesson was posted; this task was meant to be solved collaboratively. Lesson 1 was followed by the group task of sharing students' individual time schedules and commenting on their peers' plans (peer feedback Task 1). After Lesson 2, participants were asked to discuss the cognitive learning strategies taught in the lesson and how to apply those strategies to the mathematical chapters (peer feedback Task 2). The group task for Lesson 3 was to reflect on their time management in the preparation course to date and to adjust their learning goals if necessary (peer feedback Task 3). Although discussion regarding the content of the mathematical preparation course was not forbidden, the instructional topics were only related to strategies of self-regulated learning behavior. Inspection of the bulletin boards revealed that participants focused on the instructed group tasks.

All instructions for the discussions were also presented in videos. When members of a group did not participate in the group discussion, the experimenters reminded and encouraged participants to engage; however, no pressure was applied. In the final evaluation, participants rated their personal active engagement in the peer feedback groups on a six-point Likert scale. Mean active engagement was $M$ = 3.18 ($SD$ = 1.57).

## Instruments

### Self-Regulated Learning Questionnaire

The self-regulated learning questionnaire comprised 26 items with seven subscales. The overall score had a Cronbach's α of .85. The sub-scales were goal-setting (four items, Cronbach's α = 0.66, e.g., "*I choose my goals so that they are a challenge for me.*"), planning (four items, Cronbach's α = 0.63, e.g., "*I write down all important tasks and appointments.*"), self-motivation (three items, Cronbach's α = 0.71, e.g., "*I recall my past achievements to motivate myself for difficult tasks.*"), volition (four items, Cronbach's α = 0.71, e.g., "*I can modify my mood so that I find everything easier.*"), elaboration (three items, Cronbach's α = 0.71, e.g., "*When reading, I try to connect the things I am reading about with what I already know.*"), metacognition (four items, Cronbach's α = 0.64, e.g., "*I regularly think about my learning behavior.*"), and reflection (four items, Cronbach's α = 0.78, e.g., "*At the end of a day, I ask myself whether I am satisfied with my performance.*"); all subscales were determined to be sufficiently reliable. The questionnaire was developed in the context of prior studies to match the content of the WBT. Most items were newly created, except for three items from the LIST (Wild and Schiefele, 1994) and six items from the VCQ (Kuhl and Fuhrmann, 1998).

### Self-Regulated Learning Knowledge Test

The SRL knowledge test included 20 multiple-choice items (Cronbach's α = 0.81). Participants were required to choose one of four possible answers: One choice was the correct answer and three were distractors. Calculating the number of correct answers resulted in a total score of 0 to 20 points. The questions concerned constructs that were explained in the WBT, e.g., "According to the process model of self-regulated learning, what should you do in the pre-action phase? (a) set goals (right answer), (b) concentrate (distractor), (c) reflect (distractor), (d) relax (distractor)."

### Self-Efficacy

We applied the Generalized Self-Efficacy Scale (Schwarzer and Jerusalem, 1999), which comprises ten items (Cronbach's α = 0.78, e.g., "*I can always manage to solve difficult problems if I try hard enough.*").

### Mathematics Test

The mathematics test, comprising 52 problems (Cronbach's α = 0.84), was created by mathematicians who were responsible for the preparation course. Each problem addressed one of the chapters in the course. In two parallel versions (before and after the mathematics course), participants were allotted 60 min; the time investment was measured to identify lack of engagement in the test. With one point for each correct solution, the *mathematics overall score* ranged from 0 to 52.

Additionally, participants were requested to choose ten chapters to particularly focus on, according to their individual needs. The corresponding ten problems on the mathematics test were calculated to determine the *mathematics focus score* (ranging from 0 to 10).

### Time Investment

We collected logfile data from the learning platform *Moodle* on which the mathematics course was hosted. Each click on the platform created a logfile entry containing the username, time and date, and the content being clicked on. Learning sessions were defined as a sequence of logfiles without interruptions of more than 30 min. For each participant, we calculated the duration of each learning session and added these durations as a measure of time investment.

## RESULTS

### Screening Procedure

We compared the time investment on the mathematics pre- and post-tests to identify participants who did not apply sufficient effort on the post-test. The rationale behind this comparison was that participants may have simply opened the mathematics test to fulfill the criteria for the lottery drawing. We therefore excluded participants who spent 20% less time on the mathematics post-test than the same participants spent on the mathematics pre-test, resulting in a sample of 136 participants.

Descriptive statistics for all dependent variables in the final sample are shown in **Table 1**. For all dependent variables, we calculated one-way ANOVAs with the pre-test data in order to check whether starting conditions between the four experimental groups differed significantly. This was not the case for any of the variables: SRL knowledge test [$F_{(3,132)} = 0.58$; $p = 0.631$]; self-efficacy [$F_{(3,132)} = 0.62$; $p = 0.607$]; SRL overall score [$F_{(3,132)} = 0.95$; $p = 0.420$]; Mathematics overall score [$F_{(3,132)} = 0.31$; $p = 0.817$]; Mathematics focus score [$F_{(3,132)} = 1.18$; $p = 0.320$].

**TABLE 1 |** Mean and standard deviation for each experimental group for self-regulated learning (SRL) knowledge, self-efficacy, overall SRL score, SRL subscales, mathematics overall score, and mathematics focus score on pre- and post-tests.

| | Group C ($n$ = 34) | Group D (n = 28) | Group TD ($n$ = 40) | Group TDP ($n$ = 34) |
|---|---|---|---|---|
| | ***M*** **(SD)** | ***M*** **(SD)** | ***M*** **(SD)** | ***M*** **(SD)** |
| SRL knowledge test | | | | |
| Pre-test | 3.34 (1.76) | 3.50 (1.59) | 3.74 (1.55) | 3.81 (1.79) |
| Post-test | 3.28 (2.07) | 3.54 (2.10) | 7.69 (1.35) | 8.43 (0.83) |
| Self-efficacy | | | | |
| Pre-test | 4.23 (0.76) | 4.16 (0.74) | 4.04 (0.69) | 4.03 (0.78) |
| Post-test | 4.10 (0.69) | 4.25 (0.77) | 4.23 (0.69) | 4.31 (0.69) |
| SRL overall score | | | | |
| Pre-test | 3.52 (0.56) | 3.72 (0.59) | 3.50 (0.61) | 3.65 (0.66) |
| Post-test | 3.52 (0.65) | 3.65 (0.68) | 3.81 (0.67) | 4.17 (0.67) |
| SRL goal-setting | | | | |
| Pre-test | 4.78 (0.76) | 4.90 (0.75) | 4.54 (0.83) | 4.79 (0.79) |
| Post-test | 4.50 (0.88) | 4.79 (0.73) | 4.56 (0.74) | 4.92 (0.61) |
| SRL planning | | | | |
| Pre-test | 3.48 (0.97) | 3.38 (1.09) | 3.42 (1.17) | 3.60 (0.84) |
| Post-test | 3.54 (0.93) | 3.66 (1.09) | 3.98 (1.02) | 4.40 (0.79) |
| SRL self-motivation | | | | |
| Pre-test | 4.31 (1.28) | 4.44 (1.04) | 4.18 (1.02) | 4.05 (1.24) |
| Post-test | 4.28 (1.25) | 4.07 (1.09) | 4.50 (0.93) | 4.55 (0.92) |
| SRL volition | | | | |
| Pre-test | 3.21 (0.79) | 3.62 (0.98) | 3.24 (0.85) | 3.40 (0.93) |
| Post-test | 3.32 (0.84) | 3.35 (1.06) | 3.57 (0.95) | 3.88 (1.08) |
| SRL elaboration | | | | |
| Pre-test | 4.38 (1.00) | 4.45 (1.00) | 4.03 (1.06) | 4.40 (0.98) |
| Post-test | 4.06 (0.97) | 4.26 (0.97) | 4.23 (0.83) | 4.64 (0.91) |
| SRL metacognition | | | | |
| Pre-test | 2.10 (0.64) | 2.24 (0.82) | 2.23 (0.71) | 2.31 (0.93) |
| Post-test | 2.29 (0.74) | 2.42 (0.84) | 2.67 (0.75) | 3.19 (1.20) |
| SRL reflection | | | | |
| Pre-test | 2.79 (1.09) | 3.35 (0.98) | 3.16 (1.00) | 3.29 (1.21) |
| Post-test | 2.96 (1.02) | 3.23 (0.99) | 3.44 (1.04) | 3.82 (1.06) |
| Mathematics overall score | | | | |
| Pre-test | 19.48 (6.62) | 19.93 (7.40) | 19.89 (5.87) | 18.63 (5.45) |
| Post-test | 19.08 (7.41) | 21.16 (8.10) | 21.66 (5.91) | 20.69 (7.00) |
| Mathematics focus score | | | | |
| Pre-test | 2.95 (1.51) | 2.44 (1.57) | 2.64 (1.61) | 2.27 (1.53) |
| Post-test | 2.98 (1.92) | 3.18 (1.94) | 3.20 (1.71) | 3.50 (1.62) |

### Evaluation of Training Effects

We calculated three separate repeated-measures MANOVAs with group and time as the independent variables and different sets of dependent variables. In the first MANOVA, we entered SRL knowledge, self-efficacy, mathematics overall score, and SRL overall score as the dependent variables. The results showed a statistically significant effect of the group [Pillai's trace = 0.51, $F_{(3,132)} = 6.70$; $p < 0.001$], a statistically significant main effect of time [Pillai's trace = 0.66, $F_{(1,132)} = 61.78$; $p < 0.001$], and a statistically significant interaction between the factors [Pillai's trace = 0.71, $F_{(3,132)} = 10.19$; $p < 0.001$], justifying running univariate ANOVAs for the four dependent variables. As seen in **Table 2**, SRL knowledge, self-efficacy and the SRL overall score showed statistically significant interaction effects in the hypothesized direction, with Group TDP showing the most prominent gains among treatment groups and Group C showing either constant levels or even negative developments. **Figure 1** depicts the increases in the SRL overall score for all four experimental groups. The interaction effect for the mathematics overall score, however, marginally missed the level of statistical significance although descriptive statistics indicated the hypothesized direction.

For the second MANOVA, we replaced the mathematics overall score with the mathematics focus score, which was calculated individually for the ten chapters that each participant personally chose as the most important. The rationale was that improved SRL competency after the intervention may lead

**TABLE 2 |** Univariate repeated-measures ANOVAs for self-regulated learning (SRL) knowledge, self-efficacy, overall SRL score, SRL subscales, mathematics overall score, and mathematics focus score on pre- and post-tests.

| | Main effect group | | | | Main effect time | | | | Interaction effect | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *df* | *F* | *p* | $\eta^2 p$ | *df* | *F* | *p* | $\eta^2 p$ | *df* | *F* | *p* | $\eta^2 p$ |
| SRL knowledge test | 3, 132 | 38.20 | <0.001 | 0.46 | 1, 132 | 206.34 | <0.001 | 0.40 | 3, 132 | 59.23 | <0.001 | 0.34 |
| Self-efficacy | 3, 132 | 0.06 | 0.978 | 0.00 | 1, 132 | 9.44 | 0.003 | 0.06 | 3, 132 | 5.914 | <0.001 | 0.11 |
| SRL overall score | 3, 132 | 2.49 | 0.063 | 0.05 | 1, 132 | 29.40 | <0.001 | 0.15 | 3, 132 | 12.55 | <0.001 | 0.19 |
| SRL goal-setting | 3, 132 | 1.67 | 0.177 | 0.04 | 1, 132 | 0.99 | 0.322 | 0.01 | 3, 132 | 2.34 | 0.076 | 0.05 |
| SRL planning | 3, 132 | 2.03 | 0.112 | 0.04 | 1, 132 | 43.70 | <0.001 | 0.23 | 3, 132 | 5.94 | <0.001 | 0.09 |
| SRL self-motivation | 3, 132 | 0.04 | 0.989 | 0.00 | 1, 132 | 3.479 | 0.064 | 0.01 | 3, 132 | 6.79 | <0.001 | 0.13 |
| SRL volition | 3, 132 | 1.75 | 0.322 | 0.03 | 1, 132 | 6.69 | 0.011 | 0.04 | 3, 132 | 4.58 | 0.004 | 0.09 |
| SRL elaboration | 3, 132 | 1.34 | 0.263 | 0.03 | 1, 132 | 0.01 | 0.973 | 0.00 | 3, 132 | 3.88 | 0.011 | 0.08 |
| SRL metacognition | 3, 132 | 3.37 | 0.020 | 0.07 | 1, 132 | 41.07 | <0.001 | 0.22 | 3, 132 | 5.66 | 0.001 | 0.09 |
| SRL reflection | 3, 132 | 3.06 | 0.030 | 0.07 | 1, 132 | 7.73 | 0.006 | 0.05 | 3, 132 | 2.37 | 0.074 | 0.05 |
| Mathematics overall score | 3, 132 | 0.44 | 0.727 | 0.01 | 1, 132 | 11.50 | <0.001 | 0.08 | 3, 132 | 2.50 | 0.062 | 0.05 |
| Mathematics focus score | 3, 132 | 0.06 | 0.978 | 0.00 | 1, 132 | 17.31 | <0.001 | 0.11 | 3, 132 | 2.69 | 0.049 | 0.05 |

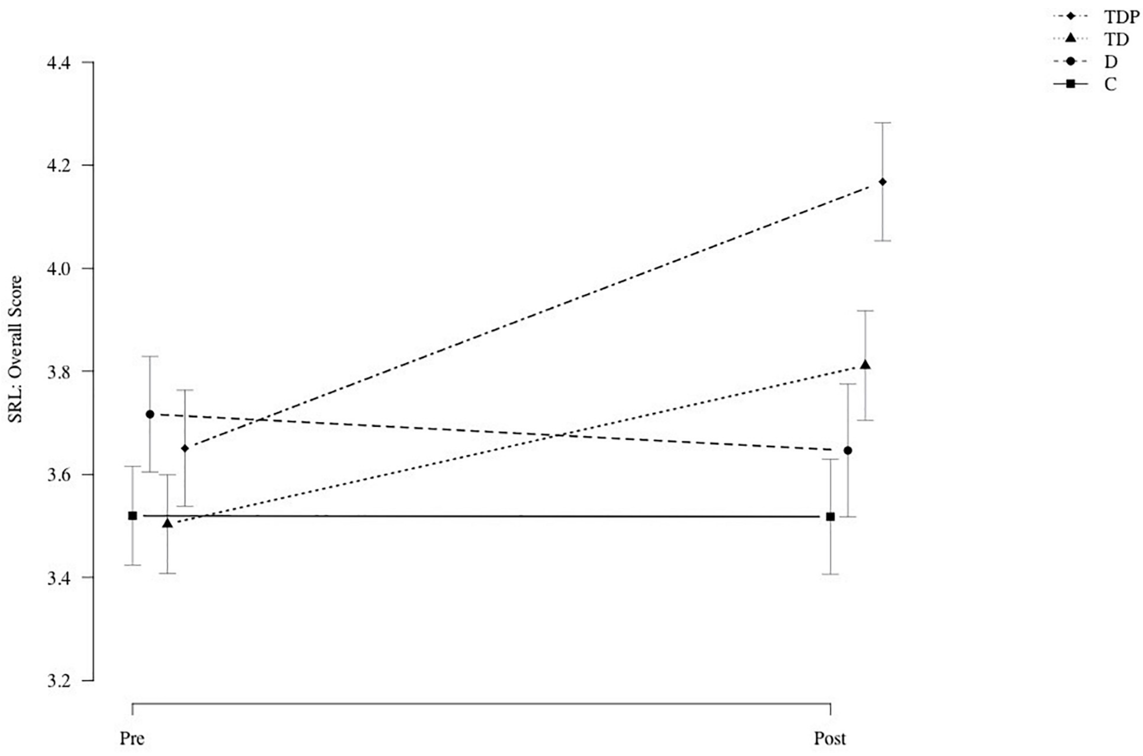


**FIGURE 1 |** Self-regulated learning (SRL) overall scores on pre- and post-tests for Groups C (control group), D (diary), TD (training + diary), and TDP (training + diary + peer feedback intervention).

to a stronger focus on personal goals rather than improved performance in all chapters (including those chapters outside of individual focus). Because the mathematics focus score was calculated only on chapters that participants chose to be personal goals, it appears reasonable that gains were manifested in this score rather than the overall score. Again, the MANOVA showed a statistically significant main effect of the group [Pillai's trace = 0.51, $F_{(3,132)} = 6.66$; $p < 0.001$], a statistically significant main effect of time [Pillai's trace = 0.66, $F_{(1,132)} = 62.22$; $p < 0.001$], and a statistically significant interaction of the two factors [Pillai's trace = 0.73, $F_{(3,132)} = 10.49$; $p < 0.001$]. The univariate ANOVA for the mathematics focus score in fact revealed a statistically significant interaction effect between group and time (see **Table 2**). Gains for the four experimental groups in the mathematics focus score are presented in **Figure 2**.

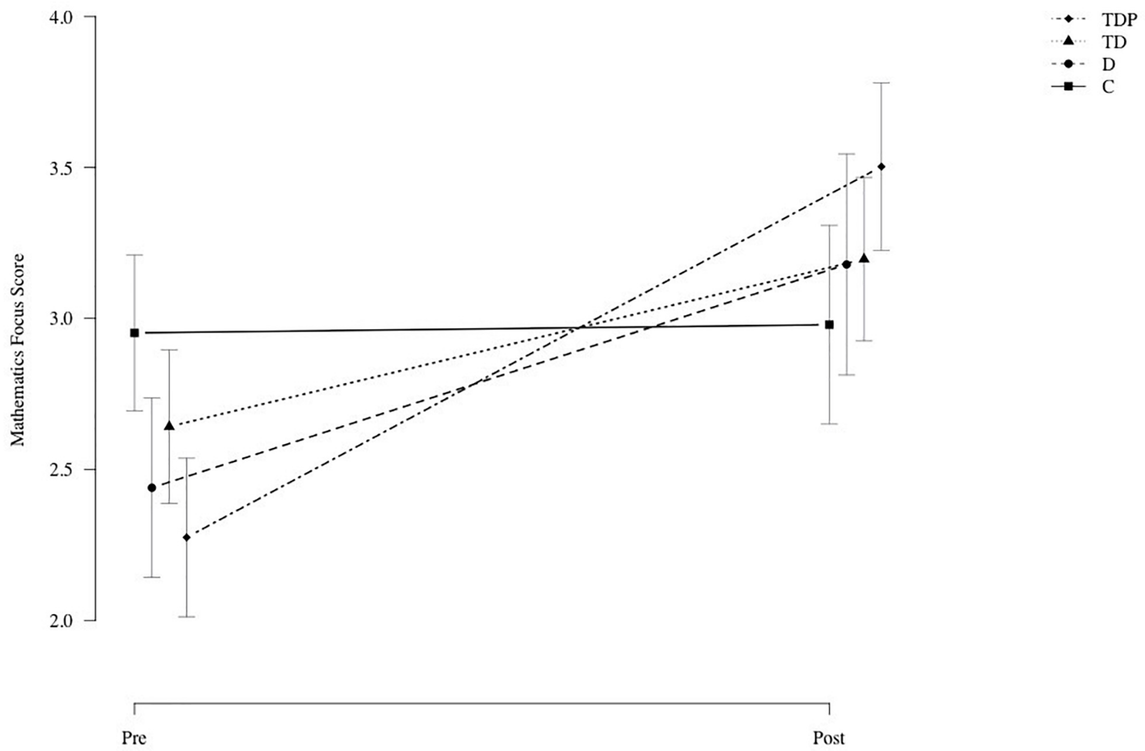


**FIGURE 2 |** Mathematics focus scores on pre- and post-tests for Groups C (control group), D (diary), TD (training + diary), and TDP (training + diary + peer feedback intervention).

To investigate the group differences in depth, we calculated contrasts for the selection of dependent variables used in the second MANOVA. We tested whether the gains of the four experimental groups (e.g., mathematics focus score for Group TD in the post-test minus mathematics focus score for Group TD in the pre-test) differed from zero in a statistically significant manner.

As seen in **Table 3**, Group TD showed statistically significant increases in SRL knowledge (β = 3.95; $p < 0.001$), in the SRL overall score (β = 0.31; $p < 0.001$) and in self-efficacy (β = 0.20; $p = 0.04$) but not in mathematics scores. Similarly, for Group TDP, the increases in SRL knowledge (β = 4.61; $p < 0.001$), in the SRL overall score (β = 0.52; $p < 0.001$) and in self-efficacy (β = 0.28; $p < 0.01$) were determined to be statistically significant. By contrast to Group TD, Group TDP showed statistically significant increases in the mathematics focus score (β = 1.23; $p < 0.001$). Groups C and D showed no statistically significant increases in any dependent variable.

In the third MANOVA, we examined the influence of the interventions on the SRL subscales goal-setting, planning, self-motivation, volition, elaboration, metacognition, and reflection. Here as well, we observed a statistically significant main effect of group [Pillai's trace = 0.62, $F_{(3,132)} = 3.23$; $p < 0.001$], a statistically significant main effect of time [Pillai's trace = 0.70, $F_{(1,132)} = 28.15$; $p < 0.001$], and a statistically significant interaction between the two factors [Pillai's trace = 0.85, $F_{(3,132)} = 4.98$; $p < 0.001$]. The results of the following univariate ANOVAs are presented in **Table 2**. The subscales planning, self-motivation, volition, elaboration, and metacognition all revealed statistically significant interaction effects consistent with our hypotheses, with Group TDP outperforming the other two intervention groups and control Group C showing no positive or negative trends. For the subscales goal-setting and reflection,

**TABLE 3 |** Planned contrasts: gains of the four experimental groups from pre-test to post-test.

| | Group C (*N* = 34) | Group D (*N* = 28) | Group TD (*N* = 40) | Group TDP (*N* = 34) |
|---|---|---|---|---|
| | β (SE) | β (SE) | β (SE) | β (SE) |
| SRL knowledge test | −0.06 (0.32) | 0.04 (0.35) | 3.95 (0.30)*** | 4.62 (0.32)*** |
| Self−Efficacy | −0.13 (0.07) | 0.09 (0.08) | 0.20 (0.07)* | 0.28 (0.07)** |
| SRL overall score | 0.00 (0.08) | −0.07 (0.08) | 0.31 (0.07)*** | 0.52 (0.08)*** |
| SRL goal−setting | −0.28 (0.11) | −0.12 (0.13) | 0.02 (0.11) | 0.13 (0.11) |
| SRL planning | 0.06 (0.13) | 0.29 (0.15) | 0.55 (0.12)*** | 0.80 (0.13)*** |
| SRL self−motivation | −0.04 (0.14) | −0.37 (0.16) | 0.32 (0.13) | 0.50 (0.14)** |
| SRL volition | 0.12 (0.15) | −0.28 (0.16) | 0.33 (0.13) | 0.48 (0.15)* |
| SRL elaboration | −0.32 (0.14) | −0.19 (0.16) | 0.20 (0.13) | 0.23 (0.14) |
| SRL metacognition | 0.19 (0.14) | 0.18 (0.15) | 0.44 (0.13)** | 0.88 (0.14)*** |
| SRL reflection | 0.16 (0.16) | −0.12 (0.18) | 0.28 (0.15) | 0.52 (0.16)* |
| Mathematics focus score | 0.03 (0.30) | 0.74 (0.33) | 0.56 (0.28) | 1.23 (0.30)*** |

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.*

the interaction effects missed statistical significance although descriptive data indicated the hypothesized direction.

Again, we calculated contrasts for the selection of the dependent variables used in the third MANOVA to investigate gains of the four experimental groups (see **Table 3**). Although Group C and Group D showed no statistically significant increases in any of the SRL subscales, Group TD showed statistically significant increases in planning (β = 0.55; $p < 0.001$) and in metacognition (β = 0.44; $p < 0.01$). Group TDP also showed statistically significant increases in planning (β = 0.80; $p < 0.001$) and in metacognition (β = 0.88; $p < 0.001$); in addition, Group TDP showed statistically significant increases in self-motivation (β = 0.50; $p < 0.01$), volition (β = 0.48; $p = 0.01$), and reflection (β = 0.52; $p = 0.02$). However, gains in goal-setting and elaboration remained statistically non-significant for Group TDP.

Using a one-way ANOVA, we analyzed time investment in the preparation course measured by log files. Because there was no pre-test score for this measure, we could not include this variable in the MANOVA models described above. The differences between group means (Group C: $M$ = 21.03 h, $SD$ = 17.56; Group D: $M$ = 28.23 h, $SD$ = 14.13; Group TD: $M$ = 29.32 h, $SD$ = 17.79; Group TDP: $M$ = 33.56 h, $SD$ = 18.87) were determined to be significant ($F(3, 132) = 3.08$; $p = 0.030$; $\eta_p^2 = 0.06$). Contrast analyses revealed that differences between adjacent Groups C and D ($p < 0.01$), D and TD ($p = 0.02$), and TDP and TD ($p = 0.03$) all were significant. Notably, the log files only reflected time spent on the mathematics platform; the files did not include time spent with the three interventions learning diary, WBT, and peer feedback groups.

## DISCUSSION

The present study investigated the effects of three separate interventions that all proposed to foster self-regulated learning in an e-learning environment. A sample of 136 prospective students (after dropout and data cleansing) participated in an online mathematics preparation course for four weeks before beginning their first university semester in mathematically oriented fields. Participants were randomized into one of four experimental groups that had access to either a learning diary (Group D), a combination of a diary and web-based self-regulation training (Group TD), a combination of a diary, web-based training and a peer-feedback intervention (Group TDP), or none of the interventions (control Group C). We measured the effects on an SRL knowledge test, an SRL questionnaire, and a self-efficacy questionnaire. To assess mathematical performance, we administered a mathematics test that covered all the chapters from the preparation course. In addition to the overall score for this test, a focus score was calculated for a selection of mathematical problems that each participant chose to be particularly important to that participant personally. Furthermore, log files from the mathematics learning platform were analyzed with regard to time investment.

We conducted a series of analyses that began on a rather broad top level (MANOVA for all dependent variables), followed by a more detailed middle level (separate ANOVAs for each dependent variable), and ending on a quite specific low level (separate contrasts for gains of each experimental group in each dependent variable). Lower levels of analyses only occurred if significant results on the respective higher level warranted deeper inspection of the effects. All top-level MANOVAs showed significant interaction effects, indicating that different developments in the four groups occurred in at least some of the dependent variables. The following ANOVAs revealed statistically significant interaction effects for all dependent variables, except for the mathematics overall score and the SRL subscales goal-setting and reflection. Because these findings did not provide information regarding the exact groups between which statistically significant differences occurred, we relied primarily on the contrast analyses to decide whether to accept or reject our hypotheses.

In Hypothesis 1, we postulated positive effects of the learning diary on self-reported SRL behavior, self-efficacy, mathematics performance, and time investment. None of the increases reached statistical significance. We only observed a greater time investment for the diary group compared with the control group. In the context of the present preparation course, this result may be regarded as desirable. Although in other learning scenarios, an increased time investment is not necessarily beneficial, a mean time investment of only 21 h in the control group cannot possibly be sufficient to review all chapters of the preparation course when the responsible lecturers estimated a duration of 4 weeks of full-time work. A mean increase of seven hours in Group D, although desirable, is not satisfactory.

We therefore reject the first hypothesis. The learning diary used in the present study clearly did not provide substantial help to participants. This result matches findings from Bellhäuser et al. (2016), who observed no positive effects of a learning diary in a setting comparable to the present study. Perhaps the diary should have been accompanied by a tutorial explaining the potential benefits of learning diaries as demonstrated in other studies (Korotitsch and Nelson-Gray, 1999; Schmitz and Perels, 2011).

In Hypothesis 2, we postulated positive effects of the web-based self-regulation training on declarative SRL knowledge, self-reported SRL behavior, self-efficacy, and mathematics performance, exceeding the effects of the diary-only intervention. As expected, both groups with access to the web-based training increased declarative knowledge regarding SRL. This result may be regarded as a manipulation check that was positive. For the SRL questionnaire, we observed statistically significant increases in Group TD that were not present in Group D, indicating that the additional WBT was responsible for this improvement. Investigating the seven subscales of the SRL questionnaire provided even more detailed insights: Group TD outperformed Group D on the subscales planning and metacognition. Clearly, the WBT was particularly successful in conveying these contents. Furthermore, we observed a statistically significant increase in self-efficacy for Group TD although less prominent than the gains on the SRL questionnaire. For mathematics performance, we did not observe gains in Group TD beyond the general positive main effect for time that was observed for all experimental groups. Concerning time investment, we observed a statistically significant difference between Groups TD and D (and therefore necessarily also between TD and C).

Combining the results of the web-based training on SRL, we concluded that our hypothesis can be accepted with one exception: The WBT helped participants improve their SRL knowledge, their SRL behavior (predominantly in the domains of planning and metacognition), their self-efficacy, and their time investment but not their mathematics performance. Comparing these results to Bellhäuser et al. (2016) leads us to believe that the WBT has been substantially improved in the present study because the prior study revealed small, yet negative effects of the WBT on mathematics performance.

Hypothesis 3 postulated positive effects of the peer feedback intervention groups on self-reported SRL behavior, self-efficacy, mathematics performance, and time investment, above and beyond the effects of the pure web-based training. We found significantly positive effects in most of the dependent variables for Group TDP that were either non-significant in Group TD (e.g., mathematics focus score or volition) or less pronounced (e.g., SRL overall score or self-efficacy).

As expected, the participants in Group TDP experienced increases in declarative SRL knowledge identical to the gains in Group TD. For self-reported SRL behavior, both the overall score and the subscales planning and metacognition showed gains, mirroring the results from Group TD and Group TDP. However, whereas Group TD experienced no statistically significant increases in any of the other subscales, Group TDP showed statistically significant improvements in self-motivation, volition, and reflection. The additional peer feedback intervention appears to have facilitated better use of the strategies concerning self-motivation, volition, and reflection taught in the WBT.

Because the peer feedback tasks involved discussions regarding the individual time schedule (Task 1 after Lesson 1 of the WBT), cognitive learning strategies (Task 2 after Lesson 2 of the WBT), and reflection on their progress to date (Task 3 after Lesson 3 of the WBT), we believe that all SRL subscales were targeted by the peer feedback intervention: Goal-setting and planning were addressed in peer feedback Task 1 and Task 3; self-motivation, volition, and reflection were primarily addressed in peer feedback Task 3; elaboration and metacognition were primarily addressed in peer feedback Task 2. We therefore deem it plausible that Group TDP showed greater gains than Group TD on most SRL subscales. Nevertheless, no statistically significant increases could be detected for the subscales goal-setting and elaboration. For goal-setting, this may be the result of a ceiling effect—this subscale showed the highest pre-intervention scores, leaving less room for improvements than the other subscales. In the case of elaboration, the rather general learning strategies taught in the WBT may not have been sufficiently adjusted to the exact context of the mathematics preparation course. The peer feedback following Task 2 (discussing the use of the learning strategies taught in the WBT) can clearly only improve elaboration (as measured by our questionnaire) if the strategies taught in the WBT in fact fit the needs of participants in the preparation course. For self-efficacy, we observed slightly higher gains in Group TDC compared with Group TD. However, this positive effect appears to be rather small.

