AFFECTIVE LEARNING IN DIGITAL EDUCATION

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AFFECTIVE LEARNING IN DIGITAL EDUCATION

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Editorial: Affective Learning in Digital Education

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Editorial on the Research Topic

Affective Learning in Digital Education

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Digital education opens up novel avenues for students and teachers to learn and interact together. The evolution of digital tools for learning and the constant transformation of educational technology inspire research that seeks to understand how students' adaptive motivations and emotions for learning might be supported and how learning environments can be personalized. There is an urgent need for evidence-based development, as the recent COVID19 pandemic has led to the use of online and digital tools in education at all levels. These tools include webinars (Ebner and Gegenfurtner), digital games (Näykki et al.), hypermedia-based tutoring systems (Wortha et al.), virtual laboratories (Pietarinen et al.), adaptive learning environments (Molenaar et al.), social networks (Näykki et al.), and online courses (Francis et al.; Knigge et al.; Quesada-Pallarès et al.; Stephan et al.). These are embedded within asynchronous, blended, hybrid, interactive, mobile, online, synchronous, virtual, or web-based learning environments. When we seek to understand how and why students learn in these digital education scenarios, then a focus on students' affective processes is particularly useful, where "affective" is understood as an umbrella term to include processes such as the motivations, intentions, emotions, interests, satisfaction, values, goals, and attitudes of leaners, which can be individually or socially regulated.

This Research Topic brings together studies on the nexus of motivation science and educational technology to explore affective learning in digitally mediated scenarios. Aiming to expand what we know about learning and motivation in digital contexts, this Research Topic has three main objectives. The first is to deepen our understanding of how learning and motivation processes interrelate and co-evolve in digital environments. For example, situated in a hypermedia-based tutoring system, Wortha et al. find that positive emotion pattern scores before the learning activity and negative emotion pattern scores during the learning activity predicted learning, but not consistently. Similarly, Testers et al., in a study on non-traditional students in asynchronous online education, reported that the motivation to learn, expected positive personal outcomes, and learner readiness were the strongest predictors of transfer intentions. These and other studies in this Research Topic explore the interrelations between motivation and learning in digital education.

A second objective of the Research Topic is to evaluate how effective digital tools, media, and infrastructure are in supporting affective learning. The study by Molenaar et al. demonstrates that young learners need performance feedback to support correct self-evaluation and drive their regulatory actions in adaptive learning environments. Knigge et al. note a significant increase in empathic concern after working with video-based online teacher training. Focusing on the differences between digital and face-to-face learning environments, Stephan et al. show that teacher

TABLE 1 | Studies contributing to the Research Topic.

Authors	Research focus	Educational technology	Educational context	Analytic approach	Level of analysis
Ebner and Gegenfurtner	Satisfaction	Webinar, asynchronous online course	Higher education, professional training	Meta-analysis	Individual
Francis et al.	Academic motivation, expectancy, value, cost, interest	Asynchronous online course	Higher education	Structural equation modeling	Individual
Järvenoja et al.	Socially shared regulation processes	Technology-supported learning environment	K12 education	Multimodal analysis of multichannel data	Group
Knigge et al.	Affective well-being and attitudes	Video-based online training	Teacher education	Latent change models	Individual
Martens et al.	Affective states, intrinsic motivation	Wearables	Higher education	Multimodal analysis of multichannel data	Individual
Molenaar et al.	Intentions for regulation	Adaptive learning technologies	K12 education	Analyses of variance	Individual
Näykki et al.	Emotional experiences	Social networks, games, digital fabrication	Early childhood, primary, higher education	Qualitative case analysis	Group
Pietarinen et al.	Affect	Virtual laboratory	K12 education	Video-based frequency analysis	Group
Quesada-Pallarès et al.	Motivational and self-regulation learning strategies	Asynchronous online course	Vocational education and training	Confirmatory factor analysis, multiple regression	Individual
Stephan et al.	Achievement emotions, technology acceptance	Asynchronous online course	Teacher education	Analyses of (co)variance	Individual
Testers et al.	Motivation to learn, intention to transfer	Asynchronous online course	Higher education	Structural equation modeling	Individual
Wortha et al.	Emotional profiles	Hypermedia-based tutoring system	Higher education	Person-centered and variable-centered cluster analysis	Individual

education students attending an asynchronous online course (compared to a synchronous face-to-face course) reported a higher level of boredom, anxiety, and anger, but less enjoyment. This finding is echoed by Ebner and Gegenfurtner who indicate meta-analytically that learners in asynchronous online courses are less satisfied than in synchronous webinars. However, Francis et al. and Quesada-Pallarès et al., report that online and face-to-face students may differ overall in academic outcomes but not in their motivation, task value, or metacognitive self-regulation. These studies are fascinating, as they address individual differences and the effectiveness of digital tools to support affective learning.

Finally, a third objective of the Research Topic is to review and evaluate the development of frontline innovations in the methods, measures, and technologies used for the investigation and promotion of the processes and products of affective learning. It presents a number of emerging multimodal methods that use digital tools for data collection and analysis. These tools and measures include, but are not limited to, wearables, handhelds, heart rate measures, as well as electroencephalographic and electrodermal activity (Järvenoja et al.; Martens et al.; Näykki et al.). We also see detailed interaction analyses of collaborative learning processes and the socially shared regulation of learning and emotion (Näykki et al.; Pietarinen et al.). Furthermore, Wortha et al. describe an innovative integration of person-centered and variable-centered approaches to cluster analysis. Overall, the studies in this Research Topic illustrate multimodal and multimethod analyses of affective multichannel data in digital learning contexts.

These three objectives are relevant for research that addresses digital education for people of different ages—from learners in early childhood education (Näykki et al.) to K12 (Järvenoja et al.; Molenaar et al.; Näykki et al.; Pietarinen et al.) and higher education (Ebner and Gegenfurtner; Francis et al.; Knigge et al.; Martens et al.; Näykki et al.; Stephan et al.; Testers et al.; Wortha et al.) up to vocational and professional training contexts (Ebner and Gegenfurtner; Quesada-Pallarès et al.)—and for studies that are situated within various disciplinary fields, such as science education (Francis et al.; Pietarinen et al.), maker education (Näykki et al.), medical education (Ebner and Gegenfurtner), and teacher education (Knigge et al.; Stephan et al.). A total of twelve studies addressed these objectives using empirical data from learners studying in a number of countries, including Finland, Germany, Spain, the Netherlands, and the US. **Table 1** provides an overview of studies contributing to this Research Topic.

Reflecting on the future of research on affective learning in digital education, studies on the processes and products of affective learning in digital education will increasingly be based on multimethod and mixed method analyses of multimodal data, on individual and group levels of analysis. Digital technologies will continue to evolve fast, thus affording novel contexts both for educating learners and for collecting data of their (shared) affective learning processes. Major challenges lie in the synthesis of evidence on the effectiveness of technology-supported tools for digital and face-to-face education as well as in the integration of multimodal analyses of affective learning processes. This Research Topic addresses these challenges, which have gained further relevance during the COVID19 pandemic. We hope that you will enjoy reading the contributions as much as we did.

AUTHOR CONTRIBUTIONS

AG, SN, LF, SJ, and JH: writing, review, and editing. All authors contributed to the article and approved the submitted version.

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SYSTEMATIC REVIEW
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Learning and Satisfaction in Webinar, Online, and Face-to-Face Instruction: A Meta-Analysis

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Kirkpatrick's four-level training evaluation model assumes that a positive correlation exists between satisfaction and learning. Several studies have investigated levels of satisfaction and learning in synchronous online courses, asynchronous online learning management systems, and synchronous face-to-face classroom instruction. The goal of the present meta-analysis was to cumulate these effect sizes and test the predictive validity of Kirkpatrick's assumption. In this connection, particular attention was given to a prototypical form of synchronous online courses—so called "webinars." The following two research questions were addressed: (a) Compared to asynchronous online and face-to-face instruction, how effective are webinars in promoting student learning and satisfaction? (b) What is the association between satisfaction and learning in webinar, asynchronous online and face-to-face instruction? The results showed that webinars were descriptively more effective in promoting student knowledge than asynchronous online (Hedges' $g = 0.29$) and face-to-face instruction ($g = 0.06$). Satisfaction was negligibly higher in webinars compared to asynchronous online instruction ($g = 0.12$) but was lower in webinars to face-to-face instruction ($g = -0.33$). Learning and satisfaction were negatively associated in all three conditions, indicating no empirical support for Kirkpatrick's assumption in the context of webinar, asynchronous online and face-to-face instruction.

Keywords: adult learning, computer-mediated communication, distance education and telelearning, distributed learning environments, media in education

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INTRODUCTION

The middle of the 1990s witnessed the slow advent of Internet-based education and early applications of online distance learning (Alnabelsi et al., 2015). Since then, there has been a significant increase in the number of available e-learning resources and educational technologies (Ruiz et al., 2006; Gegenfurtner et al., 2019b; Testers et al., 2019), which have gained more importance in the higher education and professional training contexts (Wang and Hsu, 2008; Nelson, 2010; Siewiorek and Gegenfurtner, 2010; Stout et al., 2012; Knogler et al., 2013; McMahon-Howard and Reimers, 2013; Olson and McCracken, 2015; Testers et al., 2015; McKinney, 2017; Goe et al., 2018). To date, various possibilities regarding the implementation of e-learning in educational contexts exist, one of which is the use of webinars—a prototypical form of synchronous online courses. The most obvious advantage of webinars is the high degree of flexibility they grant to participants. Whereas, traditional face-to-face teaching has locational limitations—i.e., the tutor and students have to be in the same physical space—webinars can be accessed ubiquitously via computer devices at students' homes or in other locations (Alnabelsi et al., 2015; Gegenfurtner et al., 2017; Tseng et al., 2019) without the need for students to travel long distances in order to participate synchronously in lectures or seminars (Gegenfurtner et al., 2018, 2019a,c).

Synchronicity and Modality in Learning Environments

Learning environments can be classified in terms of their synchronicity and modality. First, synchronicity refers to the timing of the interaction between students and their lecturers. Synchronous learning environments enable simultaneous and direct interaction, while asynchronous learning environments afford temporally delayed and indirect interaction. Second, modality refers to the mode of delivery used in learning environments. Online environments afford technology-enhanced learning using the Internet or computer devices, while offline environments afford traditional instruction without the use of digital tools and infrastructure. Learning environments can be clustered into four groups according to their levels of synchronicity and modality. **Figure 1** shows prototypical examples of these clusters. Specifically, webinars afford synchronous online learning, learning management systems afford asynchronous online learning, and traditional classroom instruction affords synchronous offline learning.

Compared to traditional face-to-face education, the use of online environments is accompanied by certain advantages and disadvantages. Webinars, for example, use video-conferencing technologies that enable direct interaction to occur between participants and their lecturers without the need for them to be in the same physical location; this geographical flexibility and ubiquity are an advantage of webinars. The synchronous setup makes it possible for participants to communicate directly with their instructors who are able to provide immediate feedback (Gegenfurtner et al., 2017). Any comments or questions that arise can, therefore, be instantly brought to the tutor's attention. Moreover, the modality allows for real-time group collaboration between participants to occur (Wang and Hsu, 2008; Siewiorek and Gegenfurtner, 2010; Johnson and Schumacher, 2016; Gegenfurtner et al., 2019a).

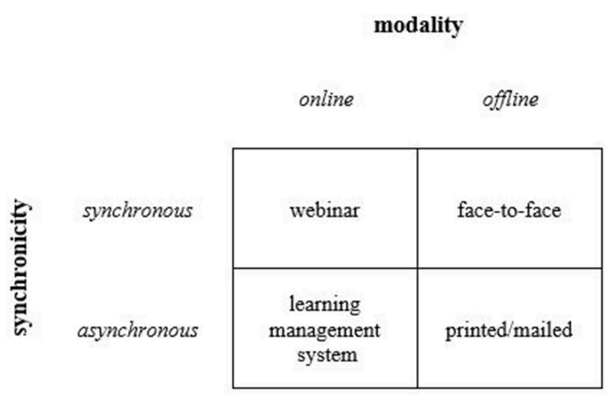

FIGURE 1 | Learning modalities.

Asynchronous learning management systems use forum and chat functions, document repositories, or videos and recorded footage of webinars that can be watched on demand. These systems provide flexibility with regard to location and time. Using suitable technological devices, participants are able to access course content from anywhere. Furthermore, students are given the opportunity to choose precisely when they want to access the learning environment. However, this enhanced flexibility also has disadvantages. According to Wang and Woo (2007), it is difficult to replace or imitate face-to-face interaction with asynchronous communication; this is primarily due to the lack of immediate feedback (Gao and Lehman, 2003) and the absence of extensive multilevel interaction (Marjanovic, 1999) between students and lecturers (Wang and Hsu, 2008).

The Evaluation of Learning Environments

The increasing use of webinars in educational contexts was followed by studies that have examined the effectiveness of webinars in higher education and professional training under various circumstances (e.g., Nelson, 2010; Stout et al., 2012; Nicklen et al., 2016; Goe et al., 2018; Gegenfurtner et al., 2019c). According to Phipps and Merisotis (1999), research on the effectiveness of distance education typically includes measures of student outcomes (e.g., grades and test scores) and overall satisfaction.

A frequently used conceptual framework for evaluating learning environments is Kirkpatrick's (Kirkpatrick, 1959; Kirkpatrick and Kirkpatrick, 2016) seminal four-level model. This framework specifies the following four levels: reactions, learning, behavior, and results. The first two levels are particularly interesting because they can be easily evaluated in training programs using, for example, questionnaire and test items that assess trainee satisfaction and learning. A basic assumption is that reactions as affect, such as satisfaction, lead to learning. This positive association between learning and satisfaction is a cornerstone of Kirkpatrick's model. However, empirical tests of the predictive validity of this association indicate limited support. For example, in their meta-analysis of face-to-face training programs, Alliger et al. (1997) reported a correlation coefficient of 0.02 between affective reactions and immediate learning at post-test. More recently, Gessler (2009) reported a correlation coefficient of −0.001 between satisfaction and learning success in an evaluation of face-to-face training. Additionally, Alliger and Janak (1989), Holton (1996), as well as Reio et al. (2017), among others, offered critical accounts of the validity of Kirkpatrick's four-level model. However, although Kirkpatrick's model is widely used to evaluate levels of satisfaction and learning in webinar-based and online training, no test of the predictive validity of a positive association has been performed to date.

The Present Study

The present study focused on comparing levels of learning and satisfaction in webinars, online asynchronous learning management systems, and face-to-face classroom instruction. A typical problem related to the examination of webinars and other online environments is small sample size (e.g., Alnabelsi et al., 2015; Olson and McCracken, 2015); consequently, the findings might be biased by artificial variance induced by sampling error. Another problem relates to study design: Quasi-experimental studies often have limited methodological rigor, which can bias research findings and prohibit causal claims. To overcome these challenges, the present study used meta-analytic calculations of randomized controlled trials (RCTs) comparing webinar, online, and face-to-face instruction. The objective of the study was to test the predictive validity of Kirkpatrick (1959) four-level model, particularly the assumed positive association between satisfaction and learning. The following two research questions were addressed: (a) Compared to online and face-to-face instruction, how effective are webinars in promoting learning and satisfaction? (b) What is the association between satisfaction and learning in webinar, online, and face-to-face instruction?

TABLE 1 | Inclusion and exclusion criteria.

Criterion	Inclusion	Exclusion
Study design	Randomized controlled trials	Studies without randomization and/or without control condition
Condition	Webinar, online, face-to-face instruction	Other conditions
Psychometric information	Mean, standard deviation, sample size	Studies not reporting psychometric information
Learning	Objective knowledge test	Self-ratings
Satisfaction	Satisfaction scale	Other scales (e.g., self-efficacy, attitudes)
Publication date	January 2010–August 2018	Prior to 2010
Publication type	All publication types	–
Publication language	All languages	–

METHODS

Inclusion and Exclusion Criteria

This meta-analysis was performed in adherence to the standards of quality for conducting and reporting meta-analyses detailed in the PRISMA statement (Moher et al., 2009). The analysis identified the effect sizes of RCTs on learning and satisfaction in webinar, online, and face-to-face instruction. The inclusion and exclusion criteria that were applied are reported in **Table 1**. A study had to report mean, standard deviation, and sample size information for the webinar and control conditions—or other psychometric properties that could be converted to mean and standard deviation estimates, such as the median and interquartile range (Wan et al., 2014)—in order for it be included in the meta-analysis. In an effort to minimize publication bias (Schmidt and Hunter, 2015), we included all publication types: peer-reviewed journal articles, book chapters, monographs, conference proceedings, and unpublished dissertations. Studies were omitted if they did not randomly assign participants to the webinar and control conditions (face-to-face and asynchronous online), and they were included if learning was measured objectively using knowledge tests. Studies using self-report learning data were omitted. The meta-analysis included various satisfaction scales.

The Literature Search

Based on these inclusion and exclusion criteria, a systematic literature search was conducted in two steps. The first step included an electronic search of four databases: ERIC, PsycINFO, PubMed, and Scopus. We did not exclude any publication type or language but omitted articles that were published before January 2003, as this enabled us to continue and update Bernard et al. (2004) meta-analysis about effectiveness of distance education. The following relevant keywords were used for the search: *webinar*, *webconference*, *webconferencing*, *web conference*, *web conferencing*, *web seminar*, *webseminar*, *adobeconnect*, *adobe connect*, *elluminate*, and *webex.* These were combined with *training*, *adult education*, *further education*, *continuing education*, and *higher education* and had to be included in the titles or abstracts of the potential literature.

The searches conducted in the stated databases led to 601 hits, of which 94 were from ERIC, 68 from PsycINFO, 120 from PubMed, and 323 from Scopus. Duplicates that appeared in more than one database were identified and removed by two trained raters. Using this process, 151 duplicates were removed, leaving 454 articles. Subsequently, both raters screened a random subset of $k = 46$ articles—both independently and in duplicate—with the objective of measuring interrater agreement. As interrater agreement was high (Cohen's $k = 0.93$; 95% $CI = 0.79$–1.00), one rater screened the remaining articles for eligibility by reading titles and abstracts. The screening resulted in the exclusion of 403 articles because they reported qualitative research, were review papers or commentaries, or focused on asynchronous learning management systems or modules.

Subsequently, both raters read the full texts of the remaining 51 articles to ensure their eligibility. At this point, 44 articles were omitted for various reasons. Specifically, 29 articles did not contain RCTs and were, thus, removed. Another 10 articles were removed because they did not include a fully webinar condition. Five articles were ineligible for the meta-analysis because they did not report any satisfaction scales. Additionally, four articles were non-empirical, and one did not report sample size. When data were missing, the corresponding authors were contacted twice and asked to provide any missing information. Following the first step of the literature search, two articles (Constantine, 2012; Joshi et al., 2013) remained and were included in the meta-analysis.

The second step of the literature search contained a cross-referencing process that included articles that were used to identify other relevant studies. Using a backward-search process, we checked the reference list at the end of each article to find other articles that were not included in the database search but could potentially be eligible for inclusion in the meta-analysis. Pursuing the same goal, we then conducted a forward search, using Google Scholar to identify studies that cited the included articles. We also consulted the reference lists of 12 earlier reviews and meta-analyses of online and distance education (Cook et al., 2008, 2010; Bernard et al., 2009; Means et al., 2009, 2013; Martin et al., 2014; Schmid et al., 2014; Liu et al., 2016; Margulieux et al., 2016; Taveira-Gomes et al., 2016; McKinney, 2017; Richmond et al., 2017). This second step of the literature search resulted in another three publications (Harned et al., 2014; Alnabelsi et al., 2015; Olson and McCracken, 2015) that met all the inclusion criteria.

In summary, the two articles obtained from the electronic database search and the three resulting from the cross-referencing process led to the inclusion of five articles in the meta-analysis. **Figure 2** presents a "PRISMA Flow Diagram" about the study selection. In the list of references, asterisks precede the studies that are included in the meta-analysis.

Literature Coding

Following the completion of the literature search, two trained raters coded the included articles, both independently and in duplicate, using the coding scheme detailed in **Table 2**.

With regard to publication characteristics, we coded the name of the first author of the publication, as well as the publication year and type. Regarding publication type, we distinguished between peer-reviewed journal articles and unpublished dissertations. Regarding the control conditions, we distinguished between asynchronous online training and synchronous face-to-face training. Furthermore, we apprehended the sample sizes of the webinar and control group at pre- and post-test.

TABLE 2 | Coding scheme.

Main category	Sub-category
Author	Name of first author
Publication year	Coded as year
Publication type	1 = peer-reviewed journal article
	2 = unpublished dissertation
Control condition	1 = asynchronous online training
	2 = synchronous face-to-face training
Sample size	Sample size *N* of the webinar group (pretest)
	Sample size *N* of the webinar group (post-test)
	Sample size *N* of the control group (pretest)
	Sample size *N* of the control group (post-test)
Effect size	Cohen's *d* of the post-test difference between webinar and control group in terms of knowledge (knowledge)
	Cohen's *d* of the post-test difference between the webinar and control group in terms of satisfaction (satisfaction)

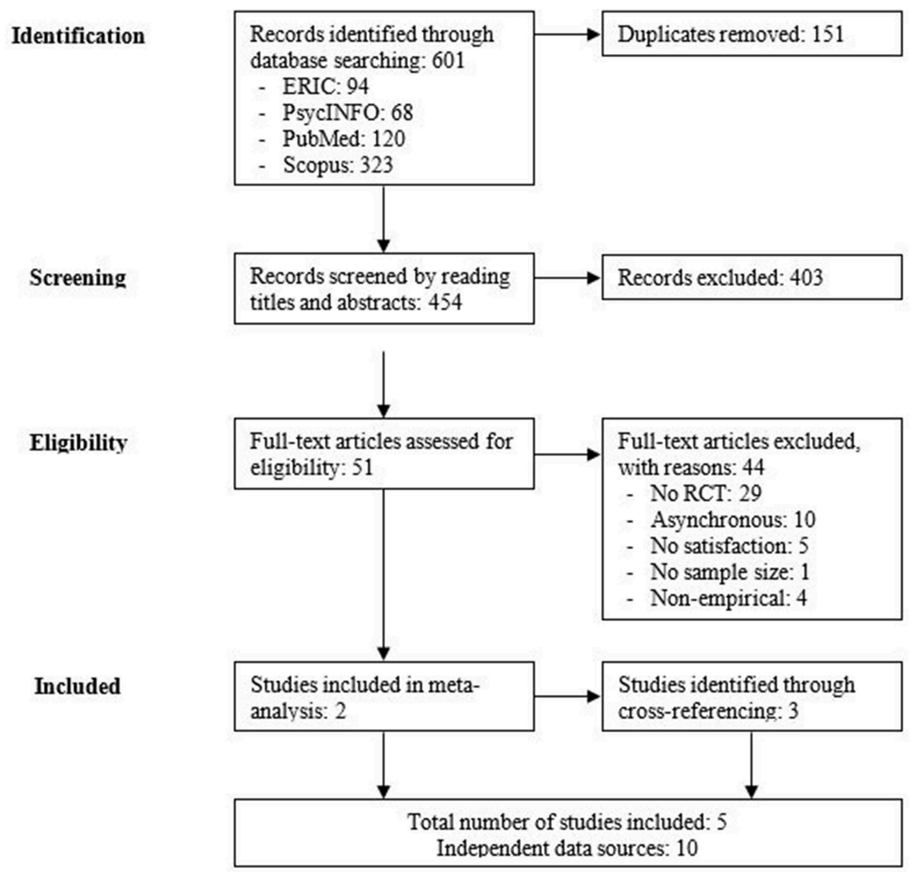

FIGURE 2 | Study selection flow diagram.

The extracted effect sizes included the standardized mean difference Cohen's *d* (Cohen, 1988) of the knowledge post-test scores between the webinar and control group, as well as the standardized mean difference Cohen's *d* of the post-test satisfaction scores between the webinar and control group (elaborate explanation of statistical calculations is provided in section Statistical Calculations).

Interrater Reliability

To ensure the quality of the essential steps taken within the meta-analysis, two trained raters identified, screened, and coded the studies both independently and in duplicate. An important measure of consensus between the raters is represented through interrater reliability (Moher et al., 2009; Schmidt and Hunter, 2015; Tamim et al., 2015; Beretvas, 2019). To statistically measure interrater reliability, Cohen's kappa coefficient (κ) was calculated separately for the single steps of the literature search (identification, screening, and eligibility) and literature coding. Cohen's κ estimates and their standard errors were calculated using SPSS 24, and the standard errors were used to compute the 95% confidence intervals around κ.

According to Landis and Koch (1977), κ values between 0.41 and 0.60 can be interpreted as moderate agreement, values between 0.61 and 0.80 as substantial agreement, and values between 0.81 and 1.00 as almost perfect agreement.

For the literature search, Cohen's κ was estimated separately for the identification, screening, and eligibility checks of the studies, as detailed in the study selection flow diagram in **Figure 1**. The results of the statistical calculations of interrater reliability showed Cohen's κ values: $\kappa = 0.99$ (95% $CI = 0.98$–1.00) for study identification, $\kappa = 0.93$ (95% $CI = 0.79$–1.00) for screening, and $\kappa = 1.00$ (95% $CI = 1.00$–1.00) for eligibility. For the literature coding, interrater reliability was $\kappa = 0.91$ (95% CI= 0.82–0.99).

In summary, the values for interrater reliability showed an almost perfect agreement (Landis and Koch, 1977) between the two raters. This applied to both the literature search and the literature coding. If there was any disagreement between the two raters, it was resolved with consensus.

Statistical Calculations

Two meta-analytic calculations were conducted. The first calculation included a primary meta-analysis with the objective of computing corrected effect size estimates. In a second step, meta-analytic moderator analysis was used to identify the effect of two a priori defined subgroups on the corrected effect sizes. Correlation- and regression analyses were subsequently conducted to examine the relationship between participant satisfaction and knowledge gain.

The primary meta-analysis was carried out following the procedures for the meta-analysis of experimental effects (Schmidt and Hunter, 2015). As this calculation included a comparison between the post-test knowledge scores for the webinar and control conditions (face-to-face and asynchronous online), Cohen's *d* estimates were calculated based on the formula $d = (M_{Web\ post} - M_{Con\ post})/SD_{pooled}$, as detailed in Schmidt and Hunter (2015). In this formula, "$M_{Web\ post}$" and "$M_{Con\ post}$" represent the mean knowledge scores obtained in the post-test by the webinar and the control group (face-to-face and asynchronous online) and SD_{pooled} describes the pooled standard deviation for the two groups. Given that mean and standard deviation estimates were not reported in an article, the formulae provided by Wan et al. (2014) were used to estimate these two variables based on sample size, median, and range. The resulting *F* values were then converted into Cohen's *d* using the formulae provided by Polanin and Snilstveit (2016). Finally, all Cohen's *d* values were transformed into Hedges (1981) *g* with the objective of controlling for small sample sizes.

The primary meta-analysis was followed by a meta-analytic moderator estimation to examine the influence of two control condition subgroups (face-to-face and asynchronous online) on the results of the corrected effect sizes of the primary meta-analysis. These categorical moderator effects were estimated using theory-driven subgroup analyses.

Finally, a two-tailed bivariate correlation analysis and a regression analysis were conducted to examine the relationship between the standardized mean differences in satisfaction and learning in webinar and control conditions (face-to-face and asynchronous online). Furthermore, the Pearson correlations of the mean estimates between learning and satisfaction for each subgroup (face-to-face, webinar, and online) were calculated. These computations were conducted to verify Kirkpatrick's (Kirkpatrick, 1959; Gessler, 2009; Kirkpatrick and Kirkpatrick, 2016) postulated causal relationship between satisfaction and learning.

RESULTS

Description of Included Studies

The included $k = 5$ studies offered a total of 10 effect sizes. The total sample size across conditions and measures was 381 participants. On average, the studies had 37 participants in the webinar condition and 38 in the control condition; in original studies, this small sample size signals the presence of sampling error, which tends to justify the use of meta-analytic synthesis to correct for sampling error. In the face-to-face subgroup, the average sample size was 27 control participants (compared to 26 webinar participants), while in the asynchronous online subgroup, the average sample size was 45 control participants (compared to 45 webinar participants). **Table 3** presents information on the number of data sources and participants per condition and subgroup.

The included studies addressed a variety of topics. Alnabelsi et al. (2015) compared traditional face-to-face instruction with webinars. Two groups of medical students attended a lecture on otolaryngological emergencies either via a face-to-face session or by watching the streamed lecture online. The two modalities were then compared in terms of the students' knowledge test scores and overall satisfaction with the course.

Constantine (2012) examined the differences in performance outcomes and learner satisfaction in the context of asynchronous computer-based training and webinars. The sample comprised health-care providers in Alaska who were trained in telehealth imaging.

TABLE 3 | Number of data sources and participants per condition and subgroup.

	Webinar	Control
All		
Total *k*	5	5
Total *N*	189	192
Average *N*	37.80 (±25.96)	38.40 (±25.89)
Face-to-face		
Total *k*	2	2
Total *N*	53	55
Average *N*	26.50 (±2.12)	27.50 (±3.54)
Online		
Total *k*	3	3
Total *N*	136	137
Average *N*	45.33 (±33.65)	45.67 (±33.71)

Means (±standard deviations). k, number of studies; N, sample size.

Harned et al. (2014) evaluated the technology-enhanced training of mental health providers in the area of exposure therapy for anxiety disorders. The participants were randomly assigned to an asynchronous condition or to a condition that included a webinar.

Joshi et al. (2013) examined pre-service sixth-semester nursing students to determine the differential effects of webinars and asynchronous self-paced learning. One group attended audiovisual lectures (webinars) on essential newborn care, while the other group participated in a traditional classroom environment.

Finally, Olson and McCracken (2015) compared the effectiveness of either a fully asynchronous or a mixed asynchronous and synchronous course design. The sample consisted of undergraduate students, and the measures included course grades and satisfaction.

Learning

Figure 3 presents a forest plot of the learning effect sizes. Meta-analytic moderator estimation examined two subgroups: face-to-face and online. For the face-to-face subgroup, Hedges' g was 0.06 (95% $CI = -0.37; 0.49$), favoring webinar instruction over synchronous face-to-face instruction. For the online subgroup, Hedges' g was 0.29 (95% $CI = 0.05; 0.53$), favoring webinar instruction over asynchronous online instruction. The magnitude of the Hedges' g estimates indicates that, although the learning outcomes were better in webinars compared to asynchronous learning management systems and face-to-face classrooms, the effects were negligible in size.

Satisfaction

Figure 4 presents a forest plot of the satisfaction effect sizes. Meta-analytic moderator estimation examined two subgroups: face-to-face and online. For the face-to-face subgroup, Hedges' g was −0.33 (95% $CI = -1.87; 1.21$), favoring synchronous face-to-face instruction over webinar instruction. For the asynchronous online subgroup, Hedges' g was 0.12 (95% $CI = -0.11; 0.36$), favoring webinar instruction over asynchronous online instruction. All effects were negligible in size and differences were statistically insignificant.