In our first analysis, the effect on the mathematics performance remained below the level of statistical significance because we evaluated the mathematics overall score (including all problems from the mathematics test). When examining mathematics focus scores (including only those problems from chapters that participants chose as important to those participants personally) we observed statistically significant increases for Group TDP. However, this increase was rather small and should not yet be regarded as strong empirical evidence. We assume that changes in self-regulated learning behavior need more time than the given 4 weeks in this study in order to have an impact on learning performance.

The mean time investment in Group TDP was 33 h, which is longer than time spent in the other groups but nevertheless still failed to meet the expectations of the responsible lecturers of the preparation course. However, voluntary mathematics preparation courses without face-to-face interaction with tutors and peers, particularly in the age group of approximately 20-year-olds, may have had little chance to convince participants to sacrifice more of their leisure time.

The results from the peer feedback intervention groups support Hypothesis 3: The combined intervention in Group TDP helped participants increase their declarative SRL knowledge, improve their SRL behavior (in all but two subscales), increase self-efficacy, increase their time investment, and improve their mathematics performance. Compared with the results of Bellhäuser et al. (2016), the supplementary peer feedback tasks appeared to substantially improve the quality of the intervention. Because the time span of the present study was only four weeks and the combined intervention only took a few hours (including all three lessons of the WBT, the corresponding peer feedback tasks, and the learning diary), we consider the combined intervention quite successful and efficient.

## Limitations

The major limitation of the present study concerns the sample of participants: Because the mathematics course serves to prepare students for mathematically oriented fields (computer science, civil engineering, mechanical engineering, and mathematics), our sample was predominantly male and may not be representative of students from other fields. The rather large dropout rate in our study exacerbates this issue. However, we could only identify statistically significant differences between dropouts and remaining participants in conscientiousness and the mathematics test with the majority of the other variables showing no differences. The number of dropouts in our study, however, can be described as typical for the learning scenario: The voluntary online mathematics course took place before the regular university courses started and was not reinforced, controlled, or graded. The responsible lecturer reported dropout rates of up to 80% in the recent years. Therefore, dropout in our study might also have been due to a general dropout in the mathematics course.

Another limitation arises from our study design: We did not separate the three different interventions (diary, WBT, and peer feedback intervention) but rather chose a nested design that tested a selection of three different combinations against one another. This approach was selected partially because the peer feedback intervention tasks were inherently cumulative to the web-based training and would not have made sense in isolation. A completely balanced design with all eight combinations of interventions was therefore not feasible; the sample size within each cell could have been problematic as well. We opted to leave out a possible Group T (web-based training without diary or peer feedback intervention) because Bellhäuser et al. (2016) included such a condition in their design. However, we implemented instead the diary-only Group D, mostly to collect time-series data for participants without access to the WBT although the present paper does not include these analyses.

One concern regarding our study may be that improvements in the mathematics test across all experimental groups are relatively small. Of 53 possible points, the global mean was 19.5 on the pre-test and 20.7 on the post-test. Although this main effect of time did reach statistical significance, the effect did not meet expectations (similar to the manner in which the time investment of participants was not satisfying either). Part of this result may be attributed to the target group: The preparation course aimed at gaps in mathematics school knowledge, therefore strong students might have decided to never take the course in the first place. Further, the mathematics test perhaps was too difficult or that the allotted time was too restrictive. Also, the overall time investment was very low even in the experimental groups—students might simply have underestimated how much time they would need in order to complete the course. Another reason may be that participants were more motivated and concentrated more during the pre-test than the post-test, particularly because the test had no consequences for the students' future field of study. Without the external pressure, the primary motivation for good performance may have been to evaluate one's own knowledge and possibly compare oneself to future peers. Because the pre-test had previously provided crucial feedback evaluating current knowledge, when the time came for the post-test, some participants may have felt only the need to complete the test for the lottery—the self-evaluating aspect of the mathematics test may have been less important. Furthermore, allocating one uninterrupted hour for the mathematics test and trying to focus as much as possible on that test may have been easier for participants at the beginning of the preparation course (one month before beginning of the semester) than at the end of the course (a few days before the first lectures). Organizational problems such as moving to a different city or managing a household for the first time on one's own possibly conflicted more with academic aspirations on the post-test than on the pre-test.

## Summary and Future Research

Our results indicated that the combined intervention comprising the learning diary, web-based training, and self-regulated learning with subsequent peer feedback intervention was the most successful, with beneficial effects on self-regulated learning, time investment, and self-efficacy. The effect on mathematics performance was only found for the focus score—a selection of personally relevant topics—and was only very small. However, it remains possible that the improved learning strategies had a delayed effect on performance. There are examples of SRL interventions in which positive effects were stronger in follow-up tests than immediately after the intervention [e.g., Stoeger et al. (2014)].

The combination of the learning diary and web-based training without peer feedback intervention was determined to have statistically significant yet slightly less pronounced effects on self-regulated learning, time investment, and self-efficacy but not on mathematics performance. Using a learning diary without supplementary interventions did not appear to improve self-regulated learning. However, as learning diaries can detect fluctuations in motivation (Bellhäuser et al., 2021), they still seem to be a promising intervention approach when developed further to provide adaptive situation-specific feedback (Loeffler et al., 2019).

Because WBT, once that training is created, can serve virtually unlimited numbers of participants, we advocate its application in educational settings in which large groups of students require support in their self-regulated learning, particularly in distance learning environments that prevent face-to-face training. The additional peer feedback intervention appears to be a useful supplement to WBT, and its organizational costs are comparably low: Participants were assembled into groups of five and were given a group discussion task after each of the three lessons of the WBT. These group discussions regarding their individual learning schedules, their learning strategies, and their progress in the preparation course appeared to substantially increase the beneficial effects of the WBT.

Future studies should investigate the mechanisms of the peer feedback intervention. The mere act of forming small groups could have increased motivation, particularly because the online preparation course may be experienced as a rather solitary task. Our choice of group discussion tasks was theoretically grounded in the process model of SRL (Schmitz and Wiese, 2006); however, it would be possible to create different group tasks to investigate the effects of the exact formulation of the task. In our study, participants did not receive instruction on how to give feedback. As shown by Gielen et al. (2010), explaining to students the criteria of good peer feedback can increase the effectiveness of peer feedback. Also, providing guidance for the assessment of peers' performance (e.g., rubrics) can improve the quality of peer feedback (Bürgermeister et al., 2021). Finally, visualizations of the performance of relevant peers (e.g., sharing similar goals or prior knowledge) might enable students to develop a realistic estimate for their own goal setting (Konert et al., 2016).

A completely different yet certainly also promising approach would be to have learning groups discuss the actual learning content rather than their learning behavior on a meta-level. In the case of the online preparation course, members of a learning group could be asked to discuss their understanding of mathematical problems or even solve complex problems collectively. Possibly the best support for learners would be to combine group tasks that cover the actual learning content with a task that focuses on self-regulated learning.

Although the overall effect of the peer feedback intervention was convincing, not all groups benefitted to the same extent. It appears worthwhile to investigate the causes of inter-group differences. One approach may be to improve group formation by considering personality traits when determining the composition of groups (Bellhäuser et al., 2018; Müller et al., 2022). Also, technical expertise appears to be a key variable for virtual teams, and group composition should perhaps consider a minimum level of technical expertise for every team.

Another approach may be to provide more support for the teamwork process. In particular, asynchronous communication appears to be an issue (Durnell Crampton, 2002). Inactivity or delayed activity on virtual teams can lead to problems in communication; participants may require instruction on how to address the resulting ambiguity. Although we are not aware of conflicts in any of the peer feedback intervention groups in our study, generally, virtual teams appear to be more prone to conflicts than face-to-face groups (Mortensen and Hinds, 2001). Again, this issue may require prior instruction.

As a general remark, we endorse preregistrations for all future studies in this field. This way, researchers' degree of freedom in the statistical analyses can be limited, thereby increasing the credibility of findings (Simmons et al., 2011; Gelman and Loken, 2013; Chambers and Tzavella, 2022).

## DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

## AUTHOR CONTRIBUTIONS

HB designed the interventions, conceptualized the study design, and organized the data collection under the supervision of BS. PL and HB performed the statistical analyses. HB wrote the first draft of the manuscript, PL and BS provided the feedback. All authors contributed to manuscript revision, read, and approved the submitted version.

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# Ace Your Self-Study: A Mobile Application to Support Self-Regulated Learning

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Without guidance, students typically overestimate their understanding and memory of learning materials, which can have detrimental effects on the learning process. However, most students do not receive guidance or instruction about how to study. Moreover, students are largely unaware of strategies to self-regulate their learning and study effectively. Research has shown that prompting both cognitive and metacognitive strategies is effective to support self-regulated learning (SRL). Therefore we developed a mobile application, the Ace your self-study app, to prompt both cognitive and metacognitive strategies to support learning processes. In this article a theoretical background, description of the app's features and design choices are presented. Also, data from the application in presented to give provide an idea of how the app has been used.

**Keywords: self-regulated learning, mobile application, m-learning, metacognitive strategies, cognitive strategies**

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## INTRODUCTION

Self-regulation is an important skill in many domains of life. For example, to fight addiction (Baumeister and Vonasch, 2015), to remediate weight problems (Johnson et al., 2012), or to excel in athletics (Cleary and Zimmerman, 2001). Self-regulation in an academic setting, could be defined as self-regulated learning (SRL), and refers to the interaction of cognitive, motivational and contextual factors that promote academic achievements (e.g., Dinsmore et al., 2008; Schunk, 2008; Dent and Koenka, 2016). Especially in online learning environments students often have to operate autonomously, which makes the ability to self-regulate learning processes even more important (e.g., Wong et al., 2019; Jansen et al., 2020). Moreover, students need to be equipped with strategies to regulate their own learning and development throughout their lives [i.e., lifelong learning (European Commission/EACEA/Eurydice, 2015)] To self-regulate their learning students need to be able to accurately keep track of their own learning process (i.e., monitoring) and use that information to regulate their learning process [e.g., select appropriate learning tasks (Zimmerman, 2008; Bjork et al., 2013)].

Yet, studies have shown that SRL is difficult for students (e.g., Bjork et al., 2013) because they are not capable of accurately judging their own learning processes and use this judgment to regulate further learning (e.g., Dunning et al., 2003; Dunlosky and Lipko, 2007; Thiede et al., 2009). However, most students do not get instruction about how to study (Bjork et al., 2013) and students are largely unaware of learning strategies which could help them to study effectively (e.g., McCabe, 2011; Blasiman et al., 2017; Dirkx et al., 2019; Cervin-Ellqvist et al., 2020). Without instructional support, students often overestimate their understanding (Thiede et al., 2009) and memory of learning materials (Dunlosky and Lipko, 2007), which can have detrimental effects on subsequent learning activities (Dunlosky and Rawson, 2012), academic success, and their capacity to become life-long learners. Therefore, we developed a mobile application to support students SRL processes and provide them with information on how to use effective study strategies. In this article a theoretical background, description of the app's features and design choices are presented. Also, data from the application in presented to give provide an idea of how the app has been used.

## Theoretical Background

Self-regulated learning (SRL) is the degree to which people are "metacognitively, and behaviorally active participants in their own learning process" (Zimmerman, 1989, p. 4). According to the model of SRL by Zimmerman (2008) there are three phases in SRL: the forethought, performance and reflection phase. In the forethought phase students prepare their learning session, for example, by analyzing the task and setting their goals. Then in the performance phase students monitor and control their learning and use strategies to execute the learning task. In the third phase, the reflection phase, students evaluate their learning session and reflect on it (e.g., satisfaction). In this model of SRL both cognitive and metacognitive processes take place. Metacognitive processes for example are, students setting learning goals, monitoring learning processes, and controlling their learning. Using study strategies during the performance phase entails all kinds of cognitive processes, such as elaboration or self-testing.

There have been numerous studies on supporting student's cognitive and metacognitive activities to enhance learning processes and outcomes. Indeed, a meta-analysis by Dent and Koenka (2016) showed that cognitive strategies and SRL are significantly correlated to academic performance. Moreover, Dent and Koenka (2016) suggest that the metacognitive processes that allow students to self-regulate their learning and choose which cognitive strategies to use, may be more important than applying cognitive strategies. In other words, knowing what type of action to take in the learning process at what moment seems crucial. Also, research has shown that both prompting cognitive and metacognitive strategies is effective to support SRL (Devolder et al., 2012). Interventions to support SRL processes based on metacognitive theories, like metacognitive reflection (Dignath and Büttner, 2008) and planning strategies (Dignath et al., 2008), work well for students in secondary education and beyond. In addition, a recent review on writing journals as a promising tool for learning by Nückles et al. (2020) confirmed the benefits of combining cognitive and metacognitive prompts when supporting students during learning. Moreover, research has shown that the most optimal sequence of prompts consists of metacognitive prompts first followed by cognitive prompts (Roelle et al., 2017). Thus it seems promising to support students' SRL processes by designing effective scaffolds in which both metacognitive and cognitive strategies are elicited in order for students to get the most out of it.

Yet, when supporting students, it is crucial to provide the right information at the right time (see Van Merriënboer et al., 2002). Indeed, several studies have shown that using daily diaries or interactive ambulatory assessments can provide important insights into students' SRL behaviors (e.g., Fabriz et al., 2014; Wäschle et al., 2014; Liborius et al., 2019) and can even support SRL and subjective learning experiences (e.g., Loeffler et al., 2019; Broadbent et al., 2020). An interesting way to provide students access to scaffolds for their (self-regulated) learning processes at anytime and anywhere, is using mobile technology (e.g., Loeffler et al., 2019; Palalas and Wark, 2020). That is, almost every student has a mobile phone and with this mobile device supportive applications can be brought close to the student's learning process at anytime and anywhere.

Using mobile technology to support learning or to create a learning environment is also called mobile learning (m-learning) and can be formal, informal or in a combination (Viberg et al., 2021). It was found to be related to study success in educational, non-educational as well as informal learning settings (e.g., Wu et al., 2012; Crompton and Burke, 2018; Shadiev et al., 2020). A recent review on the relationship between m-learning and SRL (Palalas and Wark, 2020) showed that m-learning enhanced SRL, and the other way around. One of the conclusions of the review was that because of the flexibility and portability of mobile technologies, they offer students the opportunity to exercise their agency and use their mobile device as a cognitive and metacognitive tool (Palalas and Wark, 2020). Therefore, mobile technology seems very suitable for supporting SRL.

For example, a study by Tabuenca et al. (2015) showed that tracking time during the learning process using mobile devices with graduate students had a positive effect on time management. In a study by Loeffler et al. (2019) it was found that providing prompts and feedback about metacognitive strategies during the preparations for a written exam using mobile technology, promoted metacognitive strategies, internal resource management and subjective learning experiences. Also, a study by Broadbent et al. (2020) replicated and extended a study by Bellhäuser et al. (2016) using a web-based SRL training and a mobile-app based diary to improve SRL. Specifically, the web-based SRL training provided students with information about the three phases of the Zimmerman SRL model (i.e., forethought, performance, and reflection) during three sessions which were spread across 21 days. In addition, on each of those 21 days students were prompted *via* the mobile app to answer whether they were planning to study that day and if so, what SRL strategies they were going to use and how they felt (positive or negative affect). Also, after studying, students were also prompted to report the strategies they had used and report on their affect. Broadbent et al. (2020) found positive effects in terms of resource management (i.e., time and space), metacognitive and cognitive strategies of using the domain-independent web-based SRL training module and a mobile-app in which students wrote short diary entries. Interestingly, the combination of the web-based training module and the mobile-app, was found to benefit the students' use of SRL strategies the most. Moreover, using the mobile-app for daily diaries only did not seem to improve students' SRL strategies compared to a control condition. The authors highlight that self-monitoring *via* a daily diary only, is probably not enough if someone does not know *how* to self-regulate his or her learning. Hence the combination of information on the three SRL phases with prompts at the beginning and ending of a study session seem to really support students to self-regulate their learning.

Extending these findings and exploring a more coherent way to scaffold both cognitive (i.e., study strategies) and metacognitive processes (i.e., planning and reflection) to improve SRL by students, we developed the Ace your self-study app (Study app in short[1]). In the Study app processes from the forethought, performance and reflection phase are prompted to support students' SRL processes while engaging in self-study. Also, 20 evidence-based study strategies are offered with a short description and a video on how to use them (see **Supplementary Appendix A**). This combination of features provides the student with the information on how to self-regulate their learning using study strategies but also prompts them to plan, monitor and reflect on their own learning processes during self-study.

## DESCRIPTION OF ACE YOUR SELF-STUDY APP FEATURES

### Forethought Phase

In the forethought phase, when students open the app, they will start with making a study plan for the study session they are about to start (**Figure 1**). After clicking on "start session," they are invited to choose the task they will be working on, that is, "studying text," "solving problems," "writing assignments," "test and assessment," or "other." Based on this choice, a selection of study strategies will be shown. Offering this selection of study strategies is based on the idea that learning is a generative activity during which students actively construct meaning from the materials they are studying by reorganizing and integrating it into their already existing knowledge. This process is dependent on how students make sense of their learning materials, for example, by using learning or study strategies (Fiorella and Mayer, 2016). In addition, some strategies can be applied more effectively in certain learning contexts compared to others (Schunk, 2014; Fiorella and Mayer, 2016). Therefore, based on the learning context in which strategies were investigated or described in the research literature, we organized study strategies into the categories "studying text," "solving problems," "writing assignments," and "test and assessment." Just in case these categories would not suit the students' aim of the study session, we included the category "other."

If a student would choose "studying text" the following strategies would be highlighted as a suggestion for students: summarizing (e.g., Wittrock and Alesandrini, 1990; King, 1992; Gil et al., 2010), concept mapping (e.g., Nesbit and Adesope, 2006), organize and elaborate (e.g., McDaniel and Einstein, 1989; Wade, 1992; Mintzes et al., 1997), note taking (e.g., Barnett et al., 1981; Benton et al., 1993; Peverly et al., 2003), mnemonics (e.g., Wang and Thomas, 2000; Rummel et al., 2003; Soemer and Schwan, 2012; Ormrod, 2016), self-testing (e.g., Roediger and Karpicke, 2006; Hartwig and Dunlosky, 2012; Fiorella and Mayer, 2016), self-explaining (e.g., Chi et al., 1989; Renkl, 2002; Ainsworth and Th Loizou, 2003; Fiorella and Mayer, 2016), drawing (e.g., Fiorella and Mayer, 2016; Fiorella and Zhang, 2018), imagining (e.g., Fiorella and Mayer, 2016), spacing (e.g., Carpenter et al., 2012), and self-managing cognitive load (e.g.

[1]www.aceyourselfstudy.nl

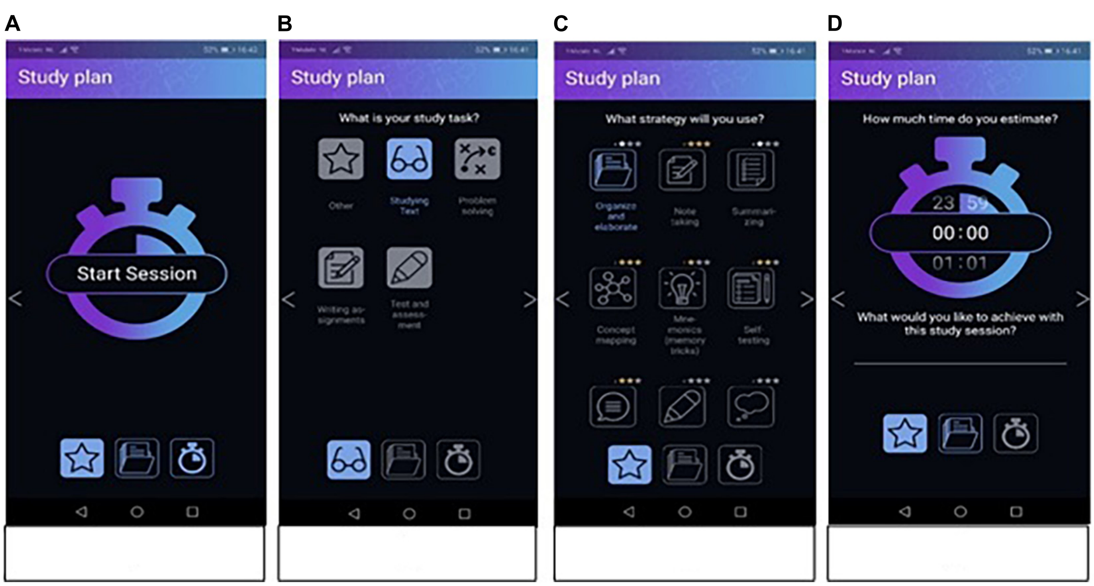


**FIGURE 1 |** Screenshots from the forethought phase, panel **(A)** shows the first "study plan" screen to start a session, panel **(B)** shows the second "study plan" screen at which students choose the type of task, panel **(C)** shows the third "study plan" screen at which students choose a strategy. Panel **(D)** shows the fourth "study plan" screen at which students can set the time and fill out their goal.

Roodenrys et al., 2012; Sithole et al., 2017; Eitel et al., 2020). If a student would choose "problem solving" the following strategies would be highlighted: generate and test (e.g., Schunk, 2014), analogical reasoning (e.g., Gick and Holyoak, 1980, 1983; Halpern et al., 1990), brainstorming (e.g., Mayer, 1992; Schunk, 2014), worked-out examples (e.g., Sweller et al., 1998, 2019; Van Gog and Rummel, 2010), self-testing, self-explaining, drawing, imagining, and self-managing cognitive load. If a student would choose "writing assignments" the following strategies would be highlighted: models for writing, clear writing goals, plan-draft-revise, and organize ideas for writing (e.g., Graham and Perin, 2007; Graham et al., 2013). If a student would choose "test and assessment" the following strategies would be highlighted: self-testing and expressive writing (e.g., Ramirez and Beilock, 2011). Students can select a strategy for this study session by clicking on it. They will get more information on the strategy including a text, an image and a short video on how to use the strategy. For an overview of the strategies per task type see **Supplementary Appendix A**. After selecting a strategy, students are asked to set the time for their study session in hours and minutes. In addition, they can choose to set a goal for their session (**Figure 1**).

## Performance Phase

After students have made their study plans in the forethought phase they start the actual study session in the performance phase. In this phase, there is little to see or do in the application itself, because it is considered important that the students do not work on their phones. Instead, they are only supposed to use the mobile application on their phone to help them plan, monitor and control their learning processes. Therefore, the only option students have during the performance phase other than reading their study task, is looking back at their study plan including information about the study strategy that was chosen (**Figure 2**).

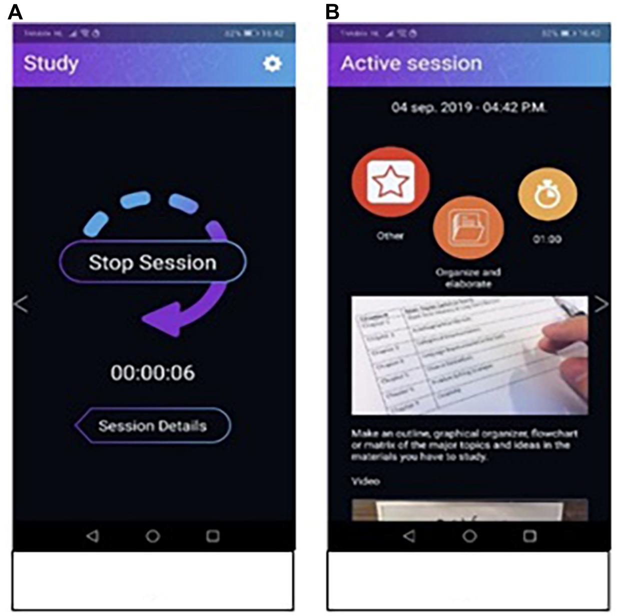


**FIGURE 2 |** Screenshots from the performance phase. Panel **(A)** shows the defaults screen during the performance phase which shows a timer. Panel **(B)** shows the summary of the "study plan" made in the forethought phase.

## Reflection Phase

When students decide to stop their study session, they enter the reflection phase, in which they are prompted to reflect on the result of their study session (**Figure 3**). They are asked to rate their satisfaction with the study strategy they have used and with their learning during the session using a 5-point rating scale with smileys. Also, students were asked to indicate whether they had studied alone or together with other students. Note, this feature only allows capturing this information for the log files for the purpose of reflection on the learning process. There are no other features in the app that support social interaction through the app in the current version. After providing these ratings, students can use the log to look at the summary of their session or a summary across multiple sessions. These logs provide them with information on the strategies, ratings, studying alone or together and time they have planned and actually spent. That way, the app can support the reflection phase in SRL.

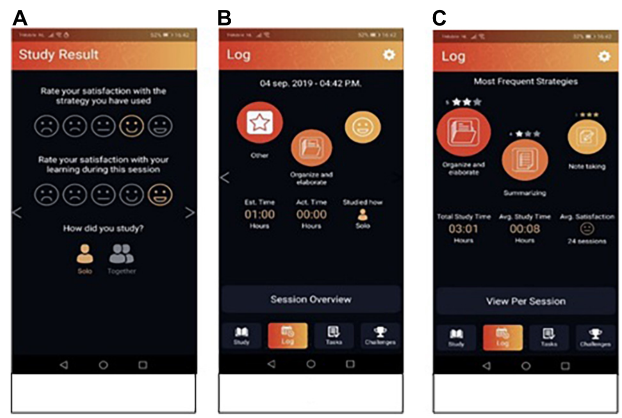


**FIGURE 3 |** Screenshots from the reflection phase. Panel **(A)** shows the two ratings students have to fill out. Panel **(B)** shows the log for a single session. Panel **(C)** shows the log across sessions.

## Gamification Elements

Research has shown that gamification elements such a as levels, points and scoreboards, can increase student motivation and performance. Gamification elements provide clear goals and rewards for students which keeps them engaged and motivated (Su and Cheng, 2015; Mekler et al., 2017). Therefore, both in the tab "Tasks" and the tab "Challenges" some gamification elements were implemented in the app. In Tasks students can find all the types of tasks and all the strategies (**Figure 4**). Here the student can also see how many stars (i.e., levels) per strategy are earned already. The last tab Challenges provides the student with some challenges in terms of planning sessions and using a variety of learning strategies. For example, "Lucky number, use 7 different strategies." Both the stars and the challenges are gamified elements to stimulate the users to use the app and the

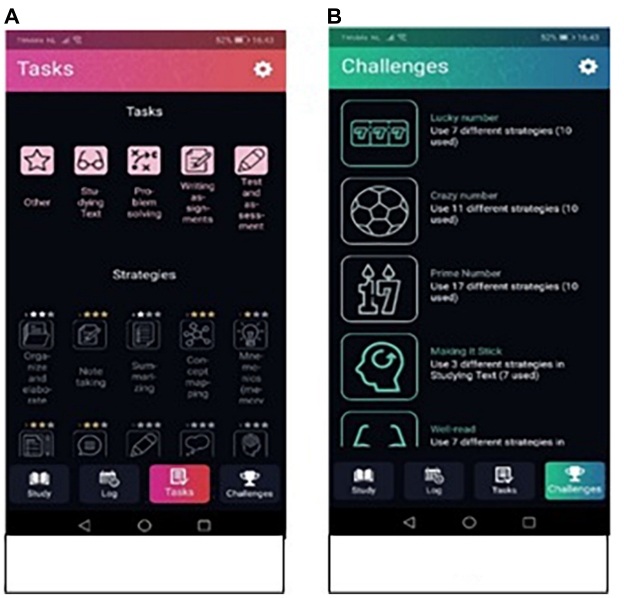


**FIGURE 4 |** Screenshots of gamification elements in app. Panel **(A)** shows the overview of the strategies with the level of use depicted in stars. Panel **(B)** shows the challenges students can take when using the app.

strategies in the app to its full potential for learning. All the challenges are provided in **Supplementary Appendix B**.

## CONCEPTUAL DESIGN AND DESIGN PROCESS

The intention behind the conceptual design was to create a streamlined user experience with the least amount of friction caused by "trying to figure out the app." Two design principles were selected by the designer to guide the conceptual design of the current app (Lidwell et al., 2010). The first is the 20/80 rule (a.k.a. Pareto principle) which governs how a few critical features create the most significant effect. The sizeable stand-alone "*start session*" button found on the app's main screen represents this concept. In this case students can clearly only choose to click "start session" (**Figure 1A**) which is a significant choice. The second is the Flexibility–Usability Tradeoff principle, which states that when flexibility increases usability and performance decrease. The "wizard" or linear session set-up, which allows students to create a step-by-step study plan, is an example of this concept. Both of these principles were used as guidelines to design the Study app.

The app follows a design-driven UX (User Experience) approach to development, including the co-design and creation with researchers, students, and developers. The purpose of a design-driven approach is to select technology for the best impact and avoid the typical pitfall of "we want an app" syndrome (e.g., using the technology simply because it is available). That is, the app was specifically designed to create the best impact for its purpose. The design process started with an analysis phase to define the purpose of the app and followed the exploratory investigation of paradigms used in apps popular with the target audience. The approach to deciding the interaction and app flow started with a diagram that documented the architecture. From the initial sketch, a wireframe of each screen was mocked up with a preliminary positioning of interactive elements (e.g., buttons). Using Adobe XD software, a basic interactive mock-up called a click-through was created based on the wireframes and architectural flow. The click-through was then black-box tested, that is, given to co-designers to explore without explanation for usability and usefulness for the research goals. The resulting feedback from the user tests was then used to improve interaction. The next click-through version included a visual aesthetics (e.g., colors, icons, fonts, etc.) upgrade, which was then tree tested by the target audience. The tree testing method was used to determine if the target audience could navigate and discover the core functionality of the app. Feedback from the play-test was used to again iterate on the visual design and interaction design. At this point, the design hypothesis was considered solid enough to begin the development of the app. Native iOS and Android programming languages were used to develop the app for deployment to smartphones and tablets. Additionally, a CMS (content management system) was created to allow researchers to add and edit content and manage user data.

### Gamification Design Process

Gamification is the term used to describe the application of game principles and patterns to motivate users to accomplish daily activities. The aim is to drive user activity by closing or tightening the feedback loop (e.g., scoring points) and allow users a way to track their progression (e.g., achieving a high score). Game principles also include the use of player communities to create competition, cooperation, peer-pressure, or social connectivity. The app's gamification aimed to encourage students to explore different types of study strategies and adhere to studying with the app. Two kinds of gamification elements are used to accomplish these aims. *Challenges* are intended to stimulate students to explore different types of study strategies. Users can find a list of challenges they try to fulfill by using the Study app. For example, the challenge "Lucky number" states: "Use 7 different strategies" (see **Supplementary Appendix B** for an overview of the challenges). When students finish a challenge, the challenge will be highlighted in their list of challenges. *Stars* allow the user to track their use of a single study strategy. For each instance a study strategy is used, the next level will be reached which will then be indicated by a star depicted with the strategy name (see **Figure 4**). A maximum of three stars can be earned.

The gamification design process began with setting the design goals, followed by a pitch to the project researchers of game elements that could accomplish these goals. From the concept pitch, there was a brainstorm session with students to gather ideas on how they would be best motivated to use the app. The result of these initial activities were ideas for a *star* system, a *challenge* system, and a *cooperative user-sharing* system. However, due to project constraints, not all these features could be built. Eventually, a decision was made to implement the *star* and *challenge* systems. Lastly, a usability black-box user test was done to determine if users and stakeholders understood the gamification.

## SYSTEM ARCHITECTURE

The system architecture includes a CMS accompanied by a public website and two apps (iOS and Android). The system architecture facilitates researchers with features for managing content, moderating users, exporting data, and website customization.

The CMS is a back-end interface and website built using open-source software and hosted on a LAMP (Linux-Apache-MariaDB-PHP) server. The relational database on the server stores all log records. Communication with the app occurs through a RESTful API (Application Programming Interface). All connections and webpages of both the CMS and website are encrypted using SSL (Secure Sockets Layer). More information about the source code is available upon reasonable request.

Administrators of the CMS can assign different roles or access rights to different CMS users, including the moderation of the study tasks, strategies and challenges available in the app, insight into sessions and account data, and customization of the webpage content. The CMS provides researchers with various functionality that includes adding and editing content, moderating users, exporting research data, and editing the public website content. A researcher can add or edit the tasks, strategies, and challenges to the app without technical support. Students (end-users) encounter these changes to the content when online and after restarting the app. The system determines by equal distribution if a student will have a gamified or non-gamified version of the app. Researchers can also manually set a student's app to gamified or non-gamified. Furthermore, user account and session data can be exported as CSV or TAB-delimited files for research purposes. Session data exports include the following:

| | |
|---|---|
| Account: | User ID, date of birth, and gender. |
| Current type: | Indicates if the app used during the session is gamified or standard. |
| Task: | The type of study task done during the session. |
| Strategy: | The type of study strategy selected for the session. |
| Goal: | The study session goal that was entered by the student. |
| Estimated time: | The student's estimated time (minutes) for the study session. |
| Actual time: | The student's actual time (seconds) of the study session. |
| Study session rating: | Indicates on a scale (1–5) the student's satisfaction with the strategy and learning; and if the session was alone or partnered. |
| Start: | Provides a timestamp for the beginning of the session. |
| Stop: | Provides a timestamp for the end of the session. |
| Sync: | Provides a timestamp for when the user's data was synchronized with the database. |

The implementation of the system architecture took into account the need to include future functionality, for example, including a feature for language localization, connecting to an LMS (learning management system), and more in-app questionnaires.

The app is built with SWIFT (for iOS) and Java/XML (for Android), while a local SQLite database is implemented for each app installed on a specific device. The rights to the source code for the apps belong to the developer. Students are required to create an account with a valid email address and a password in order to be able to use the app. A verification email is sent to the supplied email address on account creation. The user has to click on a link in this verification email before logging on and starting using the app. The registration process also includes collecting research data regarding the students' year of birth and gender. The local SQLite database is used to store a duplicate of all task, strategy, and challenge data needed for the use of the app, which allows the app to be used even when a user is not online. All study sessions are stored locally and uploaded to the CMS when an offline user goes online again. This setup also allows for migrating an account to a different device or use of the app by the same user on multiple devices, such as smartphones and tablets.

The process to develop the CMS, website, and apps included an initial evaluation of the available technology. During the evaluation, considerations relevant to the project's needs were determined. For example, other development frameworks may allow for publishing for iOS and Android from a single code base but may not allow essential features such as push notifications. After the evaluation, it was decided to develop the apps natively, i.e., create two separate code bases in the native programming languages of Android and iOS. Android was chosen to be developed first because of the developer's familiarity with JAVA/XML and the ease with which the app could be tested on Android devices. When developing for Android, the developer can build an APK and distribute it by several means to be installed on a device for testing. In contrast, iOS requires users to install an app that manages the installation and testing of apps. The CMS and website were developed simultaneously during the development process, while the iOS version was developed last.

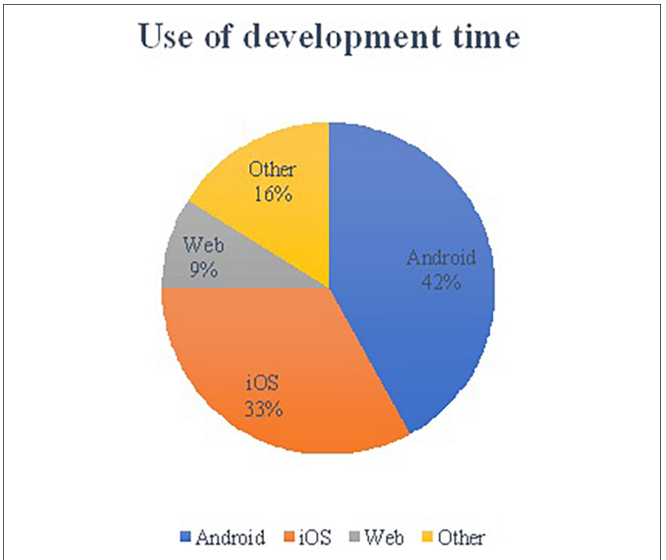


**FIGURE 5 |** Use of development time.

Building natively in iOS and Android means two separate apps need to be developed. Six hundred and fifty hours were used to develop the initial system. **Figure 5** provides the percentage of time needed to develop all the aspects of the system. There was a slight gain in efficiency for the developer by being familiar with the app's interaction design when developing the app again for iOS.

Google Play and Apple Store are distribution platforms needed to distribute apps to students (end-users) efficiently. When submitting to these stores, additional development time may be needed for minor changes to the app to meet the standards and criteria established by the distribution platforms.

Once an app is available through a distribution platform, it does not guarantee that it will continue to function. For example, updates to operating systems will eventually make an app obsolete and no longer run on a device. For this reason, an SLA (service level agreement) is created with the developer. The purpose of the SLA is to ensure that the app is managed and maintained to keep the app functional. Furthermore, it determines how a developer prioritizes solving issues, helping end-users, managing the stores, and making minor improvements.

In summary, our guidelines for developing an app system architecture would be as follows:

- Evaluate the available technology; and thoroughly understand the trade-offs of each available platform.
- Work as a multi-disciplinary team.
- Design and develop iteratively.
- Include an interaction designer that can bridge research, psychology, computer science, and human-centered design.
- Build and test regularly.

## ORGANIZATIONAL CONTEXT

In Marc Prensky, (2001, p.2) wrote: *"Our students have changed radically. Today's students are no longer the people our educational system was designed to teach"*.

Stating that the students had become digital natives with a high level of understanding the digital language and the educators are digital immigrants speaking an outdated language, his words have an even greater value today. In this day and age our students have changed even more and are matured digital natives. Smartphones, laptops, and tablets are mainstream devices and present not only in our students daily life but also in our educators daily life. Fortunately, the gap between students and educators when it comes to being a digital native is not as large or definite as some might suggest (Helsper and Eynon, 2010). Breadth of use, experience and educational levels also play a role in having advanced interaction with the internet. Moreover, it is possible for adults to become digital natives. Hence, if used the right way, smartphones and tablets can act as engaging platforms to help educators to immerse these students into educational content.

Back to Prensky, the same statement can be made for universities. The primary task of a university is not to design, develop, and deploy new educational technologies. It is a fact that IT projects are notorious for running late, being over budget and failing on all levels (Williams, 2017). Designing, developing, and deploying mobile applications within a university context is an even more costly and time consuming process. The life cycle for an app development starts with picturing the entire range of stages and procedures to go through. Next to designing, developing, and deploying the app all parties involved need to take several things in consideration in the implementation phase.

Firstly, teams might encounter several legal questions in regards to privacy issues and intellectual property rights. In regards to privacy issues (mostly concerning the GDPR) the data that is collected from the data subjects contribute to the underlying goals of the research. GDPR-proofing the application also includes a full privacy statement, an End Users License Agreement (EULA) and general terms and conditions for usage. To check whether an application is GDPR proof it is important to check the following:

- Determining the data subject.
- Determine the goal and purpose of storing the data of the data subject.
- Determine if sensitive personal data of the "data subject" is being requested/stored?
- Determine if personal data is being requested/stored.
- Determine if a combination of "general data" can lead to a (in)direct identification of the data subject.
- Determine which party is the "data controller."
- Determine if the app is working with "data processors," if so, identify the data processors.
- Determine the duration of the data storage.
- Determine the storage location of the data.
- Determine the method of removing personal data in order to comply with the right to be forgotten.
- Determine a plan of action in case of a data breach.
- Determine how consent for data processing is obtained.
- Determine if a processor agreement is necessary.

Most of these points are covered by the universities privacy policy, however, the importance of safeguarding personal data cannot be understated.

### Intellectual Property Rights

In this specific case we have developed a mobile application, which is a software application designed to run on a mobile device, i.e., a smartphone. To protect applications from infringement by third parties it is eminent to determine the ownership of the application. In general software applications such as the Ace your self-study app can be protected by several intellectual property rights. The most obvious questions related to intellectual property rights are:

### Patent

A patent is usually obtained to protect technical inventions that are novel. In this specific case obtaining a patent for the app would be a lost cause. The app is an obvious next step in the advancement of technology.

## Trademark

Due to the highly competitive nature of the industry the protection of the name, logo, patterns, shapes, colors and other characteristics that distinguishes the application from other available applications on the market can be obtained by registering a trademark.

## Copyrights

All mobile applications are software applications designed with a unique source code that allows it to run on a specific device. Due to the unique composition of every code written, it meets the standards of copyright protection.

## Design Protection

This guarantees the project team the exclusive rights to use the design and to protect the appearance of the application or parts of it, including contours, colors, and shapes.

Secondly, it is recommended to draft a Service Level Agreement with an independent trusted third party. Most universities do not have the capacity to maintain and update the licenses needed for the application. This can be circumvented by hiring a third party. Considering the fact that most development teams only calculate a sufficient budget for the development, it is highly recommended to have a healthy budget in place for new releases, hosting, maintenance, security, software updates, and app store licenses.

Last but not least, connecting research to a mobile application is highly risky undertaking. The research can only be conducted as long as the application is running.

# DATA FROM THE ACE YOUR SELF-STUDY APP

In September 2021, 4,254 accounts were registered for the Ace your self-study app between December 2017 and September 2021. Most users were presumably invited to use the app by their teachers or trainers in higher education settings as the app was presented at several national and international meetings and conferences on educational innovations, teaching and learning for researchers and educational professionals (e.g., EARLI conference, SURF education days). It is also possible for learners to have found out about the app by themselves, *via* conferences they attended or because it is freely available in the App and Play Store and they found it there. From the persons who registered for an account 1,134 indicated they are male and 3,120 indicated they are female. Their mean age in years is 24 years (SD = 9.05). The most frequent age was 20 years old. These users have completed 6,505 study sessions in total. To provide an idea about what these study sessions looked like, we will present data on the number of sessions, the duration of sessions, the strategy choices, the satisfaction with the strategy that was

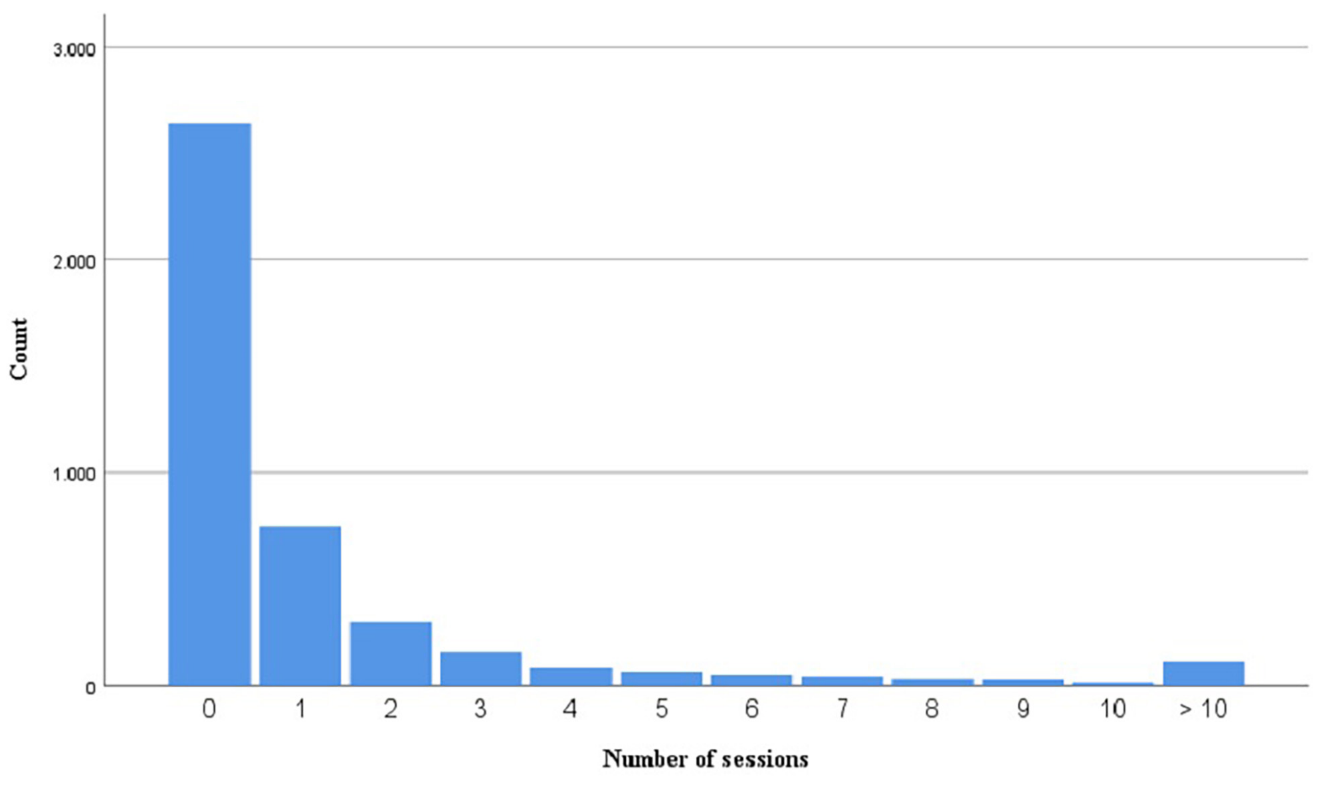


**FIGURE 6 |** The count of users with a certain number of sessions.

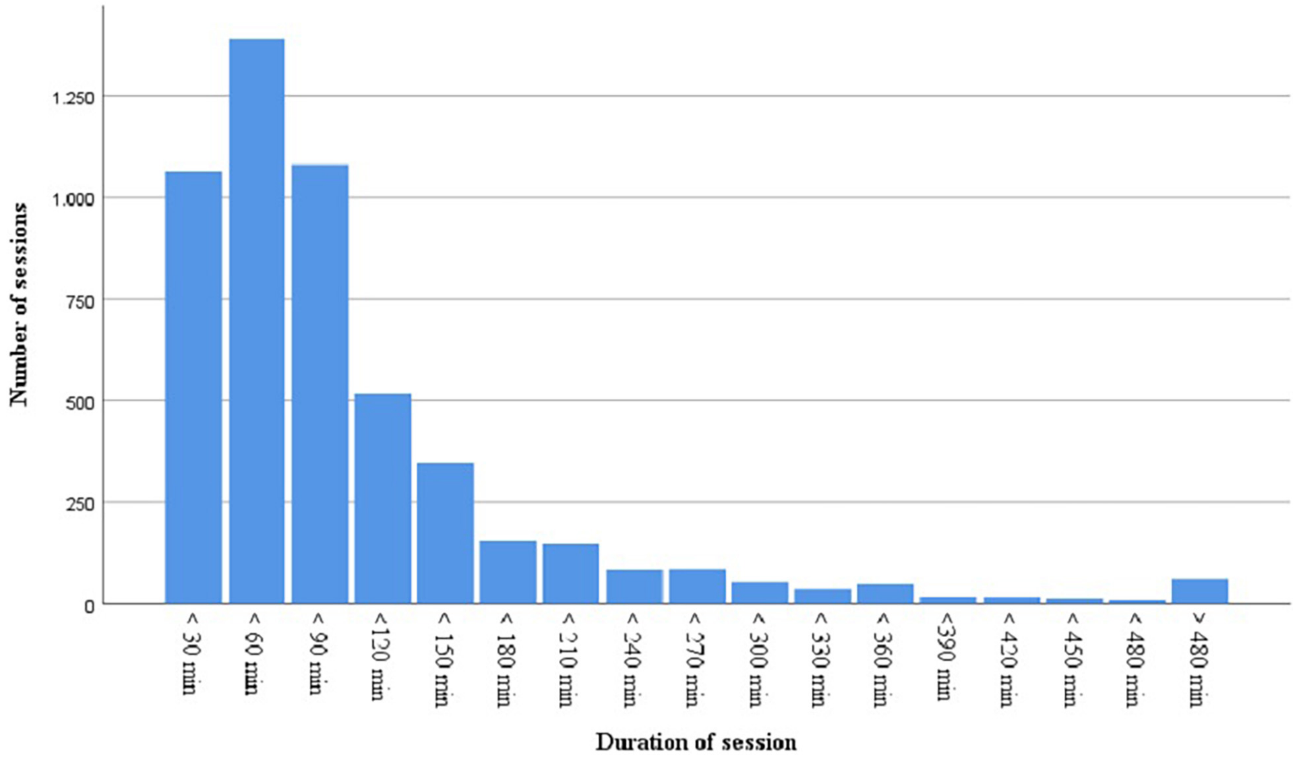


**FIGURE 7 |** The number of sessions of a certain duration.

chosen and the satisfaction with learning during the self-study session in general.

## Number of Sessions

**Figure 6** shows that very often users did not create a study session but most likely just explored the app ($n$ = 2,643). Many users choose to have 1 study session ($n$ = 745). Fewer users had 2 ($n$ = 300), 3 ($n$ = 155), 4 ($n$ = 84), 5 ($n$ = 62), or more sessions. As the data are skewed, we used a Mann–Whitney U test to explore differences in the number of sessions by gender. No differences in the number of sessions between males ($Mdn$ = 0) and females ($Mdn$ = 0) were found, $U(N_{males}$ = 1,134, $N_{females}$ = 3,120) = 1,822,898.00, $z$ = 1,822,898.00, $p$ = 0.080. In addition, year of birth was not significantly correlated to the number of sessions participants had, $r$ = 0.028, $p$ = 0.065.

## Duration of Sessions

To get an idea of the duration of valid study sessions, we selected the sessions that lasted from 1 min up to 12 h ($n$ = 5,597). Sessions that were shorter than 1 min ($n$ = 626) or longer than 12 h ($n$ = 290), were not considered here. For sessions shorter than 1 min it seems highly unlikely a user would have had the chance to set up a study session and for sessions longer than 12 h it is very likely a user forgot to stop the study session. Most sessions lasted between 30 and 60 min ($n$ = 1,398), followed by 30 min or less ($n$ = 1,065), and between 60 and 90 min ($n$ = 1,081). There are also quite some sessions of 2 h ($n$ = 518), 2.5 h ($n$ = 346), 3 h ($n$ = 155), and 3.5 h ($n$ = 147). Only 8% of the sessions ($n$ = 428) lasted 4 h or longer (see **Figure 7**). As the data are skewed, we used a Mann–Whitney U test to explore differences between male and female users in the duration of sessions. It was found that the duration of sessions was significantly different for males ($Mdn$ = 59.43) compared to females ($Mdn$ = 60.94), that is, females were found to have a slightly longer duration of their sessions, $U(N_{males}$ = 1,183, $N_{females}$ = 4,414) = 25,751,397.00, $z$ = 2,751,397.00, $p$ = 0.004. Note that because of the high number of sessions, a small difference in the duration of the sessions, reached significance. In addition, age was not significantly correlated to the duration of sessions, $r$ = 0.021, $p$ = 0.118.

## Study Strategies

As shown in the pie chart below, all kinds of strategies were chosen by the users. There are 20 different strategies in the chart. Notetaking was chosen most often (36%), followed by summarizing (19%), organize and elaborate (12%), self-testing (5%), self-explaining (5%), and concept mapping (3%). For the remaining strategies the percentages are small (only 1–3%, see **Figure 8**).

## Satisfaction With Strategies and Learning

Users ($N$ = 1,246) were quite satisfied with the strategy they had chosen during their study sessions. On a 5-point scale the users indicated 3.44 on average (SD = 1.50) as their satisfaction

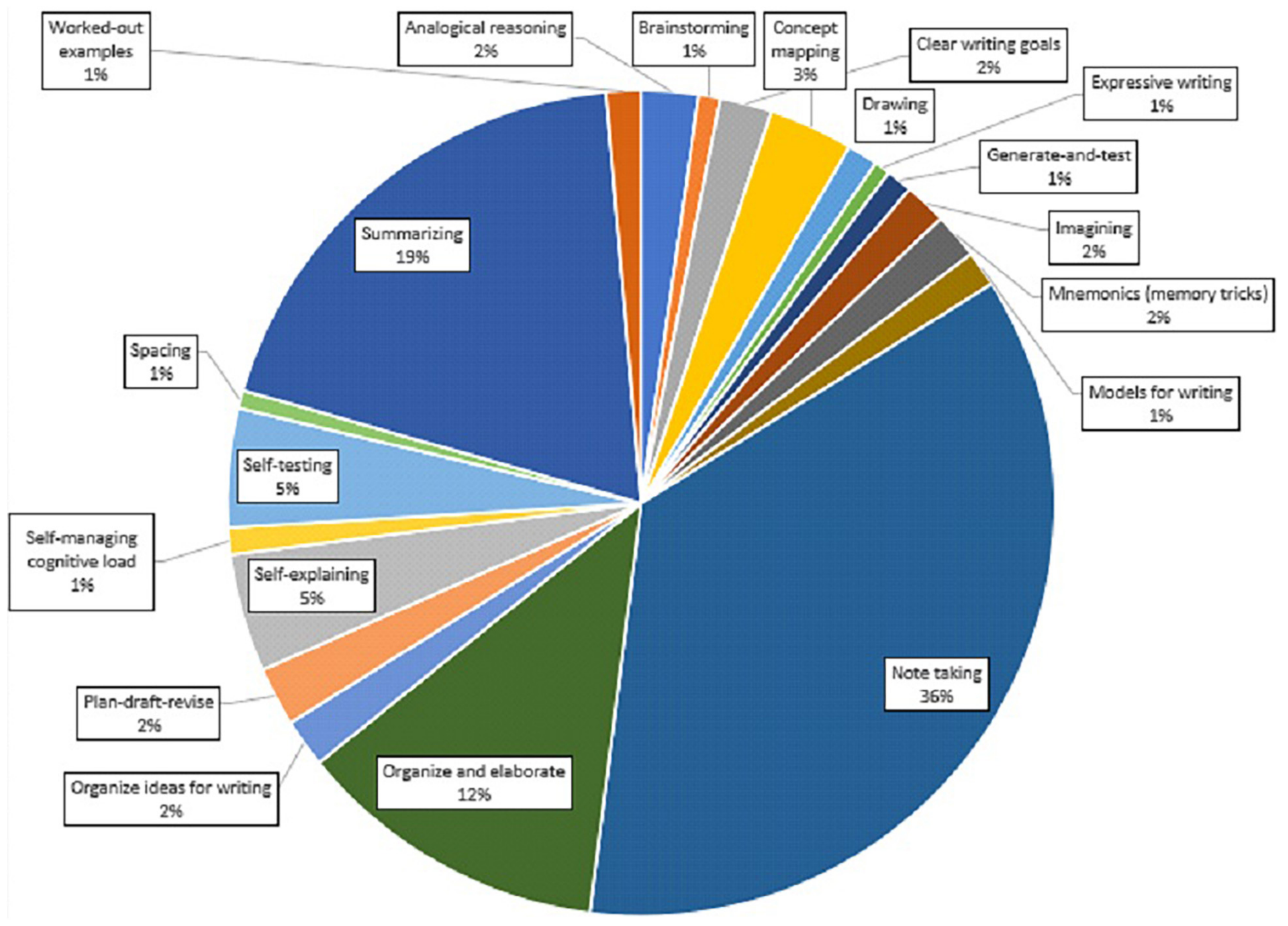


**FIGURE 8 |** A pie chart showing the percentage for each strategy' in the total of strategy' choices.

score with the strategies they had chosen. As the data are skewed, we used a Mann–Whitney U test to explore the effect of gender on the satisfaction with the strategy. No difference in the satisfaction with strategies was found between males ($Mdn$ = 4.00) and females ($Mdn$ = 4.00), $U(N_{males} = 303, N_{females} = 943) = 148{,}774.50$, $z = 148{,}774.50$, $p = 0.271$. In addition, the age of the users was significantly correlated to the satisfaction with strategies, $r = -0.152$, $p < 0.001$. This seems to suggest that the older the users were the less satisfied they were with the strategies they had used.

The users satisfaction with their learning during the study session was slightly, 3.33 (SD = 1.50) on a 5-point scale, lower but still moderate. As the data is skewed, we used a Mann–Whitney U test to explore the effect of gender on the satisfaction with learning. No difference was found in the satisfaction with learning between males ($Mdn$ = 4.00) and females ($Mdn$ = 4.00), $U(N_{males} = 303, N_{females} = 943) = 140{,}244.00$, $z = 140{,}244.00$, $p = 0.626$. In addition, the age of the users was significantly correlated to the satisfaction with strategies, $r = -0.138$, $p < 0.001$. This seems to suggest that the older the users were, the less satisfied with their learning they were.

**TABLE 1 |** Descriptive statistics.

| | Mean (SD) | Minimum | Maximum |
|---|---|---|---|
| Evaluation questions (total) | 5.69 (0.88) | 2.25 | 7 |
| Easy to understand strategies | 5.80 (0.99) | 2 | 7 |
| Clearly described strategies | 5.78 (1.00) | 3 | 7 |
| Easy to navigate app | 5.71 (1.04) | 3 | 7 |
| Intuitive to use app | 5.47 (1.01) | 2 | 7 |

## Usability

A group of 45 college students ($M_{age}$ = 20.84, 39 females and 6 males) in an undergraduate psychology program used the Study app for one self-study session to test the usability of the app. They used the Study app in a 60 min self-study phase during which students studied a scientific article. At the end of the session, students answered four questions to evaluate the use of the Study app (see **Supplementary Appendix C**). As shown in **Table 1**, the Study app was evaluated quite positively with 5.69 out of 7 points on average. Specifically, students rated the app as quite easy to understand, easy to navigate, intuitive to use, and the strategies to be clearly described.

## DISCUSSION AND CONCLUSION

Especially in online learning environments the ability to self-regulate learning processes is important to learn effectively in an autonomous or independent way (e.g., Wong et al., 2019). Yet, many studies have shown that SRL, that is, effectively monitoring and regulating one's own learning processes, is difficult for students (e.g., Dunning et al., 2003; Dunlosky and Lipko, 2007; Thiede et al., 2009). This means there is a need for support and instruction on how to self-regulate learning and use study strategies. However, most students do not get this support or instruction about how to study (Bjork et al., 2013). In addition, most students are unaware of learning strategies which could help them to study effectively (McCabe, 2011; Dirkx et al., 2019). This is problematic as it was found that without instructional support, students often overestimate their learning processes (e.g., Dunlosky and Lipko, 2007; Thiede et al., 2009) and prematurely stop studying (Dunlosky and Rawson, 2012). Therefore, we developed a mobile application to support students' SRL processes and provide them with information on how to use effective study strategies.

To accommodate the often autonomous learning situation of students in higher education which could take place anytime or anywhere, we have used mobile technology to create an application to support self-study activities, the Ace your self-study app (Study app). In the Study app processes from the forethought, performance, and reflection phase based on the model of SRL by Zimmerman (1989, 2008) are prompted to support student's SRL processes while studying. Next to these phases, 20 evidence-based study strategies are offered with an explanation on how to use them. Because gamification elements such as levels, points and scoreboards, can increase student motivation and performance (Su and Cheng, 2015; Mekler et al., 2017), some gamification elements were implemented in the app. Students can earn stars (i.e., levels) per strategy and they are challenged in terms of planning sessions and using a variety of learning strategies.

The conceptual design was chosen to create a streamlined user experience with the least amount of friction caused by "trying to figure out the app." The app follows a design-driven UX approach to development, in which the co-design and creation with researchers, students, and developers is central. The development of the mobile application followed an iterative design, built, test and evaluate cycle in which all stakeholders were involved. Next to the development and design of the Study app, several legal questions about privacy issues and intellectual property rights are important. With regards to privacy issues, the data that is collected from the data subjects contribute to the underlying goals of the research. Therefore, GDPR-proofing the application also included a full privacy statement, an EULA and general terms and conditions for usage. Also, a Service Level Agreement with an independent trusted third party to maintain and update the licenses needed for the application was created. This is particularly of importance when considering future research plans involving the usage of the app.

Looking at the data, very often users did not create a study session but most likely just explored the app. Of the users who started a session, most users chose to have one study session and fewer users had two or more sessions. The fact that only 1,246 out of 4,254 registered accounts had study sessions, is a remarkable finding. Potentially this could be the case because of a mismatch between the user's needs and what the Study app offered. That is, the Study app was developed to support SRL activities during self-study sessions. Yet, research has shown that people often overestimate their learning (e.g., Bjork et al., 2013) and know little about study strategies (e.g., McCabe, 2011) that can help them to learn more effectively. Hence, perhaps potential users thought they did not need an app to help them regulate their learning and use effective study strategies during self-study. Future research could look into the experiences of persons who have used the app for self-study and those who have looked at the app but decided not to use it. Moreover, it would be interesting to investigate if applications that provide more guidance instead of leaving it up to the user, would have a different effect on user behavior. For example, a mobile application could also include push messages to provide suggestions or feedback with SRL activities. In addition, integrating the Study app into educational programs could allow for teachers or trainers to guide their students when it comes to using the app and the SRL support within the app to their benefit.