Finally, **Table 4** gives a summary of the single-study results with regard to learning and satisfaction in webinars compared to the respective control conditions (face-to-face and asynchronous online). Positive Hedges' g values signify higher learning or satisfaction in webinars compared to the control condition. Negative Hedges' g values indicate the opposite effect.

The Association Between Satisfaction and Learning

To determine whether satisfaction and learning are associated, a two-tailed bivariate correlation analysis was performed. The Pearson's correlation coefficient was $r = -0.55$, $p = 0.33$. A sample size-weighted regression analysis almost reached statistical significance, with a standardized $\beta = -0.87$, $p = 0.06$. Thus, correlation and regression analyses showed a non-significant negative association. Note that these estimates do not represent a meta-analytic correlation between the mean estimates of both variables—because none of the studies reported correlations between these variables—but instead represents a correlation of the standardized mean differences in satisfaction and learning between the webinar and control conditions (face-to-face and asynchronous online).

If we calculate the Pearson's correlations of the mean estimates between learning and satisfaction, then $r = -0.55$, $p = 0.34$ in the webinar group, $r = -1.00$, $p < 0.01$ in the face-to-face group, and $r = -0.58$, $p = 0.61$ in the asynchronous online group. Sample size-weighted regression analyses showed $\beta = -0.87$, $p = 0.06$ for the webinar group, $\beta = -1.00$, $p < 0.01$ for the face-to-face group, and $\beta = -0.49$, $p = 0.68$ for the asynchronous online group. All of these estimates were negative, indicating no support for Kirkpatrick's assumption in the context of webinar-based, online-based, and face-to-face instruction.

DISCUSSION

The goal of the current meta-analysis was to test the predictive validity of Kirkpatrick's (1959) assumption that a positive association between learning and satisfaction exists. This assumption was meta-analytically examined by comparing levels of learning and satisfaction in the contexts of webinars, traditional face-to-face instruction, and asynchronous learning management systems. The following sections summarize (a) the main results of the statistical calculations, (b) the implications for practical use of the different learning modalities, and (c) a discussion of the study limitations and the directions for future research.

The Main Findings

The research questions regarding the effectiveness of webinars in promoting post-test knowledge scores and the satisfaction of participants were answered using meta-analytic calculations that compared the webinars to the control conditions (face-to-face and asynchronous online) based on cumulated Hedge's g values. Meta-analytic moderator estimations identified the extent to which the two subgroups in the control conditions differed

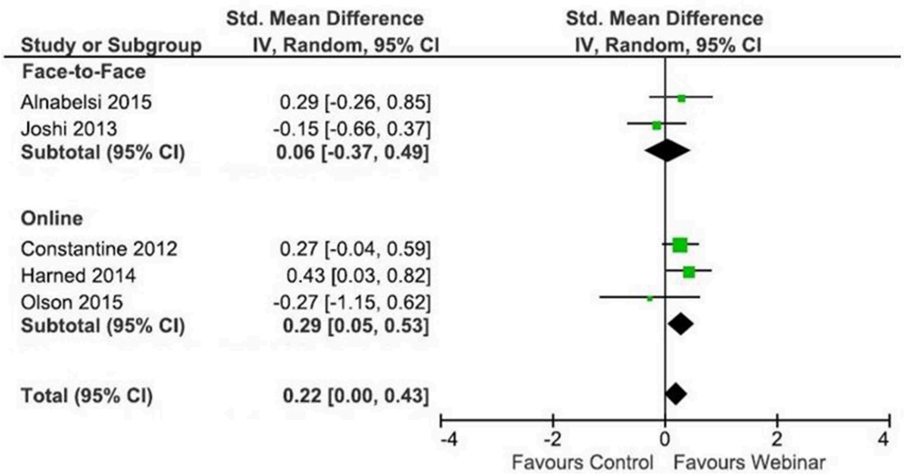

FIGURE 3 | Forest plot of learning effect sizes.

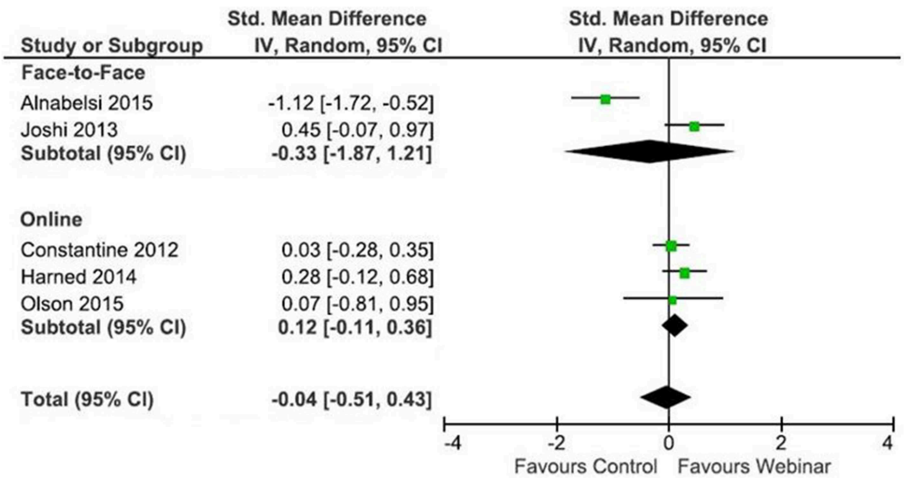

FIGURE 4 | Forest plot of satisfaction effect sizes.

in comparison to the webinars. Finally, correlation analyses were conducted to examine the association between student satisfaction and post-test knowledge scores.

With regard to participant learning, webinars were more effective in promoting participant knowledge than traditional face-to-face (Hedges' $g = 0.06$) and asynchronous online instruction (Hedges' $g = 0.29$), meaning that the knowledge scores of the synchronous webinar participants were slightly higher at post-test compared to the two subgroups. In summary, the results concerning student learning show that webinars are descriptively more effective than face-to-face teaching and asynchronous online instruction. Nevertheless, as the differences between webinars and the two subgroups were marginal and statistically insignificant, one can assume that the three modalities tend to be equally effective for student learning.

With regard to student satisfaction, meta-analytic calculations showed that Hedges' g for the face-to-face subgroup was -0.33, favoring synchronous face-to-face instruction over webinar instruction. In contrast, Hedges' g for the asynchronous online subgroup was 0.12, favoring webinar instruction over asynchronous online instruction. Descriptively, it seems that student satisfaction in synchronous webinars is inferior to traditional face-to-face instruction, whereas synchronous webinars seem to result in slightly higher participant satisfaction when compared to asynchronous online instruction. However, despite descriptive differences, the extracted effects were negligible in size and thus it can be assumed, that satisfaction in webinars is about as high as in face-to-face or asynchronous online instruction.

Correlation analyses were conducted to determine the association between student satisfaction and participant

TABLE 4 | Summary of single-study results.

Study	Population	Control group	N_{Web}	N_{Con}	Results (Hedges' *g*) Learning	Satisfaction
Alnabelsi et al., 2015	Higher Education	Face-to-Face	25	25	0.29	−1.12
Joshi et al., 2013	Higher Education	Face-to-Face	28	30	−0.15	0.45
Constantine, 2012	Profess. Training	Async. Online	77	77	0.27	0.03
Harned et al., 2014	Profess. Training	Async. Online	49	50	0.43	0.28
Olson and McCracken, 2015	Higher Education	Async. Online	10	10	−0.27	0.07

knowledge at post-test, and the results showed negative relationships between the two variables in all learning modalities (webinar, face-to-face, and online). Therefore, Kirkpatrick's predicted positive causal link between satisfaction and learning could not be confirmed. For instance, the high satisfaction scores of the face-to-face subgroup were not associated with stronger post-test knowledge scores, compared to the lower satisfaction scores of the webinar group. This finding coincides with the results of other research that examined Kirkpatrick's stated positive causality between participant reaction (satisfaction) and learning success. A review article by Alliger and Janak (1989) calls Kirkpatrick's assumption "problematic," and individual studies (e.g., Gessler, 2009; see also Reio et al., 2017) underline this critical view, with results showing no positive correlation between reaction and learning.

Implications for Practical Application

The results of the meta-analysis gave some indication of the useful practical application of e-learning modalities in higher education and professional training.

With regard to learning effects, webinars seemed to be equal to traditional face-to-face learning, whereas the effect sizes implied that asynchronous learning environments were at least descriptively less effective than the other two learning modalities. This could be a result of the previously discussed didactic disadvantages of asynchronous learning environments—namely, the lack of immediate feedback (Gao and Lehman, 2003; Wang and Woo, 2007) or the absence of extensive multilevel interaction (Marjanovic, 1999) between the student and the tutor. Nevertheless, marginal effect sizes indicate that the three learning modalities are roughly equal in outcome. In terms of effectiveness with regard to student satisfaction, traditional face-to-face learning seemed to have the strongest impact, followed by webinar instruction. Again, the asynchronous learning environment was inferior—if only marginally—to synchronous webinars. The latter pattern of results coincides with the findings of a recent study by Tratnik et al. (2017), which found that students in a face-to-face higher education course were generally more satisfied with the course than their online counterparts. Nevertheless, similarly to the analysis of learning effects—differences between subgroups were marginal and one can assume that the three compared modalities led to comparable student satisfaction.

These findings have implications for the practical implementation of e-learning modalities in educational contexts. As the three compared learning modalities were all roughly equal in their outcome (learning and satisfaction), the use of each one of them may be justified without greater concern for major negative downsides. Nevertheless, extracted effect sizes—even if they were small—from the current meta-analysis could inform about the possible use of specific modalities in certain situations.

Considering both dependent variables of the meta-analysis, traditional face-to-face instruction seems to be slightly superior to online learning environments in general. Therefore, if there is no specific need for a certain degree of flexibility (time or location), face-to-face classroom education seems to be an appropriate learning environment in higher education and professional training contexts.

Indeed, if there is a need for at least spatial flexibility in educational content delivery, webinars can provide an almost equally effective alternative to face-to-face learning. The only downside is the slightly reduced satisfaction of participants with the use of the webinar tool in comparison to the face-to-face variant. However, this downside is somewhat counteracted by the negative correlation between student satisfaction and knowledge scores. In terms of promoting post-test knowledge, webinars were slightly more effective than their offline counterpart, although the difference was only marginal.

If there is no possibility to convey content to all participants simultaneously, asynchronous learning environments can offer an alternative to face-to-face learning and webinars. For instance, if the participants in an educational course live in different time zones, face-to-face learning is almost impossible, and webinars cause considerable inconvenience. Aside from this extreme example, asynchronous learning environments can be used as a tool that complements other learning modalities.

The latter implications concerned the isolated use of every learning modality on their own. Nevertheless, regarding practical application, the combined use of the stated learning modalities can be useful. Depending on the participants' necessities, e-learning modalities can be combined with traditional face-to-face learning to create a learning environment that makes the most sense in certain situations. In summary, e-learning modalities in general and webinars in particular are useful tools for extending traditional learning environments and creating a more flexible experience for participants and tutors.

Limitations and Directions for Future Research

Some limitations of the current meta-analysis need to be mentioned. The first limitation is the small number of primary studies included in the meta-analysis. Research examining the effectiveness of webinars in higher education and professional training using RCTs is rare, and even less frequent are studies reporting quantitative statistics on the relation between knowledge scores and student satisfaction. On the one hand, the strict selection of RCT-studies in this meta-analysis was carried out to exclude research with insufficient methodological rigor that may be affected by certain biases. On the other hand, the fact that only five suitable RCT-studies were found could have led to other (unknown) bias in the current work. Nevertheless, although the small number of individual studies and the associated small sample sizes indicate a risk of second-order sampling error (Schmidt and Hunter, 2015; Gegenfurtner and Ebner, in press), the need for a meta-analysis of this topic was apparent, as the results of some existing individual studies pointed in heterogeneous directions.

Second, although the use of Hedges' *g* as a measure of effect sizes is suitable for small sample sizes, original studies might be affected by additional biases, such as extraneous factors introduced by the study procedure (Schmidt and Hunter, 2015). These factors could not be controlled in this meta-analysis, and this may have affected the results.

Finally, directions for future research should include the expansion of individual studies examining the effects of webinars on participant learning and satisfaction in higher education and professional training. As e-learning technologies advance rapidly, there is an urgent need for researchers to keep pace with the current status of technology in educational contexts to enable them to expand traditional face-to-face learning by introducing e-learning modalities. For instance, specific research could focus on comparing the effectiveness of different webinar technologies (e.g., AdobeConnect or Cisco WebEx). Furthermore, future research is needed to address different instructional framings of webinar-based training, including voluntary vs. mandatory participation (Gegenfurtner et al., 2016), provision of implementation intentions (Quesada-Pallarès and Gegenfurtner, 2015), levels of social support and feedback (Gegenfurtner et al., 2010; Reinhold et al., 2018), as well as different interaction treatments (Bernard et al., 2009).

Conclusion

As e-learning technologies become increasingly common in educational contexts (Ruiz et al., 2006; Testers et al., 2019), there is a need to examine their effectiveness compared to traditional learning modalities. The aim of the current meta-analysis was to investigate the effectiveness of webinars on promoting participant knowledge at post-test and the satisfaction scores of participants in higher education and professional training. Additionally, Kirkpatrick's assumption of a positive causal relationship between satisfaction and learning was investigated. To answer the associated research questions, meta-analytic estimations and correlation analyses were conducted based on five individual studies containing 10 independent data sources comparing 189 participants in webinar conditions to 192 participants in the control conditions. Additionally, the influence of two subgroups (face-to-face and asynchronous online) was examined. Summarizing the results, webinars provide an appropriate supplement for traditional face-to-face learning, particularly when there is a need for locational flexibility.

DATA AVAILABILITY

All datasets generated for this study are included in the manuscript/supplementary files.

AUTHOR CONTRIBUTIONS

CE was responsible for the main part of the manuscript. AG supported by checking statistical calculations and rereading the paper.

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OFFENE HOCHSCHULEN

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The Costs of Online Learning: Examining Differences in Motivation and Academic Outcomes in Online and Face-to-Face Community College Developmental Mathematics Courses

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Although online courses are becoming increasingly popular in higher education, evidence is inconclusive regarding whether online students are likely to be as academically successful and motivated as students in face-to-face courses. In this study, we documented online and face-to-face students' academic motivation and outcomes in community college mathematics courses, and whether differences might vary based on student characteristics (i.e., gender, underrepresented ethnic/racial minority status, first-generation college status, and adult learner status). Over 2,400 developmental mathematics students reported on their math motivation at the beginning (Week 1) and middle (Weeks 3, 5) of the semester. Findings indicated that online students received lower grades and were less likely to pass from their courses than face-to-face students, with online adult learners receiving particularly low final course grades and pass rates. In contrast, online and face-to-face students did not differ on incoming motivation, with subgroup analyses suggesting largely similar patterns of motivation across student groups. Together, findings suggest that online and face-to-face students may differ overall in academic outcomes but not in their motivation or differentially based on student characteristics. Small but significant differences on academic outcomes across modalities (Cohen's *d*s = 0.17–0.28) have implications for community college students' success in online learning environments, particularly for adult learners who are most likely to be faced with competing demands.

Keywords: developmental mathematics, community college, online learning, academic motivation, adult learners

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INTRODUCTION

Online courses are increasingly popular in higher education, with over 3 million students nationwide having participated in at least one online course (Bennett and Monds, 2008; Green and Wagner, 2011). Growing access to online learning holds promise for Science, Technology, Engineering, and Mathematics (STEM) education, as online math and science courses augment both the number and diversity of students entering into STEM majors (Drew et al., 2015). Online courses also offer increased flexibility for non-traditional learners, such as adult learners, in terms of scheduling and transportation (Hung et al., 2010; Yoo and Huang, 2013). However, there is contradictory evidence on whether students fare equally well in online courses as they do in face-to-face courses. Some studies indicate no differences in performance by modality (e.g., online versus face-to-face courses, Bernard et al., 2004; O'Dwyer et al., 2007; Driscoll et al., 2012). Other studies, by contrast, suggest that online students drop out more often than their face-to-face counterparts (Patterson and McFadden, 2009; Boston and Ice, 2011). Low achieving students may face particular difficulties in online courses (Harrington, 1999), raising the question of whether online courses are benefitting the students who are most likely to enroll in them. Given the increasing popularity and contradictory evidence associated with online learning, it is critical to understand who is likely to be successful in online courses and the underlying mechanisms that may explain differential success.

Students' academic motivation, or reasons for engaging in a task, is an important predictor of academic success that has been under-investigated in the online learning space (Jones and Issroff, 2005; Ortiz-Rodríguez et al., 2005; Yoo and Huang, 2013). In the current study, we examined whether community college students enrolled in online and face-to-face math courses received different academic outcomes, and whether any differences might be a function of students' incoming motivation and changes in motivation. We focused on developmental mathematics courses, which are designed for students who place below college-level math, because they are characterized by notoriously low pass rates and serve as a significant barrier to degree completion (Bailey et al., 2010; Hughes and Scott-Clayton, 2011).

Learning Context: Community College Developmental Mathematics Courses

We chose to conduct this study in developmental mathematics courses at a community college given the high-stakes nature of developmental mathematics courses, dearth of evidence on online learning in community college settings and exponential growth of online courses in community colleges (Johnson and Mejia, 2014; Allen and Seaman, 2016). Community colleges serve more than one-third of degree-seeking U.S. citizens, and include proportionally more students from underrepresented groups (Levin, 2007; Ma and Baum, 2016). Over half of community college students are placed into at least one developmental course, which are designed for students who place below the college-ready level. Developmental math courses serve as a prerequisite to credit-bearing mathematics classes, are characterized by notoriously low pass rates, and can serve as a barrier to degree completion (Bailey et al., 2010; Hughes and Scott-Clayton, 2011). For instance, Silva and White (2013) reported that over 75% of students in developmental courses fail to achieve college-level readiness even after several semesters of remediation. As such, community college developmental mathematics courses serve as a high-stakes area to understand the effect of online learning on academic motivation and outcomes.

Online Learning Environments

Over the past two decades, online learning enrollment has consistently outpaced traditional student enrollment (Oblinger and Hawkins, 2005; Allen and Seaman, 2016), with the number of students enrolled in at least one online course increasing by 32% from 2006 to 2008 (Bennett et al., 2010). These trends are most pronounced in community colleges, higher education institutions which offer 2 years associate's degrees (Allen and Seaman, 2016). Community colleges accounted for more than one-half of all online enrollments from 2002 to 2007, with one in five students at such institutions taking at least one online course between 2011 and 2012 (Johnson and Mejia, 2014). Given the impressive growth in online course enrollment, it is necessary to gain a better understanding of whether online learning is beneficial or detrimental to student success. Some researchers suggest that students fare better when engaging in online courses. For instance, Feintuch (2010) concluded from a review of more than 1000 articles that students in online learning environments spent more time engaged with course materials. She also argued that online students could benefit from personalized instruction and real-time feedback. Similarly, other researchers have lauded the potential for online course offerings to support enrollment among traditionally underserved students (e.g., adult learners, underrepresented ethnic/racial minority students) due to increased flexibility (Hung et al., 2010; Yoo and Huang, 2013), particularly in fields with a lack of diversity such as STEM (Drew et al., 2015). By contrast, other researchers have argued that students enrolled in online courses perform worse than they would in face-to-face courses. For example, researchers cite that dropout rates can be as much as 10–20% higher in online courses than in comparable face-to-face courses (Harris and Parrish, 2006; Xu and Jaggars, 2013). Still other researchers report no difference between academic outcomes in face-to-face and online learning environments (e.g., Bernard et al., 2004; Steinweg et al., 2005; Zhao et al., 2005).

To complicate matters further, researchers have called into question the academic rigor of existing studies. For example, Phipps and Merisotis (1999) noted that many studies failed to use valid and reliable measures or account for students' attitudes. Other scholars assert that conclusions depend on how academic success is operationalized. For example, findings from the Public Policy Institute of California indicated that online learning was correlated with negative short-term outcomes, including course pass rates that were 11–14% lower than face-to-face courses even when controlling for overall grade point average and school characteristics. However, the same report suggested that participating in an online course may have long-term benefits for community college students, including greater likelihood to attain an associate's degree and enroll in a 4 years institution (Johnson and Mejia, 2014).

Differences by Student Characteristics

Researchers are increasingly attending to the fact that online learning may be more beneficial for some types students compared to others. One group that has received substantial attention is adult learners (i.e., individuals who are 24 or older; Yoo and Huang, 2013). On the one hand, online courses provide increased access for adult learners, who are more likely to have work and family obligations to balance alongside attaining a degree (Hung et al., 2010; Yoo and Huang, 2013). Adult learners may be expected to perform better in online courses because they tend to be more self-directed and autonomous (Arghode et al., 2017). On the other hand, they may be less familiar navigating online learning environments, which can affect their performance (Chang, 2015; Lai, 2018).

Results comparing success rates for adult and traditional-aged learners are inconsistent. A number of studies found that adult learners perform more poorly in online learning environments than in face-to-face learning environments (Richardson and Newby, 2006; Park and Choi, 2009; Yoo and Huang, 2013). For example, one study found that online adult learners enrolled in an MBA program were four times more likely to drop out than in face-to-face courses (Patterson and McFadden, 2009). Other studies have found that adult learners participate more often in course activities than traditional-aged learners (Kilgore and Rice, 2003; Hoskins and Van Hooff, 2005; Chyung, 2007) or found that age was not a significant predictor of outcomes (Hargis, 2001; Ke and Xie, 2009). Taken together, findings related to age and success in online courses are inconsistent. The current study not only considered academic outcomes for adult learners compared to traditional-aged students, but also characterized their incoming motivation levels.

Other student characteristics that have been examined with respect to online learning are gender (e.g., Park, 2007; Cercone, 2008) and prior achievement (e.g., Harrington, 1999; Summers et al., 2005). With respect to gender, findings suggest that females may be more actively engaged in online learning (e.g., Chyung, 2007), but this does not translate to lower dropout rates (Park and Choi, 2009). With respect to prior achievement, findings suggest that lower achieving students may be less satisfied with online compared to face-to-face courses (e.g., Summers et al., 2005) and may perform more poorly in online than in face-to-face courses or than their higher achieving classmates. Relevant to the current study, which was conducted in developmental mathematics courses, Harrington (1999) examined students' performance in online and face-to-face versions of an introductory statistics course. She found that students with low grade point averages performed more poorly in the online course than low-performing students in the face-to-face course, or than high-achieving students in either version of the course. Overall, evidence suggests some potential differences in how successful students may be in online courses based on their individual characteristics. However, the evidence is generally mixed and several important student characteristics have yet to be systematically examined (e.g., underrepresented ethnic/racial minority status, first generation college status).

Academic Motivation in Online Learning Contexts

The research on non-cognitive factors in online education has focused heavily on students' behaviors, such as self-regulated learning strategies, as predictors of success in online learning environments (Broadbent and Poon, 2015). However, differences between online learning and face-to-face environments may also affect students' attitudes in online courses (Rovai, 2002; Baker, 2004; Mullen and Tallent-Runnels, 2006). Online students may require adaptive motivation to stay engaged (Karimi, 2016; Park and Yun, 2018) and enrolled in their courses (Aragon and Johnson, 2008) more so than face-to-face students, and online courses may attract students with lower initial motivation. This study documents online learners' motivation in comparison to face-to-face students in the same courses.

To operationalize motivation, we adopted an expectancy-value-cost framework (Eccles, 1983; Barron and Hulleman, 2015) because it is well established, describes student motivation broadly, and aligns with constructs from popular conceptualizations of motivation in the online learning space (e.g., Keller and Suzuki, 2004). Expectancy-value-cost theory posits that the most proximal determinants of student motivation are expectancy (i.e., belief that one can complete a task successfully), value (i.e., belief that there is a worthwhile reason for engaging in a task), and cost (i.e., belief that that there are obstacles preventing one from engaging in a task). Because we were interested in capturing a rich description of students' motivation, we assessed a number of related motivational constructs (for a similar approach, see Hulleman et al., 2016). Related to expectancy, we assessed growth mindset (i.e., belief that intelligence is malleable and can be improved; Dweck and Leggett, 1988; Dweck, 2006). Related to value, we assessed interest (i.e., engaging in a task due to interest or enjoyment; Eccles, 1983) and social belonging (i.e., belief that one fits in to the learning context and is respected by others in that environment; Cohen and Garcia, 2008).

A growing number of studies have assessed online learners' expectancy or value. Consistent with the broader literature, expectancy-related constructs – particularly self-efficacy, or students' perception that they can successfully complete a task – were positively associated with online students' course satisfaction (Brinkerhoff and Koroghlanian, 2007), performance (Joo et al., 2000; Wang and Newlin, 2002; Lynch and Dembo, 2004; Bell and Akroyd, 2006), persistence (Holder, 2007), and likelihood of enrolling in future online courses (Lim, 2001; Artino, 2007). Overall perceived value of course content was also associated with course satisfaction (Xie et al., 2006), performance (Yoo and Huang, 2013), and future enrollment choices (Artino, 2007), although some articles reported no associations between value and final grade (Chen and Jang, 2010). Studies suggested that value was a particularly important predictor for adult learners (Kim and Frick, 2011). There is less empirical evidence suggesting that perceived cost is associated with poorer academic outcomes. However, theory suggests that cost may be lower in online courses since they do not require students to be in a particular location at a particular time. Cost may be a critical predictor for certain groups of online learners, such as adult learners who may be more likely to be balancing competing demands on their time from work, family, and school (Hung et al., 2010).

Current Study

We sought to document academic outcomes, incoming motivation, and changes in motivation for students enrolled in online and face-to-face math courses. We were interested in two primary research questions. First, do students enrolled in online courses receive lower academic outcomes (i.e., final grades, pass rates, withdraw rates) than students enrolled in face-to-face courses? We hypothesized that online students would receive lower final grades and pass rates, but higher withdraw rates, than face-to-face students (Patterson and McFadden, 2009) based on evidence that lower achieving students struggle in online learning environments (Harrington, 1999; Coldwell et al., 2008) and community college students reported negative short-term outcomes in online courses (Johnson and Mejia, 2014).

Second, do online students report lower incoming motivation than face-to-face students, and does that vary Eccles, 1983 as a function of student characteristics (i.e., gender, adult learner status, underrepresented ethnic/racial minority status, and generation status)? Given the general lack of evidence in online courses in general, and community college developmental math courses in particular, we tentatively hypothesized that online students would report (1) lower perceived cost than face-to-face students, given the argument that online courses offer increased flexibility Yoo and Huang, 2013); and (2) lower belonging, given that online courses tend to involve less interaction and synchronous learning opportunities.

MATERIALS AND METHODS

Participants

The sample included 2,411 students (M_{age} = 20.7 years, SD_{age} = 5.2 years) from a community college in the Southeastern United States. Participants were enrolled in 310 individual courses of two different developmental mathematics topics – Intermediate Algebra and College Math – taught by 63 instructors over six semesters. Participants were drawn from the control condition of a larger randomized-control trial assessing the effects of a utility-value and growth mindset intervention on students' math achievement. Participants were primarily female (60%), with 70% having applied for financial aid, 50% identifying as first-generation students (i.e., neither parent received a degree form a 4 years institution), 45% identifying as part-time students, and 13% adult learners. Approximately 31% self-reported as White, 38% Hispanic/Latino, 21% Black/African American, 2.1% Asian, and 7.9% reporting another ethnicity. The current sample is representative of the overall population of the community college (31% White, 32% Hispanic/Latino, 18% Black/African American, 6% Asian, and 13% reporting some other ethnicity). Out of the total sample, 2,036 students (84.45%) were enrolled in face-to-face courses and 375 (15.55%) were enrolled in online courses. Students in online courses were more likely to be women (66%), identify as an underrepresented ethnic/racial minority group (53%; i.e., identifying as Hispanic/Latino, Black/African American, or Pacific Islander at this institution), adult learners (i.e., 25 or older; 26%) and enrolled part time (52%) than students in face-to-face courses [59% female, $\chi^2(1, N = 2{,}384) = 6.18$, $p = 0.013$; 43% underrepresented ethnic/racial minority, $\chi^2(1, N = 2{,}227) = 17.17$, $p < 0.001$; 11% adult learner, $\chi^2(1, N = 2{,}411) = 0.65.41$, $p < 0.001$; 43% part time learner, $\chi^2(1, N = 2{,}411) = 9.52$, $p = 0.002$]. Students in online and face-to-face courses did not differ by generation status.

Measures

Academic Motivation

Student motivation was assessed via self-report survey measures for four constructs from Expectancy-Value-Cost Theory – expectancy, value, cost, and interest – at four points throughout the semester, along with growth mindset and social belonging at the beginning of the semester. Four expectancy items ($\alpha = 0.90$; e.g., "How confident are you that you can learn the material in the class?"), six value items ($\alpha = 0.91$; e.g., "How important is this class to you?"), five cost items ($\alpha = 0.78$; e.g., "How stressed out are you by your math class?"), and three interest items ($\alpha = 0.88$; e.g., "How interested are you in learning more about math?") were adapted from the Expectancy-Value-Cost Scale (Kosovich et al., 2015; Hulleman et al., 2017) to make them specific to math courses. Responses ranged from 1 (*Not at All*) to 6 (*Extremely*). Students also completed a three-item measure of growth mindset from Good et al. (2012), ($\alpha = 0.85$; e.g., "I have a certain amount of math ability, and I can't really do much to change it"; reverse-scored) on a 6-point Likert-type scale (1 = *Strongly Disagree*; 6 = *Strongly Agree*) and a three-item measure of social belonging (Manai et al., 2016; $\alpha = 0.75$; e.g., "In this class, how much do you feel as though you belong?") on a 6-point Likert-type scale (1 = *Not at All*; 6 = *Extremely*). Confirmatory factor analysis indicated that the motivation variables fit the data well ($\chi^2(231, N = 1{,}676) = 1220.54$, $p < 0.001$; CFI: 0.96; TLI: 0.95; RMSEA: [0.047, 0.053]; SRMR: 0.043).

Academic Outcomes

Administrative data were collected from the office of institutional research at the end of the semester for pass rates, withdraw rates, and numeric grade. Pass rates were calculated such that students who earned an A, B, or C in the course were coded a "1" while students who earned a D, F, W, or I were coded as "0." Withdraw rates were calculated such that students who earned a Withdraw (W) in the course were coded as a "1" while students who earned an A, B, C, D, or F were coded as a "0." Students who earned an incomplete (I, $n = 4$ students) could not be categorized. Numeric grades were coded by converting letter grades to a normal GPA scale (0–4) such that students who received an A were coded as a "4," students who received a B were coded as a "3," students who received a C were coded as a "2," students who received a D were coded as a "1," students who received an F or a W were coded as a "0."

Procedure

All students enrolled in participating developmental mathematics courses were invited to participate in the current study. Materials were administered online through the Qualtrics platform during the lab portion of students' developmental mathematics class for the face-to-face courses, and as part of an assigned homework activity on the course management platform for online courses. Overall, 91% of students enrolled in participating courses completed at least one of the 4 activities. Participants reported on their motivation during the first class period of the semester in Week 1 (Time 1, 70% response rate), as well as during Week 3 (Time 2, 77% response rate), Week 5 (Time 3, 70% response rate), and Week 12 (Time 4, 45% response rate). Given the low response rate, we did not consider motivation at Time 4 in analyses for the current study. After responding to survey items, participants provided information about their self-identified gender, race, parental education, and previous academic achievement before being thanked for their time. Instructors incentivized students to complete activities with course credit, but were given autonomy over what kind of course credit they offered (e.g., extra credit, participation grade).

Analytic Plan

Descriptive differences in student achievement, demographics, and baseline motivations by course modality were examined by conducting *t*-tests and ANOVAs Because modality comparisons were exploratory, we employed a Bonferroni adjustment for them and reduced our threshold for significance to $\alpha = 0.0056$ (see **Table 1**). Additionally, we calculated effect sizes of differences (i.e., Cohen's *d*) to consider practical significance. See the **Supplementary Materials** for the tables displaying descriptive differences in student achievement, demographics, and baseline motivation by course modality and student characteristics (gender, underrepresented ethnic/racial minority status, generation status, and adult learner status).

To determine whether students in online and face-to-face courses received different academic outcomes, we tested the influence of course modality, the interaction of course modality and student characteristics, and the latent interaction of baseline motivation and course modality on student academic achievement in the course. To determine whether students in online courses were less motivated initially than students in face-to-face courses, we tested the influence of course modality and the interaction of course modality and student characteristics on latent student baseline motivation. To do this, we fit two structural equation models – one predicting the three academic outcomes (i.e., pass rates, withdraw rates, and numeric grade) and one predicting the six latent student motivation scores (i.e., expectancy, value, cost, interest, growth mindset, and belonging). Models included course modality, course modality and student demographic interactions, and course modality and latent incoming motivation interactions (only when predicting academic achievement) as predictors. Models were estimated in the statistical program R using the "lavaan" package (Rosseel, 2012).

For all analyses predicting latent baseline student motivation, we controlled for student gender (i.e., male versus female), student underrepresented minority status (i.e., Hispanic/Latino or Black/African American versus White or Asian), student generation status (i.e., first-generation status versus continuing-generation status, adult learner status, and prior achievement (i.e., high school GPA). For all analyses predicting academic outcomes (i.e., pass rate, numeric grade, withdraw rate), we controlled the same student covariates as well as the six latent student motivation scores.

To determine if students in face-to-face courses or online courses experienced differences in their change in motivation over the course of the semester, we tested the influence of course modality on Time 3 student motivation while accounting for Time 1 student motivation. These models could not be estimated in an SEM framework, as the sample size of online students participating during surveys conducted during both Time 1 and Time 3 was too small. To answer this question, models were estimated in the statistical program R using the "lme4" package (Bates et al., 2014). This package is appropriate for cross-classified levels in data structures, which was necessary for the current study given that instructors taught courses across multiple semesters. Prior to analyses, all continuous predictor variables (e.g., Time 1 motivation composites, student's reported high school GPA) were grand-mean centered. For all analyses predicting changes in motivation over the semester (i.e., Time 3 expectancy, value, cost, and interest), we controlled for the aforementioned student covariates along with students' Time 1 composite score for the motivational construct being predicted.

TABLE 1 | Variables of interest by course modality.

	Face-to-face	Online	*T*-test	Effect size (Cohen's d)
	Mean (*SD*)			
Academic Outcomes				
Pass rate	0.66 (0.47)	0.54 (0.50)	$t(506) = -4.23, p < 0.001$	$d = -0.25$
Grade	2.06 (1.46)	1.65 (1.52)	$t(508) = -4.91, p < 0.001$	$d = -0.28$
Withdraw rate	0.13 (0.33)	0.18 (0.39)	$t(479) = 2.69, p = 0.007$	$d = 0.17$
Baseline Motivation				
Expectancy	3.81 (0.81)	3.66 (0.85)	$t(360) = -2.65, p = 0.008$	$d = -0.18$
Value	3.58 (0.92)	3.59 (0.93)	$t(369) = 0.13, p = 0.894$	$d = 0.01$
Cost	2.50 (0.84)	2.66 (0.85)	$t(368) = 2.75, p = 0.006$	$d = 0.19$
Relevance	3.20 (1.16)	3.13 (1.19)	$t(366) = -0.82, p = 0.414$	$d = -0.06$
Interest	2.71 (1.19)	2.64 (1.20)	$t(368) = -0.89, p = 0.372$	$d = -0.06$
Growth mindset	3.88 (1.20)	3.81 (1.30)	$t(354) = -0.75, p = 0.454$	$d = -0.05$
Belonging	3.67 (0.77)	3.58 (0.80)	$t(363) = -1.63, p = 0.104$	$d = -0.11$

RESULTS

Predicting Academic Outcomes by Course Modality

First, we tested whether course modality predicted students' course performance (i.e., whether students in online courses performed better, worse, or the same as students in face-to-face courses). Descriptive statistics for course performance by course modality can be seen in **Table 1**. Structural equation models were conducted in which pass rate and withdraw rate were predicted by course modality (0 = face-to-face; 1 = online). All models controlled for latent baseline student motivation scores, student gender, student underrepresented ethnic/racial minority status, student generation status, and student prior achievement. The model fit the data well ($\chi^2(1{,}480, N = 1{,}456) = 5048.12, p < 0.001$; CFI: 0.92; TLI: 0.91; RMSEA: [0.039, 0.042]; SRMR: 0.041). As shown in **Figure 1**, being enrolled in an online course was significantly negatively associated with pass rate and numeric

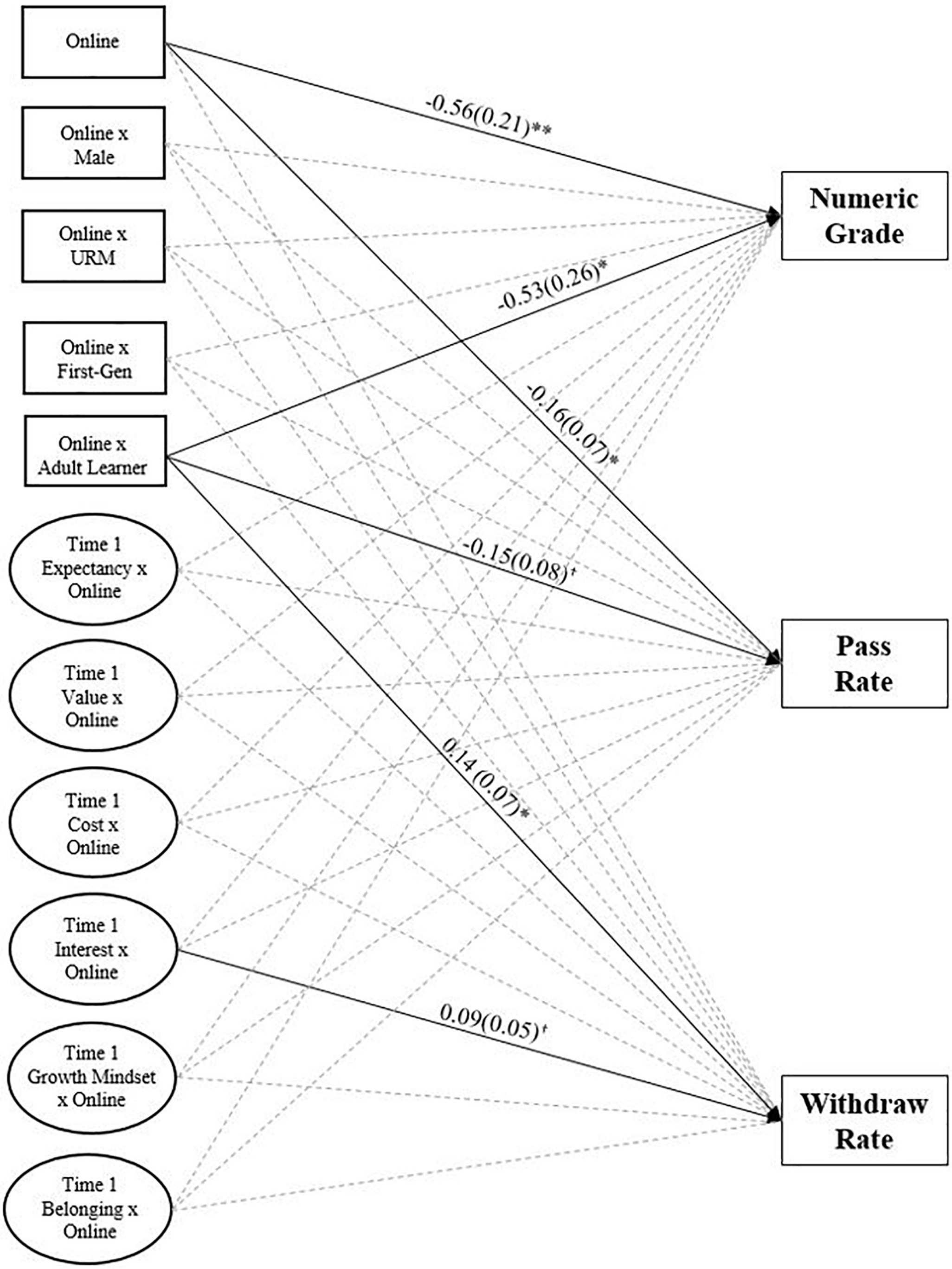

FIGURE 1 | Course modality and interactions predicting academic outcomes. $^{\dagger}p < 0.10$, $^{*}p < 0.05$, and $^{**}p < 0.01$.

grade (β = −0.56, $p = 0.007$; β = −0.16, $p = 0.021$) but did not predict withdraw rate.

This same model also included interactions of course modality and student characteristics to determine if the effect of course modality on academic achievement was differential by gender, student underrepresented racial/ethnic minority status, generation status, or adult learner status. As shown in **Figure 1**, being an adult learner in an online course was significantly negatively associated with numeric grade (β = −0.53, $p = 0.043$), marginally negatively associated with pass rate (β = −0.15, $p = 0.064$), and significantly predicted withdraw rate (β = 0.14, $p = 0.043$). These results suggest that students in online courses tend to pass less often, withdraw more often, and earn lower numeric grades than students in face-to-face courses. Further, this effect is not a function of student gender, underrepresented ethnic/racial minority status, or generation status but may be a function of adult learner status.

Modality Effects on Academic Outcomes Based on Incoming Motivation

One hypothesis was that differences in online and face-to-face students' performance is a function of their incoming motivation. To assess this possibility, we included latent interactions of baseline motivation and course modality for each motivation construct (i.e., expectancy, value, cost, interest, growth mindset, and belonging) predicting academic achievement. As shown in **Figure 1**, there were no significant interactions of course modality and Time 1 motivation predicting academic outcomes with the exception that being an online student scoring higher on interest in the course was marginally associated with withdraw rate ($\beta = 0.09$, $p = 0.080$). These results suggest that the differences in online and face-to-face students' academic performance is not a function of their baseline motivation coming into the course with the marginal exception of perceived interest in the course when considering withdraw rate.

Baseline Motivational Differences by Course Modality

Next, we examined whether students' incoming motivation significantly differed based on course modality (i.e., whether students in online courses were more, less, or equally motivated at the beginning of the semester as students in face-to-face courses). As displayed in **Table 1**, students in online courses did not differ significantly from students in face-to-face courses in any of the Time 1 motivational constructs. In terms of practical significance, effect sizes indicated that any differences were below what would be considered a small effect (i.e., Cohen's *d*s < 0.30). Results suggested that face-to-face and online students did not differ in their incoming motivation. This was further supported by the SEM model predicting latent incoming student motivation scores, which fit the data well ($\chi^2(414, N = 1{,}456) = 1393.28$, $p < 0.001$; CFI: 0.95; TLI: 0.94; RMSEA: [0.038, 0.043]; SRMR: 0.033). with the exception of online course enrollment being marginally negatively associated with latent incoming interest scores ($\beta = -0.28$, $p = 0.098$), there were no differences between online and face-to-face students in academic motivation.

We were also interested in determining whether the effect of course modality on latent baseline student motivation was moderated by student characteristics. To assess this possibility, we included interactions of course modality and student characteristics (gender, underrepresented racial/ethnic minority status, generation status, and adult learner status) predicting latent motivation scores. As shown in **Figure 2**, there were no significant interactions of course modality and student characteristics predicting latent baseline expectancy, value, cost, or interest. However, the interaction of course modality and generation status were marginally negatively associated with latent incoming growth mindset and social belonging such that first-generation students enrolled in online courses tended to report less growth mindset and less social belonging at their institution. These results suggest that course modality is unrelated to latent Time 1 student motivation (with the marginal exception of interest), and that generally, student gender, underrepresented racial/ethnic minority status, and adult student status do not moderate the relationship between course modality and latent student motivations, however, course modality and generation status are marginally negatively associated with growth mindset and social belonging.

Predicting Change in Motivation Over Time by Course Modality

Next, we examined whether course modality predicted change in motivation over the course of the semester (i.e., whether students in online courses reported greater, lesser, or equal changes in motivation across the semester as students in face-to-face courses). We conducted these analyses for expectancy, value, cost, interest, and relevance because these variables were assessed at multiple points throughout the semester. In analyses considering change in motivation over time, we operationalized change as the difference in motivation from Time 1 (Week 1) to Time 3 (Week 5). Descriptive statistics for motivation composites across Time 1–Time 3 by course modality can be seen in **Table 2**. In order to determine whether course modality predicted change in motivation over time, we fit linear multilevel models in which Time 3 motivation was regressed on course modality for each motivational construct (i.e., expectancy, value, cost, interest, relevance). All models controlled for course type, semester, student gender, student underrepresented ethnic/racial minority status, student generation status, and student high school GPA as well as the Time 1 motivation composite for the motivation being predicted. As shown in **Table 3**, being enrolled in an online course was not a significant predictor of change in motivation over the semester after employing a Bonferroni correction ($\alpha = 0.01$). Findings suggest that changes in motivation over the course of the semester were not a function of course modality.

We further investigated whether student demographics interacting with course modality predicted change in motivation over the course of the semester (i.e., whether students in online courses reported greater, lesser, or equal changes in motivation based on demographic characteristics compared to students in face-to-face courses. In order to do this, we fit linear models in which Time 3 motivation was regressed on the interaction of course modality and student demographic characteristic (gender, underrepresented ethnic/racial minority status, generation status, and adult learner status). All models controlled for course type, semester, student gender, student underrepresented ethnic/racial minority status, student generation status, and student high school GPA as well as the Time 1 motivation composite for the motivation being predicted. As shown in **Table 3**, there are no significant interactions of course modality and student demographic predicting change in motivation after employing Bonferroni corrections ($\alpha = 0.013$) with the exception of the interaction of course modality and adult learner status on change in cost [$\beta = -0.50$, $t(1{,}125) = -2.71$, $p = 0.007$]. Adult learners in online courses tended to experience less of an increase in

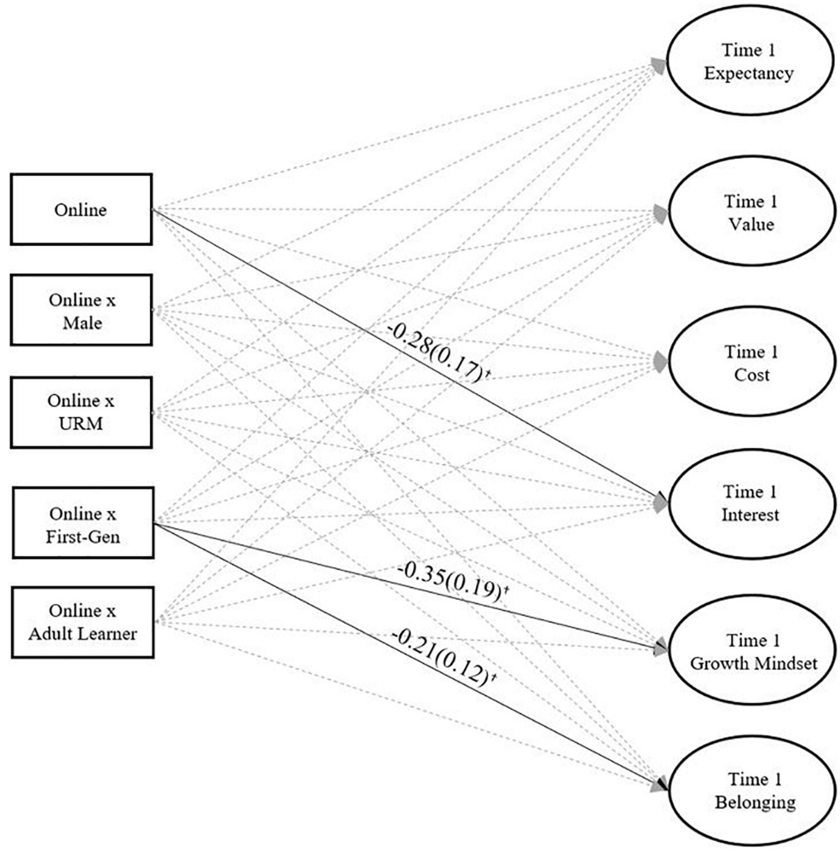

FIGURE 2 | Course modality and interactions of course modality and student characteristics predicting latent baseline student motivation. $^{\dagger}p < 0.10$.

TABLE 2 | Motivation across time points by course modality.

Baseline motivation	Time 1 Mean (*SD*)		Time 2 Mean (*SD*)		Time 3 Mean (*SD*)	
	Face-to-face	Online	Face-to-face	Online	Face-to-face	Online
N	1,426	266	1,618	267	1,471	217
Expectancy	3.81 (0.81)	3.66 (0.85)	3.74 (0.94)	3.56 (1.01)	3.62 (0.99)	3.45 (0.97)
Value	3.58 (0.92)	3.59 (0.93)	3.68 (0.98)	3.71 (0.93)	3.51 (1.04)	3.69 (0.96)
Cost	2.50 (0.84)	2.66 (0.85)	2.58 (1.04)	2.80 (1.08)	2.64 (1.06)	2.88 (1.08)
Relevance	3.20 (1.16)	3.13 (1.19)	2.96 (1.24)	2.94 (1.17)	3.04 (1.22)	3.09 (1.26)
Interest	2.71 (1.19)	2.64 (1.20)	2.56 (1.24)	2.52 (1.22)	2.58 (1.22)	2.51 (1.26)

cost over the course of the semester than adult learners in face-to-face courses and traditional-aged learners in general. These results indicate that changes in motivation over the course of the semester were not a function of course modality and student demographics with the exception of adult learners in online courses and their experience of cost over time.

DISCUSSION

Online courses have become increasingly available and popular in higher education, particularly in community college (Bennett et al., 2010; Allen and Seaman, 2016). While some have lauded online courses as an opportunity to increase access for non-traditional and historically underrepresented learners (Yoo and Huang, 2013; Drew et al., 2015), others cite poor performance and high dropout rates as significant drawbacks (Patterson and McFadden, 2009; Boston and Ice, 2011). Evidence is inconsistent on whether students who engage in online learning are as motivated and successful as students who engage in traditional face-to-face learning, and for whom online courses may be most beneficial or detrimental (Phipps and Merisotis, 1999; Bernard et al., 2004; Johnson and Mejia, 2014). This study documented the motivational experiences of students in online and face-to-face courses, along with their academic performance. We focused on developmental mathematics courses, which

TABLE 3 | Course modality and demographics predicting change in motivation (Weeks 1–5).

	Change in expectancy	Change in value	Change in cost	Change in interest
Course modality	−0.03 (0.08)	0.16 (0.08)	0.12 (0.09)	−0.03 (0.08)
Gender	0.08 (0.05)	0.03 (0.05)	−0.11 (0.05)	0.20*** (0.05)
Ethnic/Racial minority status	−0.11 (0.05)	0.07 (0.05)	0.09 (0.05)	0.02 (0.05)
Generation status	0.04 (0.05)	0.03 (0.05)	0.04 (0.05)	−0.02 (0.05)
Adult learner status	−0.02 (0.07)	0.06 (0.07)	0.02 (0.08)	−0.03 (0.07)
Course modality × Gender	0.01 (0.15)	−0.07 (0.15)	−0.01 (0.17)	0.04 (0.15)
Course modality × Ethnic/racial minority status	−0.12 (0.13)	−0.19 (0.13)	0.06 (0.15)	−0.09 (0.13)
Course modality × Generation status	0.11 (0.13)	0.26 (0.13)	0.08 (0.15)	0.07 (0.13)
Course modality × Adult learner status	0.02 (0.16)	−0.01 (0.17)	−0.50* (0.19)	0.24 (0.17)
N	1,129	1,128	1,127	1,118

All models controlled for course type, semester, high school GPA (centered), and baseline (Time 1) motivation. The reference groups for course modality, gender, ethnic/racial minority status, generation status, and adult learner are "face-to-face," "female," "Non-URM," "continuing-generation," and "traditional age," respectively. $^{***}p < 0.001$ *and* $^{*}p < 0.05$.

serve academically underprepared students and are notorious barriers to graduation. Taken together, our findings suggest that there are few differences in online and face-to-face students' incoming motivation and motivational change over time, and that motivational experiences do not differ systematically based on students' gender, generation status, underrepresented ethnic/racial minority status, or age.

Do Face-to-Face Students Outperform Online Students?

One of the primary arguments against online learning is that online students perform worse and drop out at higher rates than face-to-face students (Harris and Parrish, 2006). However, multiple syntheses concluded that there are no significant differences between the two modalities (e.g., Russell and Russell, 1999; Bernard et al., 2004; Zhao et al., 2005) and that negative effects are only present for certain subgroups of students. Findings from the current study indicated that online learners received lower course grades, lower pass rates, and higher withdrawal rates than their classmates in face-to-face courses. Although significant, it is important to note that the size of effects was small (Cohen's ds = 0.17–0.28). When interpreting these findings, we are also mindful of Johnson and Mejia's (2014) work with community college students in California, who concluded that online students displayed negative short-term effects (i.e., course-level performance and persistence) but positive long-term outcomes (i.e., degree attainment, enrollment in 4 years institution). Future analyses with this sample will assess participants' longer-term outcomes, such as how many math courses they pursue and whether they are successful in future higher education or employment contexts.

When considering findings by subgroup, results suggested that the only significant interaction between student characteristic and course modality was for adult learner status. Online adult learners received significantly lower course grades and pass rates than face-to-face adult learners or traditional-aged learners in either online or face-to-face courses, with a consistent marginal finding for withdraw rates. This finding is of interest because adult learners are one of the most commonly cited reasons for providing online education options and comprise a sizable percentage of the online learner population (Yoo and Huang, 2013).

Do Online Students Report Lower Motivation Than Face-to-Face Students?

Motivation is a critical predictor of academic success (Wigfield and Cambria, 2010), and has been identified as a theoretically-meaningful component of online learners' success (Hartley and Bendixen, 2001; Hu and Kuh, 2002; Keller and Suzuki, 2004). We documented students' motivation using an expectancy-value-cost framework (Wigfield and Eccles, 2000; Barron and Hulleman, 2015) and additional key constructs such as growth mindset and belonging. Results indicated that incoming students reported comparable expectations that they could be successful in the course, value for the course, and perceived cost of being involved in the course regardless of whether they enrolled in an online or face-to-face version of the class. This lack of difference counters any hypothesis that students may be differentially selecting to enroll in online courses because they are more or less motivated to take the course, at least among the current sample.

We were also interested in how students' motivation changed over time, and documented students' motivation at the beginning (Week 1) and middle (Weeks 3, 5) of the semester. We focused on this time period because it aligned with the add/drop period for the course, and consequently could be an important predictor of course drop out. Similar to findings for incoming motivational levels, descriptive results indicated that face-to-face and online students did not show differential patterns of motivational change. This suggests that, at least for the first half of the semester, online students' changes in expectancy, value, and cost are not meaningfully different from those of face-to-face students. However, we were not able to meaningfully assess motivational change from the beginning to end of the semester given a low response rate (45%) to our survey administered in Week 12. Future research may wish to collect data on longer-term changes in motivation. Future studies could also assess motivational change at a more fine-grained level by collecting data more frequently to determine when – if ever – online and face-to-face students' motivational trajectories diverge.

We were also interested in whether incoming academic motivation could account for differences in online and face-to-face students' academic outcomes. Findings from our structural equation model (**Figure 1**) indicated no significant interaction between any of the incoming motivational variables and online versus face-to-face courses. The fact that this finding applied across a sample of students drawn from six semesters provides some assurance that these findings are replicable in the current sample of community college developmental mathematics students. Future research, however, could help determine whether this lack of relation replicates in other learning contexts, which would suggest that academic motivation is not a meaningful explanatory factor accounting for differences between online and face-to-face students' academic success, or is unique to the community college or developmental mathematics setting.

Limitations and Future Directions

The current study provides a broad description of online students' motivational experiences in an important setting in higher education. It also provides preliminary evidence suggesting that the small but significant differences in academic performance between online and face-to-face courses does not appear to be a function of students' incoming motivational beliefs. Although this information contributes to our understanding of online students' affective experiences, there are a number of additional potential explanatory mechanisms that were not assessed. Future research may wish to consider constructs such as self-regulated learning strategies (e.g., time management; Broadbent and Poon, 2015) as reasons why online and face-to-face learners may receive different academic outcomes. Students' prior experiences in online courses may also be an important factor to consider. Like motivation, the extant literature on prior experience is mixed, with some studies finding no relation between prior online experience and course performance (e.g., Arbaugh, 2005) and others finding effects of prior online experience on retention and completion rates (e.g., Dupin-Bryant, 2004). Similarly, students' reasons for enrolling in online courses and the percentage of courses that students take online versus face-to-face may also affect students' academic outcomes and course motivation. Future studies should assess these background variables and account for them in subsequent analyses.

The current study was also limited to assessing short-term motivation (i.e., from the beginning to middle of the semester) and outcomes (i.e., course grade, pass rate, and withdraw rate). However, prior research suggests that there are benefits to measuring longer-term change in motivation (Kosovich et al., 2017) and that the pattern of effects of taking online courses for short-term and long-term outcomes can vary substantially (Johnson and Mejia, 2014). Future research may wish to collect longer-term data from online and face-to-face students in terms of their motivation, perceptions of instructors, and academic outcomes. Finally, the current study was correlational. Because students chose to enroll in online or face-to-face versions of their courses, we cannot make claims regarding causal effects of online course enrollment on academic outcomes or motivational change. To enable such claims, future studies may wish to randomly assign students to complete online or face-to-face versions of courses, then assess their academic outcomes. Causal evidence from a randomized controlled trial could augment the current evidentiary basis by providing more definitive evidence on the effect of online course enrollment for student motivation and success.

DATA AVAILABILITY

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by University of Virginia Institutional Review Board Valencia College Institutional Review Board. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

MF contributed to the conceptual framing of the study, helped determine and execute the analytic plan, helped conduct a literature review, and was the primary author of the methods and results sections. SW contributed to the conceptual framing of the study, provided the theoretical framework from which the study was based, helped conduct a literature review, helped determine an analytic plan, was the primary author of the introduction and discussion sections, and provided substantive direction and feedback on the methods and results sections. CH contributed to the conceptual framing of the current study and the larger project from which it was drawn, oversaw all efforts to collect data, and provided substantive feedback on the manuscript.

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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.2019.02054/full#supplementary-material

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Students' Achievement Emotions and Online Learning in Teacher Education

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Online learning has become widely accepted and is considered as an important approach that can overcome the limitations of on-campus learning, especially in higher education. The acceptance of learning technologies generally depends on technology related beliefs and the perceived ease of use. It can be assumed that students' emotional experiences, among other factors, have an impact on their use of learning technology. Although research on emotions in technology-supported learning environments has increased in recent years, the question how students experience online learning environments emotionally, and how these emotions are intervened with technology acceptance has not yet been answered in more detail. Up to now, only a limited number of studies has focused on emotions and technology acceptance of university students, especially in teacher education. Therefore, the purpose of this study is to analyze students' technology acceptance and achievement emotions after participating in an online course (in comparison to an on-campus course) in teacher education. Survey data from 182 students (88 of them participated in an on-campus course, 94 students attended an online course) revealed a higher level of positive emotions than of negative emotions, regardless of the learning environment. Students who attended the online course reported a higher level of boredom, anxiety, and anger, but less enjoyment. Furthermore, the results show that online students reported significantly higher levels of achievement task value and technological control. Technological value correlated significantly with enjoyment. In contrast to the theoretical assumptions, no systematic differences were found between the two learning environments for the achievement emotions hope, shame, hopelessness, and anxiety. Regardless of the learning environment, enjoyment was essential for the value that students attach to both, learning content and technology. The online and the on-campus group differed in terms of domain specific achievement outcome. However, these differences cannot be explained by the covariates, the two control and value scales, the technology related beliefs, and age. Main results of the study regarding the control-value theory and implications for online learning environments, as well as limitations of the study are presented and discussed.

Keywords: achievement emotions, online-learning, technology acceptance, on-campus learning, teacher education

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INTRODUCTION

It is becoming increasingly common in higher education institutions to offer online-learning environments. They are considered as an important teaching approach in university that can overcome limitations related to on-campus learning. For example, the internet allows educators to provide learners independent of time and place with new and innovative virtual environments-an attempt to stimulate and enhance their learning process (Brown, 2002). It is well-known that learning environments have an impact not only on cognitive but also on emotional and motivational aspects of learning. But productivity gains and benefits to students and academic institutions promised by learning technologies cannot be realized unless they are accepted and effectively used (Iivari and Ervasti, 1994; Schmid et al., 2017; Hawlitschek and Fredrich, 2018). Studies on emotions in technology-supported learning environments have increased in recent years (Loderer et al., 2018). For example, it was shown that emotional experiences in technology-enriched learning environments are different from those in traditional on-campus courses (Daniels and Stupnisky, 2012; Regan et al., 2012; Butz et al., 2015). Nevertheless, the question how students experience online-learning environments emotionally has not been answered sufficiently, so far. Especially in teacher education there are relatively limited empirical studies on students' emotions in online-learning environments (Keengwe and Kang, 2013; Loderer et al., 2018). To contribute to this research field a study is presented that analyzes the relation between students' control and value appraisals, achievement emotions, their technology acceptance and their learning outcome in the context of an on-campus and an online course in teacher education.