Based on the data from active users, we found that most sessions lasted between 30 and 60 min, followed by 30 min or less, and between 60 and 90 min. In a total of 6,505 study sessions notetaking was chosen most often (36%), followed by summarizing (19%), organize and elaborate (12%), self-testing (5%), self-explaining (5%), and concept mapping (3%). Users were quite satisfied with their strategy choices and learning in general during the sessions. Also, from the pilot study in which a small group of students used the Study app to study a scientific article, we found that students were generally satisfied with the app. They evaluated the Study app on different levels such as easy to understand, clarity of the strategies, easy to navigate the app and intuitive to use the app and scored moderately high on these aspects. However, this was a first pilot study and did not involve students actual study tasks at that moment. Therefore, future research could investigate a more ecological valid study situation in which students use the app for their self-study activities related to the courses they are taking. A first study in a more ecological setting has recently been carried out with first year psychology students during their first course (Baars et al., 2022). In the study of Baars et al. (2022) students were invited to use the Study app during their self-study sessions. The use of the study app was investigated in relation to motivation and SRL across the course. Results showed a significant increase in motivation and SRL across the 5-week course but this was not related to Study app use during the course. Yet, most students used the app only for a limited number of self-study sessions. As this was a correlational study, it is hard to conclude anything about the effect of the app. Future research could apply randomized controlled trial (RCT) studies to investigate the effect of the app on SRL. Moreover, in terms of generalizability and validity, it would be valuable to investigate the use of the Study app in other fields besides psychology and other levels of education (e.g., secondary education) as well.

Although the Study app made use of several gamification elements (i.e., levels and challenges), it might not have been enough to affect the users. Possibly students can "game the system" by selecting strategies that could help them earn stars and finish challenges without actually using these strategies during their self-study session. After all, using the study strategies is something that happens outside the app (e.g., on paper or pc). Of course, if this happens, the app will most likely not support the regulation of the learning process during self-study sessions. Another limitation on gamification in the app was that there were no options for social interaction within the app. Options for users to share experiences or accomplishments in terms of self-study and using study strategies might be an interesting way to add social interaction as a form of gamification to the app (Sailer and Homner, 2020). Future research could look into the benefits of more social interaction and gamification on self-study effectiveness in terms of cognition, motivational and behavioral change.

The development of the Ace your self-study app and the results from the pilot study can provide valuable input for a discussion on applying theoretical knowledge to develop tools to support SRL. That is, the development of the app provides an example of a more holistic approach to supporting self-study sessions combining both cognitive and metacognitive strategies within the cycle of SRL proposed by Zimmerman (2008). As a practical implication, the app could provide teachers and students with a tool that provides evidence-based support for SRL processes during self-study. Yet, the holistic approach in the app based on all three phases of SRL including study strategies, could also cause limitations to researching the effect of the app. Namely, it complicates investigating the effect of the different aspects of the support that is offered in the Study app and differentiating which part would be causing what effect on SRL. Future research should, therefore not only focus on the effect of the app as a whole, but also on disentangling the contributions of the different aspects of support.

In sum, to support students' self-study activities for them to effectively self-regulate their learning processes, a mobile application called the Ace your self-study app was developed. The choices involved in developing and designing the application were described in the current manuscript in which we presented the mobile application, the current state of use and pilot results on usability. In doing this we included the information and perspectives of the multidisciplinary team that worked on creating the Study app. Future research could investigate the effectiveness of the Study app with different types of self-study activities, educational levels, and study designs (e.g., randomized controlled trials) to provide more insight into using a mobile application with gamification elements to support SRL processes.

## DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

## AUTHOR CONTRIBUTIONS

MB, FZ, MH, EJ, and FP contributed to conception and design of the application. MB, FZ, MH, and EJ organized the database. MB performed the statistical analysis and wrote the first draft of the manuscript. FZ, MH, and EJ wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2022.793042/full#supplementary-material

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# Capturing Sequences of Learners' Self-Regulatory Interactions With Instructional Material During Game-Based Learning Using Auto-Recurrence Quantification Analysis

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Undergraduate students ($N$ = 82) learned about microbiology with Crystal Island, a game-based learning environment (GBLE), which required participants to interact with instructional materials (i.e., books and research articles, non-player character [NPC] dialogue, posters) spread throughout the game. Participants were randomly assigned to one of two conditions: *full agency*, where they had complete control over their actions, and *partial agency*, where they were required to complete an ordered play-through of Crystal Island. As participants learned with Crystal Island, log-file and eye-tracking time series data were collected to pinpoint instances when participants interacted with instructional materials. Hierarchical linear growth models indicated relationships between eye gaze dwell time and (1) the type of representation a learner gathered information from (i.e., large sections of text, poster, or dialogue); (2) the ability of the learner to distinguish relevant from irrelevant information; (3) learning gains; and (4) agency. Auto-recurrence quantification analysis (aRQA) revealed the degree to which repetitive sequences of interactions with instructional material were random or predictable. Through hierarchical modeling, analyses suggested that greater dwell times and learning gains were associated with more predictable sequences of interaction with instructional materials. Results from hierarchical clustering found that participants with restricted agency and more recurrent action sequences had greater learning gains. Implications are provided for how learning unfolds over learners' time in game using a non-linear dynamical systems analysis and the extent to which it can be supported within GBLEs to design advanced learning technologies to scaffold self-regulation during game play.

**Keywords: game-based learning, auto-recurrence quantification analysis, self-regulation, hierarchical modeling, eye tracking, log files**

## 1. INTRODUCTION

Self-regulated learning (SRL) refers to learners' ability to dynamically monitor and modify their cognition, affect, metacognition, and motivation to control their learning (Winne, 2018). SRL, within this study, is captured from learners' observable events of self-regulatory processes and strategies during game-based learning. Several studies have examined how learners engage in SRL processes and employ SRL strategies to increase their learning outcomes across math (Roick and Ringeisen, 2018; Sun et al., 2018; Musso et al., 2019; Gabriel et al., 2020), reading (Snow et al., 2016; Thiede and de Bruin, 2018; Harding et al., 2019), writing (Sophie and Zhang, 2018; Nuckles et al., 2020; Sun and Wang, 2020), and science (Garcia et al., 2018; Gandomkar et al., 2020; Li et al., 2020; Taub et al., 2020) domains and technologies including hypermedia, intelligent tutoring systems, and games (Azevedo et al., 2019). In this article, we examine and analyze how learners engage in SRL behaviors as they learn within a science game-based learning environment (GBLE) to discuss how to best support learners' deployment of SRL strategies and examine the relationship between SRL behaviors and learning.

To accomplish this goal, this article: (1) defines and describes the several interacting components of SRL according to Winne's (2018) COPES model, a traditional conceptualization of SRL; (2) defines what a complex system is and defends SRL as a complex system using Winne's COPES as system components; (3) explains how SRL can be supported by GBLEs; and (4) discusses how non-linear dynamical systems theory (NDST) can measure SRL within GBLEs. From these discussions, this article introduces research questions that are grounded in and supported by the multiple theories considered in the introduction. Our ultimate goal and novel contribution to the study of SRL is the examination of dynamical SRL strategy deployment its relationship to learners' prior knowledge, agency within a GBLE, and learning outcomes, all through the lens of complex systems theory using NDST analytical tools.

## 2. SELF-REGULATED LEARNING

As previously mentioned, SRL is the ability for learners to enact processes and strategies that both monitor and modulate cognitive, affective, metacognitive, and motivational processes (Winne, 2018). SRL primarily encompasses cognitive and metacognitive strategies that are deployed by the learner, such as reading instructional materials (i.e., books, research articles, posters, dialogue with non-player characters [NPCs]), gathering information important for achieving the overall goal, and retaining information required to increase domain-specific knowledge. Learners typically deploy SRL strategies throughout the phases of learning including: (1) prior to a task (i.e., forethought); (2) during a task (i.e., performance); and (3) after a task (i.e., reflection). These phases are mentioned recursively throughout SRL models and literature including Zimmerman and Moylan's (2009) SRL model, Winne and Hadwin's (2008) information-processing theory of SRL, Pintrich's (2000) model of SRL, and Nelson and Narens' (1990) metamemory framework.

To support the current article and ground the research questions, we specifically focus on Winne's (2018 conditions, operations, products, evaluations, and standards (COPES) model of SRL. This model details COPES components as occurring throughout the four phases of learning from Winne's (2018) information-processing model of SRL. This model states leaning occurs in 4 phases: (1) defining the learning task; (2) identifying and setting goals as well as plans to achieve those goals prior to interacting with their environment or starting the task; (3) deploying cognitive and metacognitive strategies that aid learners in achieving their goals; (4) adapting their learning strategies, goals, and plans to better achieve their goals. Through this COPES model, we review SRL literature that examines the relationships between learners' cognitive and task conditions, operations deployed during learning, and their products. However, this study does not incorporate evaluations nor standards when examining SRL behaviors as these were not directly measured by the learning environment. Therefore, this study specifically reviews learners' SRL behaviors in terms of how learners' conditions were related to the operations that were deployed during learning and how the interaction between these two components elicited learners' products.

### 2.1. Conditions

*Conditions* refer to the cognitive and task resources and constraints learners encounter when interacting with instructional materials. *Cognitive conditions* can include the level of prior knowledge a learner has before engaging in a learning task. Typically, learners with greater prior knowledge engage in greater SRL strategies which contribute to higher learning outcomes (Bernacki et al., 2012; Yang et al., 2018). *Task conditions* refer to constraints imposed on a learner by their environment. These constraints can refer to the environment's (e.g., game-based learning environment) restriction on learners' agency throughout the task where agency refers to learners' control over their own actions. As such, restricted agency limits the number of choices and actions a learner can perform throughout the learning process, including their deployment of SRL strategies (Bandura, 2001; Martin, 2004; Code, 2020). While full agency has been hypothesized to increase learning outcomes due to increased interest and engagement related to discovery learning (Mayer, 2004; Kirschner et al., 2006), learners are notoriously incapable of engaging in effective SRL. This is perhaps due to the difficulty of information, learners' lack of metacognitive knowledge of which SRL strategy to apply, or the open-ended nature of most learning environments (de Bruin and van Merriënboer, 2017; Schunk and Greene, 2018; Seufert, 2018; Winne, 2018; Munshi and Biswas, 2019).

### 2.2. Operations

Learners' task and cognitive conditions can influence their *operations* which refer to the cognitive strategies a learner can employ when interacting with instructional materials. The operations that are enacted center around searching for information across different sources, monitoring the learned information and their relevance toward their goal (i.e., content evaluation; Azevedo and Cromley, 2004; Greene and Azevedo, 2009; Dever et al., 2020; Azevedo and Dever, 2022), assembling several different sources into a coherent representation of information, rehearsing information in working memory, and translating information that was collected into a different type of representation (e.g., mental representation vs. concept map; Winne, 2018). Operations deployed during SRL are essential to the synthesis, (mis)understanding of information, and memorization of information for situation transfer (e.g., from virtual to classroom) and information recall. As such, it is necessary to examine how learners interact with information during SRL to examine how behaviors influence learning outcomes. Specifically, we question: How do learners' operations of selecting information throughout a complex learning task influence learning?

## 2.3. Products

*Products*, or the information that is formed using the instructional material from the environment, is perhaps the most straightforward process within the COPES framework. Simply, products can be represented by the changes in knowledge representation where products are a representation of learning. In using learning gains to represent the new knowledge learners obtain during the learning task, we can assess how the learners' task and cognitive conditions have influenced their (in)accurate deployment of operations that (dis)allowed learners to gain knowledge within a specific domain. As such, this study utilizes a formula developed by Marx and Cummings (2007; see Section 6.5) that identifies how much has been learned while accounting for learners' prior knowledge.

# 3. DEFINING SRL AS A COMPLEX SYSTEM

SRL includes dynamically and accurately monitoring and regulating cognitive, affective, metacognitive, and motivational processes and adapting them to meet the internal (e.g., evolving understanding) and external demands and constraints of an activity (Azevedo et al., 2019). According to Favela (2020) and the assumptions of Winne's (2018) COPES model, complexity science offers a lens to understand and analyze cognitive and psychological processes that emerge as a function of complex systems. Complex systems theory describes how systems that demonstrate changing behavior due to interacting components can be explained and predicted (Favela, 2020). For the current study, we align this framework with SRL literature in which learners' conditions, operations, and products are components of SRL that change and interact with each other as learning occurs. Complex systems are generally characterized by three criteria: (1) self-organization; (2) interaction dominance; and (3) emergence (Haken, 2006; Favela, 2020).

According to these three criteria, this article argues that SRL qualifies as a complex system (see Li et al. (2022)). Constraints such as cognitive resources fluctuate with the instructional content provided in the learning environment (i.e., prior knowledge on genetic diseases vs. viruses); Operations such as cognitive strategy use shift based on task demands and goals which may change over time (McCardle and Hadwin, 2015; Cloude et al., 2021); and products are also likely to change over time as learners acquire new knowledge incrementally (Shute and Sun, 2019). While existing literature supports SRL as occurring cyclically (Winne and Azevedo, 2014; Schunk and Greene, 2018), analytical methods used within current literature does not account for the non-linear, dynamic, and complex nature of self-regulatory behaviors during learning about a difficult topic (e.g., microbiology) with a game-based learning environment. As such, it is essential to start employing complex systems theory to SRL literature to explain how learners deploy SRL strategies during learning.

*Self-organization* refers to changing behavior from which order arises out of disorder but without the influence of a central controller or programmer (Haken, 2006; Heylighen, 2008). Consistent with the concept of self-organization, SRL components mutually coordinate and constrain each other to elicit order in executed SRL behaviors which would have otherwise been chaotic (Dale et al., 2013). Initially, one may presume the central controller is the individual learner or their executive and metacognitive control functions. However, various SRL processes mutually influence one another in the context of a complex environment that may include, for example, task conditions (i.e., environmental constraints) and standards imposed on learners' processes. Moreover, learners' prior knowledge (Cognitive Conditions) can restrict which SRL strategy a learner deploys during learning. Similarly, the affordance of full agency (Task Conditions) could contribute to an unsystematic deployment of (in)accurate SRL strategies, thereby minimizing learning outcomes. In this way, processes outside of executive control interact to support SRL.

Complex systems are also characterized by their *interaction dominance* in which behavioral order and control of a system arises from the interactions between system components, not just the additive value of the components (Holden, 2009). Relative to current models of SRL, and more specifically when dealing with COPES, this characteristic of complex systems denotes the importance in considering SRL components as interactive rather than independent. Studies examining SRL have traditionally examined the impact of one component on another (e.g., Bernacki et al., 2012; Yang et al., 2018), but rarely have SRL studies examined the dynamic relationship between components. Under the interaction dominance characteristic of complex systems, there is not just an additive or unidirectional relationship between system components which elicit a certain behaviors. Rather, SRL is possible through the interaction between cognitive and metacognitive strategies across time and SRL phases. It is important to note that since SRL is theoretically aligned with complex systems, there is much to be gained from leveraging analytical techniques based in complex systems theory (i.e., NDST) that can extract the very nature of dynamically interacting components.

Similarly, although definitions vary, the criteria of *emergence* often refers to how the behavior of an entire system cannot be broken down into just the sum of the components (Favela, 2020). In other words, the behavior of the whole system supersedes the behaviors of the individual components. In the case of COPES, this means that SRL cannot be isolated into either conditions, operations, or products. Additionally, SRL cannot be broken into separate cognitive and metacognitive strategies as SRL requires the oscillation of all components and both types of strategies throughout the learning process. The conceptualization of SRL as a complex system is made increasingly evident when we consider non-traditional environments with high levels of learner-environment interactivity such as that found during game-based learning.

## 4. SUPPORTING SRL DURING GAME-BASED LEARNING

The goal of a game-based learning environment (GBLE) is to make multimedia instructional materials accessible in a non-linear fashion which increases agency during learning *via* the deployment of SRL strategies while maintaining the interest, engagement, and motivation of a learner (Clark et al., 2016; Sawyer et al., 2017; Mayer, 2019; Plass et al., 2019; Shute and Sun, 2019; Taub et al., 2020). Because of this, GBLEs are increasingly being used in order to support learning through their combination of (1) narrative to increase engagement and interest, (2) tasks to support domain learning, and (3) game elements to promote engagement with both the task and the instructional materials presented throughout the environment. This uniquely positions learners within GBLES, relative to other learning environments, to have the agency to control their learning progression and direction without having too much freedom they are overwhelmed by choice.

During game-based learning, it is essential for learners to engage in SRL strategies to meet the demands of learning activities and comprehend instructional materials essential for attaining domain knowledge in pursuit of a goal (Winne and Azevedo, 2014). Although, the open-ended nature of GBLEs both facilitates and limits the successful use of SRL strategies. On one hand, GBLEs allow learners agency to engage in and develop self-regulation through goal-setting and the use of monitoring and cognitive strategies (e.g., reading, note-taking, summarizing) and tools (e.g., instructional materials, help-seeking; Winne and Hadwin, 2013; Nietfeld, 2018). Alternatively, the open-ended nature may not provide the needed support for the learner to coordinate the several cognitive and metacognitive strategies required for successful SRL (Josephsen, 2017). Because of this, there is a need for GBLEs to be developed with scaffolds that guide learners' interactions with instructional materials to simultaneously support successful SRL and increase domain-specific learning gains. The balance between support and freedom provided by GBLEs calls for the incorporation of a complex systems theory concept, far-from-equilibrium.

### 4.1. Far-From-Equilibrium Systems

Adapting the concept of far-from-equilibrium from physical sciences, behavior can be described as learners' patterns of, or oscillations between, stable and unstable states (Veerman et al., 2021). That is, healthy cognitive systems, such as learners' SRL behaviors, are demonstrated by behaviors which maintain a balance between stability (i.e., rigidity) and adaptability (i.e., chaotic). To support this healthy behavior, the GBLE should promote the balance of SRL behaviors that are not too rigid (i.e., no agency) nor too chaotic (i.e., discovery-based learning). A too-rigid SRL system would demonstrate a greater repetition of SRL strategies during learning, such as only attending to one instructional material (i.e., book, research article, non-player character), perhaps promoted through the restricted agency imposed by the GBLE. Behaviors which could be too chaotic would demonstrate significantly greater novelty not conducive to content learning, potentially encouraged through full agency afforded to learners by the GBLE.

Applying the far-from-equilibrium concept of complex systems theory, healthy SRL behaviors should be demonstrated by learners' balance between stable and adaptable SRL strategies and actions during learning with a GBLE. This balance can be supported and maintained through cognitive conditions available to (i.e., prior knowledge) and task conditions imposed on (i.e., restricted agency) the learner. Task resources and constraints include the environmental features and mechanics that directly influence how a learner will interact with instructional materials within the GBLE. To guide learners' interactions with instructional materials, a GBLE may intentionally restrict the amount of agency learners have while still promoting their freedom in choosing the SRL strategies to be deployed. While agency as scaffolds (i.e., restricted agency as guiding learners throughout the GBLE) have been found to increase learning outcomes (Sawyer et al., 2017; Dever and Azevedo, 2019a; Dever et al., 2020), we must ask if agency promotes a healthy balance between rigidity and adaptability as learners deploy SRL strategies to interact with instructional materials in a GBLE. A methodological approach to study this question is to use a non-linear dynamical systems theory (NDST) analytical method for understanding learners' SRL behavioral shifts during learning with a GBLE.

### 4.2. A Non-linear Dynamical Systems Approach to Measuring SRL

NDST describes how numerous interacting components have a multiplicative effect on system-level behavior, where small changes in component processes can produce sudden (non-linear) behavioral shifts (Riley and Holden, 2012; Amon et al., 2019). Because of this, NDST can be used to evaluate and measure the repetition and predictability in learners' SRL strategy use, denoting the degree to which a learners' SRL strategy use throughout a GBLE follows the far-from-equilibrium concept. Due to the interdependent nature of non-linear dynamical systems, global behavior both constrains and is constrained by its underlying component processes, such that reciprocal feedback entrains processes at various levels (Amon et al., 2019). Because SRL behaviors change over time due to the constantly changing interactions with GBLEs as well as the acquisition of domain-specific knowledge, SRL can be measured using an NDST approach. While NDST has yet to be used to understand SRL with GBLEs from a complex systems theory stance, a study by Garner and Russel (2016) has applied NDST and sequence-oriented techniques to understand how learners deploy SRL while reading multiple texts. This study found differences of recurrent patterns between learners who took notes vs. those who did not while reading instructional materials. Building on the findings from this study, this article acknowledges the complex SRL strategies that occur during game-based learning and based on a GBLE's environmental affordances of agency.

This study utilizes auto-recurrence quantification analysis (aRQA), an NDST method, to examine how learners adaptively shift between repetitive and novel sequences of interactions with a GBLE. This method is also used to describe the relationship between these sequences and task conditions, learning gains, and SRL ability. aRQA quantifies the degree of repetition or "recurrence" within a single time series (Webber and Zbilut, 2005), indicating the extent to which a system returns to the same states across various time lags. Because NDST is a central part to studying the relationship between agency and SRL behaviors within this study, it is important to understand how learners' time series data is used to identify SRL behavioral patterns.

**Figure 1A** demonstrates the time series of the events in chronological order. **Figure 1B** shows how RQA first transforms a participant's time series—in this case, with categorical data—into the **Figure 1B** distance matrix representing the Euclidean distance between the values that represent areas of interest where participants were looking (i.e., Books, Posters, or NPC). When a participant is looking at the same area of interest at two different time points (e.g., time points t1 and t8), then the recurrent state is highlighted black. The diagonal represents the line of identity (LOI), where the time series is recurrent with itself at lag 0. Diagonal lines parallel to the LOI represent successively greater time lags between the points that are being compared in terms of distance. The Panel C recurrence matrix is created by applying a radius parameter that defines the threshold at which points are considered sufficiently similar enough to be considered recurrent. Thus, a very small radius value is used such that only exact matches are counted as recurrent, such that the recurrence matrix highlights points where the same area of interest is returned to at different time lags. Unique to the authors' approach (e.g., Amon et al., 2019; Necaise et al., 2021), we include an additional procedure to "color-code" the matrix (**Figure 1D**) to identify the distinct behaviors that underlie the recurrent points in the matrix.

We examine an RQA metric called percent determinism (DET), where determinism refers to the relative predictability of the system; i.e., the extent to which the system's future state can be predicted by the system's current state. In terms of RQA, DET technically refers to the percentage of the points that form diagonal lines, representing repeated sequences of behavior. For example, a time series with areas of interest *A, B, C, A, B, A* would include one recurrent sequence (A, B) depicted as a two-point diagonal on either side of the LOI. For this study, we use learners' interactions with instructional materials (i.e., books, research articles, posters, non-player characters) which hold all information needed to develop domain knowledge. Specifically, learners' interactions with these instructional materials are represented by learners' operations or time-evolving strategies that they deploy during gameplay and dynamically alter to fit their present needs. For the purposes of our study, more repetitive behavioral sequences of instructional material may give insight into how deployed SRL strategies interact with cognitive and task conditions to result in learners' products, or learning outcomes. Thus, aRQA provides a unique lens through which to understand SRL in terms of how task and cognitive conditions are related to how learners interact with instructional materials and the resulting learning gains.

## 5. CURRENT STUDY

While previous studies have examined SRL using NDST methods (Garner and Russell, 2016), few studies in SRL literature: (1) examine how SRL strategies are deployed during game-based learning (Cloude et al., 2020; Taub et al., 2020; Dever et al., 2021); (2) operationalize SRL as a sequence of dynamic, temporally unfolding processes and examine the direct relationships between these processes simultaneously using eye tracking data; and (3) use an NDST approach to analyzing how SRL occurs during learners' time in a GBLE. The goal of this study was to address these gaps in current literature by examining SRL using the lens of complex systems theory and analytically investigate how learners use SRL strategies within a GBLE through applying NDST methods. To address these gaps and further the SRL field conceptually, methodologically, and analytically, we propose three research questions:

**Research Question 1: To what extent do learners' SRL behaviors and dwell times differ across instructional material throughout gameplay?** This first research question examines how long a learner dwelled, or attended to, instructional materials, and how this duration varied as a function of relative game time, type of instructional material, and relevance of the instructional material to the pre-test. As prior studies have shown that learners are typically unable to engage in meaningful SRL and accurately deploy SRL strategies that will significantly increase their learning gains (Josephsen, 2017), we hypothesize that there will be significant main and interaction effects to explain within-person variability, but do not assume a direction. However, as individual differences (e.g., prior knowledge, task conditions, etc.) can significantly change how learners deploy SRL strategies during game-based learning, we propose that there will be significant between-person variability in the relevant vs. irrelevant instructional material dwell times.

**Research Question 2: To what extent are learners' task and cognitive conditions, learning outcomes, and sequences of SRL behaviors with instructional material related to dwell times on instructional materials throughout gameplay?** This second research question builds off of the first research question and aims to understand the full picture of how SRL processes can be examined and related to each other when examining eye gaze dwell times across relevant and irrelevant instructional materials. First, we hypothesize that learners with restricted agency will have greater learning gains than those with full agency, as supported by previous literature (Bradbury et al., 2017; Sawyer et al., 2017; Dever and Azevedo, 2019a; Dever et al., 2020). Further, we hypothesize that learners with restricted agency, greater prior knowledge, and greater learning gains will demonstrate

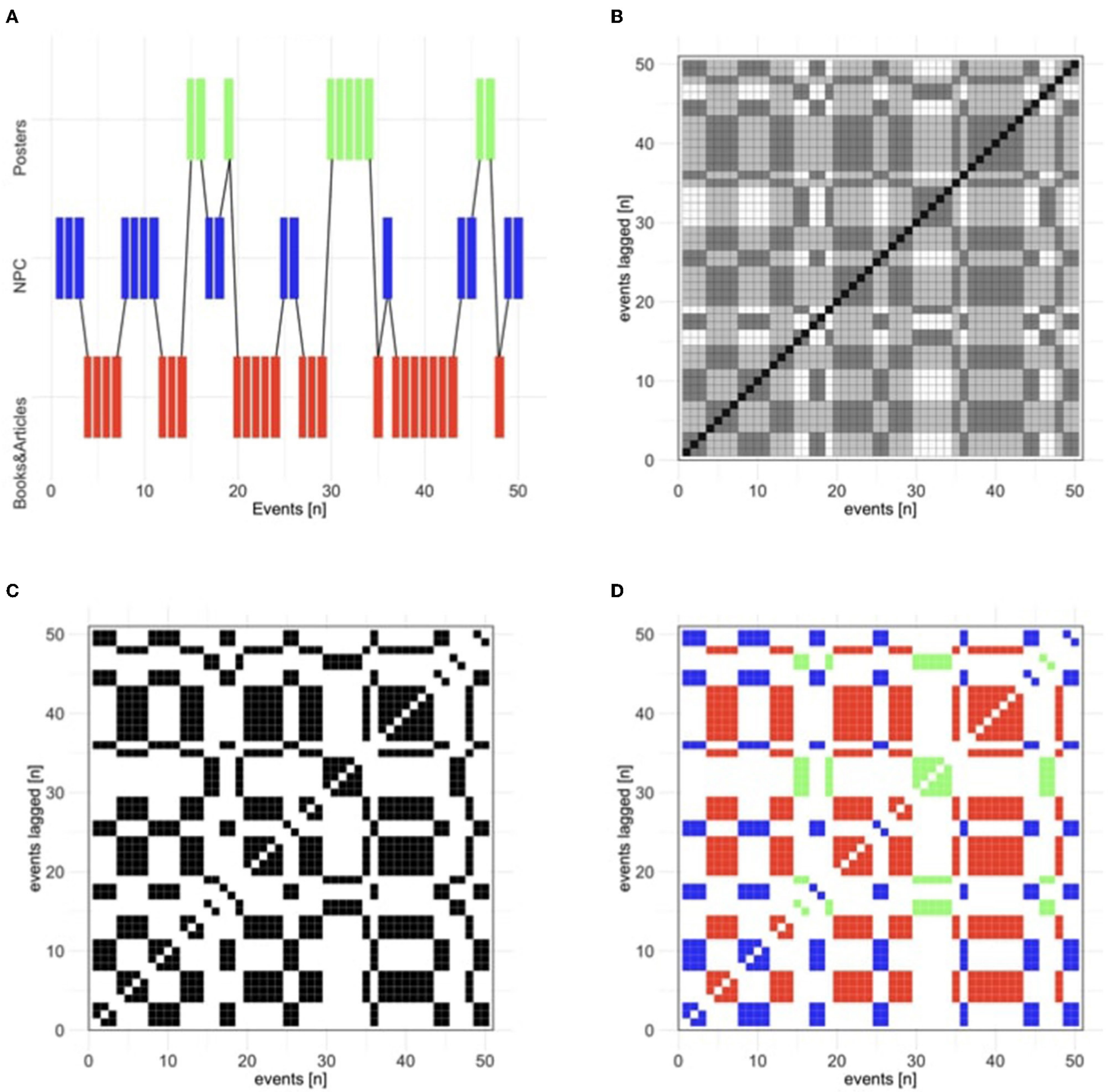


**FIGURE 1 | (A)** Time series of events in the chronological order (or events on the main diagonal) that are transformed into the **(B)** distance matrix, **(C)** recurrence plot, and finally, into the **(D)** color-coded recurrence plot (Books in red, NPC in blue, and Posters in green).

increased dwell times on relevant instructional materials as they can better evaluate content relevance. It is possible that a relationship between the experimental manipulation and subsequent learning gains is a product of constrained interaction and, in turn, more repetitive eye gaze sequences. As such, we further hypothesize that learners with more repetitive sequences of SRL behaviors with instructional materials will have greater gaze dwell times on relevant, rather than irrelevant, instructional materials.

**Research Question 3: How do learners' task conditions, cognitive conditions, and learning gains relate to their sequences of SRL behaviors?** This research question is used to explore how learners differ in how often learners deploy repetitive sequences of SRL behaviors between task and cognitive conditions and its relationship with learning gains. For this research question, we hypothesize that learners with more repetitive eye-gaze sequences (i.e., more rigid behaviors), will be associated with restricted agency but related with higher learning gains. Further, we hypothesize that learners with higher prior knowledge will demonstrate more novel behaviors as they use instructional material interaction diversity as an SRL strategy to keep far-from-equilibrium interactions.