ACHIEVEMENT EMOTIONS, LEARNING PROCESSES, AND OUTCOMES

Emotions that are directly linked to learning processes and achievement outcomes are classified as achievement emotions (Pekrun and Stephens, 2010). Achievement emotions have an effect on learning and achievement, mediated by attention, self-regulation, and motivation (Pekrun et al., 2002; Pekrun, 2006); they direct the person toward or away from learning matters in learning situations (Ellis and Ashbrook, 1988). In the traditional academic context, Pekrun et al. (2011) explored achievement emotions, showing that positive emotions can predict creative thinking and reflecting, thereby supporting academic performance, whereas negative emotions are more associated with lower levels of performance. More precisely, positive emotions such as enjoyment, hope, and pride were positively associated with student effort, self-regulation and more elaborated learning strategies, whereas anger, shame, anxiety and boredom have been associated with lower performances and more external regulation (Pekrun et al., 2011). Furthermore, positive emotions facilitate self-regulated learning (Carver and Scheier, 1990; Boekaerts et al., 2000). Students' perceived self-regulation correlates positively with positive emotions, perceived external regulation correlates with negative emotions (Pekrun et al., 2002). In terms of motivation, the experience of competence and autonomy in learning has been emphasized as important for self-regulation and self-determination (Deci and Ryan, 1985; Ryan and Deci, 2000). Gender-specific differences, are inconsistent and domain-specific, as some studies in school and higher education reported (Frenzel et al., 2007; Zembylas, 2008; Yukselturk and Bulut, 2009; Götz et al., 2012).

Pekrun (2006) classifies achievement emotions based on the control-value theory according to valence (positive vs. negative), degree of activation (activating vs. deactivating) and object focus (activity, outcome prospective and outcome retrospective). Appraisals of control and value are critical antecedents of achievement emotions. Specifically, control is relevant to refer to the perceived causal influence of an agent of achievement. Value (according to Wigfield and Eccles, 1992) describes the perceived importance of actions and outcomes associated with four dimensions of achievement: intrinsic value (personal enjoyment in a given task), attainment value (fulfillment of one's self-schema), utility value (reaching long and short-term goals) and cost (the consequences of engaging in a particular activity) (cf. Butz et al., 2015). Previous empirical work has shown a significant relation between control and value appraisals to achievement emotions. Pekrun et al. (2002) found perceived control to have significant positive correlations with positive activating emotions and significant negative correlations with negative activating emotions. Furthermore, a significant positive correlation between high task value and students' positive activating emotions was described. Students' achievement emotions were also strongly linked to their learning outcome in traditional learning environments (Pekrun et al., 2011).

ACHIEVEMENT EMOTIONS AND ONLINE-LEARNING IN HIGHER EDUCATION

For online-learning environments D'Errico et al. (2016) demonstrated that students' positive emotions across different online-learning activities are higher than negative emotions, particularly during synchronous activities with a teacher and with peers. They also found that experiencing positive emotions during exam preparation strongly correlates with students' motivation supporting students learning process and learning outcome.

Some studies were carried out in technology-enriched environments based on Pekrun's (2006) control-value theory. For example, students' emotions were analyzed in virtual tutoring systems (Lehman et al., 2012) and self-paced online courses (Artino and Jones, 2012). Specifically, Marchand and Gutierrez (2012) showed that students' utility value significantly predicted frustration, in both online and on-campus courses. In virtual tutoring systems, Lehman et al. (2012) showed in an experimental study that limiting students' control in a technology-enriched environment caused higher levels of students' negative emotions.

Students' achievement emotions are, to a great extent, related to domains (Goetz et al., 2007). While achievement emotions were analyzed in different content domains (like school subjects e.g., mathematic, Tulis, 2010; Götz et al., 2012; Bieg et al., 2017), research in teacher education is widely missing. For example, there are some studies on specific math anxiety of pre-service primary school teachers and students' emotions in teaching internship (Malinsky et al., 2006; Jackson, 2015; Yuan and Lee, 2016). Especially in the teacher-education-domain of "school education" there is a lack of research on students' emotions.

Furthermore, a domain represents the general frame or structure and may be defined as learning environment. It may be assumed that online learning environments are different from traditional, face-to-face instruction regarding students' emotions (control and value appraisals), motivation, and learning outcome. In contrast to on-campus courses, students explore online learning environments only individually with regard to their structure and features. In terms of control-value theory, this means that students' achievement emotions may relate not only to the content itself but rather to the digital learning environment. Butz et al. (2015) showed that there are not only significant differences between achievement emotions of students attending an on-campus course and students attending an online course, but that the control value beliefs of students attending the online course also differ with regard to their content-related and technology-related attribution.

ACHIEVEMENT EMOTIONS AND TECHNOLOGY ACCEPTANCE

In general but especially with respect to online learning environments, it may be assumed that students' acceptance and use of technology is a crucial condition of emotional experience and the quality of the learning process and outcome. For example, Daniels and Stupnisky (2012) argued that emotion research in online learning has made it "more important than ever to consider the source of the emotion in addition to the emotion itself," asserting that students are likely to "experience emotions in response to the technology itself." Accordingly, Regan et al. (2012) suggested that the factors affecting emotions in technology-enriched learning environments are different from those that influence emotions in traditional, on-campus environments. Therefore, domain-specificity, as well as technology acceptance and use are both important determinants for analyzing achievement emotions of university students in an online learning environment.

Numerous studies describe how technology is used in different domains. For example, Schmid et al. (2017) showed that teacher students in Germany are in comparison to students of other disciplines the most skeptical one is when it comes to the use of digital media. Moreover, teacher students are less motivated than other students to use digital media.

Research on technology acceptance tries to find factors that explain user attitudes, behavioral intention, and ultimate usage behavior. Davis (1985) postulated the expected benefits (value) and the expected user-friendliness (control) as important predictors of user acceptance in technology enriched learning environments. Technology acceptance is not only reflected regarding the frequency of using technology, but rather affective experience is closely linked to the concept of acceptance: "Acceptance includes a relatively permanent cognitive and affective perceptual component, coupled with a positive willingness to react to an e-learning system (attitude level), as well as a behavioral component that implies an actual use of the system (behavioral level)" (Olbrecht, 2010; translated from German).

The technology acceptance model (TAM) developed by Davis (1985) and Venkatesh and Davis (2000) theorizes that perceived usefulness influences attitudes and beliefs toward technology usage, and it is an important determinant of individuals' intentions to use the technology. Furthermore, Venkatesh (2000) argued that in addition to perceived usefulness the perceived ease of use is an important determinant for attitudes toward technology. Perceived control, intrinsic motivation (playfulness), and emotion (anxiety) have been tested as influencing users' perceptions about technology ease of use. The empirical results indicated that up to 60% of the variability of perceived ease of use was explained in this model (Venkatesh, 2000).

According to TAM, a student's intention to use an online learning system is determined by one's beliefs and attitude toward using the online system and the perceived usefulness of the system. Consequently, when the online learning system is perceived as easy to be used, the higher will be the student's perceived ability to use this online system successfully, and hence the student will experience more positive emotions and perform better in an online course (Venkatesh and Bala, 2008). Individual variables, such as self-efficacy, intrinsic motivation, cognitive absorption (Saadé and Bahli, 2005), and computer anxiety were all confirmed as determinants of the perceived ease of use (Gefen and Straub, 1997; Chang and Cheung, 2001; Gefen et al., 2003). External variables, such as characteristics of the learning environment affect the perceived usefulness directly or indirectly through the perceived ease of use (Compeau et al., 1999).

For example, Wong (2015) showed that teachers in Hong Kong have a positive attitude toward technology, with perceived usefulness having a greater impact on behavioral intention than perceived usability. In Germany, the TAM was used to evaluate the acceptance of the learning management system of the University of Oldenburg by students, lecturers, and administrators (Hamborg et al., 2014). It has to be considered that technology based learning environments may hinder the learning process if the technology is perceived by students being too complex and not useful to enhance their performance. Saadé and Kira (2006) showed in a study based on a structured equation modeling simulation that the influence of emotions (anxiety and pleasure) on perceived usefulness is indirectly moderated through the perceived ease of use.

Further studies focused on information systems and investigated the TAM constructs with respect to affect and anxiety (Agarwal and Karahanna, 2000; Venkatesh and Davis, 2000; Saadé and Kira, 2009). However, research is missing that applied TAM not only to anxiety and affect but also to different positive and negative achievement emotions, and to an online learning environment in teacher education.

AIM AND RESEARCH QUESTIONS

As mentioned above, theoretically it may be assumed that academic performance may be affected by achievement emotions. According to the control value theory, perceived achievement emotions depend on the perception of control and values. We assume that the perception of control values can not only be related to aspects of content, but is also influenced by the learning environment (online vs. on-campus). In an online learning environment, technology acceptance is an integral part of the students' control value beliefs. However, research findings showed that student teachers in particular are skeptical about digital media. But technology acceptance is influenced on the one hand by attitudes and beliefs, on the other hand it affects achievement emotions, and can therefore foster or hinder the learning process. There is still a lack of studies that analyze achievement emotions of teacher students in the online- and on-campus teaching context, and in particular in the domain of "school education," which is an important domain in teacher training. Therefore, this study examines (Pekrun, 2006) control-value theory of achievement emotions in the context of an online and an on-campus learning university course in the domain of school education. Furthermore, technology acceptance based on the technology acceptance model (Davis, 1989; Venkatesh and Davis, 2000) is focused. The study presented in this paper covers a retrospective comparison between students who attended an online or an on-campus course with respect to measures of technology related control-and value-appraisals, domain specific achievement task value and academic control, achievement emotions, and domain specific achievement.

The aim of this study was (1) to analyze to what extent there are differences in the experience of achievement emotions and in the perception of control and value based on individual characteristics (students' age, gender, and high school diploma). It was (2) tested whether differences can be identified with regard to the learning environment (in an online vs. an on-campus course) in terms of control- and value-appraisals, achievement emotions, and technology related beliefs. It is assumed that the online learning environment influences learners' perception of control and value differently (in comparison to an on-campus learning environment), and consequently affects learners' achievement emotions and domain specific learning outcome.

METHODS

Sample

The study was carried out in the context of a university course preparing students for the state teacher examination in the domain school education at a German university. The course was administered as on-campus course until summer semester 2018 and then transferred to an online learning course in the following semester. The teacher training students had therefore no possibility to choose between the online course and the on-campus course. Rather all students participated voluntary because they were highly interested in a systematic preparation for their state teacher examination. Both courses focused on the same domain and topics (theory of education, instructional models and designing learning environments in school), and they were comparable regarding information input, performance records, and literature compendium. In addition, the online course included video-sequences from a lecture at the university, and free accessible video examples from school instruction. The online course consisted of theoretically based scripts, a variety of work sheets, and further literature. In addition, the students used a self-assessment tool. Two tutors supervised the online course and gave feedback regarding the results of self-assessment. The online platform applied in this course is well-established at the university. All slides, working material, literature, and general information were published on the online platform including a forum to pose and discuss questions.

Both courses were equal with respect to workload and educational objectives and contributed equivalently to students' preparation for the state teacher examination. The introduction and implementation of the online-course was consistent for all students. The lecturer who provided the on-campus course was involved in the development of the online-course. Therefore, it can be assumed that students perceived both environments as valuable for their learning process. Hence, endeavors have been made to foster the fidelity of implementation (O'Donnell, 2008). Data collection took place at the end of both courses based on a paper-pencil interrogation. Attendance in both courses, as well as participation in the study was voluntary at all times. All respondents were informed orally before the survey and in writing on each questionnaire about the objectives of the research project, anonymous use of collected data and the voluntariness of their participation. Informed consent was obtained from the participants, contact details for questions and objections were provided. The participants were throughout of full age and neither in need of protection (in contrast to children, sick or unstable persons), nor negative consequences for health or well-being were imperiled by the study. An ethics approval was not required as per applicable institutional and national guidelines and regulations and the informed consent of the participants was obtained by virtue of survey completion. The total sample consisted of $N = 182$ students with predominantly female students (82% female), enrolled in teacher education program. This is generally the case in teacher education. The mean age of the whole sample was $M = 23.12$ ($SD = 2.30$) years. As the course was a preparation course for state teacher examination, most of the students were enrolled in a higher semester ($M = 6.81$; $SD = 2.51$). In the on-campus course participated 88 students (83% female and 17% male; age from 20 to 32 years; $M = 23.20$; $SD = 2.43$). In the online course 94 students took part (82% female and 18% male between 20 and 33 years; $M = 23.03$; $SD = 2.39$). 128 students (63 students in on-campus and 65 students in online-course) completed an achievement test. The participation in the achievement test was also voluntary for all participants in both courses.

Measures

Achievement Emotions Questionnaire (AEQ)

Based on a 5-point scale (1 = not at all; 5 = very much so), students indicated the extent to which they experienced discrete emotions measured with Pekrun et al.'s (2005) Achievement Emotions Questionnaire (AEQ). The following eight emotions were measured: enjoyment, hope, pride, anger, fear, shame, hopelessness, and boredom. The emotions varied in terms of valence and activation: positive activating (enjoyment, hope, and pride), negative activating (anger, anxiety, and shame), positive deactivating (not measure) and negative deactivating (hopelessness, boredom). Participants rated their emotions separately in relation to (1) their overall experience in the on campus-, respectively, the online-course. In total, emotion scales of the AEQ comprised 80 items.

The perceived academic control scale was used to measure the content-related control (e.g., "The more effort I put into my courses, the better I do in them."). The scale for content-related value (achievement task value) was used in orientation to Butz et al. (2015), adapted from Wigfield and Eccles' (1992) study of achievement task value (e.g., "It is important to me that I do well in the course in teacher education").

For all achievement emotion scales good or excellent reliability using Cronbach's α coefficients (between $\alpha = 0.65$ and $\alpha = 0.95$) were received. However, reliability coefficients for the appraisal scales (perceived academic control, achievement task value) were weaker but still good or at least acceptable (between $\alpha = 0.63$ and $\alpha = 0.73$).

Technology Acceptance Model Questionnaire (TAM)

To measure technological control and technological value a part of the TAM questionnaire (Venkatesh and Bala, 2008) was applied. Venkatesh and Bala (2008) originally developed the TAM questionnaire for the use in the business sector. The TAM has been proven to be a powerful tool for examining the technology acceptance of pre- and in-service teachers (Scherer et al., 2019), therefore it was slightly adapted for the higher education context. All Items were measured on a 5 point Likert scale (1 = not at all to 5 = very much so). All items have been translated from English into German language. The reliability coefficients of technological control (e.g., "I have control over using the system." $\alpha = 0.65$) and technological value (e.g., "I find the system to be useful for the course in teacher education," $\alpha = 0.70$) were good or at least acceptable. Technological control and technological value are not the only predictors of teacher students' behavioral intentions (Scherer et al., 2019). Therefore the technology related beliefs scale (e.g., "Technology threatens people more than it benefits them," $\alpha = 0.65$) (Kaspar et al., 2002; Claßen, 2012) was applied in this study, as well.

Domain specific learning outcomes were measured by an achievement test (18 tasks, scoring with a maximum of 31 points) at the end of both courses. The achievement test developed for this study covered single choice questions and open questions with topics for the state teacher examination.

For group sizes, being nearly equal ANOVA is robust to violations of normality in terms of F-accuracy and power (Field, 2013). Shapiro-Wilk-test was significant for technology related beliefs ($p = 0.01$), perceived academic control ($p = 0.04$), achievement task value ($p \leq 0.01$), achievement outcome ($p \leq 0.01$), and all negative emotions ($p \leq 0.001$). For the remaining scales a normal distribution was confirmed. Reliability coefficients and normality are described in **Table 1**.

Rationale for Analysis

All calculations were carried out using SPSS 25, effect sizes were computed with G*Power 3.1. In order to compare means between online and on-campus courses, as well as gender differences, we assessed t-tests. Correlations between continuous variables were calculated by using Spearman's rank correlation coefficient. For each emotion, as well as achievement outcome, analysis of covariance (ANCOVA) was computed using the General Linear Model Procedure (GLM 2). All dependent variables were used simultaneously to test the emotional effects of the online and on-campus course. As covariates, we integrated control appraisals (perceived academic control, technological control), value appraisals (achievement task value, technological value), gender, mean grades of the high school diploma as preceding achievement, and technology related beliefs. As effect size measure, we report Cohen's d values of 0.20 as small effects, above 0.50 as medium, and values of 0.80 as huge effects, correlation coefficients r_s above 0.10 as small effects, 0.30 as moderate effects, and above 0.50 as strong effects, effect size Cohen's q for differences between Fisher-z-correlations of 0.10 as small effects, around 0.30 as moderate, and above 0.50 as strong effects, and partial Eta squared values η^2 of 0.01 as small effects, values above 0.059 as medium effects, and values of 0.138 or bigger as large effects (Cohen, 1988).

RESULTS

In total, descriptive results showed that negative achievement emotions were spread on a low level amongst students while mean levels for positive achievement emotions, control and value appraisals were on a medium level (see **Table 1**). Altogether, students experience more positive than negative emotions in university courses in teacher education.

Gender and Group Differences

Despite huge differences in group size, gender differences regarding appraisals and emotions (see Fischer, 2000) were tested, independently of the learning environment. As for appraisals, perceived academic control [$t_{(170)} = 2.08$, $p = 0.04$, $d = 0.43$], technological control [$t_{(175)} = 2.00$, $p = 0.05$, $d = 0.39$], and achievement task value [$t_{(169)} = 2.53$, $p = 0.01$, $d = 0.55$] showed significant gender differences for females scoring consistently higher than males. Regarding achievement emotions, only for hope [$t_{(168)} = 3.41$, $p \leq 0.001$, $d = 0.71$] significant gender differences were found, females showing more hope. There is no significant gender difference for achievement. It should be noted that only 15 males visited the on-campus course (in comparison to 73 females) and 17 males attended the online course (77 females). Because of the small group size for males (usually at least 20 participants per group are required, see Field, 2013; Huber et al., 2014) and the maladjustment of sample size between both groups, gender was not included as a covariate in further analyses of variance.

TABLE 1 | Descriptive statistics, reliability (Cronbach's α), and normality.

	Items	M	SD	Cronbach's α	Skew (SD)		Shapiro-Wilk
Age	–	23.12	2.30	–	1.76	0.18	$p \le 0.001$
Mean grades high school diploma	–	2.41	0.49	–	−0.31	0.18	$p = 0.06$
achievement outcome	–	17.64	5.43	–	−0.50	0.21	$p \le 0.01$
Technology related beliefs	6	3.74	0.55	0.65	−0.22	0.18	$p = 0.01$
Perceived academic control	8	3.76	0.57	0.73	−0.14	0.19	$p = 0.04$
Achievement task value	4	3.29	0.68	0.63	−0.34	0.19	$p \le 0.01$
Technological control	51	3.77	0.60	0.65	−0.48	0.18	$p = 0.08$
Technological value	51	2.86	0.55	0.70	0.18	0.19	$p = 0.19$
Joy	10	3.02	0.68	0.89	−0.30	0.19	$p = 0.13$
Hope	8	3.58	0.66	0.90	−0.01	0.19	$p = 0.07$
Hopelessness	10	1.43	0.62	0.93	1.52	0.19	$p \le 0.001$
Boredom	11	1.65	0.72	0.94	1.13	0.19	$p \le 0.001$
Shame	11	1.60	0.70	0.94	1.35	0.19	$p \le 0.001$
Pride	9	2.88	0.66	0.83	0.25	0.19	$p = 0.58$
Anxiety	12	1.84	0.83	0.94	1.05	0.19	$p \le 0.001$
Anger	9	1.73	0.68	0.89	0.90	0.19	$p \le 0.001$

Some of the appraisal variables showed significant differences between the online and on-campus group. Achievement task value was rated higher in the on-campus group [$t_{(169)} = 2.53$, $p = 0.02$, $d = 0.55$], while technological control was higher in the online group [$t_{(168)} = 3.41$, $p \le 0.001$, $d = 0.71$]. As for remaining appraisal scales, as well as for age and mean grades of high school diploma, we did not find significant differences.

Regarding achievement emotions, the online group showed less enjoyment [$t_{(167)} = 3.73$, $p \le 0.001$, $d = 0.57$] but more boredom [$t_{(167)} = 2.31$, $p = 0.02$, $d = 0.35$], anxiety [$t_{(168)} = 2.10$, $p = 0.04$, $d = 0.32$], and anger [$t_{(166)} = 3.77$, $p \le 0.001$, $d = 0.58$] than the on-campus group. No significant differences between the two learning environments were found for hope, pride, shame, and hopelessness. Domain specific achievement was significantly higher for the on-campus course than for the online course [$t_{(126)} = 2.20$, $p = 0.03$, $d = 0.39$].

Correlations

Due to non-normality of some scales, correlations were computed as Spearman's rank correlation coefficients. As for the total sample, most of the correlations between perceived academic control, achievement task value and emotions were significant, as theoretically expected (Pekrun et al., 2002; Pekrun, 2006; Pekrun and Perry, 2014). High correlations were found between achievement task value with enjoyment ($r_s = 0.57$, $p \le 0.001$) and hope ($r_s = 0.53$, $p \le 0.001$), respectively medium correlations with boredom ($r_s = -0.41$, $p \le 0.001$), pride ($r_s = 0.40$, $p \le 0.001$), and anger ($r_s = -0.42$, $p \le 0.001$). Academic control showed medium correlations with hope ($r_s = 0.42$, $p \le 0.001$), hopelessness ($r_s = -0.38$, $p \le 0.001$), shame ($r_s = -0.33$, $p \le 0.001$), anxiety ($r_s = -0.41$, $p \le 0.001$), and anger ($r_s = -0.48$, $p \le 0.001$). Correlations for technological control, technological value and technology related beliefs were inconsistent and weaker. While technological value showed medium correlations with enjoyment ($r_s = 0.30$, $p \le 0.001$), hope ($r_s = 0.38$, $p \le 0.001$), and pride ($r_s = 0.40$, $p \le 0.001$), as well as weak significant correlations with hopelessness ($r_s = -0.23$, $p \le 0.01$) and anger ($r_s = -0.20$, $p = 0.01$), only few significant but very weak correlations were found for technological control and technology related beliefs (see **Table 2**). Regarding students' age, we identified significant correlations only for boredom ($r_s = -0.16$, $p = 0.04$) and anxiety ($r_s = -0.18$, $p = 0.02$). Domain specific achievement was significantly positive related to hopelessness ($r_s = 0.23$, $p \le 0.01$) and anxiety ($r_s = 0.20$, $p = 0.03$) but neither with other emotions nor with any appraisals, while mean grades of high school diploma were not significantly correlated to emotions or appraisals at all, except for technological control ($r_s = -0.26$, $p \le 0.01$).

Looking at correlations separately for the two groups, some differences between the online course and on-campus course are remarkable. While effect sizes of most of the correlation differences between the two groups were weak, significant differences were confirmed for technological value and positive emotions: For the online group, technological value seems to be more substantial for the arousal of enjoyment ($r_s = 0.10$, $p = 0.39/r_s = 0.46$, $p \le 0.001$, $q = 0.40$) and pride ($r_s = 0.28$, $p = 0.02/r_s = 0.52$, $p \le 0.001$, $q = 0.29$) as for the on-campus group. The online group also showed higher correlations of achievement task value and enjoyment ($r_s = 0.06$, $p = 0.62/r_s = 0.26$, $p = 0.02$, $q = 0.29$), as well as for perceived academic control, and anxiety ($r_s = -0.25$, $p = 0.02/r_s = -0.52$, $p \le 0.001$, $q = 0.32$) than the on-campus sample. Remarkable differences of correlations between the groups were also shown for domain specific achievement. We found medium differences for achievement task value ($r_s = -0.21$, $p = 0.11/r_s = 0.19$, $p = 0.13$, $q = 0.41$) and technology related beliefs ($r_s = -0.32$, $p \le 0.01/r_s = 0.10$, $p = 0.40$, $q = 0.43$), both showing

TABLE 2 | Correlations for total sample and sub-samples with effect size for differences.

r_s		Perceived academic control	Achiev. task value	Techno. control	Techno. value	Technol. related beliefs
Joy	Total sample	0.18*	0.57**	0.00	0.30**	−0.07
	On-campus sample	0.06	0.44**	−0.08	0.10	−0.09
	Online sample	0.26*	0.64**	0.17	0.46**	−0.12
	q	0.21	0.29	0.25	0.40	0.03
Hope	Total Sample	0.42**	0.53**	0.15	0.38**	0.16*
	On-campus sample	0.36**	0.49**	0.09	0.29*	0.21
	Online sample	0.46**	0.56**	0.29**	0.47**	0.08
	q	0.12	0.10	0.21	0.21	0.13
Hopeless- ness	Total Sample	−0.38**	– 0.28**	−0.18*	– 0.23**	−0.10
	On-campus sample	−0.33**	– 0.37**	−0.17	– 0.25*	−0.16
	Online sample	−0.43**	– 0.17	−0.24*	– 0.21	−0.07
	q	0.12	0.22	0.07	0.04	0.09
Boredom	Total Sample	−0.24**	– 0.41**	−0.10	– 0.13	−0.12
	On-campus sample	−0.12	– 0.43**	−0.13	– 0.03	−0.22*
	Online sample	−0.31**	– 0.29**	−0.15	– 0.18	−0.09
	q	0.20	0.16	0.02	0.15	0.13
Shame	Total Sample	−0.33**	– 0.16*	−0.15	0.06	−0.12
	On-campus sample	−0.23*	– 0.25*	−0.15	– 0.02	−0.14
	Online sample	−0.39**	– 0.07	−0.21	0.10	−0.13
	q	0.18	0.19	0.06	0.12	0.01
Pride	Total sample	0.05	0.40**	0.05	0.40**	0.06
	On-campus sample	−0.05	0.41**	0.05	0.28*	0.09
	Online sample	0.15	0.43**	0.04	0.52**	−0.01
	q	0.20	0.02	0.01	0.29	0.10
Anxiety	Total sample	−0.41**	– 0.13	−0.21**	– 0.09	−0.10
	On-campus sample	−0.25*	– 0.12	−0.14	– 0.14	−0.13
	Online sample	−0.52**	– 0.11	−0.30**	– 0.08	−0.11
	q	0.32	0.01	0.17	0.06	0.02
Anger	Total Sample	−0.48**	– 0.42**	−0.17*	– 0.20**	−0.17*
	On-campus sample	−0.42**	– 0.43**	−0.32**	– 0.11	−0.23*
	Online sample	−0.50**	– 0.35**	−0.19	– 0.27*	−0.17
	q	0.10	0.09	0.14	0.17	0.06
Achiev. outcome	Total sample	−0.02	0.03	−0.07	0.04	−0.13
	On-campus sample	0.06	– 0.21	0.06	– 0.01	−0.32**
	Online sample	−0.12	0.19	−0.07	0.06	0.10
	q	0.84	0.41	0.13	0.07	0.43

***Correlation is significant at p ≤ 0.01 level, *Correlation is significant at p ≤ 0.05 level.*

negative correlations with achievement outcome for the on-campus sample and positive correlations for the online sample. Weak differences were found for both control appraisals with correlations for perceived academic control ($r_s = 0.06$, $p = 0.62/r_s = -0.12$, $p = 0.35$, $q = 0.18$) and technological control ($r_s = 0.06$, $p = 0.65/r_s = -0.07$, $p = 0.57$, $q = 0.13$) being negative for the online sample and slightly positive for the on-campus sample. In total, for the online group we found higher correlations for all perceived academic control and most of the technological value correlations, while for achievement task value, technological control and technology related beliefs correlation differences between the two groups were weaker and inconsistent (see **Table 2**).

Variance Analyses

For the appraisal scales showing many significant correlations with emotion scales, both control and both value scales, as well as technology related beliefs and age were included as covariates in further analyses of variance. Analyses of covariance (ANCOVA) were computed to test differences of students' achievement emotions between the online- and the on-campus group.

Testing the independence of treatment variable and covariate, the means for perceived academic control [$F_{(1,\,170)} = 0.88$, $p = 0.35$], technological value [$F_{(1,\,168)} = 0.47$, $p = 0.49$], technology related beliefs [$F_{(1,\,179)} = 0.07$, $p = 0.79$], mean grades of high school diploma [$F_{(1,\,174)} = 0.18$, $p = 0.67$], and gender [$F_{(1,\,180)} = 0.03$, $p = 0.86$] are not significantly different. But due to the small group size for males and the maladjustment of sample size between both groups, gender was not be included as a covariate in ANCOVA. As already mentioned, t-tests suggest, that achievement task value [$F_{(1, 169)} = 5.67$, $p = 0.02$] and technological control [$F_{(1, 175)} = 15.18$, $p \leq 0.001$] are not independent from the learning environment.

For enjoyment, no significant main effect of the learning environment was confirmed after controlling for the covariate effects, $F_{(1, 155)} = 3.72$, $p = 0.06$, partial $\eta^2 = 0.02$. Significant effects of covariates were found for achievement task value [$F_{(1, 155)} = 45.21$, $p \leq 0.001$, partial $\eta^2 = 0.23$] and technological value [$F_{(1, 155)} = 6.63$, $p = 0.01$, partial $\eta^2 = 0.04$]. Effects of value appraisals—as shown by t-tests—mainly explained significant differences in students' enjoyment between both groups.

For hope, t-test showed no significant difference in emotion value. The main effect of the learning environment on hope after controlling for covariates was not significant, $F_{(1, 155)} = 0.15$, $p = 0.70$, partial $\eta^2 = 0.00$. The covariates perceived academic control [$F_{(1, 155)} = 18.52$, $p \leq 0.001$, partial $\eta^2 = 0.11$], achievement task value [$F_{(1, 155)} = 22.66$, $p \leq 0.001$, partial $\eta^2 = 0.13$], and technological value [$F_{(1, 155)} = 13.62$, $p \leq 0.001$, partial $\eta^2 = 0.08$] correlated significantly with students' hope.

Also no significant differences between the groups were found for pride, but ANCOVAS showed a significant main effect of the learning environment after controlling the effects of the covariates, $F_{(1, 153)} = 7.84$, $p = 0.01$, partial $\eta^2 = 0.05$. Significant effects of covariates were shown for achievement task value [$F_{(1, 153)} = 20.26$, $p \leq 0.001$, partial $\eta^2 = 0.12$] and technological value [$F_{(1, 153)} = 13.66$, $p \leq 0.001$, partial $\eta^2 = 0.08$]. Hence, the effects of the value appraisals seemed to cover the effect of the learning environment on students' pride.

Regarding negative emotions, in$t$-tests we did not find significant differences between the online- and on-campus group for shame and hopelessness. There was no significant effect of the learning environment for shame [$F_{(1, 154)} = 1.59$, $p = 0.21$, partial $\eta^2 = 0.01$] and hopelessness [$F_{(1, 154)} = 0.77$, $p = 0.38$, partial $\eta^2 = 0.01$]. The only significant covariate for both emotions was perceived academic control [shame: $F_{(1, 154)} = 18.44$, $p \leq 0.001$, partial $\eta^2 = 0.11$, hopelessness: $F_{(1, 154)} = 22.88$, $p \leq 0.001$, partial $\eta^2 = 0.13$].

The learning environment had no significant effect on students' anxiety after controlling the covariate effects, $F_{(1, 155)} = 3.75$, $p = 0.06$, partial $\eta^2 = 0.02$. As only significant covariate, perceived academic control [$F_{(1, 155)} = 20.10$, $p \leq 0.001$, partial $\eta^2 = 0.12$] explained significant differences in students' anxiety between the online and on-campus group.

The strongest main effect of the learning environment after controlling for covariates in this study was confirmed for anger, $F_{(1, 153)} = 10.66$, $p \leq 0.01$, partial $\eta^2 = 0.07$. Perceived academic control [$F_{(1, 153)} = 26.12$, $p \leq 0.001$, partial $\eta^2 = 0.15$] and achievement task value [$F_{(1, 153)} = 5.55$, $p = 0.02$, partial $\eta^2 = 0.04$] were significant covariates for students' anger.

Finally, both covariates perceived academic control [$F_{(1, 153)} = 4.18$, $p = 0.04$, partial $\eta^2 = 0.04$], as well as achievement task value [$F_{(1, 153)} = 7.07$, $p = 0.02$, partial η^2 $p \leq 0.01$] correlated significantly with students' boredom. But there was no significant main effect of the learning environment on boredom after controlling for the covariate effects, $F_{(1, 153)} = 3.12$, $p = 0.08$, partial $\eta^2 = 0.02$.

Therefore, the covariate effects can explain significant differences in students' boredom between the online- and on-campus samples.

Surprisingly, for domain specific achievement, neither the main effect, nor the covariates showed significant effects, although the t-test confirmed a significant difference between the groups.

A multivariate analysis of covariance (MANCOVA) was computed to test differences of students' achievement emotions and domain specific achievement between the online- and the on-campus group including all covariates and dependent variables at once. Significant main effects of the learning environment after controlling for the covariate effects were confirmed for anger [$F_{(1, 112)} = 11.72$, $p \leq 0.01$, partial $\eta^2 = 0.10$], pride [$F_{(1, 112)} = 6.92$, $p = 0.01$, partial $\eta^2 = 0.06$] and boredom [$F_{(1, 112)} = 4.55$, $p = 0.04$, partial $\eta^2 = 0.04$], but not for domain specific achievement outcome [$F_{(1, 112)} = 2.70$, $p = 0.10$, partial $\eta^2 = 0.02$]. Significant effects of covariates on emotions were found for academic control (except for pride) and only on positive emotions for achievement task value, technological control, and technological value. For technology related beliefs' the only significant effect was on enjoyment [$F_{(1, 112)} = 6.21$, $p = 0.01$, partial $\eta^2 = 0.05$]. No significant effects by covariates were found for domain specific achievement.

Discussion

Based on the control-value theory of Pekrun (2006), the aim of this study was: (1) to analyze to what extent there are differences in the experience of teacher students regarding their achievement emotions and control and value appraisals with respect to individual characteristics, and (2) to compare teacher students' who attended an on-campus vs. an online-course regarding their achievement emotions, control- and value-appraisals, technology-related beliefs, and finally their domain specific achievement. The second research question refers to the assumptions of the technology acceptance model from Davis (1985). With regard to technology-based learning, our study focuses on a very topical issue. However, these research results cannot easily be applied to teacher training programs. The research project has concentrated in particular on the preparation of teacher students for the state examination in school education. First, the descriptive results showed that negative achievement emotions were on a low level for all students participating in this study while mean levels for positive achievement emotions, control and value appraisals were on a medium level. Altogether, students experience more positive than negative emotions in university courses in teacher education.

Regarding the first research question, the results interestingly showed no systematic gender or group differences regarding achievement emotions, and achievement. This is somewhat surprising since research shows that females report more intensively and more frequently on positive, as well as negative emotions than men, in general (Fujita et al., 1991; Barrett and Lally, 1999; Brebner, 2003). But in online learning environments male students made more socio-emotional contributions than women (Barrett and Lally, 1999). In the present study females scored higher for control and value appraisals and technological control. Following Bandura (2001) it may be argued that in the past students' educational development was largely determined by the schools and universities' learning environment to which they were assigned. However, the internet provides much more opportunities for students to control their own learning (Bandura, 2001). Controlling the own learning means self-regulated learning which is an important determinant in the context of online courses. Female students are more related to self-regulated learning than male students do (Joo et al., 2000). This result may be interpreted in line with previous studies (Yukselturk and Bulut, 2009; Cuadrado-García et al., 2010; Anderson and Haddad, 2019). However, it should be noted that these results might also be caused by the maladjustment of sample size regarding gender distribution.

Further results regarding achievement emotions and their appraisals showed that achievement task value was rated higher in the on-campus group while technological control was higher in the online group. Consequently, domain specific achievement was higher in the on-campus group. This supports the previous assumption that for some students it seems to be difficult to learn self-regulated.

Students in the online course reported higher levels of anger, anxiety and boredom than students in the on-campus course do. These results are in line with some previous studies. For example Regan et al. (2012) claimed that online environments have a distinct overall emotional tone that differs from traditional educational settings. Other studies show that technology-based learning environments lead to a bit more pleasure and less anxiety, although these results are not significant (Loderer et al., 2018). It is argued that the resources (especially the ability to learn self-regulated) students have may have an impact on their emotional experience. Students who learn self-determined need less learning time for a better performance, whereas anxious learners need more time and still achieve worse results, which could explain a higher level of anger (Marchand and Gutierrez, 2012; Schulmeister, 2018). In addition to the student-related determinants, the design of the e-learning environment can also intensify negative emotions. It should also not be underestimated that this course prepares for an important exam (the state teacher examination). In this context, besides direct support when questions arise, encouragement from a teacher can reduce anxiety. This personal face-to-face support is missing in the online course. In this context, it is important to note that, in contrast to the on-campus course, the online course was introduced the first time in the teacher training program. This may have caused a maladjustment regarding criteria for implementation quality due to the fact that the online learning environment was novel for both students and lecturers/tutors. Although the implementation of the online course was based on the intervention's program theory and strictly aligned to the established on-campus course, there may be a certain lack in fidelity of implementation (O'Donnell, 2008).

Regardless of the learning environment significant correlations for academic control and achievement task value with most of the achievement emotions support the control-value-theory (Pekrun, 2006; Pekrun and Perry, 2014). Findings for specific technological control, technological value and technology related beliefs were inconsistent and weak in effect size.

Interestingly, with regard to the second research question, some differences between the online and on-campus course are important to note. For the online group higher correlations were found for all perceived academic control and most of the technological value correlations, while for achievement task value, technological control and technology related beliefs correlation differences between both groups were less strong and inconsistent. Teacher students in online courses have emotions that are more negative and the experience less enjoyment. Contrary to our expectations, these differences are not mainly caused by the effect of the different learning environment, but more rather explained by the effects of control- and- value appraisals. Only for anger and pride, significant differences between both groups were explained by the different learning environment but the effect sizes was just medium following (Cohen, 1988) classification.

The differences in terms of feeling anger may have different causes. For example, the user-friendliness of the online course (technology-related control), the lack of personal contact with the lecturer, or the high demand for self-regulated learning, or trouble with interacting with other students could evoke anger. Less experienced pride compared to the on-campus course could be related to the fact that online learning courses offer less opportunities to compare oneself with others or, for example, to receive direct and personal positive feedback. Online assistance such as forums or tutors who give written feedback do not seem to be able to countervail the lack of personal contact and interaction.

Overall, the effect sizes are relatively small, suggesting that significant influence variables regarding achievement emotions were not considered in the two groups. As for domain specific achievement outcome, neither the main effect, nor the covariates showed significant effects. Previous studies on the relationship of emotions and achievement outcomes in e-learning environments are rare and ambiguous. Liew and Tan (2016) conclude that negative emotions reduce learning success. In contrast, they found no significant influence on positive emotions. In a study by Um et al. (2012), however, positive emotions led to improved performance in a transfer test but not in an understanding test.

It seems that other factors besides collected variables may play a more decisive role for achievement outcomes, e.g., intelligence, previous knowledge or achievement motivation. Due to the fact that achievement outcomes were not in the main focus of this study, those factors have not been examined.

Low effect sizes for achievement outcomes may be underestimated due to an attrition effect toward the achievement test. This voluntary test was completed by only 70% (69% in online course, 72% in on-campus course) of the students, so that the relatively small sample size of the study was even more reduced. As effect sizes being sensitive to the sample size, this may have caused lacking significance of the findings. Also the range of measured achievement and therefore the potential explanation of variance could be restricted through reduced sample size. In addition, the shrinking of participants in the achievement test may be a self-selection, given that e.g., only very (extrinsic) motivated and/or unconfident students took part. Opposite effects of these extreme groups may collide and lead to weak overall effects. As having no detailed information about not participating students and the reasons for their absence, potential consequences stay notional and vague.

In sum, it has been shown in this study that the learning environment might affect students' achievement task value and technological control. On the other hand, the results indicate that the learning environment (of online vs. on-campus course) seemed to have only weak effects on students' achievement emotions in this study, but these direct effects might be underestimated as they may be mediated through control- and-value appraisals. Therefore, further analyses are needed.

Regarding the existing research, this study applied Pekrun's (2006) control-value theory in the context of an empirical comparison of an online and an on-campus learning environment in a specific domain, namely teacher education. Furthermore, we measured technology acceptance. Taken together, this study's focus on an online learning environment, along with the application of Pekrun's (2006) control-value framework and the technology acceptance model (Venkatesh and Bala, 2008), is a new contribution to the research field of emotions in teacher education and online learning.

Limitations and Future Research

Regarding the cross sectional design of the study it is a clear limitation that the on-campus and the online courses were rated by students just one time and only with a retrospective focus. Measuring learning processes and emotions several times would have given the opportunity to test for longitudinal effects. Furthermore, the sample was relatively small and with a high percentage of female students—although this gives a representative picture of the distribution between female and male students in teacher education. With such a sample, gender effects have to be interpreted very carefully. Beyond, it was not possible to select students randomly to control for possible influencing factors on the individual level.

Students' technological control, technological value and technology related beliefs correlated only weak and ambiguously with achievement emotions, so that the contribution to the clarification of effects of the different learning environment was rather small. Therefore, the results should only be interpreted with caution. It may be assumed that the learning environment is only one of many other influencing factors, which have an impact on emotions, as well as on the learning process and outcomes. In future studies, further variables should be measured, such as self-regulation ability, self-efficacy, subject specific competencies, and personality. It would be also relevant to measure contextual factors such as support by a lecturer, quality of learning material, or accessibility to core technological features, such as to the online-chat.

Finally, it has to be pointed out that the online course analyzed in this study has just been established without a testing phase, while a very experienced lecturer has conducted the on-campus course in the same way for several semesters. Additionally it should be noted that research on achievement emotions mainly uses self-reports depending on subjectivity and social desirability. Further research in this field should apply research methods that allow a process oriented measurement, as well as observation of students to provide an added value with respect to different (cognitive, subjective, expressional, and behavioral) dimensions of emotions.

To conclude, technology based learning environments are a meaningful future educational setting, and many university students are already used to them. But there is still little known about the emotional and cognitive learning experiences in this environment. With the introduction of e-learning courses, students should also be supported in acquiring self-regulation strategies. While online learning environments may improve access to higher education, it should be considered that these learning environments affect the relationships between students' control and value appraisals, emotions, and achievement in a specific way. Especially for designing effective online learning environments, these relationships have to be taken into account.

From our point of view, further research should focus on specific aspects and tools of online learning environments and analyze them in more detail. The application of different qualitative (e.g., interviews, video observation) and quantitative methods (e.g., state-measurements, scripts of using online tools) may be fruitful. Finally, experimental studies (with variations of different structures and tools of online learning environments based on longitudinal designs would allow a process oriented and differential analysis of the relationships between students' control and value appraisals, achievement emotions, and performance.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

MS performed the measurements. MG-Z supervised the work. SM and MS analyzed the data. MG-Z, SM, and MS were involved in planning and drafted the manuscript. MG-Z took the lead in writing the manuscript, closely supported by MS and SM. All got involved in the interpretation and provided critical feedback and helped shape the research, analysis, and manuscript.

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Affective Learning in Digital Education—Case Studies of Social Networking Systems, Games for Learning, and Digital Fabrication

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Technological innovations, such as social networking systems, games for learning, and digital fabrication, are extending learning and interaction opportunities of people in educational and professional contexts. These technological transformations have the ability to deepen, enrich, and adaptively guide learning and interaction, but they also hold potential risks for neglecting people's affective learning processes—that is, learners' emotional experiences and expressions in learning. We argue that technologies and their usage in particular should be designed with the goal of enhancing learning and interaction that acknowledges both fundamental aspects of learning: cognitive and affective. In our empirical research, we have explored the possibility of using various types of emerging digital tools as individual and group support for cognitively effortful and affectively meaningful learning. We present four case studies of experiments dealing with social networking systems, programming with computer games, and "makers culture" and digital fabrication as examples of digital education. All these experiments investigate novel ways of technological integration in learning by focusing on their affective potential. In the first study, a social networking system was used in a higher education context for providing a forum for online learning. The second study demonstrates a Minecraft experiment as game-based learning in primary school education. Finally, the third and the fourth case study showcases examples of "maker" contexts and digital fabrication in early education and in secondary school. It is concluded that digital systems and tools can provide multiple opportunities for affective learning in different contexts within different age groups. As a pedagogical implication, scaffolding in both cognitive and affective learning processes is necessary in order to make the learning experience with emerging digital tools meaningful and engaging.

Keywords: affective learning, collaborative learning, digital education, digital fabrication, maker education, social networking systems

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INTRODUCTION

Current technological transformations in society bring new abilities for sensing, adapting, and providing information to users within their environments (Laru et al., 2015; Chang et al., 2018; Huang et al., 2019). This can, for example, deepen, enrich, and guide educational and professional interactions (Rummel, 2018; Stracke and Tan, 2018). Technologies have already been used to improve participants' cognitive learning experiences, to create efficient and constructive communication, and to effectively use shared resources, as well as to find and build groups and communities (Jeong and Hmelo-Silver, 2016).

However, research has also shown that technology can alter social interactions. For instance, technology can affect the self-disclosure and identity management of individuals (Yee and Bailenson, 2007) as well as provide an arena for bullying (Santiago and Siklander, in review), thus running the risk of inhibiting productive social interactions or providing less than optimal support for them. In terms of group interactions and technologically enhanced collaborations in particular, challenges may relate to a cognitive load too excessive to efficiently handle content and task related activities simultaneously with social and technological factors (Bruyckere et al., 2015; May and Elder, 2018; Pedro et al., 2018) or the lack of available important social cues for social information processing, particularly in text-based communications (Kreijns et al., 2003; Walther, 2011; Terry and Cain, 2016). This discussion of technology's challenges is particularly relevant in bigger online learning communities and social networking systems, but also in small group collaboration (Bodemer and Dehler, 2011; Davis, 2016), such as in the context of games for learning, digital fabrication, and "maker" education.

Social networking systems, games for learning, and digital fabrication (making) will be further examined in this paper with case study examples. These case examples are chosen with regard to their likely impact on learning and instruction in current and future educational designs (Woolf, 2010; Chang et al., 2018; Huang et al., 2019). One of the main challenges that teachers face in the context of adopting contemporary technologies to support learning activities is the fact that professional knowledge and competencies are needed in both technology and pedagogy (Valtonen et al., 2019). This means that in addition to technical aspects, it is important that teachers understand and consider the basic processes of how people learn as an individual and as part of collaborative group (Häkkinen et al., 2017). Therefore, it is essential to explore and characterize learning and interaction processes, including cognitive and affective components, when digital tools and learning environments are implemented in educational contexts.

This paper is grounded in the premise that technologies should enhance the cognitive and affective learning processes in collaboration. Emotional experiences and expressions are recognized as an especially central part of successful collaborative learning (Baker et al., 2013). The use of potential technological enhancements in collaboration necessitates an interdisciplinary understanding of the social factors and emotional dynamics influencing the learning and interaction processes. We argue that when the affective interactions are more thoroughly accounted for and enhanced through technology, they can have positive implications for cognitively effortful and affectively meaningful collaborations, thus contributing to better competence building, social equity, and participation in group workings (Järvenoja and Järvelä, 2013; Isohätälä et al., 2017; Järvenoja et al., 2018).

COLLABORATIVE LEARNING AS A COGNITIVE AND AFFECTIVE LEARNING PROCESS

Collaborative learning is a specific type of learning and interaction process in which learners in a group share their overall learning process by negotiating their goals for learning and coordinating their mutual learning processes together (Roschelle and Teasley, 1995). Since the process of collaborative learning consists of discussions, negotiations, and reflections on the task at hand, it has the potential to lead to deeper information processing than individuals would achieve alone (Dillenbourg, 1999; Baker, 2015). The premise for successful collaborative learning is that group members are actively engaged in building, monitoring, and maintaining their shared learning processes on cognitive and affective levels (Barron, 2003; Näykki et al., 2017b; Isohätälä et al., 2019a). This means that interpreting and understanding who you are working with, what is being worked on, and how your actions and emotions affect others is essential to obtain successful collaborative learning (Linnenbrink-Garcia et al., 2011; Miyake and Kirschner, 2014). We follow the conceptualization that views successful collaborative learning as a combination of an outcome (deeper understanding and developed individual and group learning skills), and an experience (a student's own evaluation and interpretation of how [s]he succeeded) (Baker, 2015).

In general, affective processes play an important role in individuals' learning as well as in groups' learning and interaction processes (Linnenbrink-Garcia et al., 2011; Järvenoja et al., 2015; Polo et al., 2016; Isohätälä et al., 2019b). Students' emotions, such as enjoyment, boredom, pride, and anxiety, are seen to affect achievement by influencing their involvement and attitude toward learning and learning environments (e.g., Pekrun et al., 2002; Boekaerts, 2003, 2011; Pekrun and Linnenbrink-Garcia, 2012). These emotional experiences naturally have a great effect on how students and/or groups work on their task assignments. In our research, we have been particularly interested in the role of emotions as a part of groups' coordinated learning processes—how group members experience emotions and how they express their emotions in order to maintain and restore (when needed) a socio-emotionally secure atmosphere for learning and collaboration (Näykki et al., 2014). This has been done by observing student groups' interaction processes to understand how emotions are expressed, reflected, and shaped by social interaction (Baker et al., 2013; Isohätälä et al., 2017; Näykki et al., 2017a).

We ground this study in the increasing empirical understanding of the multifaceted interaction processes involved in collaborative learning, integrating cognitive, and affective components as the core of collaboration (Volet et al., 2009; Järvel et al., 2010, 2013; Näykki et al., 2014; Ucan and Webb, 2015; Sobocinski et al., 2016; Isohätälä et al., 2019a; Vuopala et al., 2019). In theory, collaborative learning requires group members to be aware of and to coordinate with their cognitive, metacognitive, motivational, and emotional resources and efforts (Hadwin et al., 2018). In practice, this involves students sharing their thinking and understanding, as well as showing verbally and behaviorally their commitment to the task and to the group (Järvelä et al., 2016; Isohätälä et al., 2017).

HOW TO ENHANCE OPPORTUNITIES FOR COGNITIVE AND AFFECTIVE LEARNING PROCESSES WITH PEDAGOGICAL DESIGNS AND DIGITAL TOOLS

Prior research has suggested that students need a scaffolding to engage with and progress in active and effective collaborative learning (Kirschner et al., 2006; Belland et al., 2013). In order to favor the emergence of productive interactions and thus to improve the quality of collaborative learning, different pedagogical models, and design approaches have been developed in collaborative learning research (Hämäläinen and Häkkinen, 2010). One example of a strategy to enhance the process of collaboration is to structure learners' actions with the aid of scripted cooperation (Fischer et al., 2013). Scripting is defined as "a set of instructions prescribing how students should perform in groups, how they should interact and collaborate and how they should solve the problem" (Dillenbourg, 2002, p. 63). In other words, scripts support collaborative processes by specifying, sequencing, and distributing the activities that learners are expected to engage in during collaboration (Dillenbourg, 2002; Kollar et al., 2006). Scripts typically aim to smooth coordination and communication, but there are also scripts that aim to promote high-level socio-cognitive activities—e.g., explaining, arguing, and question asking (Weinberger et al., 2005; Fischer et al., 2013; Tsovaltzi et al., 2017)—or acknowledge and promote socio-emotional activities (Näykki et al., 2017a).

In addition to designing certain learning activities with the scripting approach, previous research in the field of technologically enhanced learning has demonstrated how technology can function as a tool for individuals' and groups' learning, allowing meaningful learning interactions to occur (Jeong and Hmelo-Silver, 2016; Rosé et al., 2019). Recently, more generic digital tools such as social networking tools, games, or mobile phones have been increasingly popular among educators and instructional designers (Ludvigsen and Mørch, 2010; Laru et al., 2015). Such tools are being progressively more used in educational contexts but are not usually specifically designed to help students to engage in cognitively effortful interaction such as problem solving, collaborative knowledge construction, or inquiry learning (Gerjets and Hesse, 2004). Nor are these tools often designed for affectively meaningful interactions such as expression and reflection of emotional experiences (Jones and Issroff, 2005; Jeong and Hmelo-Silver, 2016).

Altogether, these tools rarely offer specific instructional guidance concerning collaborative learning (Kirschner et al., 2006). Instead, both generic and specific cognitive tools (Kim and Reeves, 2007) typically provide an open problem space, where learners are left to their own devices. In such spaces, learners are free to choose (a) what activities to engage in with respect to the problem at hand and (b) how they want to perform those activities (Kollar et al., 2007). Modern social networking systems, games for learning, and contexts for digital fabrication and making can be categorized into open problem spaces where learning is often supported without tightly structured socio-technological instructional design (Laru et al., 2015; Hira and Hynes, 2018).

CASE EXAMPLES IN DIGITAL EDUCATION

We present and explore four cases (**Table 1**) involving social networking systems, games for learning, and digital fabrication where emergent and contemporary technologies are used to support collaborative learning in open problem spaces, especially focusing on cognitively effortful and affectively meaningful learning in groups. These emergent digital tools, with their respective socio-technical designs, were selected because they each represent different ways to provide opportunities for affective learning—for experiencing and expressing emotions as well as for supporting equal participation and a safe group atmosphere (cf. Baker et al., 2013). Traditionally all these technologies and activities have mainly been present in informal contexts as associated with social lives of the users, and thus, it can be assumed that this is one reason why they are able to access emotions in powerful ways. These technologies also hold the potential for learning in formal education as well, as a part of learning activities organized by educational institutions (Pedro et al., 2018).

CASE 1: Social Networking Systems for Supporting Equal Participation and Collaborative Argumentation

Social Networking Sites (SNS), such as Facebook, Twitter, and Instagram, are widely used communication platforms worldwide because of easy access and unrestricted interactivity (Bowman and Akcaoglu, 2014). They are mostly used for informal, everyday communication, but these platforms also offer possibilities to education by allowing idea sharing and a knowledge co-construction process (Laru et al., 2012; Vuopala et al., 2016; Tsovaltzi et al., 2017) where learners are interacting and building new frameworks to extend the knowledge and understanding of each individual student (Janssen et al., 2012). These productive interactional processes include sharing ideas, negotiating, asking thought-provoking questions, and providing justified arguments (Vuopala et al., 2016). Studies have also shown that the use of SNS can be beneficial for learning purposes by, for example, fostering affective interactions in academic life, allowing students to share emotional experiences, and providing support for socio-emotional presence (Pempek et al., 2009; Bennett, 2010; Ryan et al., 2011; Wodzicki et al., 2012; Bowman and Akcaoglu, 2014).

However, previous studies have proven that in SNS the level of knowledge co-construction and argumentation is often superficial, lacking solid arguments as well as affective interaction (Bull et al., 2008; Dabbagh and Reo, 2011). Engaging in these cognitive and affective processes is not necessarily spontaneous, therefore, it is essential to support students' learning processes. One way to promote productive collaborative learning is through the use of pedagogical scripts that have been used for guiding

TABLE 1 | Summary of the case examples: social networking systems, games for learning, maker education, and digital fabrication.

Case number	Case title	Context	Participants (N)	Learning environment	Time	Pedagogical support	Affective and cognitive focus
CASE 1	Social Networking System	University course	University students ($N = 88$)	Facebook group	7 weeks	Micro-script	Equal participation, collaborative argumentation
CASE2	Games for learning	After school club (K.-12 students)	Primary school students ($N = 16$)	Minecraft EDU with tailored map and selected modifications	8 weeks	Game narrative and teacher as one player	Creativity, problem solving, programming skills
CASE3	Makers education and digital fabrication	Early childhood education	Daycare children ($N = 16$)	Daycare unit, forest, Fab Lab	2 weeks	Playful making process	Playfulness, maker education, understanding healthy food
CASE 4	Digital Fabrication	School visits in Fab Lab	Primary school students ($N = 41$), teachers ($N = 5$) and facilitators ($N = 2$)	Fab Lab	3–5 days	Open ended, ill-structured hands-on problem solving	Digital fabrication, problem solving, creativity, programming skills

learners to engage both in knowledge co-construction and in affective processes (Dillenbourg, 2002; King, 2007; Fischer et al., 2013; Näykki et al., 2017a; Wang et al., 2017).

This case study presents research in which Facebook was used as a platform for argumentation. Higher education students ($N = 88$) from one German and two Finnish universities participated in a seven week long online course named "CSCL, Computer Supported Collaborative Learning" (Puhl et al., 2017). The course included the following learning topics: scripting, motivation and emotions, and metacognition. Students worked in ten groups with four participants in each. The first phase of the course was orientation and introduction (1 week). The main aim of the orientation week was to allow group members to meet each other (online) and to create a safe group atmosphere. After the orientation phase, each small group had a 2 week period to discuss each presented topic (overall, 6 weeks) in their own closed Facebook group.

Small group collaboration was supported with a micro-script (Weinberger et al., 2007; Noroozi et al., 2012), which guided learners into knowledge co-construction and argumentation. The study was particularly focused on exploring how different preassigned roles and sentence openers supported argumentation (Weinberger et al., 2010) and contributed to the groups' affective interactions especially by encouraging students to participate equally and motivating the group atmosphere. The roles given to each student were especially designed to prompt not only productive argumentation but also socio-emotional processes. The roles assigned to the students were: captain (motivated the group members' participation), contributor (identified and elaborated pro-arguments), critic (identified and elaborated counter-arguments), and composer (constructed a synthesis of the pro- and counter-arguments). To support their enactment of the named role, the students were given specific sentence openers, such as: "Have you all understood what is meant by..." (captain), "My claim is…" (contributor), "Here is a different claim I think needs to be taken into account …" (critic) and "To combine previously mentioned perspectives it can be concluded…" (composer). The script was faded out as the course proceeded. During the first 2 weeks, both the roles as well as the sentence openers were used to guide productive collaboration. Next, only the roles were given as a script, without sentence openers. However, students got a different role compared to the first week. And after that, the whole script was faded out; it was expected that, by that time, the learners had internalized the script and were thus able to interact purposefully without external support (Wecker and Fischer, 2011; Noroozi et al., 2017).

To reach an understanding of how the students interacted during the course, all discussion notes on Facebook were analyzed (Puhl et al., 2017). This was done by categorizing the discussion notes according to their transactivity to the following categories: quick consensus building, integration-oriented consensus building and conflict-oriented consensus building and in terms of their epistemic dimension: coordination, own explanation, misconception, learning content (Weinberger and Fischer, 2006). In general, students participated equally in the joint discussions according to the roles given to them, but the actual use of the sentence openers was more random. The main results indicated that, with this design, students engaged actively in argumentative knowledge co-construction, and that there were no significant differences in terms of the amount of activity between the differently scripted studying phases. All the assigned roles were treated as equally important in terms of both cognitive and affective aspects of learning even though they promoted different aspects of socio-emotional processes. However, during the course it came clear that the role of captain was especially crucial in promoting a good group atmosphere and keeping the motivation level high. The following examples from group discussions illustrate the captain's contributions:

> "Thanks for your comments. These are all interesting thoughts. I agree with you that there is not a 'one fits for all' solution. While regarding thought on 'obligation', well I agree that there is that component as well in any learning situation."

"If you have some questions while you are reading, if something is unclear or something is just interesting, I'd like to encourage you to post something into the group that we can talk about it. So, enjoy the rest of your weekend and have a nice week."

These examples illustrate how the captain encouraged group members to participate in joint discussions by giving positive feedback, and by making suggestions how to proceed. The results showed that the roles functioned also for affective level learning by, for example, managing the discourse, inducing conflicts through pro- and counter-arguments, and resolving the conflicts by bringing the different perspectives together. To conclude, in this case example, the roles assisted equal participation, feelings of belonging, and good working relationships between learners. The students' interaction was supportive, and arguments were well-structured. Furthermore, roles kept the discussion on task and there was no confusion about the responsibilities (Bruyckere et al., 2015; May and Elder, 2018; Pedro et al., 2018).

This example of Facebook as a SNS shows how an actively used "everyday digital tool" provided easy access to and a familiar platform for productive collaborative learning. While students used Facebook regularly for informal communication, they actively followed study-related discussions at the same time. It was obvious that in this case informal and formal communication and collaboration supported each other. The students in this study were asked to follow a specific micro-script, and thus their opportunities for designing their own learning activities were rather limited. Another way to integrate informal and formal education and to provide more open opportunities for creative thinking and problem solving is the use of games for learning, as will be described in the following example.

CASE 2: Games for Learning as Supporting Students' Creativity, Problem Solving, and Programming Skills

Currently, there is an increasing interest in implementing games in an educational context (Nebel et al., 2016; Qian and Clark, 2016). Connolly et al. (2012) found in their systematic literature review that playing computer games is linked to a range of perceptual, cognitive, behavioral, affective, and motivational impacts and outcomes. However, previous studies have shown that the game environment itself does not guarantee deep learning and meaningful learning experiences (Lye and Koh, 2014; Mayer, 2015). The challenge is that many educational games follow simple designs that are only narrowly focused on academic content and provide drill and practice methods similar to worksheets or stress memorization of facts (Qian and Clark, 2016).

Careful pedagogical design is needed in order to implement an educational game environment as a holistic problem-solving environment. For example, game design elements can provide opportunities for learners' self-expression, discovery, and control. These types of playing activities can create a learning environment that supports students' cognitively effortful and affectively meaningful learning, for example in terms of programming skills, creativity, problem solving (Kazimoglu et al., 2012; Qian and Clark, 2016), and motivational engagement (Bayliss, 2012; Zorn et al., 2013; Pellas, 2014).

This study was designed to integrate informal and formal learning activities for students in the context of an after-school Minecraft club. Minecraft is a multiplayer sandbox game designed around breaking and placing blocks. Unlike many other games, when played in its traditional settings, Minecraft does allow players the freedom to immerse themselves into their own narrative: to build, create, and explore. Minecraft, along with modification software ("mods"), has the tools for teaching and learning programming (Zorn et al., 2013; Risberg, 2015; Nebel et al., 2016).