# 6. METHODS

## 6.1. Participants and Materials

A total of 139 undergraduate students were recruited from a large public university based in the United States to learn with a narrative-centered, game-based learning environment called Crystal Island (Rowe et al., 2011; Dever et al., 2020, 2021; Taub et al., 2020). Crystal Island was designed to foster (1) higher-order thinking skills, such as effective problem solving and scientific reasoning, while also gaining knowledge about (2) microbiology content. For purposes of this article, a subsample of 82 undergraduates (68.3% female; $M_{\text{age}} = 20.1$, $SD_{\text{age}} = 1.69$) were included in the analysis based on meeting the following criteria: (1) completed the entire study with Crystal Island; (2) were randomly assigned to either the full or partial agency conditions; (3) had no prior experience interacting with Crystal Island before participating in the study; and, (4) did not have missing data points across all converging data channels captured before, during and after game-based learning, including both log files and performance measures (e.g., pre/post-test assessments).

Most participants reported their race as "White/Caucasian"(68.30%; $n = 56$), while the remaining reported "American Indian or Alaskan Native" (1.22%; $n = 1$), "Asian" (12.20%; $n = 10$), "Black or African American" (7.32%; $n = 6$); "Hispanic or Latino" (7.32%; $n = 6$), and "Other" (3.66%, $n = 3$). The subsample also indicated that they "Did not play video games at all" (18.29%; $n = 15$), "Rarely played video games" (35.37%; $n = 29$), "Occasionally played video games" (21.95%, $n = 18$), "Frequently played video games" (15.85%; $n = 13$), and "Very frequently played video games" (58.54%; $n = 7$). The subsample also reported having "No video game skills" (14.63%; $n = 12$), "Limited skills" (21.95%; $n = 18$), "Average" (37.80%; $n = 31$), "Skilled" (20.73%; n = 17), and "Very skilled" (4.88%; $n = 4$). The majority of the sample indicated they played a total of "0–2" (68.29%; $n = 56$), "3–5" (13.41%; $n = 11$), "5–10" (7.32%; $n = 6$), "10–20" (9.76%; $n = 8$), and "Over 20" (1.21%; $n = 1$) hours per week. This study was approved by the university's Institutional Review Board before recruiting participants and informed consent was gathered before collecting data.

To assess participants' understanding of microbiology, a 21-item, 4-option multiple choice, pre/post-test assessment was administered before and after game-based learning with Crystal Island see **Figure 2**, regardless of whether or not participants successfully solved the mystery. The assessments were designed with 12 factual (e.g., "*What is the smallest type of living organism?*") and 9 procedural items (e.g., "*What is the difference between bacterial and viral reproduction?*"). Participants answered between 6 and 18 correct items across on the pre-test assessment ($Med = 11$, $M = 55\%$, $SD = 0.14$), while participants answered between 9 and 19 correct items ($Med = 14$, $M = 67\%$, $SD = 0.12$) on the post-test assessment (Rowe et al., 2011). In addition to the knowledge assessments, several self-report items were administered before and after the learning session but these data were not analyzed in this article. Game play duration ranged from 39.73 to 135 min ($M = 85$, $SD = 19$).

## 6.2. Experimental Design

In this study, participants were randomly assigned to one of two experimental conditions: (1) full agency ($n = 47$), and (2) partial agency ($n = 35$). These groups were built to experimentally manipulate the learners' level of control (i.e., agency) in the sequence of interactions with game features built into Crystal Island. In the control condition–i.e., full agency, participants were given complete control over their sequence of interactions with Crystal Island, or business-as-usual. Participants in the experimental condition–i.e., partial agency, were given restricted control over their sequence of interactions (e.g., first reading a book and then generating a hypothesis), meaning they were required to initiate a specific order of actions to progress with the learning session. For example, participants in the partial agency condition were required to first visit Kim, an NPC nurse in the camp infirmary. Once they entered the infirmary, the participant could not leave until all items within the building were interacted with (e.g., clicked on with no minimum time requirement). Once able to leave the infirmary, the next building was "unlocked." This experimental condition was designed around a particular sequence of interactions that scaffolded higher-order thinking skills such as effective problem solving and scientific reasoning activities *via* game features and restricted agency.

It is important to note that between the conditions, dwell times on instructional materials (i.e., how long participants looked at instructional materials indicated by eye-gaze behavior) were not restricted other than the requirement that learners in the partial agency interact with the material in some way (i.e., they could select the book, but not attend to it according to eye-tracking metrics). Additionally, all types of instructional materials were found in each building, so participants in the partial agency condition were not restricted to certain types of instructional materials as they progressed in the game.

Across all participants, participants spent an average of 86.0 min ($SD = 19.5$ minutes) in game where learners in the full agency condition spent an average of 80.2 min ($SD = 20.1$ min) and those in the partial agency conditions spent an average of 93 min ($SD = 15.7$ min).

## 6.3. Procedure

Participants were recruited using flyers across a large North American public university campus. Once participants were scheduled, they were instructed to come into the university laboratory space to obtain informed consent and complete the experiment for up to 2 h. A CITI-certified researcher greeted the participant upon their arrival and instructed them to sit at the experimental station which consisted of a computer, keyboard, and mouse. After informed consent was obtained, they were randomly assigned to one of two conditions. Participants were then instructed to complete a series of questionnaires including the pre-test assessment to gauge their level of microbiology science content understanding and self-report items on emotions, motivation, and presence.

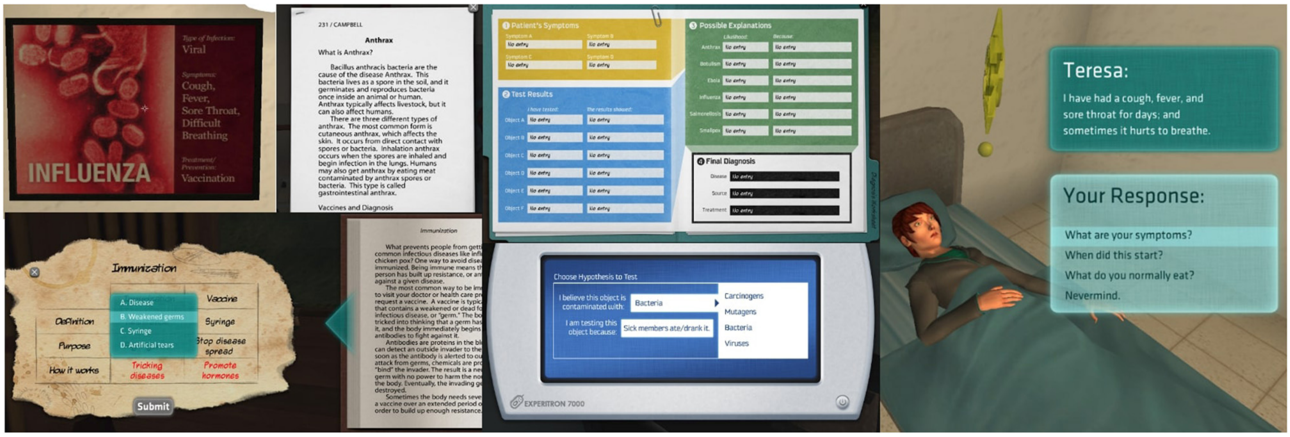


**FIGURE 2 |** Elements within the Crystal Island Environment.

Afterwards, the researcher calibrated participants to three apparati: (1) SMI EYERED 250 eye tracker using a 9-point calibration to capture their eye movements during game-based learning (SMI, 2014), (2) facial recognition software to measure their facial expressions of emotions (), as well as (3) electrodermal activity bracelet called Empatica 4 to capture their physiological arousal and stress response (iMotions, 2015). Specifically, the participant was required to view a gray screen with a neutral expression for approximately 10 s to establish a baseline for the facial recognition software and EDA bracelet. Once successful calibration was completed, participants started learning and problem solving with Crystal Island. Participants were given up to 90 min to solve the mystery. Once they completed the game, or they engaged with Crystal Island for 90 min, participants were instructed to stop what they were doing and complete a similar set of post-test items and self-report measures including the post-test assessment on microbiology. Upon their completion, participants were debriefed about the objectives of the study and their participation, thanked, and paid $10/h for their time.

## 6.4. Apparatus

Eye gaze behaviors were recorded using a table-mounted SMI EYERED250 eye tracker (sampling rate = 250 Hz). Participants were calibrated with a 9-point calibration. Participants' fixation durations, saccades, and regressions on different areas of interests (AOIs), which define the boundaries on the computer screen where specific elements or information are held. To be classified as a fixation duration, the participant was required to have relatively stable gaze behavior for at least 250 ms. These data were captured continuously using iMotions software 2015 as participants engaged in game-based learning.

## 6.5. Coding and Scoring

*Reading dwell times and instances* were established using gaze behaviors and log files. Log files collected as learners engaged with Crystal Island identified the times at which instructional materials were opened denoted by log file timestamps using event-based recording. As from just log files alone researchers cannot assume that learners were reading information from the instructional material, eye gaze behavior was used to supplement the identification of reading instances. Learners' total fixation durations on a single AOI while the instructional material was opened denoted by log files were aggregated into dwell times which identifies the total time learners spent fixating on a single AOI instance. These AOIs were laid overtop of each type of instructional material including books and research articles, posters, and the dialogue boxes as well as the NPC itself to identify NPC instances.

*Learning gains* were operationalized using normalized change scores (Marx and Cummings, 2007) which identified participants' differences in pre- and post-test scores proportional to the number of total points possible and controlling for participants' prior knowledge, or pre-test score.

*Content evaluations* were operationalized by first identifying the relationship between instructional materials and pre-test questions. Instructional materials which directly addressed a question on the pre-test were identified as relevant. If the information did not address a pre-test question, the instructional material was identified as irrelevant as the information within the text was not needed to increase learning gains. While content evaluations were not directly observable, we take the stance that learners who attend to relevant materials are making a correct content evaluation whereas attending to irrelevant instructional materials were incorrect content evaluations. This classification of relevant vs. irrelevant instructional materials is based on prior SRL (Azevedo et al., 2004) and priming literature (McNamara, 2005) where it is assumed that participants exposed to microbiology information on the pre-test may identify the same information within the GBLE as more important, and therefore more relevant to their learning. Across a total of 40 instructional materials spread throughout the Crystal Island environment, 19 were classified as relevant. Specifically, 33% (3/9) of NPCs, 57% (12/21) of books and research articles, and 40% (4/10) of posters were considered relevant to the pretest [see (Dever et al., 2021)].

*Relative game time* was calculated by taking the time at which an interaction occurred and dividing that by a participant's total time in game so that all interactions were scaled as occurring from Time = 0 to Time = 1. For example, if a participant opened a book at Time = 300s, and they spent 2382s in game, then the participant opened that book 12.6% into their game. This allows for a uniform comparison across all participants in terms of their total time spent interacting with the game.

## 6.6. Statistical Processing

To process the data and conduct analyses, several packages in R (R Core Team, 2017), including its base package, were used. For the multilevel modeling and basic reporting of statistics we used the "lme4" (Bates et al., 2015), "jtools" (Long, 2018), and "emmeans" (Lenth et al., 2018) packages. To conduct aRQA analyses and obtain the output, we utilized the "crqa" (Coco et al., 2020) package in R.

## 6.7. Model Building and Estimation

To examine how participants' sequences of SRL behaviors in reading and evaluating instructional material during game-based learning differs within and between learners, we constructed a multilevel growth model including several observation- and individual-level variables. Specifically, our overall model examined how dwell times on instructional materials (i.e., outcome variable) is influenced by observation- and individual-level variables. The dependent variable of dwell time was log transformed (with a base of 10) to normalize the data and reduce heteroscedasticity (skew and kurtosis $< |2|$). Due to the log transformation, reported estimates of the independent variables are geometric means where the estimates are exponentiated.

After transformation, several leveraging outliers ($N$ = 72 out of 4,346 total observations) were removed from analyses as the dwell times of these instances fell outside a 1.5 interquartile range of the first and third quartiles of data. After the transformations and outlier removal, two-level multilevel linear growth models were used to analyze the hierarchically structured data where observations ($N$ = 4,274) were nested within individual learners ($N$ = 82). Throughout their time in game, each learner had an average of 52.12 observations ($SD$ = 9.98with the number of observations ranging from 25 to 74 across all learners. Prior to exploration of observation- and individual-level variables, an unconditional means (null) model was estimated. This model demonstrated an intraclass correlation coefficient (ICC) of 0.05, suggesting that 5% of variation in instructional material dwell times is between learners [$t_{(82.6)} = 2.99$, $p < 0.01$]. This justifies our use of multilevel linear growth models to examine the observation- and individual-level variables influencing dwell times on instructional materials.

### 6.7.1. Observation-Level Variables

These variables included relative game time, the type of instructional material, and the relevance of the material to the pre-test. Because participants varied in the total amount of time they interacted with the game, relative game time scales each participants' time in game from 0 to 1 where the raw game time a participant initiated an action was divided by the participants' total time in game. The values of relative game time were then forced to zero for each participant to interpret the model intercepts. In other words, participants' first initiation of an action was treated as a zero (with all other interactions adjusted accordingly) so that the growth model intercept, originally representing the dwell time where time was equal to zero which does not have a meaningful value, now represents the dwell time of participants' first time interacting with an instructional material. The type of instructional material included books and research articles (informative text, no visuals), non-player characters (informative text, uninformative visuals), and posters (informative and uninformative text and visuals) that provided information about microbiology concepts.

All types of instructional material were evaluated for their relevance in relation to microbiology concepts introduced in the pre-test. For example, an item on the pre-test asks "*How do vaccines protect you?*". For this question, a book or research article on the function of vaccines would be relevant to the pre-test whereas an instructional material on genetic diseases is irrelevant for this question. The classification of an instructional material is based on priming literature (McNamara, 2005) where participants are assumed to classify (either accurately or inaccurately) instructional material as either relevant or irrelevant in reference to the pre-test (Dever et al., 2020, 2021).

### 6.7.2. Individual-Level Variables

These variables include participants' condition, their prior knowledge, and the percent determinism of their sequences of instructional material interactions. Within the models, both variables were treated as fixed. Condition refers to either the full or partial agency conditions that participants were randomly assigned prior to interacting with the Crystal Island environment (see Section 6.2). Prior knowledge in microbiology was calculated using participants' raw pre-test scores on their microbiology content quiz before interacting with instructional materials in the Crystal Island environment. Percent determinism represents the proportion of recurrent sequences within a single time series, denoting the predictability of a system where a greater proportion of recurrent sequences indicates a system with higher behavioral predictability.

An unconditional means model was run to examine the variation of the dependent variable between individuals. The model found a 0.05% intraclass correlation coefficient; in other words, 5% of variation in the dwell times on instructional materials in Crystal Island is between learners [$t_{(82.6)} = 2.99$, $p < 0.01$] and 95% is within learners. As such, several other multilevel models were constructed including: (1) an unconditional growth model with the latent time variable as an independent variable; (2) observation-level variables and their interactions; (3) significant predictors from (2) and individual-level variables; and (4) predictors from (3) and cross-level interactions.

# 7. RESULTS

## 7.1. Research Question 1: To What Extent Do Learners' SRL Behaviors and Dwell Times Differ Across Instructional Material Throughout Gameplay?

For Research Question 1, we examined the unconditional growth model (i.e., Model 1) and the growth model with observational-level predictors (i.e., Model 2). Model 1 examined how time influenced the dwell time across all instructional materials. From this model, the dwell time on participants' initial interaction with instructional material was approximately 31.5s ($SD$ = 52.7) which was significantly different from zero [$t_{(211.4)}$ = 66.6, $p < 0.01$]. However, dwell time across all instructional materials decreased by 68.0% (S.E. = 0.08) as participants' time in game progressed [$t_{(4236.1)} = -14.4, p < 0.01$] from participants' initial interaction with instructional material. Model 1 fits the data significantly better than the unconditional means model [$BIC$ = 14387.9, $D$ = 14,354; $\mathcal{X}^2_{(1)}$ = 202.1, $p < 0.01$] where, by adding a latent time variable, the growth model explains approximately 4% of individual-level variance in dwell time.

Model 2 ($BIC$ = 12,623, $D$ = 12,506) incorporated observational-level variables (i.e., type of instructional material, relevance of the instructional material to the pretest) in addition to the latent time variable to examine the effect on the variation in participants' dwell times. This model was a statistically significant better fit than the unconditional growth model [$\mathcal{X}^2_{(10)}$ = 1,848, $p < 0.01$]. Holding all other variables constant, learners' average fixation durations on instructional materials was 104.6s (SE = 0.08). There were significant main and interaction effects for and between all variables. For every unit increase in relative game time, dwell times decreased by approximately 89.0% [S.E. = 0.16; $t_{(653.86)} = -13.36, p < 0.01$].

Overall, participants had significantly greater dwell times on relevant ($M$ = 48.4 s; $SD$ = 56.5 s), rather than irrelevant ($M$ = 37.1 s; $SD$ = 48.8 s), instructional materials [$t_{(4186.7)}$ = 3.37, $p < 0.01$] by approximately 25.9% (S.E. = 0.07). Books and research articles ($M$ = 77.3 s; $SD$ = 64.3 s) had greater dwell times than dialogue with NPCs by 85.6% [S.E. = 0.07; $M$ = 22.7; $SD$ = 17.5; $t_{(4200.0)}$ = −26.8, $p < 0.01$] and posters by 91.5% [S.E. = 0.09; $M$ = 8.96; $SD$ = 5.33; $t_{(4210.6)}$ = −28.3, $p < 0.01$]. In relation to dwell times on instructional materials during participants' time in game, dwell times on books and research articles decreased by 88.9% (S.E. = 0.16) as time in game increased. Compared to books and research articles, dwell times on posters and dialogues on NPCs increased at a greater rate as the game progressed by 6-fold [S.E. = 0.20; $t_{(4209.54)}$ = 8.86, $p < 0.01$] and 9-fold [S.E. = 0.19; $t_{(4211.7)}$ = 11.85, $p < 0.01$], respectively.

When examining the relationship between participants' content evaluations, type of instructional material, and game time on dwell times, Model 2 found that participants' dwell time on pretest-relevant instructional materials decreased by 56% (S.E. = 0.18) as participants learned with Crystal Island [$t_{(4182.4)}$ = −4.65, $p < 0.01$]. When examining a three-way interaction and controlling for observation-level variables, dwell times on relevant posters [S.E. = 0.16; $t_{(4180.0)}$ = 2.65, $p < 0.05$] and dialogues with NPCs [S.E. = 0.17; $t_{(4176.8)}$ = 6.70, $p < 0.01$] increased as participants engaged with Crystal Island by 98.5 and 97.1% respectively compared to dwell times on books and research articles.

## 7.2. Research Question 2: To What Extent Are Learners' Task and Cognitive Conditions, Learning Outcomes, and Sequences of SRL Behaviors Related to Dwell Times on Instructional Materials Throughout Gameplay?

### 7.2.1. Task and Cognitive Conditions

An independent samples t-test was first run to ensure that prior knowledge did not differ between experimental conditions. Results were not significant ($p > 0.05$), so we included both as individual-level variables. However, when running Model 3 which contained the observation-level variables from Model 2 and added prior knowledge and agency conditions as individual-level variables, there was not a main effect for either condition or prior knowledge ($p > 0.05$). When examining cross-level effects of prior knowledge and condition, only the interaction between condition and type of instructional material was significant where participants in the partial agency condition had significantly greater dwell times on posters than participants in the full agency condition by approximately 29% [S.E. = 0.10; $t_{(160.1)}$ = 2.57, $p < 0.01$]. No other interaction effects were significant. Therefore, we conclude that task and cognitive conditions do not significantly relate to the dwell time on both relevant and irrelevant instructional materials as the game progresses.

### 7.2.2. Learning Outcomes

Model 4 added normalized learning gain as an individual-level variable to Model 3. However, the model did not find a significant main effect or interaction effect when adding learning gains to the model. As such, we conclude the learning outcomes are not significantly related to the dwell time on either relevant or irrelevant instructional materials as the game progresses.

### 7.2.3. Sequences of SRL Behaviors

For Model 5, percent determinism was added as an individual-level variable to Model 3. Percent determinism has a significant main effect where, with all other variables constant, for every unit increase in percent determinism, dwell times decreased by approximately 2.0% [S.E. = 0.01; $t_{(113.0)}$ = −2.68, $p < 0.05$]. There was one cross-level interaction between percent determinism and type of instructional material where, compared to dwell times on books and research articles, for every unit increase of percent determinism, dwell times on posters increased by approximately 2.0% [S.E. = 0.01; $t_{(4097.2)}$ = 2.62, $p < 0.05$], with no significant relationship between NPC dialogue and percent determinism ($p > 0.05$). From these results, we conclude that there is a significant relationship between percent determinism and the dwell times spent on instructional materials regardless of participants' content evaluations.

**TABLE 1 |** Proportional means of recurrence points across Lags 1-5 and instructional materials.

| Recurrent action | Lag1 | Lag2 | Lag3 | Lag4 | Lag5 |
|---|---|---|---|---|---|
| NPCs | 0.212 | 0.231 | 0.262 | 0.275 | 0.264 |
| Books and research articles | 0.468 | 0.482 | 0.529 | 0.548 | 0.617 |
| Posters | 0.320 | 0.287 | 0.210 | 0.177 | 0.119 |

**TABLE 2 |** Recurrent point frequency between clusters 1 and 2.

| Instructional material | Cluster 1 [M(SD)] | Cluster 2 [M(SD)] | *t*-value; *p*-value |
|---|---|---|---|
| NPCs | 1.35 (1.07) | 1.33 (0.75) | $t_{(56.7)} = 0.13$; $p > 0.05$ |
| Books and research articles | 2.21 (0.77) | 3.88 (1.10) | $t_{(74.1)} = -7.88$; $p < 0.01$ |
| Posters | 1.56 (0.82) | 2.65 (0.98) | $t_{(74.3)} = -5.40$; $p < 0.01$ |

## 7.3. Research Question 3: How Do Learners' Task Conditions, Cognitive Conditions, and Learning Gains Relate to Their Sequences of SRL Behaviors?

Information on the recurrent sequences of books and research article opens, NPC dialogues, and poster interactions were extracted from the lags outputted from aRQA analyses (see **Figure 1** for example). This information was used to first calculate the total number of recurrent points across all participants and instructional material types (see **Table 1**).

To examine how the dynamics (i.e., sequences) of instructional material interactions, cognitive conditions, and task conditions influence learning, frequencies of learners' recurrent points across Lags 1-3 were first correlated against each other to ensure multicollinearity does not affect the outcome of further comparisons. Several significant correlations existed between Lags 1–3 and across the instructional materials ($p < 0.01$), so Lag1 frequency counts of recurrent points across all instructional materials were used as variables for hierarchical clustering. Using this method, three clusters of participants were identified differing in the number of recurrent sequences of instructional materials on Lag1. Cluster 3 was removed from subsequent analyses as there were less than 10 participants ($N = 5$), the remaining clusters, Cluster 1 ($N = 34$) and Cluster 2 ($N = 43$), were used in further analyses. T-tests revealed that learners classified within Cluster 1 had significantly fewer book and research article recurrent points as well as poster recurrent points compared to learners classified within Cluster 2, but no significant difference in NPC dialog interaction recurrent points (see **Table 2**).

Using both Clusters 1 and 2 as a predictor, a multiple linear regression was run to understand how the cluster learners were classified within as well as their agency within Crystal Island influenced learning gains. Prior knowledge was not included as (1) prior knowledge does not differ between conditions; and (2) prior knowledge did not significantly interact with any variables in the hierarchical linear model (see RQ2). Overall, there was a significant multiple linear regression model [$F_{(3,37)} = 4.79$; $p < 0.01$] that accounted for 16% of variance. The multiple linear regression found a significant main effect of cluster where, keeping condition constant, participants classified as Cluster 2 ($M = 0.45$; $SD = 0.24$), with greater recurrent points on both books and research articles and posters, had significantly greater learning gains than those in Cluster 1 ($M = 0.33$; $SD = 0.28$) with less recurrent points ($t = 2.58$; $p < 0.05$). There was a second main effect of condition where, keeping cluster constant, participants in the partial agency condition ($M = 0.48$; $SD = 0.25$) had significantly greater learning gains than learners with full control over their own actions ($M = 0.33$; $SD = 0.26$; $t = 3.11$; $p < 0.01$). A significant interaction effect was also observed ($t = -2.05$; $p < 0.05$).

From this interaction, participants classified within Cluster 1 and with full agency had a significantly greater learning gains than participants in Cluster 2 with full agency. Specifically, participants within Cluster 1 with full agency had a mean learning gain of 0.23 ($SD = 0.26$) whereas participants in Cluster 2 with full agency had a mean learning gain of 0.43 ($SD = 0.23$). Meanwhile another significant effect was found where participants within the partial agency condition had a mean learning gain of 0.52 ($SD = 0.23$) if they were classified within Cluster 1, but a mean learning gain of 0.47 ($SD = 0.26$) if they were classified within Cluster 2.

In summary, results across all research questions have several main findings: (1) dwell times on instructional materials as a function of learners' content evaluations of instructional materials over gameplay where dwell time on pre-test relevant materials decrease; (2) the predictability of SRL behaviors, denoted by percent determinism, is related to learners' greater dwell times on instructional materials; and (3) learner profiles of recurrent instructional material sequences can be extracted and are related to both agency and overall learning outcomes where learning gains are greatest in participants who had restricted agency and greater recurrent interactions with instructional materials.

## 8. DISCUSSION

As very few studies have provided a comprehensive analysis of unfolding SRL processes during game-based learning, the goal of this study was to examine the emergence of SRL from a complexity science perspective. This article investigated whether cognitive strategies, task conditions, and SRL behaviors, grounded within Winne's (2018) COPES model of SRL, moderated when and for how long learners gathered information during learning with a GBLE. This study viewed SRL through the lens of complex systems theory and analyzed SRL using an NDST technique to understand how SRL should be scaffolded within GBLEs through restricted agency.

The first research question examined how dwell times on both irrelevant and relevant instructional materials vary as a function of relative game time, type of instructional material, and relevance of the instructional material. Overall, hypotheses for the first research questions were supported where significant between- and within-person variability were identified. Further, dwell times across all instructional materials decreased over learners' time in game and there were generally greater dwell times on relevant than irrelevant instructional materials. This could potentially be due to the familiarity with materials over the course of gameplay, indicating more accurate metacognitive monitoring SRL behaviors. Even though dwell times on books and research articles were significantly greater than both NPC dialogues and posters, the dwell times on NPCs and posters increased at a greater rate compared to books and research articles as learners interacted with Crystal Island.

Of most interest is the interaction between relative game time and instructional material relevance. Specifically, dwell times on pre-test relevant materials generally decreased over learners' gameplay whereas dwell times on relevant NPCs and posters increased over learners' time in game. From these results, we conclude that while learners are initially able to accurately deploy SRL strategies for information-gathering by engaging with pre-test relevant instructional materials, as time engaging in game-based learning progressed, learners' ability to consult relevant information from irrelevant books and research articles decreased. Because dwell times on books and research articles did not change during learning but time on relevant books and research articles decreased, we infer that the long blocks of text without any supporting diagrams or conversational interactions did not support learners' deployment of accurate SRL monitoring strategies (i.e., content evaluations). However, learners were generally able to deploy accurate content evaluations when interacting with posters and NPCs as they learned with Crystal Island. Our results expand prior studies such as that by Dever et al. (Dever and Azevedo, 2019b) and Taub et al. (2018) by including relative game time, dwell times, and content evaluations based on relevance to domain knowledge acquisition. These results support SRL as a complex system through and add to Winne's (2018) IPT of SRL model by examining how operations can affect how learners interact with their learning environment and how this can be captured and measured using eye-tracking and log-file data.

The second research question expanded previous results to understand how SRL processes can be examined and related to each other when examining eye gaze dwell times across relevant and irrelevant instructional materials. Hypotheses were partially confirmed where results did not find that task conditions, cognitive conditions, or learning outcomes were significantly related to dwell times on either relevant or irrelevant instructional materials during learning with Crystal Island. However, hypotheses regarding SRL sequencing behaviors were partially confirmed where the models found that as percent determinism increases, the dwell times on instructional materials increase regardless of material relevance to the pre-test. This effect may have implications for the oscillation between accurate and inaccurate use of SRL strategies due to the non-significance in dwell times on relevant and irrelevant instructional materials. Further, this result is interesting as learners who repeat sequences of information-gathering behaviors with instructional materials tend to have greater dwell times on these materials. To fully explore this effect, future analyses should examine the differences in repeated behaviors for each type of instructional material.

From these results, we conclude that SRL systems with greater predictability and less novel behaviors typically have greater dwell times across instructional materials. The findings contradict research conducted on task conditions, cognitive conditions, and overall learning which found these constructs to significantly interact. This is potentially due to how SRL within this study was measured using an NDST method to examine the stability vs. rigidity of SRL behaviors individually rather than aggregating using typical parametric methods. However, these results contribute to the dynamic and complex conceptualization of SRL as we were able to identify a positive relationship between the predictability of SRL behaviors and learning outcomes. Specifically, this result has implications for (1) Winne's (2018) model to include learners' recursive interactions with GBLE elements as an operational strategy for SRL, and (2) scaffolding design through the lens of far-from-equilibrium concept within complex systems theory. For example, treating SRL systems as complex should extend to theory as well as how GBLEs are designed. From the results of the study, GBLEs should increase the minimum time of instructional material interaction and promote learners' use of several different types of representations while still structuring their approach to how learners interact with the environment. Scaffolds within GBLEs should be designed to balance learners' exploratory behaviors with the structure provided by scaffolds to encourage behaviors that follow the far-from-equilibrium concept.

To further explore learners' sequences of instructional material interactions and how they relate to task conditions, cognitive conditions, and learning gains, the third research question extracted information from the aRQA output. In doing so, we were able to explore how learners differ in (1) the distribution of novel behavioral sequence indices over different instructional materials; and (2) the novelty of behavioral sequences between task and cognitive conditions and its relationship with learning gains. For this third research question, we hypothesized that learners with more repetitive eye gaze sequences would be present in learners with restricted agency and related with higher learning gains. Further, we hypothesized that learners with higher prior knowledge would demonstrate more novel behaviors as they used instructional material interaction diversity as an SRL strategy. Specifically, more novel behaviors denote a healthier SRL system, and as such, the use of multiple different types of materials can be considered a learning strategy employed by learners.

Overall, our hypotheses were not confirmed as prior knowledge was not included within our analyses due to previous non-significant relationships. However, when clustering all participants according to the frequency of recurrent points on Lag 1 and between all instructional materials, hypotheses were confirmed. First, we were able to identify differences between learners where two clusters identified learners as having greater books and research article recurrence (Cluster 2) or fewer recurrence in these interactions (Cluster 1) with no differences in the frequency of NPC recurrent points. From our analyses, learners who had restricted control over their own actions (i.e., the partial agency condition) demonstrated significantly greater learning gains, regardless of classified cluster profiles than learners with full control. However, when ranking the significant clusters and conditions in reference to overall learning, we conclude that learners with partial agency in Cluster 1 had greater learning gains, **demonstrating novel behavior while engaging in guided game-based learning increases overall learning gains**. These results are parallel to findings for the concept of agency (Sawyer et al., 2017; Dever et al., 2020; Taub et al., 2020) but are novel by examining learners' recursive behaviors in gathering information during game-based learning. These results are consistent with the far-from-equilibrium concept of complex systems theory which promotes the balance between rigidity (i.e., partial agency) and chaos (i.e., novel SRL behavior).

## 9. FUTURE DIRECTIONS AND CONCLUDING STATEMENT

Our findings have significant conceptual, theoretical, methodological, empirical, and design implications for future research on SRL and GBLEs. Conceptually, our use of NDST analytical methods to analyze SRL process data during game-based learning significantly contributes to the field of SRL and learning technologies by including complex systems theory (Lajoie et al., 2018; Jarvela and Bannert, 2019). While much has been published describing SRL as a dynamic, temporally unfolding process, there is no published research using complex systems theory as a theoretical grounding or dynamical systems in modeling as a method to examine the dynamics of SRL strategies, specifically information-gathering behaviors, during GBLEs (Azevedo et al., 2019; Plass et al., 2019; Favela, 2020). That is, SRL has theoretically been described as temporally dynamic, with some models assuming non-linearity as well, but we extend these assumptions by positing SRL as a complex system and used NDST analytics to empirically support this claim. To date, this article acts as one of the first studies to apply NDST methods to SRL using complex systems theory (see Garner and Russell, 2016; Li et al., 2022).

The use of non-linear dynamical systems techniques allows researchers to specify, operationally define, and make predictions about assumptions regarding the dynamics of SRL processes. More specifically, we can understand how the dynamics of each SRL process (within and across different data channels) are connected to specific complex SRL components described in Winne s COPES model. A dynamical systems approach ties each of the COPES together elegantly and produces testable hypotheses that need to be further explored by researchers (e.g., how do other cognitive conditions such as motivation or emotions relate to how learners oscillate between more recursive or novel operations?)

In addition, our findings using log-files and eye movements provide evidence of the dynamics of specific cognitive and metacognitive processes that, until recently, could only be described in an abstract manner using models such as Winne's (2018) theory of SRL. More specifically, our findings indicating that relationships between eye gaze dwell time and (1) the type of representation a learner gathers information from (i.e., large sections of text, poster, or dialogue); (2) the ability of the learner to distinguish relevant from irrelevant information; (3) learning gains; and (4) agency, could only have been established using the non-linear dynamical systems modeling and statistical techniques used in our study. As such, our findings, based on our use of multimodal data, can begin to augment current models of SRL (e.g. Winne, 2018) by adding the micro-level processes (e.g., judgments of learning, monitoring progress toward goals) that are currently hypothesized to predict learning and performance. Dynamical system modeling can be used to study task and cognitive conditions and affordances of the GBLEs (e.g., agency) as learners engage in SRL processes.

Future research should focus on how other multimodal data (e.g., physiological and facial expressions of emotions) contribute to our understanding of the dynamics of other key SRL processes such as affect and motivation. Can the dynamics capture subtle states or state transitions related to emotion regulation, emotion regulation efficacy, etc. (McRae and Gross, 2020)? What are the multimodal data that most accurately predict affective and motivational states? What specific indices can be extracted from each data channel to understand the temporal dynamics of affect and motivation during GBLE? Would non-linear dynamical modeling techniques and analytical approaches predict that the same states within and across data channels are predictive of learning, reasoning, performance, etc.? How would learning technology-specific affordances impact the dynamics of SRL across learning technologies? For example, how would the lack of autonomy embodied into an intelligent tutoring system impact the dynamics of cognitive, affective, metacognitive, and motivational SRL processes compared to a simulation?

Researchers should consider longer and different types of experiments to test how changing agency, number and types of relevant and irrelevant instructional materials, behavioral repertoire of the NPCs, etc. would impact learners' self-regulation and multimodal data. This new research strategy would also force researchers to isolate the exact dependent variables for each data channel and how they both individually and collectively contribute to our understanding of the dynamics of SRL across learners and contexts.

Our findings also have implications for the design of future GBLEs where NPCs can detect when, how, and why learners fluctuate in their accurate SRL strategy deployment. Further, complex systems theory lends support in the development of GBLEs to support the balance between rigid and complex SRL behaviors. The system's intelligence capability could lead the NPCs to engage in a conversation with the learners about why their ability to identify relevant text has changed. Further, this could serve as an opportune time to pedagogically intervene by providing different types of scaffolding or prompting to the learners. We see several innovative pedagogical interventions delivered by the NPCs. For example, "Your eye movements suggest that you are not spending enough time on the relevant textual cues. Would you like for me to model these processes? Or, would you like for me to show you your multimodal data to show you what, where, and how you have changed your overall strategy?". In summary, the use of non-linear dynamical system modeling has tremendous potential to advance the field of SRL, multimodal data, and GBLEs.

## DATA AVAILABILITY STATEMENT

The datasets presented in this article are not readily available because of written consent restraints. Requests to access the datasets should be directed to Daryn Dever, corresponding author.

## ETHICS STATEMENT

The studies involving human participants were reviewed and approved by North Carolina State University International Review Board. The participants provided their written informed consent to participate in this study.

## AUTHOR CONTRIBUTIONS

DD significantly contributed to the conceptualization and construction of this manuscript as well as the analyses that were conducted. MA and HV contributed their expertise of complex systems and non-linear dynamical systems theory and the application of auto-Recurrence Quantification Analysis. MW contributed to the analyses and data extraction as well as to the editing of this manuscript. EC wrote the methodology section and provided edits. RA significantly contributed his expertise in SRL and supported the future directions and final conclusion section. All authors contributed to the editing of the manuscript.

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# Lessons Learned and Future Directions of MetaTutor: Leveraging Multichannel Data to Scaffold Self-Regulated Learning With an Intelligent Tutoring System

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Self-regulated learning (SRL) is critical for learning across tasks, domains, and contexts. Despite its importance, research shows that not all learners are equally skilled at accurately and dynamically monitoring and regulating their self-regulatory processes. Therefore, learning technologies, such as intelligent tutoring systems (ITSs), have been designed to measure and foster SRL. This paper presents an overview of over 10 years of research on SRL with MetaTutor, a hypermedia-based ITS designed to scaffold college students' SRL while they learn about the human circulatory system. MetaTutor's architecture and instructional features are designed based on models of SRL, empirical evidence on human and computerized tutoring principles of multimedia learning, Artificial Intelligence (AI) in educational systems for metacognition and SRL, and research on SRL from our team and that of other researchers. We present MetaTutor followed by a synthesis of key research findings on the effectiveness of various versions of the system (e.g., adaptive scaffolding vs. no scaffolding of self-regulatory behavior) on learning outcomes. First, we focus on findings from self-reports, learning outcomes, and multimodal data (e.g., log files, eye tracking, facial expressions of emotion, screen recordings) and their contributions to our understanding of SRL with an ITS. Second, we elaborate on the role of embedded pedagogical agents (PAs) as external regulators designed to scaffold learners' cognitive and metacognitive SRL strategy use. Third, we highlight and elaborate on the contributions of multimodal data in measuring and understanding the role of cognitive, affective, metacognitive, and motivational (CAMM) processes. Additionally, we unpack some of the challenges these data pose for designing real-time instructional interventions that scaffold SRL. Fourth, we present existing theoretical, methodological, and analytical challenges and briefly discuss lessons learned and open challenges.

**Keywords: self-regulated learning, learning, multimodal data, intelligent tutoring systems, scaffolding, metacognition, trace data, pedagogical agents**

## INTRODUCTION: SELF-REGULATED LEARNING AND ADVANCED LEARNING TECHNOLOGIES

Self-regulated learning (SRL) is essential to learning, reasoning, and problem-solving across tasks, domains, and contexts (Pintrich, 2000; Zimmerman and Schunk, 2011; Panedero, 2017; Schunk and Greene, 2018). However, research shows that learners experience challenges in accurately, dynamically, and effectively monitoring and regulating their cognitive, affective, metacognitive, motivational, and social self-regulatory processes. A solution to this challenge has been designing and implementing learning technologies such as intelligent tutoring systems (ITSs) to measure and foster SRL (Azevedo and Aleven, 2013). This paper presents an overview of over 10 years of research on SRL with MetaTutor, a hypermedia-based ITS designed to scaffold college students' SRL while they learn about the human circulatory system. MetaTutor's architecture and instructional features are designed based on Winne (2018; 2020) model of SRL, empirical evidence on human (Azevedo et al., 2008; Chi, 2021) and computerized tutoring (Nye et al., 2014; du Boulay and Luckin, 2016; Johnson and Lester, 2016, 2018; Graesser, 2020), AI in educational systems for metacognition and SRL (Aleven and Koedinger, 2002; Azevedo and Aleven, 2013; Biswas et al., 2016; Azevedo and Wiedbusch, in press), Mayer and Fiorella (in press) principles of multimedia learning, and extensive research on SRL, ITSs, serious games, simulations, and open-ended hypermedia from our team and other researchers (Bannert et al., 2014; Biswas et al., 2018; Schunk and Greene, 2018; Azevedo et al., 2019; Sonnenberg and Bannert, 2019; Lajoie, 2021).

We present a synthesis of key research findings and the effectiveness of different versions of the system (e.g., adaptive scaffolding vs. no scaffolding of self-regulatory behavior) on learning outcomes. First, we focus on findings from self-reports, learning outcomes, and multimodal data (e.g., log files, eye tracking, facial expressions of emotion, and screen recordings) and their contributions to our understanding of SRL with an ITS. Second, we elaborate on the role of embedded PAs as external regulators designed to scaffold learners' cognitive and metacognitive SRL strategies. Third, we highlight and discuss the contributions of multimodal data in measuring and understanding the role of cognitive, affective, metacognitive, and motivational (CAMM) processes while unpacking the challenges these data pose for designing real-time instructional interventions that scaffold SRL. Fourth, we present existing theoretical, methodological, and analytical challenges and briefly discuss lessons learned with MetaTutor and open challenges.

We briefly describe Winne and Hadwin's model of SRL to contextualize our program of research investigating SRL and MetaTutor with college students over dozens of studies. We utilized Winne and Hadwin's information processing theory (IPT) of SRL (Winne and Hadwin, 1998, 2008; Winne, 2018) extensively in our research on MetaTutor. The theory states that learning occurs through a series of four cyclical phases, where metacognitive monitoring and control are the hubs of SRL. These processes are captured as events that unfold over time and across several phases. This model is appropriate because we view metacognition as a series of events (e.g., planning → cognitive strategy A → metacognitive monitoring process C → cognitive strategy F → metacognitive monitoring process W → . . .) that occur during learning. Specifically, the four phases involve (1) understanding the task, (2) setting goals and making plans to accomplish goals, (3) applying learning strategies for making progress based on (2), and (4) adapting to (2–3) as new challenges and demands emerge. In the context of MetaTutor studies, these phases would include understanding the overall learning goal provided by the system (e.g., *"you have 45 minutes to learn all you can about the human circulatory system. Make sure you learn about all the components, how they work together, and how they help support the healthy functioning of the human body"*). Once the learner understands the task, they would then be expected to generate several learning subgoals (e.g., learn how the pulmonary and systemic systems work in tandem to support the human body) to accomplish the overall learning objectives. Learners could track and accomplish their subgoals and learning objectives using MetaTutor's interface features (e.g., SRL palette to indicate to the system which SRL processes they were planning on using) and with the support of the four PAs. Self-regulating in the context of learning with MetaTutor meant learners had to use cognitive and metacognitive processes to accomplish their sub-goals such as making inferences, summarizing, making hypotheses, and others while metacognitively monitoring their learning by engaging in judgments of learning (JOL), feelings-of-knowing (FOK), monitoring progress toward goals, and evaluating the relevance of content, such text and diagrams, given their current learning goal. While self-regulating with MetaTutor, we expected learners to also experience emotional and motivational states that were captured by multimodal data using cameras, physiological devices, and embedded self-report measures.

The effectiveness of the system has been extensively tested and published widely in several cognitive, learning, instructional, and computer science refereed conference proceedings, journals, chapters, and widely disseminated at national and international conferences (Azevedo et al., 2010, Azevedo et al., 2013, 2018, 2019). MetaTutor was originally designed to be both a learning tool to foster self-regulation and a research tool to collect trace data on CAMM processes as they unfolded during learning. The system supports several learning strategies through its user interface including features that prompt learners to activate prior knowledge about content, goal setting, evaluating learning strategies, integrating information across diagrams, evaluating content, summarizing key information, note-taking, and drawing. It also scaffolds specific metacognitive monitoring processes, such as JOLs and FOKs. The unique contribution of this paper is its comprehensiveness and synthesis of all the studies conducted by our team and collaborators over more than a decade that emphasizes empirical findings across CAMM processes.

The central research questions addressed in our research on MetaTutor with predominantly Caucasian female college students, include: (1) How do different scaffolding methods influence students' learning about human biology and their SRL performance? (2) How do different scaffolds influence students' deployment, effectiveness, and quality of SRL processes during learning with MetaTutor? (3) What is the temporal and dynamic nature of students' CAMM processes while using MetaTutor to learn about complex biology topics with MetaTutor? (4) Do process-oriented multimodal trace data (e.g., log files, concurrent verbalizations, eye movements, facial expressions of emotion, and physiological sensors) reveal "signatures" of specific cognitive and metacognitive processes [e.g., ease-of-learning (EOL), JOLs]? and (5) To what extent do self-report and process-oriented multimodal trace data predict SRL behaviors, learning, and performance, based on experimental conditions and individual differences?

## MetaTutor: A HYPERMEDIA-BASED INTELLIGENT TUTORING SYSTEM FOR HUMAN BIOLOGY

MetaTutor is a hypermedia-based ITS that teaches challenging STEM content (e.g., human circulatory system) developed by Azevedo and interdisciplinary colleagues over the last decade at the University of Memphis, McGill University, Illinois Institute of Technology, North Carolina State University, and the University of Central Florida. Over the years, the design of the STEM content has included experts in several fields of STEM and biomedical sciences. **Figure 1** illustrates MetaTutor's main interface elements.

MetaTutor is aligned with theoretical, conceptual, and methodological assumptions about SRL and learning with advanced learning technologies (Winne and Hadwin, 1998, 2008; Pintrich, 2004; Azevedo, 2005; Azevedo et al., 2010, 2019; Zimmerman, 2011; Schunk and Greene, 2018; see **Figure 1**). First, CAMM processes can be detected, tracked, and modeled using online trace methodologies. Second, students deploy these processes during extended interactions with MetaTutor while instrumented and participating in our laboratory experiments (see **Figure 2** for experimental set-up). Third, the CAMM signatures collected from the various methods, techniques, devices, and sensors (e.g., facial expressions of emotion, physiological sensors, eye tracker, log files, and screen recording of student-system interactions) will have different profiles depending on real-time fluctuations in response to internal and external conditions (e.g., accumulating knowledge about the topic and feedback from the PAs, phases of learning, or generation of subgoals. Fourth, a session is characterized by learner-generated subgoals). Fifth, several types of trace, self-report, and product data are identified as critical for examining the complex nature of SRL. In our studies, trace data included think-alouds, eye tracking, log files, and physiological recordings. Product data represented three individual pretest measures that assessed different types of knowledge including declarative, procedural, and mental models; equivalent measures were also given as a posttest. We included self-report measures of motivation and emotions that were also presented at pretest, during learning, and at posttest. **Figure 3** illustrates the experimental procedure for all MetaTutor studies.

To experimentally test the effectiveness of the scaffolding provided through the system, MetaTutor features two experimental conditions, i.e., adaptive scaffolding and no scaffolding. In the former condition, PAs prompt students to engage in several learning strategies (e.g., prior knowledge activation, note-taking, or judging the relevance of a page to the current learning sub-goal) based on the student's interaction with the system (e.g., the goals they set, how much time they spent with certain contents). Further, students receive feedback for prompted or self-initiated assessments, such as quizzes. In the no scaffolding condition, no such prompts or feedback are provided. However, students are free to use any of the learning strategies incorporated in MetaTutor (see SRL palette on the right-hand side of **Figure 1**) but do not receive feedback regarding these interactions.

## MetaTutor's ARCHITECTURE

MetaTutor's architecture relies on the use of three types of external resources (see **Figure 4** for the overall architecture): (1) content and content-related resources, (2) experimental protocol resources and, (3) experimental condition resources.

The content resources include the pedagogical material on the circulatory system provided by 48.RTF files and as many.JPG images (one per page), which are displayed at the center of the interface while the student is learning with MetaTutor (see **Figure 1** for the interface overview). Three additional XML files help in structuring the content: (a) a file is used to structure the table of contents sections and subsections and to associate to each page the RTF and JPG files as well as the subgoals associated to the page, and a minimum and maximum reading times (estimated from a sample of students who read the content outside of MetaTutor), (b) a file is used to define the 7 subgoals existing in the usual version of MetaTutor and to associate to each of them a set of keywords used during the interactive subgoal setting phase at the beginning of the session and anytime a student has validated all their initial subgoals, (c) a file is used to define the questions associated to each content page (6 questions per page: 3 based on the text, 3 requiring an inference from the student) with 4 possible options (the correct answer, a "near miss" corresponding to a wrong answer close from the correct one, an incorrect answer that is related to the question and an incorrect answer that is completely unrelated)—this file is used to dynamically generate the quizzes associated to each page by randomly drawing 3 questions from amongst them. MetaTutor's seven sub-goals include the path of blood flow, how does the heartbeat, what are the functions of the components of the heart, what are the functions of the components of the blood vessels, what are the functions of the components of blood, purposes of the human circulatory system, and malfunctions of the human circulatory system.

The experimental protocol resources are used to change some overall parameters of MetaTutor to adapt to particular experiment settings. It includes a text file made of a set of attribute-values defining parameters such as whether the agent should speak or not, the name and number of the experimental conditions, the number of subgoals to set initially, the minimum time before a PA can intervene on a page, etc. The second experimental protocol file is an XML file defining the scripts associated with the PAs, such as what text is displayed in the dialog history, what is actually said by the agent with possible variations to avoid repetition. Specifically, a given script can have several different texts associated with it, and within a text, regular expressions add more variability. It is also possible to use special tags to ensure that some additional details are provided the first time an agent says this text but not later times. Finally, the experimental condition files are a set of three files for each of the experimental conditions tested (i.e., 9 files overall if there are three conditions). The first file defines as a finite state automaton the overall flow followed by MetaTutor when a student is assigned to that experimental condition. For each state, it can define, through a set of predefined tags, which PA to show, what script that agent should say and display, how to change the system interface (e.g., to show the summary interface or a self-report questionnaire), whether to pause or resume the system, etc. and the next state depending on the student's actions. It allows MetaTutor to alternate between guided phases (at the beginning and end of the learning session and every time the student engages in an SRL process) and phases where the student can freely explore the pedagogical content. The second file defines both the actions to trigger when using the SRL palette (see **Figure 1**), each PA's intervention, and what can trigger these actions. Each intervention is associated with a set of predefined conditions: (1) the student has spent more than the average reading time on a page, (2) that page is relevant to the student's current subgoal, (3) the student has not done more

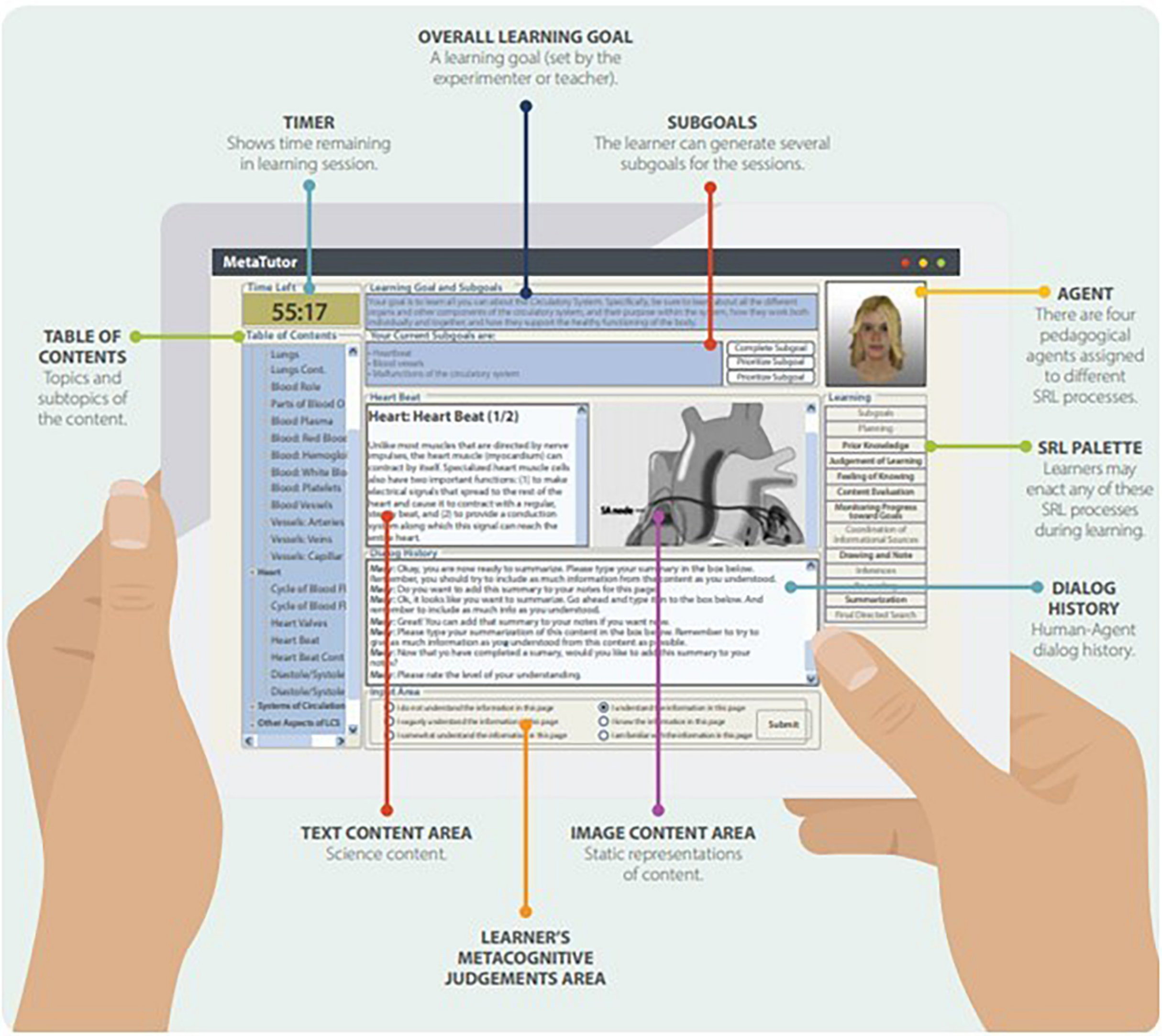


**FIGURE 1 |** MetaTutor's main interface elements.

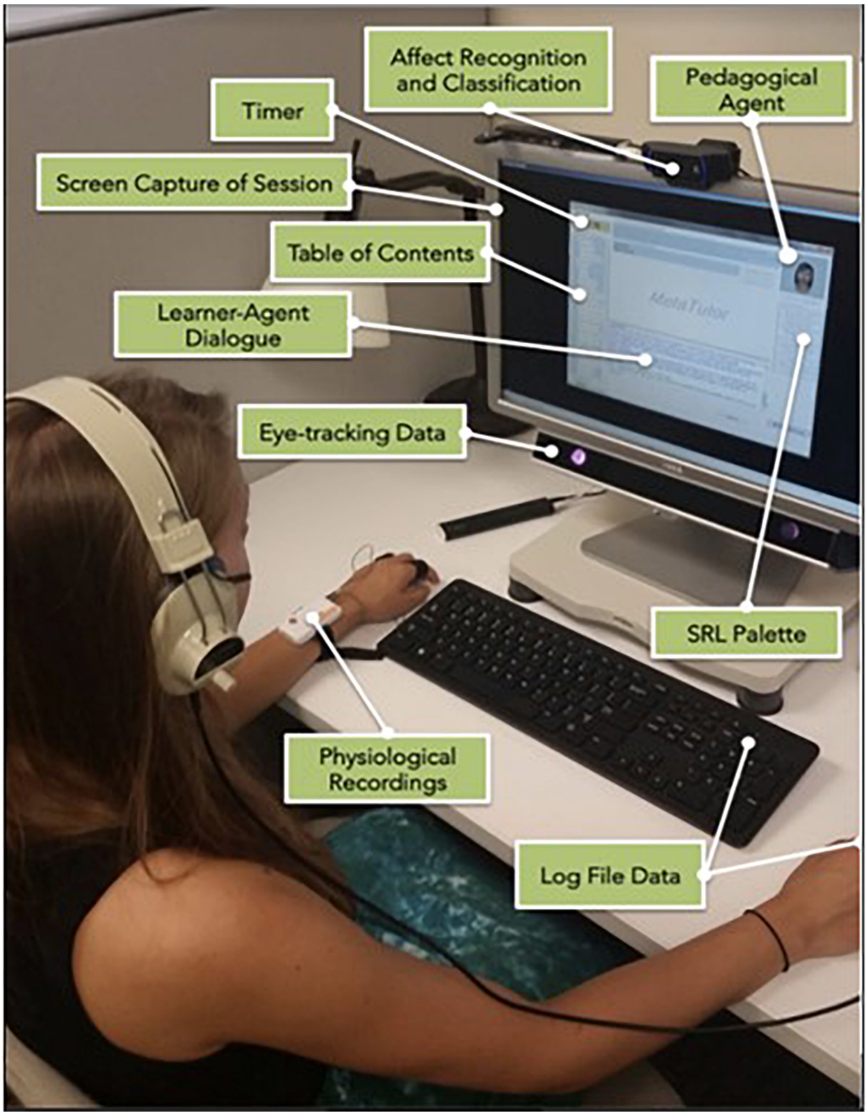


**FIGURE 2 |** Instrumented student participating in a typical MetaTutor study.

than a predefined number of content evaluations (CEs) while working on this subgoal, and (4) the student has not evaluated the relevance of the content of this page already. When conditions are met, there is a probability that a PA will intervene to ask them to monitor their learning or to deploy a learning strategy (e.g., asking them to evaluate the relevance of this content to their subgoal). Finally, the third file defines a set of meta-rules that can modify the triggering conditions of the PA's interventions, thus making the rules dynamic over the learning session based on the student's overall use of SRL processes. For instance, if a student tends to regularly assess how relevant the content of the page, they read is to their current subgoal, the associated PA's intervention will be less likely to be triggered on a page by adjusting the probability parameter of the rule. These meta-rules allow, for instance, to define a more intense prompting at the beginning of the session which will gradually decrease if the student performs the SRL strategies correctly, and even faster if they initiate them (Bouchet et al., 2016).

In the original version, four separate PAs embodying four different functions (guiding through the system, planning, monitoring, and using learning strategies) provide verbal feedback and engage in a tutorial dialogue to scaffold students' selection of relevant subgoals based on their level of understanding of the circulatory system, accuracy of metacognitive judgments, and use of learning strategies. Each of the four PAs had a different function based on SRL. One of the four PAs (Gavin, Pam, Mary, or Sam) is always displayed in the upper right-hand corner of the environment (see **Figure 1**). These agents provide varying degrees of adaptive scaffolding (i.e., prompting and feedback) throughout the learning session to scaffold students' SRL skills such as summarizing, making JOLs, and understanding content (see Azevedo et al., 2010

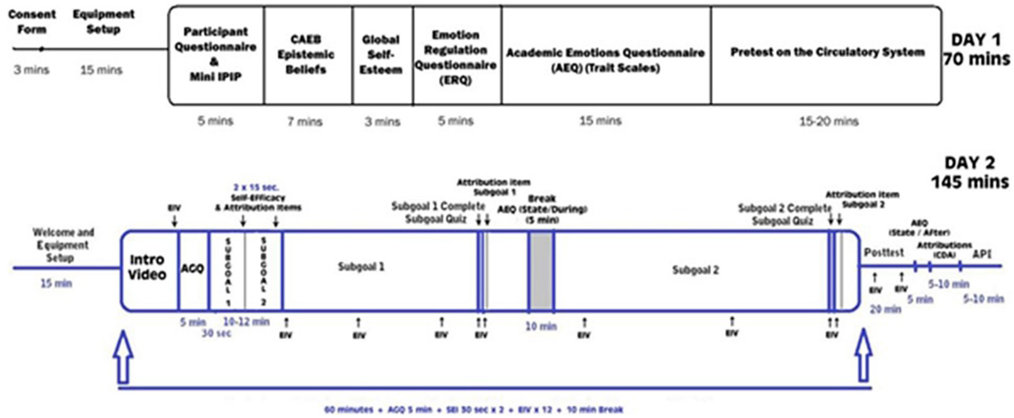


**FIGURE 3 |** Experimental procedure used for all MetaTutor studies.

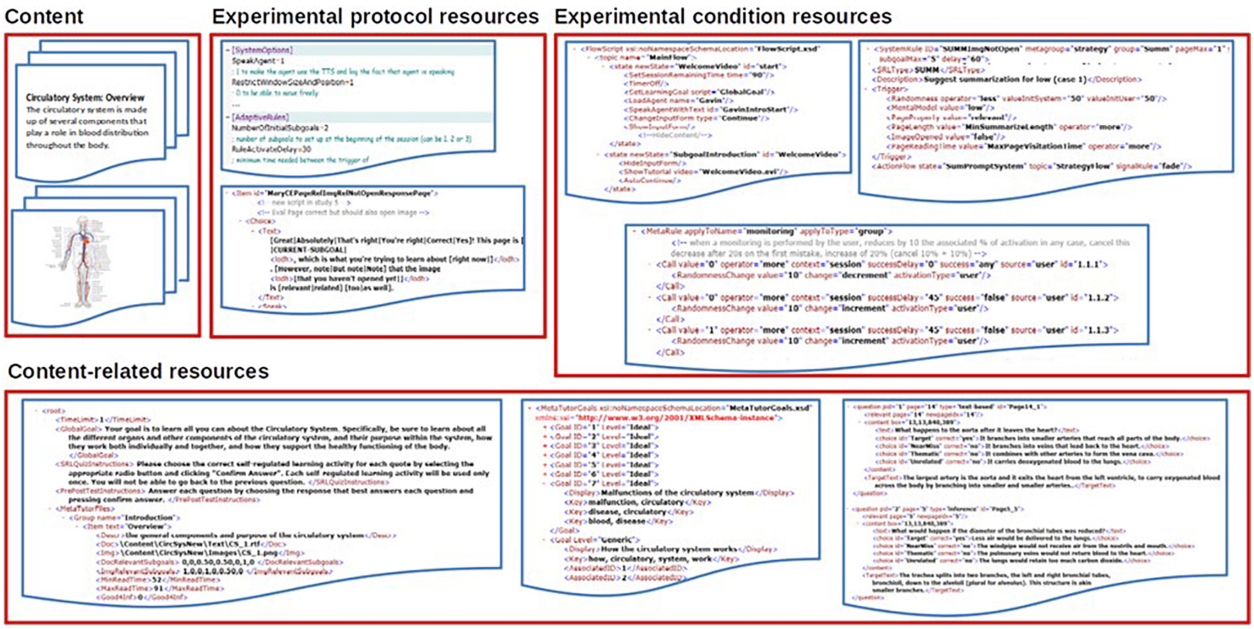


**FIGURE 4 |** MetaTutor's overall architecture.

for details). Briefly, each agent serves a different purpose: (1) *Gavin the Guide* helps students to navigate through the system and orient the students about the task; (2) *Pam the Planner* guides students in setting appropriate sub-goals by activating their prior knowledge and coordinating sub-goals; (3) *Mary the Monitor* helps students to monitor their progress toward achieving their sub-goals by prompting and scaffolding several metacognitive processes such as FOKs, JOLs, and CEs; and (4) *Sam the Strategizer* helps students deploy SRL learning strategies, such as summarizing and note-taking, making inferences, re-reading, and generating hypotheses. Learners can interact with these PAs and enact specific SRL learning processes by selecting any feature of the SRL palette displayed at the right-hand side of the interface during the learning session.