The participants in this case study were primary school students ($N = 16$, 11 boys, 5 girls, 11 years old) who participated in the after-school Minecraft club (Ruotsalainen et al., 2020). The club included eight 90-min sessions of face-to-face meetings as well as unlimited collaboration time in the virtual space between the meetings. Minecraft gameplay was based on a storyline wherein pirates tried to survive after a shipwreck, escape, and expand their territories to other islands. To be able to escape from the island, several main quests (tasks) had to be solved: tutorial (weeks 1–2), electrical power (week 3), area and volume calculations (week 4), survival of zombie apocalypse (week 5), European flags (week 6), programming (week 7), and a final meeting (week 8). The majority of these quests were ill-structured and challenging problems. Therefore, the designed structure included repetitive pedagogical phases with teacher scaffolding (described below), but also full access to all content at any time (but not guided and explained).

Each week followed a similar structure:

a) Introduction (club meeting), a basic introduction to the session's theme.
b) Guided in-game tour (club meeting) where the respective main quest was presented, trained, and materials were distributed. The Captain (teacher) provided scaffolding for pirate students.
c) Main Quest (club meeting; between meetings, students performed task(s), e.g., building structures or coding).
d) Reflection (club meeting), a group discussion at the end of each session to reflect on task design and game experiences.
e) Free to Play (gameplay between meetings), the phase where students were able to continue their existing activities or explore the game on their own.
f) Captain's Quest (gameplay between meetings), which was similar to the main quest, but tasks were voluntary for students.
g) Presentation(s) for Rewards (next club meeting), an activity where students presented what they had done in the main quest and the Captain's quest. After successfully completing quests, student pirates received rewards in the form of Minecraft objects. Without rewards, student pirates were not able to survive, form society on the island, build better houses, or complete ("win") the game.

The tools that were designed for the club were the Minecraft game, island map, and three Minecraft modifications (**Figure 1**). The game map was designed to include problem-based puzzles

FIGURE 1 | (A) Island at the start of the game when students' ship has wrecked. **(B)** Island after students have created their society (game activity between club meetings, Captain's quests). **(C)** Hall of quests, which was the place for information sharing, reflection, and teleportation to the science center. **(D)** Science center (main quests were played here) with a view into the coding quest.

(quests) and a narrative about escaping from the deserted island after a shipwreck. Modifications enabled teachers to change Minecraft's 18 game rules, alter game content, redesign textures, and give players new abilities within the game (Kuhn and Dikkers, 2015). While the island map provided context for game narrative and gameplay itself, modifications worked as an engine, which enabled real electrical power simulation (ElectricalAge), programming (ComputerCraft), and easy redesign of the learning experiences (WorldEdit) during the game. The three major structures were: a deserted island with a sunken ship (home for the students' characters), the hall of quests, which was a building on the island (main quests were presented here), and the science center located outside of the island (a place with free access to formal lessons and informal training). Collaborative learning was regarded as a fundamental element of the activity in Minecraft gameplay. Therefore, many structural elements were designed to support collaborative game experience; for example, border blocks forced students' avatars to live in a small area next to each other. However, there were no detailed structures or scaffolds designed as a support for collaboration. Students were inhabitants of the Minecraft world, where collaboration is necessary to survive. The following example explains how one student described his/her experienced reasons for collaboration in an interview that were conducted right after the each face to face meeting. In this example one student describes his actions in the main quest "survival of zombie apocalypse."

> "We all came together at the 'hall of quests', it was safe and we had time to make up a plan together since there were no zombies. All players were here and we discussed what to do to survive. Most of my friends helped me and I helped them to survive. We had to trust each other, to survive you do teamwork."

Overall, the Minecraft game in this study was designed so that knowledge acquisition was prompted (e.g., about electricity), skill acquisition was supported (e.g., programming and collaboration), and affective and motivational outcomes were rewarded (e.g., strategies to accomplish quests and reflections during the meetings). Degrees of freedom guaranteed that the original constructionist gameplay was available for more advanced players, which was needed to avoid frustration or domination during the game (Connolly et al., 2012; Nebel et al., 2016). The students underlined in an interview how emotional the game playing experience was for them: "I usually do not really like these guys, but I am kind of sad that this experiment is over. I'm going to miss our village and society a lot. I am pretty sure I won't speak to half of the players anymore."

To conclude, Minecraft is an example of a constructivist gaming experience in which players can play, modify the game, or even create their own games for learning (Kafai and Burke, 2015). In this case study, the students modified the game. This type of gaming approach has a strong pedagogical connection with another contemporary digital education phenomena: "maker's culture," making and digital fabrication. While Minecraft is about a block-based world of “digital making,” digital fabrication and making enables learners to design their own artifacts in the situated (unstructured and open-ended) problem solving contexts.

CASE 3: Digital Fabrication and Makers Education for Supporting Collaborative Learning

Making is a central concept in the maker education approach. In practice, making is “a class of activities focused on designing, building, modifying, and/or repurposing material objects, for playing or useful ends, oriented toward making a ‘product’ that can be used, interact with, or demonstrated” (Martin, 2015, p. 31). Digital fabrication is a concept in parallel with making that is commonly used to describe a process of making physical objects by utilizing digital tools for designing. Digital fabrication activities can be conducted in the context of Fab Lab, that is, a technical prototyping platform “comprised of off-the-shelf, industrial-grade fabrication and electronics tools, wrapped in open source software” (Fab Foundation, n.d.).

The basic idea of maker culture and digital fabrication places the learner firmly at the center of the learning process with a focus on a connection to real-world issues and meaningful problems. In the context of digital fabrication and Fab Labs, complex, undefined, open-ended, and unstructured problem-solving activities are typical (Halverson and Sheridan, 2014; Chan and Blikstein, 2018). Prior studies in educational contexts have found that maker culture activities hold great potential for developing a sense of personal agency, improving self-efficacy and self-esteem, and supporting learners in becoming an active member of a learning community (Halverson and Sheridan, 2014; Chu et al., 2017; Hira and Hynes, 2018). Taylor (2016) has concluded that the activities in “makerspaces” can be transformed into classroom projects that match the goals of twenty-first-century education. In other words, the overall learning experience through making can be empowering and can nurture students’ creativity and inventiveness among other twenty-first-century skills (Blikstein, 2013; Iwata et al., 2019; Pitkänen et al., 2019).

This case study presents research that was conducted in an early education context (Siklander et al., 2019). Four to 5 year-old children ($N = 16$) took part in the making process in indoor and outdoor making environments: kindergarten, a forest, and Fab Lab facilities at the university (https://www.oulu.fi/fablab/).

In this case study, a narrative was built about an owl, a hand puppet, who asked for the children’s help. The topic for learning was healthy food, and the aim was that the children learn to identify healthy and unhealthy food and to create a healthy plate through making, playing, and discussions. The experiment followed the playful learning process (Hyvönen, 2011; Hyvönen et al., 2016) and started with an orientation phase that aimed to support the children’s activation of prior knowledge by creating a concept map about the topic of “good health.” In other words, the starting point for children’s making activities was their own investigations of the concept and events closely connected with their living environments and personal experiences. After the orientation, the hand puppet owl asked for the children’s assistance in creating a healthy plate. In the first making activity, children searched for and cut out figures representing healthy food and created a healthy plate by using the selected figures. Next, the owl asked the children to cook food in the nearby forest and to serve it to the forest animals. The children orienteered to the forest, collected items in accordance with the recipe, cooked the food, and laid the table on the ground. After feasting with the children, the owl asked children to feed all the forest animals. This challenging task requested children to prepare fabricated food.

The next phase of the experiment was conducted in the FabLab. The researchers’ role (Hyvönen, 2011) was to understand and support the children’s cognitive, emotional, and social views on making activities, although the environment was technical, noisy, and adult sized. The aim was to provide an emotionally and physically safe atmosphere and to encourage children to interact, enjoy, and express themselves while working together. After using the different senses (e.g., the smell of burning wood diffusing from the laser cutter), and taking a look at the facilities, technological equipment, and displayed outcomes, the owl’s request was discussed. First, a big plate out of plywood was laser cutted. Research assistants guided the activities, and they let each child test the steering device and press the buttons. The children watched the cutting process very intensely, and were delighted while the plate was done, wanting also to touch and smell it. Finally, each child chose his or her favorite Muumin character and laser cut it to take home.

The process ended with the elaboration phase, in which the photo-elicitation method was used (Dockett et al., 2017) for reflecting on and discussing the entire process with the children. They chose photos which they felt were interesting and inspiring during the process; thus, these photos represent positive emotions. They chose photos taken from the forest trip and the FabLab activities. The most meaningful objects in the forest were the map, which facilitated orienteering, the recipe, which allowed them to find items and count them, and the fire, which they set for cooking. These elements combine affective and cognitive learning with physical actions. Children held the map each by each, and carefully looked at it and the path ahead (**Pictures 1**, **2**).

The Fab Lab was regarded also as a meaningful makerspace. With its many technologies, it provided totally new experiences for the children. It was experienced as exciting and activated the children’s collaboration, imagination, interest, and inspiration. During the experiment, the children’s interaction was filled with humor and evolved in the process of thought bouncing.

In this case study, making activities and the playfulness of this process (Hyvönen, 2011; Hyvönen et al., 2016) denoted affectivity in two ways: first, the process of making was designed to allow children to experience emotions such as curiosity, joy, agency, acceptance, and excitement, but also negative feelings such as impatience, frustration, and disappointment (see also Hyvönen and Kangas, 2007). Secondly, during the activities and interaction, children were able to learn to recognize, and regulate their emotions. This was evident particularly in collaborative situations when children had to wait their turns, or when they were together and excited to express their ideas. To conclude, it can be said that, for children, making is not a specific

PICTURE 1 | Children cooking according to the recipe. Written informed consent was obtained from the parents of all depicted children for the publication of these images.

PICTURE 2 | Children at the FabLab presenting their ideas for the owl, other children, and adults around. Written informed consent was obtained from the parents of all depicted children for the publication of these images.

type of activity, but rather the natural way of playfully being and engaging in any activity, including their own emotions, other people, and playthings (Duncan and Planes, 2015).

CASE 4. Supporting Fab Lab Facilitators to Develop Pedagogical Practices to Improve Learning in Digital Fabrication Activities

This case study was conducted also in the context of Fab Lab. The aim of this case study was to explore what technology experts should take into consideration in planning and facilitating students' learning processes in digital fabrication. This was done to provide research evidence about the design and implementation of digital fabrication activities. In practice, current undertakings in the local Fab Lab were explored from two perspectives: how current practices consider novice students' learning and how facilitators and teachers provide scaffolding in unstructured problem solving (Pitkänen et al., 2019).

The local Fab Lab was established in 2015 (see https://www.oulu.fi/fablab/). Since then, Fab Lab has arranged different types of digital fabrication activities for school groups. The activities have typically included 2D and 3D design and manufacturing, prototyping with electronics, programming, and utilizing tools and machines to fabricate prototypes (Georgiev et al., 2017; Iwata et al., 2019; Laru et al., 2019; Pitkänen et al., 2019).

In this case study (Iwata et al., in review), three schools participated in digital fabrication activities in Fab Lab (**Table 2**). The school participants, in total 41 students (aged 12–15 years old) and five teachers, were from three secondary schools. The activities were facilitated by two technology experts (facilitators), who work in the Fab Lab. In order to understand the making and digital fabrication activities, the participants were observed during the practice, and interviews of 14 students, the five teachers, and the two facilitators were conducted both during and at the end of the activities. Furthermore, the perspectives of the two expert groups (school teachers and Fab Lab facilitators) were investigated with focus group interviews.

The students worked on projects in teams with different design briefs and required conditions provided by facilitators and/or the teachers. All student projects were complex and

TABLE 2 | The three schools participating in digital fabrication activities.

Activity Design	Case I: School A	Case II: School B	Case III: School C
Period	5 days	3 days	5 days
Design Brief	Open-ended topic given by the facilitators: students were completely free to ideate their project	Open-ended theme given by the teachers: Finland 100 years; students were free to ideate their project	Design brief given by the teachers as part of ongoing project at school: Playhouse; students were free to design a playhouse for their school
Required conditions	Use Arduino Uno as a microcontroller and Use at least one actuator Fabricate mechanics using laser cutter or 3D printer Make functional artifacts in 5 days	Use Arduino Uno as a microcontroller Fabricate mechanics using laser cutter	The playhouse needs to serve the whole school community, students in 1st - 9th grade
Projects	Useless box Rail for a camera Electronic controlled lock Jukebox game Music car	Finland 100 years calendar Finland 100 years history wheel Finland's flag day clock	Two prototypes of playhouses

required knowledge and skills in multiple subjects, such as mathematics, physics, and art (STEAM concept) (**Table 2**). Yet, these projects were difficult for them to complete without collaborative problem solving. The following excerpt is from a teacher's interview:

> "One girl said that in normal group activities in school, she would have taken like the whole control, but this one was so huge, and she realized that she couldn't do that. So, she had to delegate. That was precious that she had to trust the team and that she can't control everything."

Based on the interviews six factors were identified which influenced students' learning in the Fab Lab:

1) The tasks were complex and multidisciplinary.
2) Computers and digital tools were used frequently.
3) Students' own roles and responsibilities were emphasized in the guidance given.
4) Opportunities for reflection were supported.
5) Trial and error was encouraged.
6) An appropriate range of flexibility was embraced with time frame.

The following example shows how the school teacher explained the digital fabrication activities:

> "You go and just try and error and it doesn't even matter if you totally succeed or fail on the product.… the important thing is what kind of cognitive skills and how you reflect, what you learn in the process, and if you came back, what would you do better."

However, not all students who participated in these digital fabrication activities had previous knowledge and experience in the field. Moreover, many of them were not used to applied work methods that require competencies such as self-regulation, self-efficacy, and persistence. Based on the results, there is a need for defining clear learning goals and instructions, which would help students to engage in unstructured, open-ended, problem-solving activities. Furthermore, the lack of structure in the activities made both the teachers and facilitators point out the need to scaffold learning. The following is an excerpt from the interview of a teacher which underlines this need:

> "….I feel like that we should guide them more…. giving them more guidance in choosing appropriate tasks they want to learn, because sometimes the tasks they choose might be too demanding for them to learn in a limited period time."

Based on the analysis of the observations and interviews, several suggestions can be provided for integrating instructional scaffolding in the activities, taking into consideration novice learning, and the nature of unstructured problem solving activities. The first two elements relate to developing pedagogical practices in the activities: we recommend that teachers consider cognitive and affective processes of learning as a base for activity design and provide instructional scaffolding to improve opportunities for cognitively effortful and affectively meaningful learning. The next two elements suggest designing the activities in collaboration to enhance the application of digital fabrication to formal education, recommending that we familiarize teachers with Fab Labs and digital fabrication activities and increase collaboration between Fab Lab facilitators and school teachers.

DISCUSSION—HOW TO DESIGN COGNITIVELY EFFORTFUL AND AFFECTIVELY MEANINGFUL LEARNING

Case studies of SNS, games for learning, makers education, and digital fabrication showed different ways of organizing digital education and illustrated in particular how different types of pedagogical design and digital tools have been used to support cognitively effortful and affectively meaningful learning in groups. In other words, in addition to knowledge co-construction, argumentation, and problem solving, opportunities for positive affective learning processes were provided, such as experiencing and expressing emotions in learning.

The first example, SNS, presented a learning environment that is familiar for students as an everyday communication tool. It provided an interaction arena to discuss and debate the course topics with the support of a micro-script (Noroozi et al., 2012). In terms of the cognitive and affective potential of SNS, it can be concluded that structured roles functioned as a support for affective interactions by managing the discourse, inducing and resolving conflicts, and assisting in creating equal participation and feelings of belonging between students (Isohätälä et al., 2017). However, as this case study was tightly pre-structured with a specific micro-script, the following examples presented open-ended collaborative problem-solving spaces. The second case study, the Minecraft game environment, showed how a commercial game was further designed and implemented in a primary school after school club. This was an example of a constructivist game approach where learners played but also modified their own games (Kafai and Burke, 2015). This study showed how game experience prompted students' knowledge acquisition as well as supported students' learning skills in terms of programming and collaboration. Furthermore, the study also indicated that the experience was highly emotionally engaging for the students, based on the students' descriptions of their emotional experiences of playing the game and the experiences they had when the game was over.

Minecraft is a block based world of "digital making"; digital fabrication and making enables a more thorough design experience to plan and fabricate students' own artifacts in the situated (unstructured and open-ended) problem solving contexts (Halverson and Sheridan, 2014; Martin, 2015; Taylor, 2016). Two different examples that were selected to illustrate maker education and digital fabrication showed the making activities in practice. The example from an early education context showed young children making in several contexts, including outdoor, and indoor locations (Siklander et al., 2019). These activities were observed to contribute to affectivity by allowing children to experience several different types of emotions while learning, such as curiosity, joy, and excitement, but also negative feelings such as impatience, frustration, and disappointment (Hyvönen and Kangas, 2007). These emotional expressions were particularly visible in their collaborative situations. The last case example turned the focus toward the teachers' and facilitators' point of view, investigating how they see making activities and how they understand what kind of support students need from them during these activities. This study, through the design principles of the Fab Lab activities, characterized the important factors that help teachers and facilitators to engage and support students' learning, such as implementing complex tasks, using digital tools, highlighting students' own roles and responsibilities, providing opportunities for reflection, encouraging trial and error, and providing flexibility in the timeframe (Blikstein, 2013; Georgiev et al., 2017; Hira and Hynes, 2018; Iwata et al., 2019). In addition to these principles, this study pointed out that adequate scaffolding is needed to improve opportunities for cognitively effortful and affectively meaningful learning. This is especially important in the situations where maker activities and digital fabrication procedures are introduced to novice makers, since they need to be familiarized with making culture as well as possibilities and tools for making (Gerjets and Hesse, 2004; Blikstein, 2013; Chu et al., 2017). Fab Lab and maker education differ in the use of social networking tools and games for learning, because digital tools are part of the making process and the learning environment is situated in the physical fabrication laboratory instead of online context (Kim and Reeves, 2007; Qian and Clark, 2016).

In general, SNS, digital gaming, and maker education have become increasingly interesting as a learning context in a modern education, mixing technological and creative skills, exploration and discovery, problem-solving and playfulness, as well as formal and informal education (Connolly et al., 2012; Davies and West, 2014; Georgiev et al., 2017). These types of learning opportunities have the potential to impact current and future educational practices and pedagogy. However, when critically evaluating these learning contexts' opportunities for cognitive and affective learning, it can be noted that the implementation of digital tools and environments alone is not enough (Gerjets and Hesse, 2004). Therefore, planning and facilitating learning activities in digital education requires knowledge of both technology and pedagogy (Laru et al., 2015; Häkkinen et al., 2017; Valtonen et al., 2019). For example, when designing learning with digital tools, it is important that technologies are embedded into the environment and that their use is designed prior the activities but also facilitated during the learning activities (Kirschner et al., 2006; Dillenbourg, 2013). This is the case especially in the maker education context where tools and devices for various kinds of fabrication need to be provided for the use of students with heterogeneous skills, knowledge, and aims (Blikstein, 2013; Chan and Blikstein, 2018).

In addition to pre-structured and facilitated learning activities, more spontaneous collaborative activities are recommended. This means that students should be provided opportunities to engage in learning activities which places students' needs, interests, and experiences as the starting point for their explorations. This type of learner-centered approach creates a learning environment that is built around creativity and allows personal emotional experiences, such as fun and enjoyment (Hyvönen and Kangas, 2007; Hyvönen, 2011; Hyvönen et al., 2014). A sound learning environment also guides and supports students' interest and promotes their active involvement in learning (Baker, 2015; Järvelä et al., 2016; Hadwin et al., 2018). In order to support learning activities in the ways described above, pedagogically sound practices will need to be established, and teachers' professional development will need to focus more on using technology to improve learning—not just on changing teachers' attitudes and abilities in more general ways (Davies and West, 2014). To conclude, we agree with Lowyck (2014, p. 15), who argues that "both learning theories and technology are empty concepts, when not connected to actors such as instructional designers, teachers and learners." He continues with the image of teachers and learners as co-designers, which is well-aligned with the case studies presented in this paper, by claiming that "...they are co-designer of learning processes, which affect knowledge-construction, and management as well as products that result from collaboration in distributed knowledge environments." Finally, this paper reinforces the idea suggested by Roschelle (2003) that we should focus on rich pedagogical practices and simple digital tools. In the context of the four case studies described in this paper, we can summarize that applying digital tools for education is meaningful when the aim is to provide opportunities for interactions and sharing ideas and thus increase students' opportunities to turn an active mind to multiple contexts.

This paper introduced studies that implemented the exploratory case approach and thus it can be criticized due to the lack of generalizability of the results. As case descriptions afford details and context specific illustrations, the possibility to draw general conclusions is limited (Stake, 1995; Yin, 2013). In these case studies a various different types of methods were used. For example, discussion notes from Facebook group discussions were analyzed, interviews after the each face to face meeting during the Minecraft experiment were conducted, and photo elicitation interviews as a method in a Fab Lab working was used as well as observations and teacher and student interviews were done during a second Fab lab experiment. All these case studies and related data collections illustrate participants' experiences during the digital learning. As research of affective learning in digital education emerges, a key direction for future studies is to explore how tools and technologies support affective learning and interaction, but also how different types of pedagogical designs can scaffold affective learning (Näykki et al., 2017a). Design studies could explore and develop tools and design principles to support the use of social media tools in learning, the design and use of games for learning, and the involvement of makers and digital fabrication activities in educational settings. The current study provides interesting research questions based on our observations of the case studies to be explored in the future studies. For example, it can be explored how to design tools to support affective learning in gaming or making contexts where learning designs are not usually the main focus of the activity. The contexts of the cases were unstructured or open problem spaces, although special pedagogical designs were implemented. However, much remains to be understood regarding the types and configurations of technological and pedagogical support that best promote cognitive and affective processes of collaborative learning.

The results obtained from these case studies are applicable to formal education, such as early childhood education, primary school education, teacher education, and in-service training, but also to informal learning contexts, such as game designing and Fab Lab facilitation. Engagement in creative making activities, productive group work, and seamless use of technology are essential twenty-first-century skills needed in all fields of work and in life in general. Teachers at all educational levels have an especially crucial role in developing these skills in their students, and therefore future teachers have to be offered opportunities to experience and learn within various collaborative environments.

DATA AVAILABILITY STATEMENT

The datasets generated for this study will not be made publicly available Studies involving human subjects.

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 to participate in this study was provided by the participants' legal guardian/next of kin.

ADDITIONAL REQUIREMENTS

Written informed consent was obtained from all adult participants and the parents of non-adult participants for the purposes of research participation. The raw data supporting the conclusions of this manuscript can be made available by the authors, from request, to any qualified researcher.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

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Multiple Negative Emotions During Learning With Digital Learning Environments – Evidence on Their Detrimental Effect on Learning From Two Methodological Approaches

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Emotions are a core factor of learning. Studies have shown that multiple emotions are co-experienced during learning and have a significant impact on learning outcomes. The present study investigated the importance of multiple, co-occurring emotions during learning about human biology with MetaTutor, a hypermedia-based tutoring system. Person-centered as well as variable-centered approaches of cluster analyses were used to identify emotion clusters. The person-centered clustering analyses indicated three emotion profiles: a positive, negative and neutral profile. Students with a negative profile learned less than those with other profiles and also reported less usage of emotion regulation strategies. Emotion patterns identified through spectral co-clustering confirmed these results. Throughout the learning activity, emotions built a stable correlational structure of a positive, a negative, a neutral and a boredom emotion pattern. Positive emotion pattern scores before the learning activity and negative emotion pattern scores during the learning activity predicted learning, but not consistently. These results reveal the importance of negative emotions during learning with MetaTutor. Potential moderating factors and implications for the design and development of educational interventions that target emotions and emotion regulation with digital learning environments are discussed.

Keywords: emotions, learning, digital learning environments, person-centered, variable-centered, emotion-regulation

INTRODUCTION

Learning is a complex multi-faceted process that requires students to deploy, monitor, and regulate their cognitive, metacognitive, affective and motivational processes based on the learning environment and the learning task and goal (Azevedo et al., 2018). Emotions play a central role in this context. They significantly impact and drive processes that are quintessential to learning, such as attention, perception, memory (Lewis et al., 2008; Tyng et al., 2017), and metacognition (Azevedo et al., 2017). Furthermore, a long tradition of research has shown that emotions are directly related to learning outcomes and academic achievement (Boekaerts and Pekrun, 2015). Even though initial investigations on emotions and learning has almost exclusively focused on the importance of anxiety in learning and test situations (Pekrun et al., 2002), research on emotions and learning has diverged into investigations of a broad variety of affective states and emotions in differing learning contexts (e.g., classroom settings, research with advanced learning technologies or informal learning settings; Azevedo et al., 2019). These studies have demonstrated that many different emotions are commonly experienced in learning settings (e.g., boredom, confusion, or frustration; D'Mello, 2013) and they have a significant impact on students' performance (e.g., Pekrun et al., 2002; D'Mello et al., 2014). However, some important aspects of emotional experiences still have not been extensively researched in learning contexts. For example, most of the research in this context, particularly research during learning with digital learning environments, focused on the importance of single discrete emotions or sets of discrete emotions using variable-centered approaches. Research investigating emotions in other contexts, on the other hand, has revealed that approaches that consider multiple emotions simultaneously show great promise (e.g., Fortunato and Goldblatt, 2006; Vansteenkiste et al., 2009). Only a few studies have investigated the complexity of students' (co-occurring) emotional experiences during learning using person-centered approaches (Ganotice et al., 2016; Jarrell et al., 2016, 2017; Robinson et al., 2017; Sinclair et al., 2018). These studies have found that groups of students who differ in their emotional experiences during learning in regard to multiple emotions (so called emotion profiles) also meaningfully differ in their learning outcomes and academic achievement. The goal of this study was to combine person- and variable-centered approaches to examining emotions during learning with a digital learning environment. We extended upon previous research by considering a broader range of emotion measures than previous studies (i.e., academic achievement emotions and learning-centered emotions), incorporating emotion regulation and temporal dynamics of emotions, and by substantiating person-centered analyses with a novel variable-centered approach.

Emotions During Learning With Digital Learning Environments

Emotions are an essential component of learning activities across settings. Students' emotional experiences when learning with technologies are diverse, have been investigated on the basis of several frameworks (D'Mello, 2013), and have been classified in various categories, including academic achievement emotions (Pekrun et al., 2002), epistemic or learning-centered emotions (D'Mello and Graesser, 2012; Pekrun et al., 2017b), and basic emotions (Ekman and Friesen, 1971; Ekman, 1992). Pekrun et al. (2002) and Pekrun (2006) academic achievement emotions approach distinguishes academic emotions differing in their valence (positive vs. negative) and the perceived level of control by the learner, including enjoyment (positive and high control), anxiety (negative and medium control), and hopelessness (negative and low control). Learning-centered emotions approaches (also referred to as cognitive affective states or epistemic emotions; D'Mello and Graesser, 2012; Muis et al., 2015; Pekrun et al., 2017b) focus on emotions that are directly related to knowledge-generating aspects of cognitive processes (e.g., overcoming impasses during learning), including boredom, confusion and frustration. According to Ekman (1992) six basic emotions can be distinguished across cultural contexts and reliably identified from facial expressions, including anger, happiness, and surprise. An extensive amount of research has shown that emotions significantly impact learning processes, outcomes, and academic achievement (Pekrun and Linnenbrink-Garcia, 2014). The majority of studies revealed that the way emotions impact learning and achievement is closely related to their valence. More specifically, positive emotions are positively, and negative emotions are negatively related to the learning process and learning outcomes (e.g., Pekrun et al., 2002, 2017a; Pekrun and Linnenbrink-Garcia, 2012). However, there is also evidence opposing this general pattern. For example, studies identified detrimental effects of positive emotions on the accuracy of metacognitive judgments creating an illusion of learning (Baumeister et al., 2015). Negative emotions on the other hand were positively associated with learning when they triggered deep processing of contents and were resolved by the students in a timely manner (see below, e.g., D'Mello and Graesser, 2014). This state of research indicates that, despite the overall tendency of beneficial effects of positive emotions and detrimental effects of negative emotions, further factors need to be considered to predict and explain the effects of emotions during learning.

A particular branch of research investigates (self-regulated) learning processes when learning with digital learning environments (Gegenfurtner et al., 2019), including hypermedia learning environments (e.g., Opfermann et al., 2013), intelligent tutoring systems (e.g., Azevedo et al., 2016; Harley et al., 2017), and game-based learning environments (e.g., Sabourin and Lester, 2014; Taub et al., 2018). These learning technologies have been designed and implemented to foster student learning about specific topics and have been shown to meaningfully enhance learning (Zheng, 2016). Digital learning environments include specific affordances that are directly linked to students' emotions. For example, research has demonstrated that the design of digital learning environments (e.g., shapes and colors; Plass et al., 2014), their structure (e.g., complex, non-linear structure; Arguel et al., 2019), and scaffolds incorporated in such systems (e.g., prompts and feedback by pedagogical agents; Harley et al., 2017) can impact students' emotions. More specifically, digital learning environments can elicit and alter emotional processes or assist the learner in regulating them and provide unique opportunities for research to investigate emotions in ways hardly achievable in other contexts. For instance, multi-channel trace data can be collected with digital learning environments to measure emotions with minimal interruptions to the learning process (e.g., through automated detection of facial expressions; D'Mello, 2017; Azevedo et al., 2019). The dynamics of affective states model is a prominent theoretical framework in this line of research that focuses on the dynamic unfolding of specific, learning-centered emotions

(D'Mello and Graesser, 2012)[1]. More specifically, D'Mello and Graesser (2012) posited that confusion is elicited by impasses encountered during complex learning processes. This confusion can be beneficial to learning when it can be resolved, and the impasse can be overcome. Prolonged experiences of confusion on the other hand is theorized to lead to frustration and eventually boredom, which ultimately lead to disengagement and poor learning outcomes. Given that digital learning environments challenge students with learning tasks that require to develop a deep understanding of science concepts, or a solution for complex problems, such impasses are particularly likely to occur when learning with these systems. D'Mello and Graesser (2014) found a positive relation between (partially) resolved confusion and learning in a problem-solving task and a scientific reasoning task in an intelligent tutoring system. Another study by Taub et al. (2019) furthermore showed that the experience of frustration was linked to higher accuracy in the use of cognitive learning strategies (i.e., note-taking) with MetaTutor. However, they did not find a significant relation between emotions and learning gain.

Other studies on emotions and learning with digital learning environments (e.g., intelligent tutoring systems and game-based learning environments) on the other hand found detrimental effects of negative emotions. Initial studies on the relation between emotions and learning in AutoTutor identified significant detrimental effects of boredom for learning (Craig et al., 2004; Graesser et al., 2008). Across three studies using different digital learning environments, Baker et al. (2010) found further support for these findings by showing that boredom was the most persistent emotion (i.e., students were unlikely to transition from boredom to another emotion), and that boredom was the only emotion to be associated with maladaptive behaviors (i.e., gaming the system). Sabourin and Lester (2014) identified a positive relation between positive emotions and learning gains. Furthermore, they observed a negative association of confusion and boredom with learning gains in a game-based learning environment. A study by Grafsgaard et al. (2014) revealed that indicators of facially expressed frustration were negatively predictive of learning gain.

Taken together, these studies demonstrated the importance of learning-centered emotions during learning with digital learning environments (for a recent review see Arguel et al., 2019). However, they also demonstrated a profoundly controversial relation between (negative) emotions and learning. This clearly indicates further research is needed to disentangle the manifold relation between emotions, learning, and learning outcomes by identifying factors that explain these contradictory relations. One such factor that has been rarely considered in the aforementioned studies on emotions in digital learning environments is the co-occurrence of emotions. Even though studies have shown that the emotions outlined above have differential effects on learning depending on other affective states they are accompanied by or lead to (e.g., D'Mello and Graesser, 2012; Goetz et al., 2014; Riemer and Schrader, 2019), the co-occurrence of emotions and the breadth of emotional experiences has rarely been considered in this context.

PERSON CENTERED APPROACHES TO EMOTIONS

Research on emotions during self-regulated learning has indicated that a variety of emotional states and processes impact learning and performance in meaningful ways. While these studies have greatly contributed to a comprehensive understanding of emotions in learning situations, especially when learning with digital learning environments, they have not fully considered the breadth of emotional experience of an individual. More specifically, the variable-centered approach used by these studies focuses on singular emotional states or a pre-selected set of emotions while controlling for the impact of other emotions. Emotion research on the other hand suggests that individuals can experience multiple emotions concurrently, and that these emotions affect each other reciprocally, which ultimately impacts thoughts and behaviors (e.g., Lazarus, 2006; Fernando et al., 2014). Person-centered approaches typically identify groups of students with similar emotional experiences in regard to multiple emotions at a certain point of time (often referred to as emotion profiles). These profiles are then compared to another and related to relevant outcome measures (e.g., learning and academic achievement). For example, multi-level investigations of affect in college students have revealed that spurs of negative emotions coupled with positive trait affectivity are associated with greater academic growth than positive or negative affect alone (Barker et al., 2016). Furthermore, the added value of this approach has been repetitively shown outside of educational contexts (e.g., Vansteenkiste et al., 2009; Fernando et al., 2014). In research in education settings, this approach is still quite rare. We identified five studies that used a person-centered analytical approach in different educational contexts (see **Table 1** for a brief overview).

Jarrell et al. (2016, 2017) investigated emotions when learning with a computer-based learning environment using a person-centered approach in two studies. Five discrete emotional states (enjoyment, pride, hope, shame, and anger) measured with the Achievement Emotions Questionnaire (AEQ; Pekrun et al., 2002) were used to cluster students with similar emotional experiences. In both studies, a three-profile solution including a positive, negative, and low emotional experience profile, was identified. These profiles were subsequently related to learning outcomes. The first study (N = 26) revealed no significant differences in performance between profiles. In the follow-up study (N = 30) Jarrell et al. (2017) investigated differences in diagnostic performance efficiency between emotion profiles. They found that the negative emotion profile was outperformed by at least one other profile averaged across levels of difficulty (easy, medium, hard) and for easy and hard tasks, but not for tasks with medium difficulty.

[1]The dynamics of affective states model and related research often refer to cognitive-affective states instead of emotions. For consistency, readability, and because the cognitive component of these states resembles the appraisal component of emotion theories (e.g., Moors et al., 2013) we will refer to them as emotions. However, we acknowledge arguments that these terms might not be interchangeable in all contexts.

TABLE 1 | Overview of person-centered studies on emotions during learning.

Study	Sample	Clustering variables	Identified clusters (method)	Main findings
Jarrell et al., 2016	Medical students (N = 26)	Enjoyment, pride, hope, shame, and anger	3 (k-means clustering) • Positive • Negative • Low	No significant differences in performance between profiles
Jarrell et al., 2017	Medical/Dentistry students (N = 30)	Enjoyment, pride, hope, shame, and anger	3 (k-means clustering) • Positive • Negative • Low	Negative profile is significantly outperformed by at least one other cluster
Ganotice et al., 2016	Secondary school students (N_1 = 1,147; N_2 = 341)	Enjoyment, hope, pride, anger, anxiety, shame, hopelessness, and boredom	4 (hierarchical + k-means clustering) • high positive and high shame • moderate positive and negative • high negative • high positive emotion	High positive emotions cluster showed best academic outcomes High negative emotions cluster showed worst academic outcomes
Robinson et al., 2017	Undergraduate students (N = 278)	Affect: positive/negative × activated/deactivated	4 (hierarchical + k-means clustering) • Positive • Deactivated • Negative • Moderate negative	Deactivated profile showed higher academic achievement than both negative profiles
Sinclair et al., 2018	Undergraduate students (N = 190)	Enjoyment, curiosity, pride, boredom, and frustration	3 (Latent profile analysis) • Positive • Negative (bored/frustrated) • Moderate	Students in the negative profile were least likely to change to another profile Learning gains are associated with transitions between profiles

Further investigations of emotions through a person-centered approach were conducted by Ganotice et al. (2016) in two secondary school samples. Similar to the studies outlined above, discrete emotional states (enjoyment, hope, pride, anger, anxiety, shame, hopelessness, boredom) measured through the AEQ (Pekrun et al., 2002) were used for clustering. In a domain general or a math-specific context, four emotion profiles were identified. These profiles included a high positive and high shame profile, a moderate positive and negative emotion profile, a high negative emotion profile, and a high positive emotion profile. These profiles were compared in regard to school engagement, motivation, and math performance. Results showed that profiles with high positive emotions were the most adaptive profiles while the high negative emotion profile was the least adaptive.

Robinson et al. (2017) investigated affective profiles in an undergraduate anatomy course. Other than previous person-centered studies, this research used two dimensions of affect (positive/negative × activated/deactivated, see Ben-Eliyahu and Linnenbrink-Garcia, 2013) as clustering variables. Through a two-step procedure, they identified four emotion profiles including a positive, a deactivated, a negative, and a moderate negative profile. Comparison in academic achievement revealed that the deactivated profile showed higher academic achievement than both negative profiles (negative and moderate negative) throughout three exams. Robinson et al. (2017) also found differences between the positive and the negative profile, but not throughout all exams. Lastly, they investigated the mediating role of (dis-) engagement and found that higher levels of performance for the positive and deactivated profile were mediated through lower levels of disengagement.

Lastly, Sinclair et al. (2018) investigated emotion profiles displayed in an undergraduate student sample that learned about the human circulatory system using MetaTutor (see 5.3 MetaTutor). They used five discrete emotion states (enjoyment, curiosity, pride, boredom, and frustration) measured at five time points before and during learning using latent profile analysis. Similar to the studies above, they found a positive, negative (bored/frustrated), and moderate emotion profile. Subsequently they investigated transitions between profiles and found that students from the negative profile were least likely to transition to another profile. Lastly, they found that learning gain predicted the transitions between profiles at specific, selected time points.

Taken together, these studies demonstrate that a person-centered approach can reveal emotion profiles across contexts, ranging from laboratory studies to research in schools and university. Furthermore, all studies have found that these profiles are significantly related to performance, academic achievement, and related constructs. Most of the previous studies have not incorporated learning-centered or epistemic emotions (e.g. boredom, confusion, and frustration; D'Mello and Graesser, 2012). On the other hand, previous research on emotions when learning with digital learning environments has found that these emotions significantly impact learning in varying ways. The finding that these emotions can have a positive or negative impact on learning is particularly interesting for person-centered research as the contradicting implications might be explained though co-occurring emotions (i.e., profiles that show similar levels of confusion or frustration, but varying levels of other emotions). The only study that investigated learning-centered emotions (Sinclair et al., 2018) on the other hand did not consider achievement emotions in their analysis, which makes comparisons across studies difficult. We aim to address this issue by including learning-centered emotions in addition to academic achievement emotions that were used in most of the person-centered studies outlined so far.

Furthermore, the aforementioned studies have investigated different constructs related to emotions and performance such as motivation (Ganotice et al., 2016) or engagement (Robinson et al., 2017) to substantiate their findings. None of the studies investigated the role of emotion regulation in this context. Emotion regulation is an essential component to emotional experiences in learning contexts and is a critical link between emotional experience and academic outcomes (Gross, 2015; Harley et al., 2019). It describes students' efforts to influence which emotions they experience, when they experience these emotions and how they express them (Harley et al., 2019). Emotion regulation strategies are for example the cognitive reappraisal of emotional experiences or modification of the situation that elicited the emotion (Gross, 2015). Spann et al. (2019) found that emotion regulation significantly influenced the relation between emotions and learning in a game-based learning environment. More specifically, they found that cognitive reappraisal led to higher learning outcomes for highly confused, frustrated, and engaged students, but was not as effective for students with low levels of confusion, frustration and engagement. Incorporating emotion regulation could shed light on the development of emotions in relation to specific profiles. Adaptive profiles (such as described by Ganotice et al., 2016) are potentially defined by higher levels of emotion regulation to cope with high levels of negative emotions. To investigate this subject matter, temporal investigations of emotions related to emotion profiles similar to Sinclair's approach (Sinclair et al., 2018) are necessary. This includes, investigating the self-reported use of emotion regulation strategies for the different emotion profiles, and exploring to what extent the intensity of emotional experiences fluctuates over time within profiles.

Lastly, the studies outlined above were limited to using person-centered approaches only. While the great value of this type of research has been shown, we argue that supplementing person-centered with other approaches can be essential to their understanding. More specifically, identifying if the distinguishing characteristics of profiles (e.g., varying levels of positive or negative emotion intensity) can be replicated through variable-centered approaches can provide additional insight on the origin of these profiles. Such approaches could differentiate if profiles are based on natural co-occurrence of emotions (e.g., high correlations between negative emotions) or specific combinations of individual emotional experiences (e.g., a profile with high levels of boredom and other negative emotions versus a profile with high levels of boredom and low levels of other negative emotions). Furthermore, replicating results using two different methodologies would reveal their level of robustness, which is particularly important in this context, because emotion profiles are identified through data driven approaches (guided by previous research).

CURRENT STUDY

The current study aims to address the issues outlined above by identifying emotion profiles of students who learned with MetaTutor and relate them to learning outcomes. To this end we decided to adapt the person-centered analytical procedure outlined by Vansteenkiste et al. (2009) and Robinson et al. (2017) for the identification of emotion profiles. Additionally, we demonstrate how a variable-centered approach can substantiate these results by relating patterns of emotions to emotion profiles and learning outcomes throughout different phases of learning (i.e., before the learning phase, at the start of the learning phase, and at the end of the learning phase, see section Emotion Items). More specifically, we aim to answer the following questions.

1.1 *Which emotion profiles can be identified during SRL with MetaTutor and how can they be described?* Given that the specific profiles are highly dependent on the number of clusters, no specific hypothesis can be formulated *a priori*. However, based on previous person-centered studies, we expect a negative and positive emotion profile (see Ganotice et al., 2016; Jarrell et al., 2016, 2017; Robinson et al., 2017; Sinclair et al., 2018). Additionally, further likely profiles can include a low-intensity or moderate intensity profile for all emotions.

1.2 *Are there significant differences in learning outcomes between the profiles?* Based on previous research, we expect the profile with the highest values of negative emotions to display the lowest learning gain (Ganotice et al., 2016; Jarrell et al., 2016, 2017; Robinson et al., 2017).

1.3 *Are there significant differences in self-reported use of habitual emotion regulation strategies between the profiles?* Based on research on emotion regulation, we expect profiles characterized by high negative emotion intensities to indicate lower levels of self-reported use of emotion regulation strategies (Harley et al., 2019).

2.1 *How can stable patterns of emotions can be identified throughout the different phases of the learning session and how can they be described?* Similar to our first research question, we expect a strong differentiation between negative and positive emotions in the different phases. Additionally, a strong differentiation between activating and deactivating emotions is expected (Ben-Eliyahu and Linnenbrink-Garcia, 2013). Furthermore, because neutral – per definition – refers to the absence of perceivable and detectable emotions, we hypothesize neutral to represent its own cluster (potentially paired with emotions that show low intensities overall). Lastly, based on the reoccurring finding that specific emotions are positively and/or negatively related to learning, we expect boredom, confusion or frustration to form separate cluster(s) from other negative emotions (e.g., D'Mello and Graesser, 2012).

2.2 *How are emotion profiles related to the phase-specific patterns of emotions?* We expect emotion profiles to significantly differ in regard to emotion clusters that are defined by valence as all previous studies included profiles that were defined by positive and negative emotions (Ganotice et al., 2016; Jarrell et al., 2016, 2017; Robinson et al., 2017). In an exploratory step we will investigate if these differences are stable over time or if they arise throughout specific parts of the learning session.

2.3 *How can the phase-specific patterns of emotions predict learning outcomes in the respective phases of the learning activity?* Based on previous research, we expect negative emotions to be most predictive of learning. However, the direction of this interaction will be explored, as previous research has shown controversial results in this regard.

MATERIALS AND METHODS

Participants

One hundred ninety-four (N = 194) undergraduate students (aged between 18 and 41, M = 20.46 years, SD = 2.96 years; 53% female) from three large public North American universities participated in a 2-day laboratory study. They were randomly assigned either to the *prompt and feedback* (P + F) or *control* (C) condition (see section MetaTutor), and monetarily compensated for their time ($10 per hour, up to $40). For the present study, only participants that filled out a sufficient number of emotion questionnaires (see section Emotion Items) were included in analyses, resulting in a sample size of one hundred seventy-six (N = 176) students.

Procedure

The experiment was conducted over 2 days. On the first day, participants signed a consent form, filled in demographics questions, and completed several self-report measures (e.g., the Achievement Emotions Questionnaire – Pekrun et al., 2002 and the Emotion Regulation Questionnaire – Gross and John, 2003). Lastly, after responding to the questionnaires, participants took a 30-item pretest about the human circulatory system.

On the second day of the experiment, students were first introduced to the learning task and learning environment. They were instructed to set two learning sub goals before the beginning of the learning phase. During the learning phase, participants had to engage in self-regulated learning by reading texts, inspecting

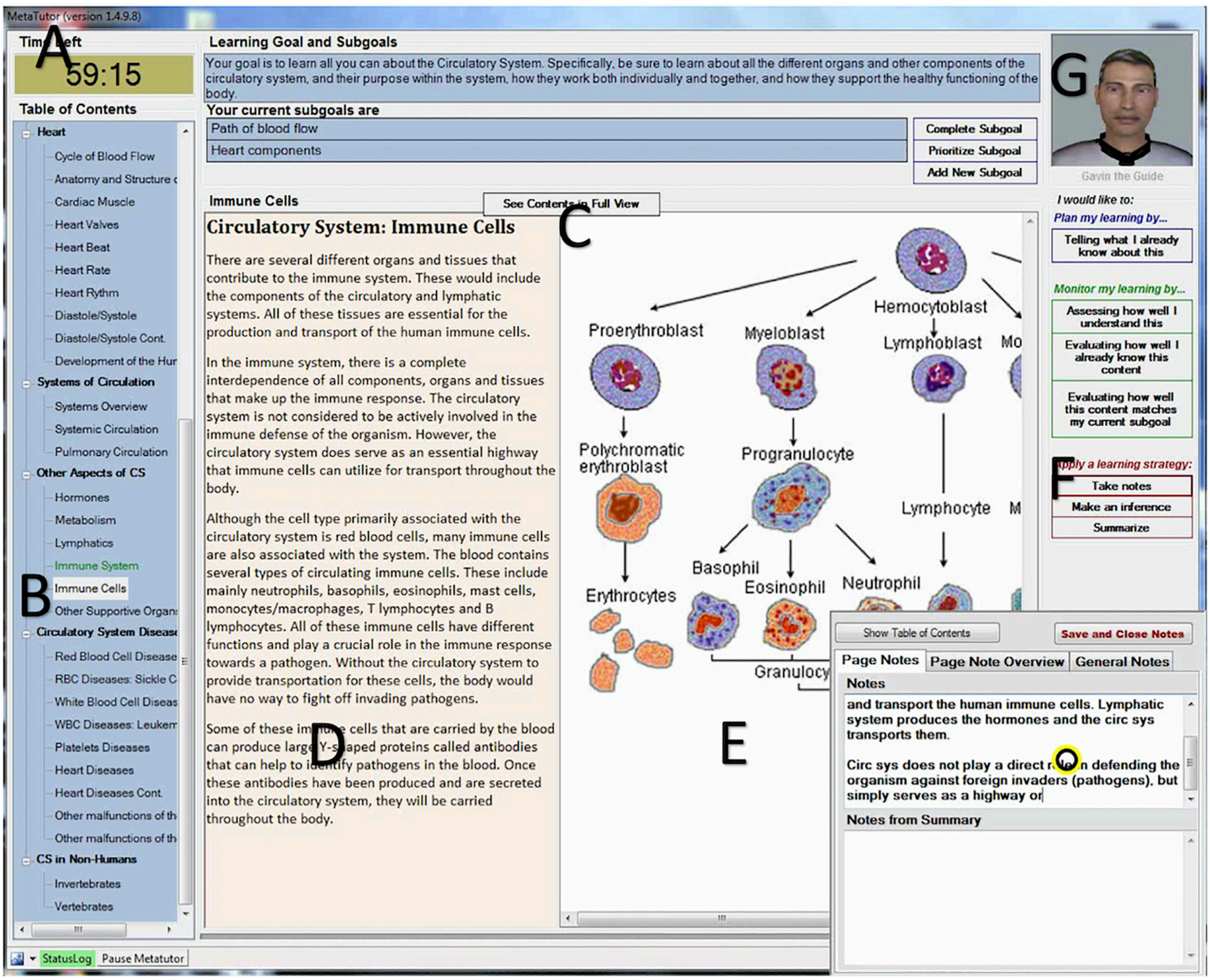

FIGURE 1 | Screenshot of the MetaTutor interface. **(A)** Timer, **(B)** Table of contents, **(C)** Progress bar, **(D)** Content text, **(E)** Content image, **(F)** SRL palette, and **(G)** The pedagogical agent.

corresponding diagrams, and completing quizzes. Moreover, regardless of the experimental condition (see section MetaTutor) students were free to indicate their use of certain cognitive (e.g., note taking) or metacognitive learning strategies and activities using the SRL palette implemented in MetaTutor's interface (see section MetaTutor). Additionally, quizzes and self-report measures (i.e., the emotion and values [EV] questionnaire; Azevedo et al., 2013) were administered based on specific rules implemented by the system (e.g., the EV was conducted on a time-based threshold – roughly every 14 min during the learning session with MetaTutor).

After the 60-min learning phase, students were directed to the post test (i.e., 30-item test about the circulatory system) and had to complete a last set of self-reports (e.g., an EV directly before the posttest) before they were debriefed by the research assistant.

During the experiment, multiple channels of multimodal data, including eye tracking, galvanic skin response, and automated analysis of facial expressions were collected. However, these process measures were not analyzed in the present study.

MetaTutor

MetaTutor is a hypermedia-based tutoring system that fosters self-regulated learning processes while learning about the human circulatory system (Azevedo et al., 2018). The system was designed using a set of production rules, which fire based on how students monitor and control their understanding of the text and relevancy of the current page to the sub-goal they are working on. In addition to the processes being prompted by the pedagogical agents based on the production rules, participants were able to engage in any process of their choice. The MetaTutor learning environment was strategically designed to foster the use of cognitive learning strategies and metacognitive monitoring processes (see **Figure 1**). For example, a timer (A) and sub goal progress bar (C) allow students to monitor their progress toward achieving their sub goals and overall learning goal. The table of contents (B) provides students all the content page titles so they can select the appropriate pages to read for achieving their sub goals. There are seven pre-set sub goals in the environment (path of blood flow, heartbeat, heart components, blood vessels, blood components, purposes of the circulatory system, and malfunctions of the circulatory system). Prior to the 60-min learning session, students are progressed through a sub goal setting phase where they are guided to set two of those sub goals. The content text (D) and diagram (E) facilitate knowledge acquisition and foster coordinating information between the text and diagram. The SRL palette (F) provides students the opportunity to select cognitive learning strategies (i.e., prior knowledge activation, take notes, summarize, make an inference) and metacognitive monitoring processes (judgment of learning, feeling of knowing, content evaluation) they want to use during learning about the human circulatory system.

There are four pedagogical agents with one present at a time (G), where each agent focuses on a specific component of SRL. Gavin (shown in **Figure 1**) guides students through the learning environment and administers self-report questionnaires. Pam fosters planning by helping students set sub goals and activate their prior knowledge. Sam focuses on strategy use. Mary emphasizes monitoring processes. The amount of assistance provided by the pedagogical agents depends on the experimental condition students are assigned to. In the P + F condition, the agents prompt students to engage in SRL processes (using time- and event-based production rules). They also provide feedback on how they performed. For example, Sam will prompt students to make a summary, and once they have done so, he will tell them it is too long, too short, acceptable, etc. In the C condition, students are not prompted by the agents, nor are they given any feedback on their performance. In this condition, students can still initiate the use of cognitive and metacognitive processes, however, they are still not given any feedback, whereas in the P + F condition, students can also self-initiate the use of these processes, and will be given feedback on their performance.

Measures

Emotion Items

Students' emotional experiences at the start, during, and at the end of the learning session were measured using the Emotion-Values Questionnaire (EV; Azevedo et al., 2013). The EV covers 15 emotional states as well as two questions asking about the perceived value and the students' ability to perform well on the current task on a five-point Likert-scale (ranging from 1 – "Strongly Disagree" to 5 – "Strongly Agree"). Additionally, two forced choice items asked the participants to select the emotion that best describes how they currently feel out of 15 (all emotional states from the EV) and 7 options (basic emotions), respectively. The emotional states included in the EV were based on extensive research on achievement emotions in academic settings (Pekrun et al., 2002; Pekrun, 2006), as well as on research on learning-centered emotions/epistemic emotions (e.g., D'Mello and Graesser, 2012; Muis et al., 2015; Pekrun et al., 2017b). The questionnaire covers the following emotions (in order of administration): enjoyment, hope, pride, frustration, anxiety, shame, hopelessness, boredom, surprise, contempt, confusion, curiosity, sadness, eureka, and neutral. A definition and an example were provided for each emotional state during each administration.

The EV was administered at fixed points of time before and after the learning phase, and time-based during the learning phase. More specifically, the questionnaire was administered directly before and after participants set their learning sub goals, and before the actual learning phase. During the learning activity the questionnaire was administered every 14 min. Lastly, the final EV was administered when the learning phase was finished, directly before the post test. The number of EVs completed varied between participants because the administration during the learning phase was postponed when key learning activities took place. In particular, the questionnaire did not interrupt any of the user- or agent-initiated learning strategies that required completing quizzes or filling out questionnaires. For example, if a student initiated the sequence of finishing the current learning sub goal, they had to fill out a 10-item multiple-choice quiz on the current topic and received feedback depending on the experimental condition (see section MetaTutor). If an EV should have been administered during that sequence, it was postponed until the end of the sequence, potentially delaying it by several minutes. This resulted in a range of four to eight EVs completed between participants. To allow for comparisons of participants, we decided to limit the EVs analyzed in the present study to six points of time relative to the start and the end of the learning session. Therefore, only participants that completed at least six EVs were considered for analyses, resulting in a final sample size of one-hundred-seventy-six students (N = 176). The following EVs were selected: (1) the first two EVs that were completed at the beginning and end of the sub goal setting phase, (2) the third and fourth EV, which took place in the first half of the learning phase, and (3) the last two EVs, which was the last questionnaire presented during the learning phase, and the final EV immediately prior to the post test. Due to missing data, "Eureka" was excluded from analyses in the current study, yielding 14 discrete emotions considered for analyses.

Pre and Post Tests

Prior knowledge and learning outcomes were measured using two 30-item multiple choice tests covering conceptual knowledge of the human circulatory system. The measures were developed by a domain expert in the subject matter. Each question had four potential answers and one correct solution. The order of two equivalent versions of the tests was randomized and counterbalanced across experimental conditions. Percent correct for both measures were computed for analyses.

Emotion Regulation Questionnaire

Students' self-reported habitual use of emotion regulation strategies was measured using the emotion regulation questionnaire (ERQ; Gross and John, 2003). The 10-item questionnaire features two sub-scales asking about the use of emotion regulation strategies using a seven-point Likert scale (ranging from 1 – strongly disagree to 7 – strongly agree). More specially, mean values for the sub-scales expressive suppression (4 items, α = 0.78; e.g., "I keep my emotions to myself.") and cognitive reappraisal (6 items, α = 0.84; e.g., "I control my emotions by *changing the way I think* about the situation I'm in.") were calculated for analyses.

Statistical Analyses

Statistical analyses in the present study were conducted using R (R Core Team, 2019), Python (Van Rossum and Drake, 2011), and SPSS (SPSS, 2012). Before the initial analyses, we investigated if the mean scores for each emotion computed over the six administrations of the EV for clustering contained significant outliers using Grubbs (1969) approach (implemented through the 'grubbs.test' function of the outlier package for R; Komsta, 2011). In total, 12 univariate outliers were replaced by the closest non-outlier value (three for shame, one for hopelessness, two for surprise, two for confusion, and five for surprise). Furthermore, investigations of the skewness and kurtosis (values $<$ 2; George and Mallery, 1999) revealed that all of the variables used for analyses (i.e., mean emotion scores, emotion cluster scores and learning measures) were within acceptable ranges of normal distribution.

The person-centered methodological approach for the identification of emotion profiles was based on previous studies investigating affective, emotional, or motivational profiles (Vansteenkiste et al., 2009; Robinson et al., 2017). More specifically, we first used the 'hclust' function of R's stats package to compute a range of profile solutions using Ward's method and extracted the cluster centroids for each profile. We used agglomeration coefficients obtained through the SPSS classification function (SPSS, 2012), minimum number of profile size (Fernando et al., 2014), and cluster fit indices from 'Nbclust' (Charrad et al., 2014) to identify the eligible range of clusters. Subsequently, k-means clustering analysis with these centroids as starting points was conducted ('kmeans' function of the 'stats' library) to obtain the most distinctive set of profiles. As a last step in the cluster identification we used the cross-validation procedure outlined by Breckenridge (2000) to assess the stability of the solution (using self-implemented function based on the 'knn' function of the 'class' library; Venables and Ripley, 2002). Together with investigations of explained variance in the clustering variables and redundancy of the clusters, this criterion was used to determine the final cluster solution. Clustering methodology was chosen because the suitability of clustering over other methodological approaches in this context has been repeatedly showcased by previous research (e.g., Robinson et al., 2017).

Subsequently we used a latent growth linear mixed effect model to investigate differences in learning outcomes between emotion profiles. Models were fit using 'lmer' from the 'lme4' library (Bates et al., 2014). Summary statistics were extracted via the 'analyze' function of 'psycho' (Makowski, 2018) and *post hoc* comparisons were conducted using 'glht' from 'multicomp' (Hothorn et al., 2008). Additionally, this analysis was repeated for all profile solutions (including the initial solutions from hierarchical clustering) to assess if the findings were stable throughout different profile configurations.

Then spectral co-clustering – a machine learning clustering approach – implemented through the 'SpectralCoclustering' function of the Python library 'scikit-learn' was used to substantiate the relation between emotions and learning identified through the profiling approach (Pedregosa et al., 2011). Specifically, we grouped emotions into clusters based on their correlation across all measurement points and separately for each time point. The emotion cluster solution was selected based on its stability over all administrations of the EV and alignment to previous research. Then, principal component analysis ('PCA' function of 'scikit-learn') with one main component was used to obtain participants' scores for each emotion cluster at each measurement point. Additionally, the internal consistency of emotion clusters was assessed though Cronbach's Alpha ('alpha' of R's 'psych' package; Revelle, 2017). The obtained scores were then used in multiple regressions for each time point separately to assess how the emotion clusters are related to learning. Regression weights were calculated using the 'lm.beta' function R's 'lm.beta' package (Behrendt, 2014).[2]

[2] Analyses scripts and data are available upon request. For analyses that required (pseudo) randomization, seeds used to obtain the results reported in this paper were documented to guarantee replicability.

Preliminary Analyses

To control for the potential effect of the experimental manipulation of the present study (i.e., the control and prompt + feedback conditions) on the results described in the following sections, all variables included in the analyses were compared between the experimental conditions using multivariate analyses of variance (MANOVAs). Results showed no systematic differences in pre- and posttest scores, emotion scores, or emotion cluster scores between the conditions (all $p > 0.05$; except negative emotions cluster scores for EV 1: $p < 0.05$). Additionally, we conducted chi-square tests for each profile solution to test if the experimental conditions were equally represented in each emotion profile. Results revealed no significant differences in the distribution of experimental conditions for any of the emotion profiles identified.

Person-Centered Approach: Emotion Profiles

Identifying Emotion Profiles

To identify emotion profiles, students with similar self-reported emotional experiences were grouped using a two-step clustering approach. More specifically, first, hierarchical clustering (Ward's method) was used on the squared Euclidian distance matrix for the mean values of each emotion for each participant throughout all six time points (see above). Each participant started as their own cluster in the hierarchical clustering analyses. Then the closest participants were merged into a cluster. This step was repeated until all participants were merged into a single cluster, resulting in a range of cluster solutions between the number of participants (i.e., each participant as their own cluster) and a singular cluster. To identify the profile solutions eligible for subsequent analyses, we used three criteria: (1) the scree-plot of agglomeration coefficients to identify the point where the addition of clusters did not substantially decrease the agglomeration coefficient, (2) a sufficient profile size for statistical analyses ($n > 10$; Fernando et al., 2014), and (3) multiple cluster fit indices (Charrad et al., 2014). Agglomeration coefficient indicated that merging a three-cluster solution into two clusters was not practical ($\Delta_{coefficient} = 233.93$). A second drop in agglomeration coefficients was identified for the addition of a sixth cluster, but was less substantial ($\Delta_{coefficient} = 73.379$). While this procedure favored solutions with more than six profiles, the second criterion limited the number of profiles to a maximum of seven, as all further profile solutions included profile(s) with less than ten participants. Lastly, we compared the solutions that were sufficient for both criteria in regard to 26 fit indices (see Charrad et al., 2014 for a complete list of the indices) and found equal support for the three to five profile solutions and little to no support for the six and seven profile solutions. Accordingly, the three-, four-, and five-profile solutions were selected for further analyses.[3] Preliminary analyses on the structure of the clusters revealed a noteworthy feature. A single emotion profile with higher negative emotion intensities than other profiles ($n = 29$) was a stable component of all solutions outlined above.