For example, students are prompted to self-assess their understanding and are then given a brief quiz. Quiz results allow the PA to provide feedback according to the calibration between students' confidence of comprehension and their actual quiz performance. Learners can also self-initiate and express these same system-initiated metacognitive judgments and learning strategies through an SRL palette of actions (see **Figure 1**). For example, they can click a button to indicate they want to make a statement about their understanding of a page and then indicate on a scale that their understanding is poor. They can also indicate that they want to summarize the content of that page and type their summary in a textbox. MetaTutor collects information from user interactions to provide adaptive feedback on deploying SRL behaviors.

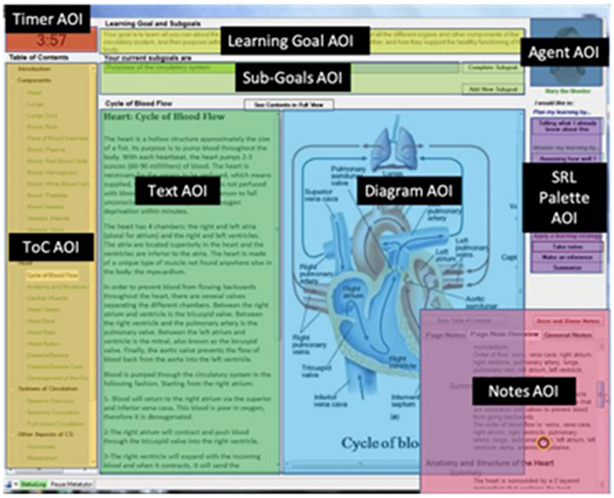


**FIGURE 5 |** Areas of interest on MetaTutor's main interface.

In the next sections, we describe our findings based on their contributions to cognitive, metacognitive, affective, and motivation processes underlying learning with MetaTutor. Please note that although we strive for consistency in structure, each section differs slightly given the number of published studies, specific research foci, and research questions that were answered based on the specific CAMM SRL process.

## ROLE OF COGNITIVE STRATEGIES DURING LEARNING WITH MetaTutor

Cognitive processes that are carried out in the service of studying and learning involve processing new information in order to transform it into long-term memory (Winne, 2018). In learning environments, such new information is predominantly represented by multimedia formats, including texts, graphics, and audio (Mayer and Fiorella, in press). Cognitive processes are applied to these new inputs to create mental representations for each modality and to form connections between new inputs and prior knowledge already stored in long-term memory, an underlying phenomenon described by Winne and Hadwin's (1998; 2008) IPT of SRL. These processes are critical during learning about complex science materials as their use allows learners to transform instructional materials into knowledge structures that change over time during interactions with systems such as MetaTutor. For example, learners can summarize instructional content or make hypotheses about blood flow after reading and inspecting relevant diagrams. Given the overall objective for MetaTutor to scaffold effective SRL processes, the design of this ITS was informed by Winne and Hadwin's (1998; 2008) IPT model of SRL to help scaffold and support cognitive operations.

Cognitive operations are the processes that transform external information into mental representations and other learning products, such as notes or essays and new mental models of how the human circulatory system works. Winne (2001) further specifies cognitive operations into several smaller grained processes: searching, monitoring, assembling, rehearsing, and translating (SMART; Winne, 2018). These specific cognitive operations, when applied individually or in combination during learning, may account for a variety of study tactics and learning strategies during the third phase (enactment) of SRL, including reading or re-reading, integrating texts and graphics and transforming information across modalities, taking notes or writing summaries, making inferences, memorizing, or elaborating. Empirical investigations of MetaTutor have largely focused on note-taking as one such cognitive learning strategy.

### Note-Taking

Note-taking is a prevalent cognitive learning strategy that allows students to "record, clarify, organize, and comprehend information" (Bonner and Holliday, 2006, p. 787; Lee et al., 2013). Depending on the quality of the execution, taking notes may support the integration of new information and the construction of a coherent mental representation of the instructional content. Beyond creating a product that may be viewed and studied later, the process of taking notes may itself be beneficial for learning (Kiewra, 1985; Morehead et al., 2019). In sum, notes taken during studying or learning provide a perspective on the cognitive processes enacted during this phase that may be relevant for successful learning.

Trevors et al. (2014) directly examined the quantity and quality of college students' notes as they learned with MetaTutor. They sought to determine whether these note-taking variables and their predictive relationship to subsequent learning varied as a function of note-takers' prior knowledge and the experimental condition to which they were assigned (i.e., prompt and feedback vs. control). To evaluate the quality of notes, Trevors et al. (2014) coded whether conceptual phrases in notes represented either a *deep* or *shallow* reflection of the instructional concepts that students were studying at the time of creation. A deep representation in notes signified that students went beyond the information presented in the instructional content to include new information or identify connections or themes across instructional texts and diagrams or between instructional content and prior knowledge. Such elaboration is thought to reflect the learner's comprehensive understanding of the underlying relevance and meaning of the instructional content beyond what is explicitly stated. Conversely, a shallow representation in notes signified a simple verbatim reproduction of the instructional content that is consistent with rote memorization or rehearsal strategies and a superficial understanding of the content. As quantitative properties of notes, the frequency and duration of note-taking episodes and the number of conceptual phrases were also examined. Findings showed that in this context, notes were largely shallow verbatim copies of instructional content that in turn negatively predicted learning. Students with low prior knowledge spent more time on this counterproductive learning strategy compared to their high prior knowledge counterparts, which suggests that the low prior knowledge group may have over-relied on a knowledge-building strategy at the expense of monitoring its effectiveness. MetaTutor system prompts and feedback substituted other SRL processes in lieu of note-taking, which was significantly lower in the experimental condition compared to the control.

In a subsequent study, Taub and Azevedo (2019) adopted different methodological and analytical approaches to studying the interrelationships between prior knowledge and note-taking within MetaTutor. In addition to mining computer log files of user interactions, Taub and Azevedo analyzed sequences of several cognitive processes together. Further, they employed eye tracking to see what instructional content and features learners were attending to on the system interface and patterns of eye gaze across these areas. They found that high prior knowledge learners engaged in sequences of learning strategies that involved note-taking or summarization more than their low prior knowledge counterparts. Consistent with this finding, Taub and Azevedo (2019) also found that high prior knowledge learners had greater frequencies of fixating on pairs of areas of interest (AOIs) that showed attention to the instructional text and the note-taking interface than their low prior knowledge counterparts (e.g., fixated more on the instructional text followed by fixating on the note-taking interface). These findings suggest that high prior knowledge students were able to cycle between content and cognitive strategies involving note-taking quickly and fluidly.

More recently, Wiedbusch et al. (2021b) examined why learners lack sufficient SRL skills to successfully implement strategies (e.g., JOL, note-taking, self-testing, etc.). The authors used principal component analysis (PCA) on log files to further explore underlying patterns in the frequency of strategy deployment occurring with and without PA scaffolding. The motivation for this study was to use a data-driven approach to find underlying structures of the system- and learner-initiated cognitive and metacognitive SRL strategy use. This study provided empirical evidence that the system's underlying architecture deployed cognitive and metacognitive processes corresponding to both the phases of learning according to Winne's (2018) theory of SRL, the familiarity of processes, and type of effort allocation. The authors highlight the potential to incorporate quality of SRL strategy use (e.g., such as the quality of note-taking measured in Trevors et al., 2014) in future work to reveal how standards (as defined in the Winne (2018) theory impact student strategy deployment. Future iterations of the design of these skills could also then incorporate quality in the conditional procedural rules.

## Goal-Setting

Setting goals is a critical part of the second phase of Winne and Hadwin's model, yet little research has examined how we set goals and how we might do so collaboratively with a PA. Harley et al. (2018) contributed to addressing this gap in the literature by drawing on theories of co- and socially shared regulated learning (Järvelä and Hadwin, 2013) to identify patterns in learner-PA interaction and, including students' compliance with the PAs' suggestions, subsequent associations with learning outcomes. Learner-PA interactions were examined across two scaffolding conditions: adaptive scaffolding and no scaffolding. Learners' compliance to follow the PA's prompts and feedback in the adaptive scaffolding condition were also examined. Results demonstrated that learners followed the PA's prompts and feedback to help them set more appropriate subgoals for their learning session the majority of the time. Descriptive statistics revealed that when subgoals were set collaboratively between learners and the PA, they generally lead to higher proportional learning gains. Taken together, the results provide preliminary evidence that learners are both willing to engage in and benefit from collaborative interactions with PAs when immediate, directional feedback and the opportunity to try again are provided.

## Lessons Learned and Future Directions

Findings from Harley et al. (2018) have implications for extending co- and socially shared regulated learning theories to include learner-PA interactions, rather than just learner-learner and learner-teacher. Findings from Taub and Azevedo (2019) suggested that learners with high prior knowledge engaged in more sequences of actions including note-taking or summarization, in contrast with findings from Trevors et al. (2014), where learners with high prior knowledge took fewer notes overall. The conflicting results may be attributable to differences between sample characteristics or changes in system versions of MetaTutor across time. However, two other salient differences between studies are the different methodological and analytical approaches used. In particular, methodologically, Taub and Azevedo used eye-tracking, which provides high temporal resolution in assessing attention allocation across studying that also allows for inferences regarding cognitive strategies. Analytically, while Trevors et al. (2014) examined individual instances of specific quantitative and qualitative variables of notes directly, Taub and Azevedo (2019) focused on patterns and sequences of learning processes rather than aggregated events. Together, these research design choices—namely, the direct observations for coding, temporal specificity, and contextual sequence in which a cognitive learning process is enacted—provide a different perspective on the same phenomenon.

Working with multimodal multichannel data to assess a variety of learning strategies and their sequences presents many different ways to study the same construct, which is a key future direction highlighted by Wiedbusch et al. (2021a). As researchers' technological capacity to collect cognitive process data grows, so too must they develop analytical frameworks to keep pace (Azevedo and Gašević, 2019; Järvelä and Bannert, 2019). A challenge for researchers will be to arrive at some consensus regarding several standardized operationalizations or, at minimum, an explicit understanding of what different channels may and may not reveal about cognitive learning strategies and ultimately learning outcomes. We argue that a multimodal learning analytic (MLA) approach could be suitable for this kind of data. MLA uses data from different sources about learning traces for doing a single analysis, finding how to combine, or fuse, the data extracted from several sources/modalities in order to provide a more comprehensive view of learning processes. To date, individual events within one channel have been integrated to assess sequences and multiple channels have been conceptually integrated into the discussion. However, true analytical integration will entail the fusing of data channels (e.g., log files, eye tracking, and think-alouds) into quantifiable units appropriate for statistical analyses. This would enable more objective, complete and valid measurements of complex cognitive processes that manifest as study tactics or multiple tactics organized into learning strategies. The need for integration and valid measurement will only grow as teaching and learning become increasingly mediated via new immersive technologies such as augmented or virtual reality and user interfaces such as ITSs.

## ROLE OF METACOGNITION DURING LEARNING WITH MetaTutor

Metacognition plays a key role in monitoring several aspects of oneself, task, learning situation, and context (Nelson and Narens, 1990; Efklides et al., 2018; Schunk and Greene, 2018; Winne, 2018; Winne and Azevedo, 2022). Accordingly, we expect students to dynamically and accurately monitor and regulate their cognitive strategies while using MetaTutor to learn about the human circulatory system. While metacognitive processes are ideally captured using trace methods such as concurrent think-aloud protocols (Azevedo and Cromley, 2004; Greene and Azevedo, 2009; Greene et al., 2021), during a MetaTutor learning session, metacognitive processes can either be prompted by the PA, or students can self-initiate the use of the same metacognitive processes via the SRL Palette (see **Figure 1**). The SRL Palette allows students to judge how well they understand the content they are currently reading (JOL), rate how familiar they are with the content they are currently reading (FOK), and assess how relevant the content text and diagram are for accomplishing their current sub-goal (CE). Students can also indicate they have read enough content pages to complete their sub-goal (monitoring progress toward goals; MPTG). We highlight that these are only four possible metacognitive judgments (Nelson and Narens, 1990; Koriat, 2015; Dunlosky and Rawson, 2019) and that students may have monitored themselves (e.g., regulated their emotions to address misunderstanding content; McRae and Gross, 2020), the task, learning situation, and context using other metacognitive processes that were not captured since our studies relied on student-PA interactions and the SRL Palette.

When investigating metacognitive processes in MetaTutor, there have been three main categories of research questions. First, *what* are the factors that impact the use of metacognitive processes during learning with MetaTutor? Second, *when* do students engage in metacognitive processes during learning with MetaTutor? Third, *how* or *how accurate* are students when engaging in metacognitive processes during learning with MetaTutor?

### Which Factors Impact the Use of Metacognitive Processes?

A first study relied on three clusters of students created from features extracted from the log files only (Bouchet et al., 2013), using differential sequential mining (Bouchet et al., 2012) to see what sequence of actions differentiated high and low performing students. It revealed that high-performing students tended to be better at quickly identifying the relevance of a page to their subgoal, were more methodical in their exploration of the pedagogical content, relying on system prompts to take notes and summarize, and were more strategic in their preparation for the post-test (e.g., using the end of their session to briefly review pages).

Further studies have investigated differences in the frequency and duration of using JOLs, FOKs, CEs, and MPTGs between groups, such as high vs. low prior knowledge (Taub et al., 2014; Taub and Azevedo, 2019), and the experimental compared to the control condition (Azevedo et al., 2011, Azevedo et al., 2016a). To investigate the impact of the use of metacognitive processes by prior knowledge group, Taub et al. (2014) and Taub and Azevedo (2019) used log files only, or eye tracking and log files, respectively, to examine how students with high or low prior knowledge engaged in frequencies of JOLs, FOKs, CEs, and MPTGs during learning with MetaTutor. Prior knowledge was defined by conducting a median split on pre-test score (score on a 30-item multiple-choice content test about the circulatory system). Results revealed that students with high prior knowledge engaged in higher frequencies of JOLs and MPTGs, and lower frequencies of FOKs and CEs than students with low prior knowledge (Taub et al., 2014). In a different study, results from eye-tracking data revealed no differences in the number of fixations on AOIs related to engaging in metacognitive (and cognitive) processes, however, there were significant differences in frequencies of engaging in AOI-pairs; i.e., fixating from the text content to one of eight other AOIs on MetaTutor's main interface (see **Figure 5**) between prior knowledge groups (Taub and Azevedo, 2019). Specifically, students with high prior knowledge engaged in significantly higher frequencies of AOI-pairs than students with low prior knowledge.

A potential interpretation of results from both studies indicates students with different levels of prior knowledge allocate resources differently for engaging in metacognitive processes during learning with MetaTutor. However, results are inconclusive because results in Taub et al. (2014) indicated a higher frequency of engaging in total metacognitive processes, but not for all micro-level metacognitive processes. Additionally, when examining total fixation duration, there were no significant differences, but there were differences when examining frequencies of engaging in fixation pairs. Thus, depending on the level of granularity (i.e., micro-level processes, single fixation vs. fixation pairs), results may be inconsistent with each other.

Another factor that has been found to impact the use of metacognitive processes during learning with MetaTutor is experimental condition. A previous study examined differences in the use of both metacognitive and cognitive processes between the prompt and feedback and control conditions during learning with MetaTutor (Azevedo et al., 2016a,b). This study examined how students self-initiated the use of these processes by clicking on the SRL palette. Results revealed that students who were provided with adaptive scaffolding (i.e., in the prompt and feedback condition) engaged in significantly more JOLs and CEs than students in the control condition (after controlling for pre-test score), and although not significant, frequencies of engaging in FOKs and MPTGs were also higher for students in the adaptive scaffolding condition. This demonstrates the beneficial effects of providing scaffolding to students as external regulation because these processes were self-initiated, and so even though students were prompted to engage in metacognitive processes, this influenced how they self-initiated the use of these processes as well. These findings show how both self- and external regulation can have beneficial effects on using metacognitive processes during learning with MetaTutor. The above-mentioned studies provide evidence for how there are different factors that have been found to impact how students use metacognitive processes during learning with MetaTutor.

## When Do Students Engage in Metacognitive Processes?

According to theories of SRL, metacognition can occur before, during, or after a cognitive process (Winne and Azevedo, 2014, in press). In the previously mentioned studies (Taub et al., 2014; Taub and Azevedo, 2019), additional analyses used educational data mining techniques to investigate sequences of metacognitive (and cognitive) processes during learning. One study used log files to investigate quintet sequences of engaging in metacognitive (and cognitive) processes (Taub et al., 2014). Results revealed that it was more common for students with low prior knowledge to engage in metacognitive processes at the end of the quintet sequence, whereas students with high prior knowledge engaged in metacognitive processes in the middle of the sequence. In addition, this study examined the use of metacognitive (and cognitive) processes by sub-goal, and results revealed that students with both levels of prior knowledge engaged in different numbers of processes for different sub-goals, where students engaged in more processes when working on a more difficult (categorized based on the content included) sub-goal.

Taub and Azevedo (2019) used sequential pattern mining and differential sequence mining to examine patterns via log files of engaging in metacognitive and cognitive processes. Results revealed students with high prior knowledge engaged in sequences that contained both cognitive and metacognitive processes, and students with low prior knowledge engaged in sequences with metacognitive processes only. Additionally, the only sequence frequency that was higher for low prior knowledge students contained inaccurate metacognitive processes.

More recently, Dever et al. (2021) examined how undergraduate students engaged in self-initiated and system-facilitated self- and externally regulated micro-level metacognitive processes (i.e., CEs, JOLs, FOKs, and MPTGs) to process MetaTutor's science content. This study explored the relationship between students' average monitoring micro-process strategy frequencies and learning gains through a person-centered approach as students interacted with MetaTutor. Using hierarchical clustering, Dever et al. (2021) found that clusters differing in metacognitive monitoring process usage had a significant difference in their learning gains where students who used a greater proportion of CEs and FOKs had greater learning gains than learners who used greater MPTG strategies. These aforementioned studies demonstrate differences of when students engage in metacognitive processes during learning with MetaTutor. Specifically, levels of prior knowledge contribute to students' differences in their deployment of cognitive and metacognitive processes and strategies.

## How Accurate Are Students at Deploying Metacognitive Processes?

In addition to examining the sequences of engaging in metacognitive processes, studies have also investigated the *quality* of making metacognitive judgments and engaging in monitoring processes during learning with MetaTutor, and what has been found to impact these judgments (Feyzi-Behnagh et al., 2011; Taub et al., 2018, 2021). For example, Feyzi-Behnagh et al. (2011) investigated the impact of three different conditions (prompt and feedback, prompt only, or control) on students' metacognitive judgments during learning with MetaTutor. They used log files to analyze the relationship between students' judgments for JOLs and FOKs (with + and—valences) and subsequent quiz performance. Results revealed that in general, students were fairly inaccurate at making JOLs and FOKs, and were fairly over-confident when making these judgments, especially in the prompt only condition. Thus, their results provided strong evidence for providing students with prompts *and* feedback for providing effective scaffolding to students during learning with MetaTutor.

Studies have also examined the accuracy of metacognitive processes, and how this has been impacted by emotions or affective states using log files and facial expressions. Taub et al. (2021) examined the relationship between evidence scores of emotions and the accuracy of metacognitive and cognitive judgments. Results found mean evidence scores of surprise negatively predicted accuracy of making FOKs (and mean evidence scores of frustration positively predicted accuracy of notes). In another study, Taub et al. (2018) also used log files and videos of facial expressions and examined the interaction between evidence of action unit (AU) 4 (eyebrow lowerer) and prior knowledge, and how they impacted the accuracy of JOLs, FOK, CEs, and MPTGs. They investigated each instance of engaging in a metacognitive process using multilevel modeling, and results found accuracy was highest for students with high prior knowledge and low levels of AU4. However, for students with low prior knowledge, accuracy was highest with high levels of AU4, demonstrating the differential impacts of emotional states on the use of metacognitive processes. These three example studies exhibit how there are different factors that have been found to impact the accuracy of engaging in metacognitive processes during learning with MetaTutor.

## Lessons Learned and Future Directions

Based on the numerous studies that have investigated the use of metacognitive processes during learning with MetaTutor, there are many take-away lessons that can be used toward assessing metacognition and developing advanced learning technologies that foster the effective use of these processes, from a theoretical and empirical perspective.

First, in line with Winne and Azevedo (2014, in press) who defined the timing of using metacognitive processes in relation to cognitive processes, it seems that to successfully examine all the components of using metacognitive processes (i.e., what, when, why, and how), we should examine both cognitive and metacognitive processes simultaneously. Prior studies have shown that students do engage in both of these processes together during learning with MetaTutor, and it is important to consider when in a sequence (if done so) one precedes or follows the other. In addition, extending these analyses to include affective and motivational processes as well (see sections below) will provide even more contextual information regarding the use of these processes (as seen in Taub et al., 2018, 2021). Without adding the affective component, it would be unclear that prior knowledge can impact metacognitive monitoring differently with different levels of expressing action unit (AU) 4.

Future studies should examine how motivation impacts engaging in metacognitive processes as well. Cloude et al. (2018) examined how goal orientation (categorized into separate groups for mastery/performance/combination of the 2, and approach/avoidance/combination of the 2) impacts the frequency of using metacognitive processes during learning with MetaTutor. However, there were no significant differences between groups. It is possible that administering the achievement goal questionnaire once was not able to capture a complete and dynamic measurement of goal orientation, and perhaps we can detect motivational differences and how it impacts metacognition by exploring a new methodology for measuring motivation, such as electrodermal activity or changes in affective states (Winne and Perry, 2000; Zimmerman, 2011). Additionally, studies demonstrated the need to use different theoretical frameworks for different research questions investigating metacognitive processes. As an implication of this, a unifying framework for metacognition should be developed to address all components of research that can be conducted to examine metacognition.

Results demonstrate that in different situations or given different contextual factors, learners might benefit from using metacognitive processes in different ways. By knowing this, do we want to continue randomly assigning them to conditions we know will not be useful to them? For example, students with low prior knowledge demonstrated a lack of use of cognitive strategies in Taub and Azevedo (2019), but do we want to inundate them with prompts when they need to allocate a substantial number of resources to learn the material? If students (regardless of prior knowledge) are not being provided with any feedback from the PA from being in the control condition, are they at a disadvantage? How does this impact how we design experimental conditions to ensure sufficient randomization? Thus, implications for future research that examines learning with advanced learning technologies should encourage researchers to employ a within-subjects design to ensure students are exposed to all possible learning contexts so they can benefit from learning with these systems. Additionally, we should consider how a learner's needs may change over the learning session (i.e., they may require prompt and feedback support early, but not later on) and over multiple learning sessions as they learn more strategies.

Finally, the abovementioned studies demonstrate the usefulness of using multimodal multichannel data to investigate metacognitive processes during learning with MetaTutor (Azevedo et al., 2018, 2019). These studies predominantly used log files, but also eye tracking and videos of facial expressions. Using more data channels provides greater insight into how students engage in metacognitive processes (in terms of the *what, when,* and *how*), and how metacognition interacts with cognitive, affective, and motivational processes when investigating self-regulatory behaviors during learning with MetaTutor.

## ROLE OF EMOTIONS DURING LEARNING WITH MetaTutor

Emotions play a critical role in SRL as they can impede and interfere with learning if not monitored and regulated dynamically and accurately during learning across tasks, contexts, and with advanced learning technologies such as MetaTutor (D'Mello and Graesser, 2012; Pekrun and Linnenbrink-Garcia, 2014; Efklides et al., 2018; McRae and Gross, 2020). The descriptive and correlational studies described in this section aimed to discover what kinds of emotions learners experienced while interacting with MetaTutor. More specifically, studies aimed to describe how emotions changed over time, associations between individual differences (e.g., trait emotions and personality traits), the alignment of different emotional expression components, and corresponding methodologies (automatic facial recognition software, skin conductance sensors, and self-reports), and emotions directed toward different virtual PAs. In order to accomplish these objectives, we drew on the control-value theory (CVT) of achievement emotions (Pekrun, 2006; Pekrun et al., 2011).

CVT was selected because it provided us with more detailed propositions than Winne and Hadwin's (2008) theory of SRL to guide the formulation of research questions and hypotheses as well as methodological decisions specific to emotions (compared to questions about cognitive and metacognitive processes used in many MetaTutor studies). Our research drew on the operational definition of achievement emotions advanced in the CVT that emotions can be characterized by valence, activation, object focus, and time frame. Valence refers to the pleasantness (i.e., positive valence; e.g., enjoyment, hope) or unpleasantness (i.e., negative valence; e.g., frustration, anxiety) of an emotion. Activation corresponds to the degree of physiological activation (i.e., arousal; Russell et al., 1989). In addition, achievement emotions can arise from a focus on either an achievement activity or an outcome (object focus). Boredom from studying a chapter is an example of an activity emotion, whereas anger about one's low score on an exam is an example of an outcome emotion. The time frame can be prospective (future-oriented), concurrent (present moment), or retrospective (past-oriented). The emotions that are elicited from recalling how one did on a test are retrospective emotions because they involve thinking about success or failure that has already occurred (e.g., joy or frustration). Prospective emotions, on the other hand, are emotions related to future activities and outcomes, for example, experiencing anxiety while thinking about one's potential grade on an exam one does not feel prepared to take. Concurrent emotions include emotions aroused from an activity one is currently undertaking, such as enjoyment or boredom during a lecture. The CVT also assumes that emotions have multiple expression components including experiential, behavioral, and physiological activation.

## Synthesis of Key Findings From Published Studies

Our first question concerning emotions in MetaTutor was the incidence of different emotions. A deceptively simple question that has layers we endeavored to tackle. The first general layer was a temporal one: How is the time period that emotional occurrence is evaluated and defined, and how stable are emotions over time? A second layer was: Which emotion expression component is supplying us with the data we are using to answer our question and does using different channels provide us with a different answer? We developed a single-item self-report measure to assess 19 different concurrent state emotions and help explore these lines of inquiry: The emotion-value (EV) questionnaire (Harley et al., 2013, 2015). The EV questionnaire was administered on five occasions during a study with MetaTutor which provided us with five snapshots of learners' present in-the-moment emotional experiences. By asking learners how they felt "right now" we were also able to align data from other emotion expression channels to assess agreement between self-report, behavioral, and physiological expression components.

### What Kinds of Emotions Did Learners Tend to Experience While Learning With MetaTutor and Did These States Change Over the Course of Their Learning Session?

In our first article using the EV and automatic facial expression recognition software (FaceReader 5), we found that neutral and positively valenced activating emotional states represented the majority of emotional states experienced with MetaTutor across channels (Harley et al., 2013). The low incidence of negative emotions was favorable, especially considering that MetaTutor did not employ gamification features (e.g., story elements; Harley et al., 2016a,b) to enhance enjoyment, nor was the content designed to be related to students' academic degree. The latter was expected to result in lower appraisals of task value, which can dampen the intensity of both positive and negative emotions (Pekrun, 2006). It is also worth noting that when using the meta-rules to trigger a more intense initial prompting from the PAs, we noticed an increase in frustration (and sometimes boredom), as well as a significantly higher level of confusion in low prior knowledge students compared to high prior knowledge students—which is consistent with the fact that high prior knowledge students are better at self-regulating their learning (Bouchet et al., 2018). Moreover, examining the PAs-directed emotions revealed the importance of feedback to maintain negative emotions at a low level, as a prompt-only condition tended to trigger more negative emotions (such as anger) than a prompt-and-feedback one (Harley et al., 2011). These negative agent-directive emotions are key to monitoring as although they do not affect the use of SRL processes, they were significantly related to negative learning gains (Mudrick et al., 2014). They seem partly related to the perceived competency of agents, as the least liked PA used to encourage students to deploy learning strategies was shown to negatively impact students' experience of enjoyment and the frequency of his interventions predicted their report of boredom while using MetaTutor (Mudrick et al., 2015). Analyzing facial expressions over some particular phases of interactions with MetaTutor such as the subgoal setting phase also confirmed the importance of considering the notion of co-occurring emotions (Conati and Maclaren, 2009), as nearly a quarter of students' embodied emotions were co-occurring ones (Harley et al., 2012).

Self-report results from this study (Harley et al., 2013) also revealed statistically significant changes in emotions over time, most often, a decline in levels of positively valenced and neutral states across the learning session. Facial expression results revealed that most learners were classified as being in a neutral state at each of the five 10-s windows before the administration of the EV where facial expression data was drawn from to align with the self-report data. In looking at transitions between the five time points, most transitions away from neutral were toward happiness (the only positively valenced emotion FaceReader classifies). Those learners who expressed a negative emotion tended not to remain fixed in that state.

Results from self-report and facial expression channels appeared to tell a different story. Self-reported emotions revealed a decline in levels of positively valenced and neutral emotional states and an increase in some negative, activating emotions (e.g., frustration) that might call for interventions to sustain positive and neutral states. On the other hand, facial expression recognition data suggested that emotional states were relatively stable and that most transitions were relatively short-lived and between positive and neutral states. These apparently conflicting results highlight the benefit of collecting data from different channels. In this case, self-report measures were more sensitive to different levels of intensity (i.e., endorsement) as well as a broader variety of emotional states (19 states vs. seven) compared to facial expression recognition software. As such, we interpreted the emotional dynamics from this study as complementary, with the EV results showcasing more granular patterns than those observed with the facial expression recognition software (Harley et al., 2013).

Another study by Cloude et al. (2020) captured and analyzed 117 college students' concurrent and self-reported negative emotions across 3 time points during learning with MetaTutor using D'Mello and Graesser (2012) model of affective dynamics: (1) confusion, (2) frustration, and (3) boredom. They found that when increases in boredom occurred across the three time points, it was related to learners initiating less accurate metacognitive monitoring processes and less learning of the circulatory system after the session. Results also suggested that when confusion persisted for too long over the time points during learning, it was related to less learning after the session (Cloude et al., 2020).

To investigate this finding more deeply, Cloude et al. (2021a,b) studied the relation between emotional dynamics and its impact on cognition and learning with MetaTutor by multiple components using Plass and Kaplan's (2016) Cognitive-Affective Model of Multimedia learning and Russell (1980) Circumplex Model of Affect. Emotions were defined by (1) temporality (i.e., increase, decrease, or no change), (2) valence, and (3) activation across six data points from 174 undergraduates' self-reported emotions. Latent growth models were calculated and revealed that the stability of negative activating emotions over time was negatively related to performance while controlling for prior knowledge and that changes in negative deactivating emotions were negatively related to time spent engaging in cognitive strategies during learning activities. Finally, a random forest classifier revealed high accuracy in predicting high (top 30%) and low-performance groups (bottom 30%) using pre-test scores, changes in negative deactivating emotions, and time engaging in cognitive strategies. These findings have important implications for designing affect-aware systems that can potentially leverage emotion interventions based on if, when, and how an emotion changed (or remained stable) to optimize time engaging in cognitive strategies and performance outcomes with emerging technologies (Harley et al., 2017; Cloude et al., 2021a).

### Were Different Emotional Expression Components Tightly or Loosely Coupled?

In order to examine the level of agreement (i.e., coupling) between emotional expression components we extended our analyses with self-report and facial expression recognition software from Harley et al. (2013) to include skin conductance level as well as more detailed between-emotion analyses of agreement (Harley et al., 2015). When comparing results from self-report and facial expressions, we found a relatively high overall agreement rate of 75.6% when similar self-reported emotions were grouped together along theoretical dimensions and definitions (e.g., anger and frustration). Agreement varied considerably, however, depending on the emotion in question. Our range of agreement included 84% for happiness and 7.14% for surprise, highlighting the emotion-dependent nature of agreement between self-report and facial expression recognition software. Our results concerning agreement of emotional states when using skin conductance were lower, with overall agreement rates of 60% (facial expressions) and 41% (self-report), though variation was observed between emotional states and self-reported endorsement levels. Of particular note, agreement levels were more than 10% higher when using Likert response items rated at the high end of the scale (5) compared to 4 or the midpoint (3). This study contributed to a small corpus of research examining coherence in emotional expressions and provided novel methodological approaches to aligning and comparing emotions in long experimental sessions, in contrast to shorter experimental trials that were more typical (Mauss et al., 2005).

### Did Learners' Traits Influence How They Felt? and Did These Feelings Differ by Object Foci?

We have also examined the role of key individual differences in predicting learners' emotions, and not just general emotions: those elicited from attending to different MetaTutor object foci, the four PAs. Significant relationships between a subset of trait emotions (trait anger, trait anxiety) and personality traits (agreeableness, conscientiousness, and neuroticism) were found for four agent-directed emotions (enjoyment, pride, boredom, and neutral), though the relationships differed between virtual PAs (Harley et al., 2016a). These results, along with those from a follow-up study examining goal orientations (Lallé et al., 2017a,b, 2018, 2021) were critical in establishing the need to contextualize the source of emotion in considering emotional interventions and the design of virtual PAs.

## Lessons Learned and Future Directions

These studies highlight a number of limitations and directions for future research. Theoretically, the CVT (Pekrun, 2006; Pekrun et al., 2011) provides valuable insight regarding sources of and processes involved in emotion generation but does not provide a detailed account of how emotions can be regulated. If research is to leverage the benefits and minimize the negative impact of emotions on academic achievement, additional theoretical guidance is needed. Fortunately, such a theory has recently been developed that integrates and extends propositions from the CVT and process model of emotion regulation (Gross, 2015): the emotion regulation in achievement situations (ERAS; Harley et al., 2019b). Though describing this theory in detail is beyond the scope of this article, ERAS provides propositions and examples about the differential effectiveness of five families of emotion regulation strategies when (a) they are implemented across achievement situations with different characteristics (individual vs. social and high- vs. low evaluative axes), (b) situations are contextualized by different object foci and time frame perspectives, and (c) different discrete emotions are targeted for regulation. In doing so, the ERAS model stands to help reveal the complexities and nuances of how emotions are regulated in achievement situations and shine a light on key affordances and constraints associated with their regulation in emerging literature.

Methodologically and analytically, these studies highlight that more research is needed for assessing different object foci, especially for complex intelligent technologies like MetaTutor, in order to better understand the relative contributions of different aspects of an environment to the emotions learners experience. We examined how learners with different personality and emotional dispositions felt about each of the four PAs, but what about the SRL palette? The educational content of different multimedia, etc.? Results from a separate program of research on emotions experienced with mobile apps provide supporting evidence that emotions and appraisal mechanisms can differ between discrete aspects of technology-rich learning environments (Harley et al., 2016a,b, 2019a,b, 2020). Future research should therefore extend emotion analyses from general retrospective accounts and even moment-specific concurrent self-reports to specific object foci. This can be accomplished through self-report measures, such as the multiple object foci emotion questionnaire (MOFEQ; Harley et al., 2016a,b, 2019a,b, 2020), that ask about specific aspects of an environment or inferred from using eye-tracking data that capture where someone was looking when an emotion was experienced.

Our results also highlighted a substantial amount of neutral affect and a limited range of emotional states (e.g., low levels of frustration). Low levels of intensity stand to make detecting emotions through facial expression recognition software and physiological measurements more challenging. Thus, a future direction for research on alignment may be to endeavor to align learning session content with learners' academic degrees to enhance appraisals of value. Another promising direction for future research is to integrate emotion regulation prompts into intelligent systems like MetaTutor, perhaps using a fifth agent, Elly the emotion regulator.

## MOTIVATION DURING LEARNING WITH MetaTutor

What drives the effort invested into a task? How might different achievement goals impact learners' approach and response to the MetaTutor environment? Such questions relate to the motivational facets of SRL (Zimmerman and Schunk, 2011; Usher and Schunk, 2018; Renninger and Hidi, 2019). Motivation has been studied within MetaTutor primarily by assessing learners' achievement goals for the learning task. In line with Achievement Goal Theory (Elliot and Murayama, 2008), learners complete a brief questionnaire to assess the extent to which they adopt the following orientations: mastery-approach, performance-approach, mastery-avoidance, and performance-avoidance. Goal orientation refers to a learner's purpose or aim for an achievement task. The goal may be to improve knowledge (mastery orientation), to perform better than others (performance-approach orientation) or to avoid failure relative to others (performance-avoidance orientation). While a combination of mastery and performance goals may be ideal for learning and achievement, mastery goal orientation is typically associated with desirable outcomes, such as high engagement, intrinsic motivation, and persistence (Linnenbrink-Garcia et al., 2016), whereas performance approach orientation has been more consistently linked with achievement (Hulleman et al., 2010b).

Research conducted to date on motivation within MetaTutor has examined how different achievement goal orientations interact with PA supports to impact SRL processes and learning outcomes (Duffy and Azevedo, 2015). For instance, if learners are more motivated to improve their knowledge, do they approach the task differently than learners driven primarily by a desire to outperform peers? Do learners with different motivations react in distinct ways to prompts and feedback? Given that achievement goals provide an overarching aim for learning tasks that direct and guide behaviors, they are expected to impact SRL processes, as well as subsequent learning outcomes (Pintrich, 2004). For instance, mastery-oriented learners may be driven by their own curiosity or desire to enhance their understanding of a topic, which may lead them to focus on material deemed most interesting at the expense of other content (Senko and Miles, 2008). On the other hand, performance-oriented learners may be more concerned with how they perform relative to others and therefore focused on covering all to-be-tested material, complying with prompts and feedback that help them to realize this goal.

While we have utilized Winne and Hadwin's (1998) theory of SRL extensively to guide our research in cognitive and metacognitive processes, here we elaborate briefly as to how this same theory has been used as a guiding framework for research on achievement goals and SRL in MetaTutor. Within this framework, achievement goals are most recognizable within the first two phases of learning: (1) *task definition;* and (2) *planning and goal setting*. For example, a mastery goal learner may perceive the task to be an opportunity to improve understanding and depth of knowledge about the circulatory system (task definition), which in turn may lead them to set a goal to improve their knowledge about a specific sub-topic of interest and create a plan to focus on this material (planning and goal setting). In contrast, a performance goal learner may perceive the task to be an opportunity to outperform peers (task definition), leading them to set a goal to attain the highest score on the test and a plan to cover as much testable material as efficiently as possible (planning and goal setting). Similarly, social cognitive models of SRL (Pintrich, 2000, 2004; Zimmerman, 2011) identify motivational variables, such as achievement goals, within the *forethought* phase. In our research on the role of motivation in MetaTutor (Duffy and Azevedo, 2015), we also posited that achievement goals activated during these initial SRL phases are likely to influence subsequent *enactment* and *adaptation* stages of SRL by influencing learner perceptions and responsiveness to PA prompts and feedback. In other words, an interaction is likely to occur between motivational profiles and PA scaffolds within MetaTutor.

### Synthesis of Findings

The findings from MetaTutor studies have largely shown that motivation indeed plays a role in learning processes and outcomes. For instance, Duffy and Azevedo's (2015) study demonstrated a significant interaction effect between PA condition (prompt and feedback vs. control) and achievement goal (performance-approach vs. mastery approach), such that learners with a performance-approach goal significantly outperformed learners with a mastery-approach goal on the post-test, but only in the condition in which learners received PA scaffolding for SRL (prompt and feedback condition). In the condition without PA support for SRL (control condition), motivational profiles had no impact on learning outcomes, which suggests that learners with different achievement goals react differently to PA scaffolding. This finding is consistent with a growing body of research that has found mastery-approach goals less consistently linked to performance compared to performance-approach goals (Senko et al., 2011). Why did performance-approach learners benefit from the scaffolds but mastery-approach learners did not? One explanation is that mastery-approach learners set self-referential goals (self-improvement), which may lead to less demanding conditions for success than those with a performance-approach who aim to obtain the highest score on the test compared to others. Linking back to Winne's model (Winne's, 2018), this suggests that the achievement goal influences the *standards* for success in SRL. Additionally, mastery learners may perceive PA scaffolds to be misaligned with their learning agenda and more of a distraction or interference in their goal pursuit, whereas performance learners may perceive agent scaffolds as helpful in realizing their goals.

Accordingly, we hypothesized that learners with a mastery-approach goal may have had more negative reactions to PAs' prompts and feedback. Exploratory case analysis of two mastery-approach learners (one from the prompt and feedback and one from the control condition) was conducted using think-aloud and facial expression data to explore whether differences emerge in response to PA scaffolds (Duffy and Azevedo, 2013). Preliminary analysis revealed the mastery-approach learner in the prompt and feedback condition demonstrated more negative emotions, whereas the mastery-approach learning in the control condition experienced more positive emotions. Subsequent MetaTutor studies sought to test this hypothesis directly (e.g., Lallé et al., 2016; Lallé et al., 2017a,b) and reported consistent findings. Specifically, Lallé et al. (2016) results revealed that performance-approach learners reported more pride and less anxiety in the prompt and feedback condition than in the control condition, whereas mastery-approach learners reported the opposite pattern: more anxiety and less pride in the prompt and feedback condition than in the control condition. Further, evidence from eye-tracking data (Lallé et al., 2017b) demonstrated that performance-approach learners showed improved learning outcomes when fixating *longer* and at a higher rate on PAs (i.e., attended more to PAs), whereas mastery-approach learners again showed the opposite pattern: they benefited when attending *less* to PAs.

Another study by Cloude et al. (2021a,b) investigated the degree to which learners engaged in metacognitive judgments initiated on pages containing information relevant to achieving either sub-goals 1 or 2. Specifically, 186 undergraduates' multimodal data were captured during learning and analyzed using latent growth models. Results showed that the stability (such that it did not increase) of page-irrelevant metacognitive judgments from the first to second sub-goal was positively related to performance, but there were no relations between achievement goal orientation and these variables. Additionally, there were no relations between page-relevant metacognitive judgments across sub-goals 1 and 2, achievement goal orientation, and performance. This study provides another example of examining motivation in relation to process data. Future research utilizing this method could provide insight into designing effective interventions based on what personally motivates learners to engage in metacognition to augment their learning and performance with emerging technologies (Cloude et al., 2021a,b).

## Lessons Learned and Future Directions

Taken together, these findings suggest that learners with different motivational profiles are likely to perceive and react to prompts and feedback differently, which in turn bears on instructional design. Whereas performance-approach learners benefited from PA support, mastery-approach learners did not. Self-determination Theory (SDT) can help to explain these distinct patterns and in particular why some learners may have less positive reactions to PAs. According to SDT, when an individual's basic psychological needs are thwarted (e.g., feels that their need for competence or autonomy is impeded), the individual is likely to react negatively to regulation efforts, whereas when these needs are met, they are likely to react positively, given that the regulation is more internalized (e.g., Ryan and Deci, 2000; Niemec and Ryan, 2009; Deci and Ryan, 2011). It may be the case that performance-approach learners find the PAs supportive of their needs, whereas mastery-approach learners perceive them to be more controlling. This is consistent with research that has found mastery-approach goals to be linked with more positive emotions and engagement in autonomy-supportive environments (Benita et al., 2014).

The findings on motivation in MetaTutor have several implications for the design of advanced learning technologies. Although the current features appear to be adaptive for performance-approach learners, those with other motivations could also be supported. First, it would be useful to modify intelligent tutor systems so that they are adaptive to a more diverse array of motivational profiles. To benefit mastery-approach learners, agents may need to provide different types of prompts and feedback that take into consideration their values while also communicating the importance of the scaffolds in achieving their goals. This may help these learners to view PA scaffolds for SRL as a support rather than a distraction. This is consistent with Expectancy-value Theory of Motivation (Wigfield and Eccles, 2000) and corresponding value-based interventions (e.g., Hulleman et al., 2010a), which suggest that increasing utility appraisals (and reducing cost appraisals) will enhance achievement. Second, PA scaffolding could be designed to enhance users' sense of autonomy by allowing learners to select the frequency and type of feedback delivered, in line with an open learner model (Bull, in press). Mastery-approach learners, in particular, may also benefit from less frequent agent interaction or from fading scaffolds over time (Belland, 2013). A key feature of the MetaTutor studies described is that they illustrate how self-report data of motivation can be examined alongside trace data to provide a richer understanding of both the motivating *goals* (questionnaires) and resultant learning *processes* (eye-tracking, log files). This was examined further in Cloude et al. (2021b) by investigating trace data and its relation to different sub-goals over the course of the learning session, which proved useful in identifying signatures of goal pursuit, potentially providing future direction for implicit measures of motivation in action rather than as a one-point-in-time assessment, which we discuss next.

From a theoretical perspective, there are several motivational frameworks that have been used to guide interpretation of findings but not yet directly tested in MetaTutor, including EVT and SDT. As previously noted, these theories could help to inform design changes in the delivery of agent scaffolding to enhance the perceived utility and internalization of SRL prompts. Examining learners' satisfaction and attributions for learning outcomes could also help us to better understand how motivation influences the standards of SRL. In terms of methodological advancements, it would be helpful to include unobtrusive measures of motivation at a finer-grained unit of analysis to examine stability and change over time. Existing MetaTutor studies involving motivation have focused on examining learners' self-reported motivation in relation to traces of learning processes. However, MetaTutor captures other types of trace data (e.g., time on task via log files) that can serve as a proxy to track other facets of motivation not addressed here, such as effort, persistence, and choice, especially to study its relation to different sub-goals over time during the learning session. This could provide more information about the *degree* of motivation, whereas data analyzed to date has focused on the *type* of motivation. Additionally, think-aloud data could also be examined for indicators of curiosity, interest, and self-efficacy. Together, these traces could provide insight into the dynamic nature of motivation. Finally, limited research has examined the regulation of motivation (Wolters, 2003; Schwinger and Stiensmeier-Pelster, 2012), which includes understanding how learners monitor and deploy strategies to boost or sustain motivation. To fully understand the role of motivation in learning, a key step will require examining motivation as the target of regulation, and non-linear dynamical systems (NLDS) could offer the tools to do just that (Gabriel et al., in press). NLDS explains dynamics that occur within a system of interconnected elements like SRL that undergoes change (Schuster, 1984; Guastello et al., 2008). In the next section, we describe the recent extension MetaTutor in addressing college students' learning disabilities and contributions of our research on MetaTutor.

## CURRENT EXTENSIONS OF MetaTutor—MetaTutorES

Recently, Dr. Cerezo and her team in Spain have created a Spanish version of MetaTutor, MetaTutorES, and conducted several studies with college students with learning disabilities, including the development of a multimodal evaluation protocol for adults with learning disabilities based on MetaTutor (Cerezo et al., 2020b). Their recent study (Cerezo et al., 2020a) examined how 119 college students both with and without learning disabilities regulate their learning with MetaTutorES. Results showed that those in the experimental group (i.e., provided with adaptive scaffolding from the PAs) used more system-initiated and self-initiated self-regulation strategies than those in the control group. In addition, all students showed some improvement in learning from pre to posttest. The results showed that students with learning disabilities can take advantage and benefit from embedded tools such as PAs' prompting and scaffolding to learn complex science topics.

In a subsequent study, Cerezo's team (Chango et al., 2021) collected and preprocessed data from 40 students using different multimodal sources: learning strategies from log files, emotions from videos of facial expressions, allocation and fixations of attention from eye tracking, and performance on posttests of domain knowledge. They used multimodal data to test whether the prediction could be improved by using attribute selection and classification ensembles of the students' processes. They carried out three experiments by applying six classification algorithms to numerical and discretized preprocessed multimodal data. The results showed that the best predictions were produced using ensembles and selecting the best attributes approach with numerical data. These findings have implications for early detection of students' challenges in self-regulating their learning using multimodal data.

## CONTRIBUTIONS TO THE FIELD OF SELF-REGULATED LEARNING AND INTELLIGENT LEARNING TECHNOLOGIES

Our extensive research on MetaTutor has contributed to current theoretical models of SRL, methodological approaches to studying SRL, and analyses of SRL processes underlying self-regulation during complex learning (Tarricone, 2011; Veenman, 2011; Greene et al., 2015; Järvelä and Bannert, 2019; Winne, 2019; Azevedo, 2020; Lajoie et al., in press). Despite these contributions, there are several theoretical, conceptual, methodological, and analytical limitations that need to be addressed in future research. For example, can we develop a comprehensive model or framework of SRL that integrates CAMM processes in a way that contributes to our understanding of each process and their combined role in self-regulation over time? What do behavioral traces of qualitative changes in metacognitive monitoring look like? Do they reside in specific trace data (e.g., concurrent verbalizations are needed to understand metacognitive monitoring along with log files to measure the duration of learning strategies) or are they evident across multiple data channels (e.g., physiology + facial expressions + screen recordings are needed to understand emotion regulation strategy use)? Are dynamical systems approaches (e.g., growth modeling, recurrence quantification analysis, etc.) better suited for analyzing the temporal and complex nature of SRL processes using multimodal data (see Favela, 2020)? If so, how can they better theoretically explain the temporal dynamics of CAMM processes and can such analyses be used to better design multi-agent intelligent systems capable of triggering more accurate pedagogical interventions through PAs? Below we pose specific theoretical, conceptual, methodological, and analytical questions that should drive future research.

Theoretically, there are key CAMM-specific questions that need to be addressed. For example, Winne's (2018) model mentions that cognitive and task conditions impact students' use of metacognitive processes, however, it does not pinpoint how or when specific metacognitive processes are used during learning. As another example, the model of metamemory (Nelson and Narens, 1990) does emphasize the use of specific metacognitive judgments (e.g., EOLs, JOLs, retrospective confidence judgment). However, this can limit analyses to only examining some metacognitive judgments when it is possible students are engaging in other metacognitive processes (e.g., Greene and Azevedo, 2009; Azevedo and Dever, in press). The same argument can be made for motivation and affective states when it comes to describing the key constructs, processes, and mechanisms for CAMM processes. Can we develop and test a unified model of CAMM SRL that is complete, affords predictions, and allows researchers to generate research questions and testable hypotheses across learners, tasks, domains, and contexts? The underlying assumptions of such a comprehensive model could be embodied in systems like MetaTutor. For example, an interface designed to facilitate cognitive processing of multiple representations of information

(Azevedo and Taub, 2020) and where the STEM content can dynamically change to account for fluctuations in motivational states by providing additional diagrams due to sustained interest in the topics detected from verbalizations, physiological sensors, and prolonged fixations. A system that includes intelligent PAs capable of integrating facial expressions with natural language processing (NLP) to detect students' emotion regulation strategy-use and providing adaptive emotional regulation scaffolding, when necessary, which may include modeling emotion regulation strategies. Also, the system could include negotiable open learner models triggering metacognitive awareness and affording students opportunities to calibrate their own metacognition by overriding the system's beliefs of their metacognitive skills. Any of the system's features can be experimentally manipulated to show the impact of CAMMs on SRL in advanced learning technologies such as MetaTutor.

Conceptually, results from our studies do not have a common consensus regarding the ideal time to engage in CAMM processes. For example, when it comes to metacognition it can be argued that in MetaTutor, a student should first assess the relevance of the page, and if relevant, judge their understanding of the text before engaging in cognitive learning strategies. However, this would take a large amount of cognitive effort, leaving little time to actually inspect and learn the material. The same argument can be leveled at cognitive, affective, and motivational processes. For example, what should a system do if it detects that students are experiencing issues with all CAMM processes? Which process does the system prioritize? Do we address the motivational and affective issues first and then proceed to the cognitive and metacognitive processes? Or does the system tackle all of them together and if so, what does it look like and what is the theoretical basis for such decisions? Thus, it remains unclear the ideal amount and sequence of engaging, or scaffolding engaging, in these processes.

Another conceptual issue relates to providing different types of scaffolding and support to students who are under- vs. over-confident, or inaccurate at making metacognitive judgments (Azevedo and Wiedbusch, in press). For example, if a student is over-confident, they will require different types of support compared to a student who is under-confident. A student who performs poorly on a quiz, but judged greater understanding is inaccurate and over-confident, and support would need to focus on helping the student acquire the domain knowledge for that content, in addition to knowledge on how to metacognitively judge their understanding. Conversely, a student who performs well on a quiz, but judged less understanding is under-confident, so the support should perhaps focus on procedural or conditional knowledge because they have demonstrated they have the domain knowledge. As a third example, a student who has a low performance, but accurately judged this will only need support for acquiring the domain knowledge. Thus, it is important to understand a student's domain knowledge in addition to their procedural or conditional metacognitive knowledge to ensure they are acquiring both sets of skills. Perhaps MetaTutor's production rules will be able to account for these different levels of knowledge in future iterations. Again, similar questions can be posed about emotions and motivation, which MetaTutor is currently not capable of scaffolding but can clearly be modified to address. For example, how do we scaffold task value, interest, self-efficacy, cognitive reappraisals, should a new agent (e.g., Megan the motivator) be created to support the regulation of emotion and motivation etc.?

Methodologically, using log files and eye-tracking to examine metacognitive processes is advantageous because they are unobtrusive and unbiased measures. However, this also requires us to make inferences that students are, in fact, engaging in metacognitive processes. For example, when students select a JOL or FOK from the SRL palette, are they really judging their understanding or familiarity with the text, or are they self-testing (i.e., want to take the 3-item quiz)? Also, through the SRL palette, we only measure processes that are externalized either verbally or behaviorally or both by the student. For instance, a JOL selected from the palette on one page might be followed by further "internal" (i.e., not uttered or behaviorally enacted) JOLs on subsequent pages, that we can't measure without triggering, prompting, or interfering with the process. Additionally, when we used eye-tracking data as indicators of monitoring behaviors (e.g., AOI-pair from text to the timer or sub-goal progress bar indicating monitoring progress), how can we be sure students are monitoring their behaviors, as opposed to looking around because they are bored or frustrated? This demonstrates the need for using multimodal multichannel data to investigate all CAMM processes together, and how different channels can be used as indicators of each process (Azevedo et al., 2019; Azevedo and Wiedbusch, in press). Additional methodological issues to be addressed in the future include identifying the right suite of tools, devices, and sensors, required to measure CAMM processes in laboratory experiments, with particular constraints if we want to ensure that this suite can be portable, scalable, etc. to be applied to other non-lab contexts (e.g., classrooms, immersive virtual learning, informal settings). How does adapting the suite of tools to the different non-lab contexts impact the quality of research, data, and what analytical challenges does it create and what are the implications for the development of a comprehensive unified theory of SRL (Biswas et al., 2018)?

Analytically, our research has made great progress in moving toward using educational data mining techniques, such as cluster analysis and sequence mining (Bouchet et al., 2012, 2013; Taub et al., 2014; Taub and Azevedo, 2019) to examine metacognitive and cognitive behaviors during learning with MetaTutor as opposed to relying exclusively on traditional inferential statistics that combine event data into a single event per participant. We have also used unsupervised machine learning techniques to examine (Lallé et al., 2018, 2021; Wortha et al., 2019; Wiedbusch and Azevedo, 2020) complex eye-tracking data and facial expressions of emotions during learning with MetaTutor. We continue to use non-traditional statistical techniques, including dynamical systems modeling (Dever et al., in press) to examine learners' emergent SRL behaviors, and MLAs to predict performance at the end of the learning session (Mu et al., 2020; Saint et al., 2020; Chango et al., 2021;

Fan et al., 2021). Despite our ability to continuously adapt and use contemporary analytical techniques that emerge from the computational, engineering, psychological, statistical, and data sciences, we as a field are still faced with a major barrier that continues to impact the educational effectiveness of intelligent systems such as MetaTutor. The issue is that these analyses are all conducted in a *post-hoc* fashion (i.e., *after* a student learns with MetaTutor), thus moving forward, it would be beneficial to analyze these processes in real-time, and provide truly intelligent, adaptive personalized support of CAMMs. Machine learning approaches are particularly promising in this regard as their focus lies in the prediction of behavior rather than (post hoc) explanations (Yarkoni and Westfall, 2017). Further, they generally are capable of addressing issues of traditional statistical analyses with regards to adequately handling large amounts of data (e.g., Dwyer et al., 2018), such as the multichannel data collected with MetaTutor. Thus, machine learning models, trained on multi-channel data, can serve as the basis for increasingly adaptive systems that can intervene in the learning processes as or before issues arise. In addition, modeling approaches that bridge the gap between theory driven psychological analyses and data driven machine learning approaches would be very beneficial for future adaptive systems. In sum, these are some of the major issues that need to be addressed by future research (see also Azevedo and Gašević, 2019; Järvelä and Bannert, 2019; Winne, 2019; Azevedo, 2020; Lajoie et al., 2020; Hadwin, 2021; Li and Lajoie, in press).

## LESSONS LEARNED AND OPEN CHALLENGES

In sum, there are some lessons learned and open challenges for interdisciplinary researchers. First, SRL takes time to develop and needs to be acquired, internalized, and practiced over time with the assistance of human and artificial agents to enhance learning and transfer. Therefore, future intelligent systems may need to scaffold learning and should encourage students to interact with such systems for a longer period of time. Second, adaptive (intelligent) scaffolding is key to supporting students' SRL with learning technologies, but this can only be achieved once we understand how CAMM processes dynamically and temporally unfold and how they relate, contribute, and impact real-time learning processes (Hadwin, 2021). To do so, it is critical that system features become more seamless in their interactions with students (e.g., hold a conversation using NLP) and use stealthier assessment (gaze-behavior analysis, etc.) to adapt itself to the needs of each individual student. If theory suggests and assumes that learning is a dynamic process that is cyclical and non-linear, the methods in which we capture and measure learning should reflect this as well as the design of future system architectures. Third, multimodal multichannel SRL CAMM data is key to understanding the dynamics of SRL during learning, problem-solving, reasoning, understanding, etc. Additional tools, methods, sensors, and techniques may be needed in the future to increase the accuracy, reliability, and validity of detecting and measuring these processes and validate the inferences researchers make about these processes to hopefully reduce the inference/increase accuracy coefficient so that intelligent systems like MetaTutor provide optimal just-in-time scaffolding. Fourth, we argue that the concepts of meta-learning, meta-thinking, and meta-reasoning from the psychological and computational sciences are key to acquiring, internalizing, using, and transferring SRL knowledge and skills across tasks, domains, and contexts (Cox, 2011; Cox et al., 2016; Ackerman and Thompson, 2017). Fifth, data visualizations of students' multimodal SRL processes are key to enhancing their understanding of SRL, just as visualizations are key in designing teacher dashboards that provide actionable data for effective instructional decision-making thus creating a human-AI complementarity (Molenaar and Knoop-van Campen, 2019; Holstein and Aleven, 2021; Wiedbusch et al., 2021b). Sixth, while we acknowledge that cognition, metacognition, and emotions are important for SRL, more attention needs to be paid to the role of motivation (as states that also fluctuate during task performance, perhaps at different time epochs, and that can be deeply intertwined to the concept of flow (Csikszentmihalyi et al., 2018). Seventh, training teachers to learn and use SRL in their classrooms is key in fostering their students' SRL (Kramarski, 2018; Callan and Shim, 2019; Dignath and Veenman, 2020; Kramarski and Heaysman, 2021) and must remain a major thrust of research and education in our field. Lastly, AI-based immersive virtual environments hold great promise to enhance students' SRL, especially with the use of AI, NLP, computer vision, and machine learning and nanomaterials (e.g., sensors) that can significantly advance and address conceptual, theoretical, methodological, analytical issues and have a major education impact on students of all ages.

## AUTHOR CONTRIBUTIONS

RA significantly contributed to the conceptualization, construction, and writing of the entire manuscript, especially the last three sections of the manuscript, integrated, synthesized, and finalized the manuscript. FB conceptualized, contributed, and wrote the MetaTutor architecture section. MD conceptualized and synthesized the studies presented in the motivation section. JH conceptualized and synthesized the studies presented in the emotion section. MT conceptualized and synthesized the studies presented in the metacognition section. GT conceptualized and synthesized the studies presented in the cognitive section. EC, DD, MW, and FW contributed to all the sections of the manuscript by synthesizing recent work on MetaTutor. RC contributed to the section of MetaTutorES. All authors were involved in the review and editing of the final version of the manuscript.

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