As a second step in the identification of emotion profiles we used k-means clustering, a non-hierarchical clustering procedure, in order to increase similarity within clusters and differences between clusters. More specifically, for the previously selected three- to five-cluster solutions, we first extracted the cluster centroids. These values were then used as starting points of the k-means clustering instead of starting with randomized seeds. In this procedure the number of clusters is defined *a priori*. Then a starting seed was used as the initial centroid of a cluster and participants that were in proximity to that centroid (measured through a distance threshold) were assigned to that cluster. This procedure was repeated for each starting seed until all participants were assigned to a cluster (Fortunato and Goldblatt, 2006). K-means clustering was chosen because this procedure simultaneously maximizes between cluster distances (i.e., increased differences between emotion profiles) and minimizes within-cluster variance (i.e., increased similarity within profiles; Eshghi et al., 2011). After obtaining the respective cluster solution, we then assessed the rate of agreement between the hierarchical and k-means approaches. Both clustering methods showed sufficient rate agreement ($K_3 = 0.76$; $K_4 = 0.78$; $K_5 = 0.78$). This indicated that the k-means clustering altered the initial profiles obtained through the hierarchical clustering but maintained the overall structure and demonstrates the robustness of the identified profiles. To test if the aggregation of self-reported emotion intensities had a significant impact on the obtained emotion profiles, we re-ran all previous steps using all six measurement points for the fourteen emotions as clustering variables. Comparison of the profiles identified by clustering means and the profiles identified by clustering all measurement points demonstrated high to very high agreement ($K_3 = 0.85$; $K_4 = 0.91$; $K_5 = 0.88$). This indicated that our data supports the use of mean values as clustering variables and further underlined the robustness of the clustering procedure.

To select the emotion profiles for subsequent analyses we first compared the explained variance in mean emotion intensities between the solutions with different numbers of emotion profiles. The three-profile solution explained moderate levels of variance for all mean emotion intensities, except neutral, surprise, anxiety and contempt (see **Table 2**). The four-profile solution explained more variance for most of the emotions, but also showed lower levels of explained variance for specific emotions (i.e., contempt and confusion). This pattern also applied to the comparison of the four- and five-profile solutions. However, while the four-profile solution added a profile that was primarily defined by boredom in addition to the neutral, positive, and negative emotion profiles of the three-profile solution, the five-profile solution only added a profile that was largely redundant to the positive emotion profile (with higher levels of curiosity, surprise and anxiety). Based on the largely redundant nature of this profile (a criteria used by Fernando et al., 2014), we decided not to consider this solution.

As the final step for selecting the most suitable cluster solution, we cross validated the three- and four-profile solutions following

[3] All subsequent analyses were also conducted for the six- and seven profile-solution. The pattern of results remained similar. These results were not reported in this study due to space constraints.

TABLE 2 | Explained variance by profile-solution.

Emotion	Profile solution		
	3	4	5
Enjoyment	0.47	0.63	0.62
Hope	0.46	0.55	0.54
Pride	0.34	0.39	0.40
Frustration	0.31	0.38	0.41
Anxiety	0.20	0.22	0.42
Shame	0.55	0.60	0.65
Hopelessness	0.64	0.67	0.68
Boredom	0.44	0.60	0.62
Surprise	0.14	0.23	0.39
Contempt	0.22	0.13	0.12
Confusion	0.40	0.34	0.43
Curiosity	0.36	0.49	0.46
Sadness	0.39	0.44	0.45
Neutral	0.10	0.15	0.23
Average	0.36	0.42	0.46

the procedure outlined by Breckenridge (2000). More specifically, we split our sample randomly into two equally large sub samples. Then, the two-step clustering procedure outlined above was separately applied to each of the sub samples. The two sub samples were subsequently compared with a k-nearest-neighbors approach. More specifically, each participant of a sub sample was assigned to a new cluster value based on their most similar counterparts in the other sub sample (their nearest neighbors). To assess the robustness, Kohen's Kappa (as a measure for agreement) was calculated based on the initial (obtained through the two-step approach) and new cluster assignment (obtained through the nearest neighbors procedure) in both samples. To increase the robustness of the cross-validation, we repeated this procedure twenty times and averaged Kappa values across all iterations (i.e., 20-fold cross validation). Results indicated that the three-profile solution ($K = 0.65$) showed sufficient stability (i.e., $K > 0.60$; Breckenridge, 2000; Asendorpf et al., 2001), but the four-profile solution did not ($K = 0.56$). Therefore, the three-profile solution was selected as the final profile solution (see **Figure 2** for a comparison of mean emotion intensities between the three profiles). Means and standard deviations for mean emotion intensities, and pre and post test scores of the three-profile solution are displayed in **Table 3**. The three profiles can be described by their most distinct features as follows[4]. The first profile ($n = 75$) displayed low to moderate levels for all emotions except boredom and neutral, which were at moderate levels. The neutral score was higher than for the other profiles. Accordingly, we refer to this profile as *neutral*. The second profile ($n = 62$) showed moderate to high levels for most of the positive emotions (joy, hope, pride, curiosity) and low levels of negative emotions (frustration, shame, hopeless, boredom, contempt, confusion, and sadness). The positive emotion intensities were higher in this profile compared to those of the other profiles. Thus, we labeled this profile as the *positive* emotion profile. The final profile ($n = 39$) was characterized by medium levels for all emotions. When compared to the other profiles, the most distinct feature of this group was their increased levels of negative emotion intensities for all negative emotions. Therefore, we referred to this group as the *negative* emotion profile. A multivariate analyses of variance (MANOVA) revealed that the emotion profiles significantly differed in regard to their mean emotion intensities [Wilks's λ (28, 320) = 0.100, $p < 0.001$, $\eta^2 = 0.68$].

Linking Emotion Profiles and Learning Outcomes

Differences in learning outcomes between profiles were analyzed using a latent growth linear mixed effect model. More specifically, we predicted learning outcomes with time (pre and post test) and profile membership as fixed factors and included a random intercept[5] based on previous studies that showed the importance of individual differences in prior knowledge when learning with MetaTutor (Taub et al., 2014). The model explained significant proportion of variance in learning outcomes ($R^2 = 68.03\%$; fixed effects: $R^2 = 16.23\%$) and showed that learning outcomes significantly improved over time for all profiles [$\beta = 0.75$, $SE = 0.06$, $t(175) = 12.36$, $p < 0.001$, $VIF = 1.00$] and that membership in the negative profile was associated with significantly lower learning outcomes [$\beta = -0.40$, $SE = 0.16$; $t(173) = -2.43$, $p < 0.05$, $VIF = 1.18$; see **Figure 3**][6]. *Post hoc* test using Tukey's HSD (honestly significant difference) showed that significant differences in learning outcomes were only found between the negative and neutral profile ($z = -2.432$; $p < 0.05$).

Linking Emotion Profiles and Emotion Regulation

Two separate ANOVAs comparing expressive suppression and cognitive reappraisal between the profiles were conducted to test if profiles differed in their self-reported habitual use of emotion regulation strategies. Results showed that there were no significant differences in expressive suppression [$F(2,163) = 0.013$; $p = 0.99$], but significant differences in cognitive reappraisal between profiles [$F(2,163) = 4.185$; $p < 0.05$]. *Post hoc* comparisons using Bonferroni correction revealed that students with a negative emotion profile had significantly lower cognitive reappraisal scores ($M = 4.62$, $SD = 1.27$) then those with a positive emotion profile ($M = 5.30$, $SD = 1.07$; $p < 0.05$).[7]

Variable-Centered Approach: Patterns of Co-occurring Emotions

Identifying Patterns of Co-occurring Emotions

To identify patterns of co-occurring emotions, correlation matrices for the 14 emotions investigated in this study were computed separately for each point of time (see procedure)

[4]Labels for the profiles were chosen based on the most dominant feature overall and in comparison to the other profiles.

[5]The step-wise model selection procedures were not reported due to space constraints. They can be found in the **Supplementary Material**.

[6]This pattern of results was consistent for all profile solutions of the two-step approach but only for the three-profile solution in the initial clustering approach.

[7]Further analyses revealed that this pattern of results stayed identical across all profile solutions (four- and five-profile solution from the k-means clustering as well as three- to five-profile solutions from the initial hierarchical clustering analyses).

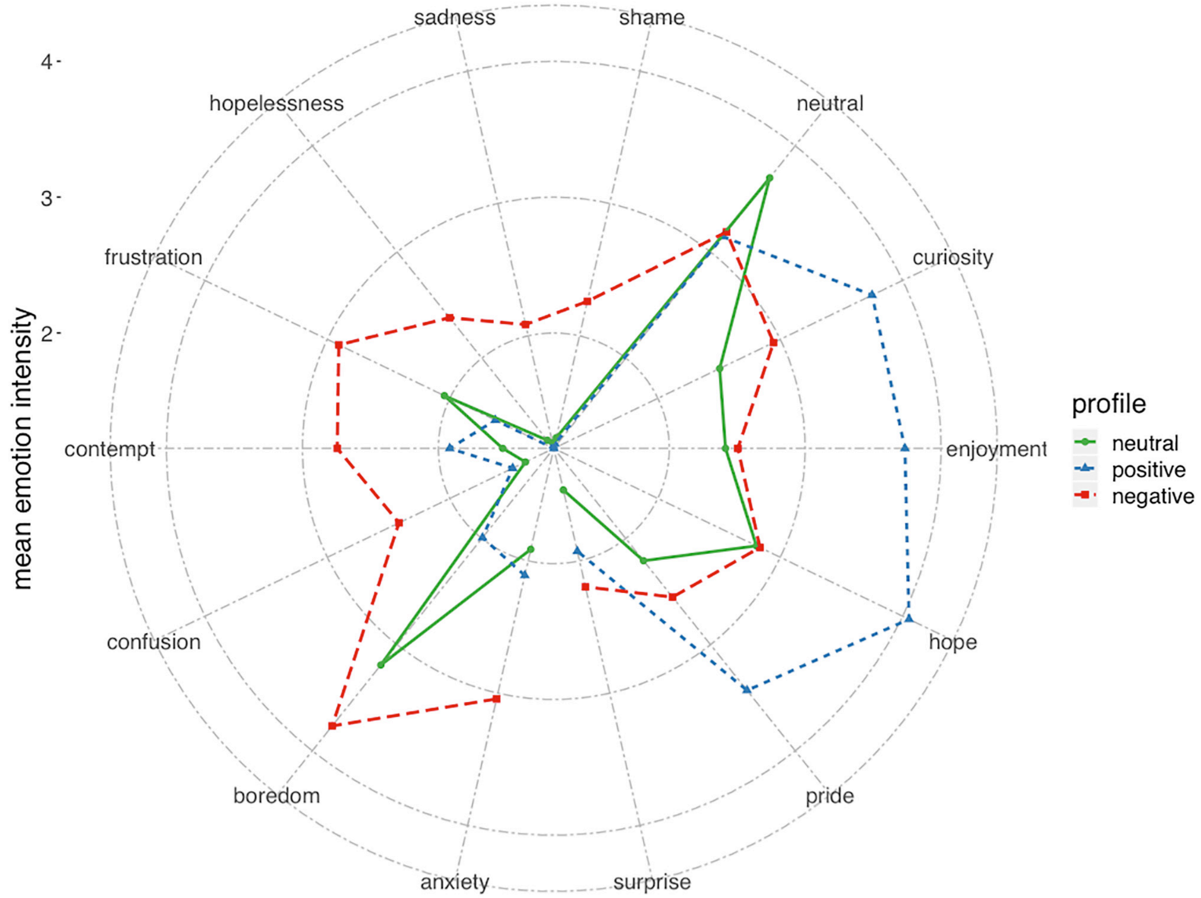

FIGURE 2 | Comparison of mean emotion intensities between profiles.

and aggregated over all points of time. Then, spectral co-clustering, a clustering technique that groups data by rows and columns simultaneously (e.g., Kluger et al., 2003), was applied to these matrices to obtain the variable-centered patterns of related emotions for each point of time and aggregated over all EV administrations. This procedure was carried out for cluster solutions ranging from three to six clusters. A four-cluster solution was the only one that displayed great stability over all time points and aggregated over all measures (the only exception is that contempt moved to the boredom cluster during the last measurement). This solution included a positive and a negative emotions pattern, as well as neutral and boredom as singular-emotion clusters (see **Table 4**). Cronbach's Alpha was calculated for the negative and positive emotions pattern separately for each time point to test if the identified cluster represented an internally consistent linear structure sufficiently well. Results showed that both the negative pattern (alpha ranging from 0.74 to 0.81) and the positive pattern (alpha ranging from 0.72 to 0.85) met this criterion.[8] We obtained participants' individual scores for each pattern and the maintained variance of each pattern through principal component analyses with one component. The maintained variance from the original Likert-scale items for each non-singular emotion pattern was sufficient in this solution (35.45% for the negative emotions pattern for EV2 and 68.40% for the positive emotions pattern for EV2, see **Table 4**). Loadings for all emotions were positive for each pattern (i.e., increases in emotion intensity was associated with an increase in pattern score).

Exploring Differences in Variable-Centered Emotion Patterns Scores Between Emotion Profiles

Differences in emotion variable-centered cluster scores between profiles over time were analyzed using latent growth linear mixed effect models. More specifically, we predicted variable-centered emotion pattern scores with time (six administrations of the EV), profile membership and their interaction as fixed factors and included a random intercept for the negative, positive and boredom emotion patterns.[9] The model for the neutral emotion pattern did not include the interaction term of time and profile membership as the addition of this factor did not improve the model significantly. Results showed significant

[8] No item had to be rescaled for these analyses, showing that all measures in the pattern correlated positively with the pattern score assigned to each participant.

[9] Random slopes were initially considered but lead to potentially overfitted models (singular fit) and were therefore not considered in final analyses. The model selection summary can be found in the **Supplementary Material**.

TABLE 3 | Means and standard deviations for emotion items, emotion regulation, and learning measures by profile solutions.

Profile solution	**3**			**4**				**5**				
Profile	**1**	**2**	**3**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**5**
n	**75**	**62**	**39**	**27**	**67**	**50**	**32**	**27**	**60**	**27**	**32**	**30**
	M (SD)	***M (SD)***	***M (SD)***	***M (SD)***	***M (SD)***	***M (SD)***	***M (SD)***	***M (SD)***	***M (SD)***	***M (SD)***	***M (SD)***	***M (SD)***
Enjoyment	2.41 (0.67)	3.73 (0.62)	2.5 (0.66)	1.66 (0.42)	2.84 (0.53)	3.84 (0.59)	2.6 (0.59)	1.66 (0.42)	2.8 (0.51)	3.55 (0.63)	2.6 (0.59)	3.94 (0.62)
Hope	2.8 (0.71)	4.05 (0.55)	2.83 (0.64)	2.29 (0.66)	3.09 (0.61)	4.19 (0.51)	2.92 (0.58)	2.29 (0.66)	3.10 (0.6)	3.69 (0.63)	2.92 (0.58)	4.37 (0.49)
Pride	2.21 (0.77)	3.43 (0.78)	2.55 (0.65)	1.78 (0.55)	2.50 (0.74)	3.53 (0.81)	2.67 (0.63)	1.78 (0.55)	2.5 (0.71)	3.03 (0.96)	2.67 (0.63)	3.75 (0.67)
Frustration	2.04 (0.84)	1.63 (0.56)	2.91 (0.61)	2.72 (0.87)	1.76 (0.68)	1.67 (0.56)	2.92 (0.57)	2.72 (0.87)	1.77 (0.68)	1.93 (0.56)	2.92 (0.57)	1.43 (0.47)
Anxiety	1.91 (0.81)	2.11 (1.00)	3.04 (0.76)	2.12 (0.81)	1.88 (0.81)	2.16 (1.01)	3.19 (0.75)	2.12 (0.81)	1.76 (0.65)	3.00 (0.84)	3.19 (0.75)	1.57 (0.74)
Shame	1.23 (0.34)	1.19 (0.3)	2.26 (0.56)	1.29 (0.34)	1.22 (0.35)	1.2 (0.32)	2.41 (0.47)	1.29 (0.34)	1.19 (0.28)	1.48 (0.45)	2.41 (0.47)	1.02 (0.05)
Hopelessness	1.23 (0.33)	1.15 (0.26)	2.38 (0.55)	1.31 (0.38)	1.24 (0.34)	1.14 (0.25)	2.52 (0.47)	1.31 (0.38)	1.23 (0.34)	1.30 (0.34)	2.52 (0.47)	1.04 (0.09)
Boredom	3.19 (0.93)	1.99 (0.68)	3.76 (0.67)	4.24 (0.56)	2.73 (0.73)	1.91 (0.67)	3.66 (0.63)	4.24 (0.56)	2.83 (0.68)	1.88 (0.63)	3.66 (0.63)	1.93 (0.68)
Surprise	1.46 (0.48)	1.93 (0.88)	2.2 (0.68)	1.23 (0.33)	1.57 (0.49)	2.04 (0.91)	2.33 (0.65)	1.23 (0.33)	1.56 (0.49)	2.56 (0.8)	2.33 (0.65)	1.47 (0.59)
Contempt	1.53 (0.74)	1.92 (1.05)	2.74 (0.66)	2.01 (0.93)	1.60 (0.87)	1.88 (1.08)	2.65 (0.55)	2.01 (0.93)	1.63 (0.9)	1.88 (0.89)	2.65 (0.55)	1.75 (1.16)
Confusion	1.38 (0.43)	1.49 (0.53)	2.41 (0.56)	1.55 (0.65)	1.40 (0.43)	1.51 (0.55)	2.45 (0.55)	1.55 (0.65)	1.40 (0.42)	1.86 (0.54)	2.45 (0.55)	1.18 (0.3)
Curiosity	2.50 (0.66)	3.75 (0.81)	2.94 (0.76)	1.93 (0.59)	2.82 (0.62)	3.89 (0.74)	3.10 (0.64)	1.93 (0.59)	2.82 (0.59)	4.02 (0.58)	3.10 (0.64)	3.54 (0.95)
Sadness	1.19 (0.37)	1.17 (0.32)	2.09 (0.61)	1.28 (0.42)	1.16 (0.34)	1.19 (0.35)	2.23 (0.55)	1.28 (0.42)	1.16 (0.34)	1.29 (0.43)	2.23 (0.55)	1.10 (0.22)
Neutral	3.70 (0.71)	3.15 (0.83)	3.19 (0.75)	3.30 (0.86)	3.79 (0.61)	3.03 (0.84)	3.20 (0.7)	3.30 (0.86)	3.90 (0.53)	2.79 (0.77)	3.20 (0.7)	3.20 (0.8)
Reappraisal	4.95 (1.09)	5.30 (1.07)	4.62 (1.27)	5.03 (1.26)	5.00 (0.92)	5.36 (1.15)	4.41 (1.30)	5.03 (1.26)	5.03 (0.88)	5.16 (1.22)	4.41 (1.30)	5.38 (1.13)
Suppression	3.97 (0.97)	3.97 (1.13)	3.94 (1.17)	3.78 (0.98)	3.97 (1.04)	4.03 (1.11)	4.01 (1.16)	3.78 (0.98)	4.03 (1.04)	4.09 (1.05)	4.01 (1.16)	3.83 (1.15)
Pre ratio	0.59 (0.13)	0.58 (0.14)	0.55 (0.17)	0.53 (0.11)	0.60 (0.13)	0.59 (0.13)	0.55 (0.19)	0.53 (0.11)	0.60 (0.13)	0.59 (0.12)	0.55 (0.19)	0.59 (0.14)
Post ratio	0.71 (0.12)	0.70 (0.13)	0.63 (0.16)	0.67 (0.10)	0.72 (0.13)	0.7 (0.13)	0.62 (0.17)	0.67 (0.10)	0.72 (0.13)	0.71 (0.11)	0.62 (0.17)	0.70 (0.14)

Reappraisal, cognitive reappraisal subscale of the emotion regulation questionnaire; suppression, expressive suppression subscale of the emotion regulation questionnaire.

differences in emotion pattern scores on average for all emotion clusters (all $p < 0.001$). Furthermore, the negative, positive, and boredom pattern scores showed significant linear growth for all participants (all $p < 0.001$). For negative emotion pattern scores (R^2 = 62.99%, fixed effects: R^2 = 40.54%) we found significantly different linear trajectories between the negative profile and the other profiles [compared to neutral profile: $\beta = 0.22$, $SE = 0.05$, $t(877) = 4.57$, $p < 0.001$, $VIF = 4.44$; compared to positive profile: $\beta = 0.21$, $SE = 0.05$; $t(877) = 4.16$, $p < 0.001$, $VIF = 4.11$; see **Figure 4**]. Linear growth in positive emotion pattern scores (R^2 = 66.10%, fixed effects: R^2 = 40.44%) were significantly different between the positive and other profiles [compared to neutral profile: $\beta = 0.08$, $SE = 0.04$, $t(877) = 1.99$, $p < 0.05$, $VIF = 3.17$; compared to negative profile: $\beta = 0.17$, $SE = 0.05$, $t(877) = 3.43$, $p < 0.001$, $VIF = 2.59$]. Boredom pattern scores (R^2 = 56.99%, fixed effects: R^2 = 25.58%) illustrated significantly different linear trajectories between the positive and the neutral profile [$\beta = 0.14$, $SE = 0.05$, $t(877) = 3.14$, $p < 0.010$, $VIF = 3.28$].

Linking of Co-occurring Emotions and Learning Outcomes

To asses if variable-centered emotion patterns can predict learning gains, separate linear regression models predicting post test score with pretest and variable-centered emotion pattern scores for each point of time were calculated. Results showed that pretest score was a significant predictor of post score in all regressions (β ranging from 0.58 to 0.62; $p < 0.01$). The

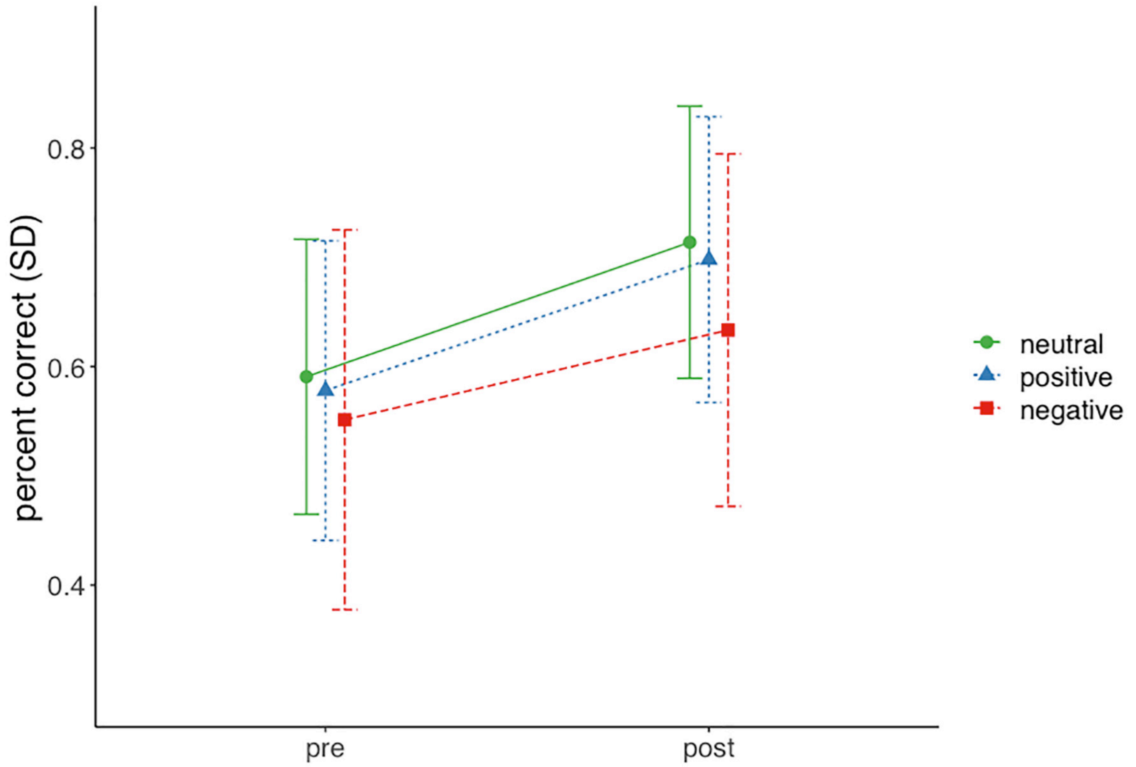

FIGURE 3 | Pre and post test scores by emotion profile.

TABLE 4 | Maintained variance and loadings for emotion patterns.

Pattern	Variable	Time point						
		Overall	EV T1	EV T2	EV T3	EV T4	EV T5	EV T6
Negative	σ^2	0.40	0.38	0.35	0.40	0.43	0.42	0.50
	Frustration	0.85	0.52	0.56	0.89	1.02	0.94	0.87
	Anxiety	0.83	0.95	0.74	0.82	0.86	0.84	0.95
	Shame	0.60	0.50	0.59	0.61	0.68	0.50	0.67
	Hopelessness	0.63	0.44	0.40	0.71	0.72	0.71	0.70
	Surprise	0.43	0.45	0.52	0.53	0.32	0.36	0.45
	Confusion	0.64	0.39	0.47	0.68	0.67	0.70	0.80
	Sadness	0.49	0.36	0.49	0.49	0.52	0.54	0.50
	Contempt*	0.52	0.58	0.54	0.65	0.49	0.65	
Positive	σ^2	0.65	0.55	0.68	0.65	0.66	0.63	0.66
	Enjoyment	0.94	0.73	0.85	0.94	0.92	1.06	1.02
	Hope	0.97	0.78	0.90	0.92	0.95	1.02	1.02
	Pride	0.86	0.77	0.89	0.89	0.88	0.87	0.98
	Curiosity	0.99	0.57	0.88	0.95	0.94	0.87	0.89
Neutral	σ^2	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Neutral	1.16	1.08	1.15	1.06	1.12	1.15	1.15
Boredom	σ^2	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Boredom	1.34	1.18	1.22	1.36	1.41	1.39	1.27
	Contempt*							0.61

*σ^2, maintained variance. EV, emotion values questionnaire. Absolute loading values were used if all loadings on the same main component were negative. *Contempt at EV T6 is the only deviation from the stable structure of emotions. It was associated with the boredom pattern instead of the negative pattern.*

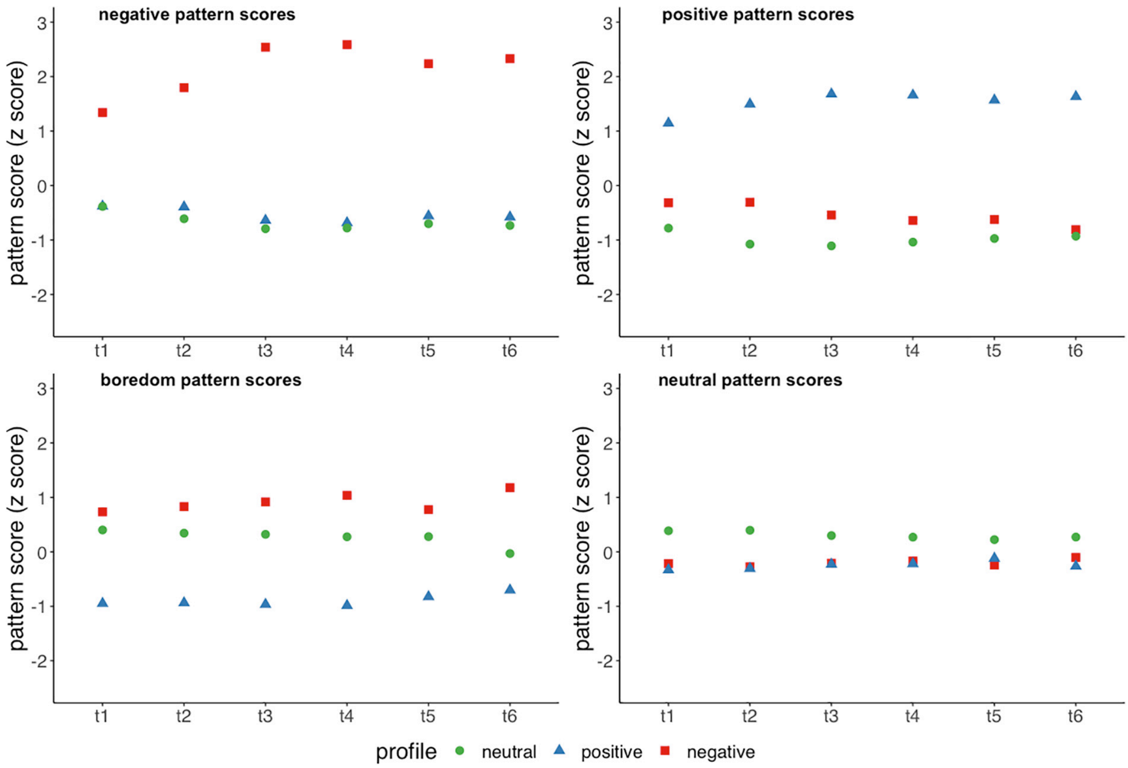

FIGURE 4 | Emotion pattern scores by emotion profile over the six measurement points.

explanatory value of variable-centered emotion pattern scores beyond the effect of pretest score throughout the different points of time varied. The positive emotions pattern was the only significant predictor besides pretest score for the first administration of the EV [before learning sub goals were set; $F(5,170) = 26.03$, $R^2 = 0.42$; $\beta = 0.15$; $p < 0.05$] and a marginally significant predictor for the second administration [after learning sub goals were set; $F(5,170) = 25.30$, $R^2 = 0.41$; $\beta = 0.14$; $p = 0.057$]. Negative emotions pattern scores significantly predicted post test score for the fourth [second EV during the learning activity; $F(5,170) = 24.22$, $R^2 = 0.40$; $\beta = -0.13$; $p < 0.05$] and sixth administrations of the EV [directly before the post test; $F(5,170) = 25.08$, $R^2 = 0.41$; $\beta = -0.17$; $p < 0.05$] and were a marginally significant predictor for the third [first EV during the actual learning activity; $F(5,170) = 24.05$, $R^2 = 0.40$; $\beta = -0.11$; $p = 0.086$] and fifth EVs [last EV during the learning activity; $F(5,170) = 23.01$, $R^2 = 0.39$; $\beta = -0.11$; $p = 0.082$]. The other patterns showed no significant relation to post test score at any time point.

DISCUSSION

This study used a person-centered approach to identify emotion profiles and a variable-centered approach to identify variable-centered emotion patterns throughout different phases of a learning session with MetaTutor. We further explored how the emotion profiles and variable-centered patterns identified through these approaches relate to learning outcomes (i.e., through a latent growth linear mixed effect model), and to self-reported habitual emotion regulations strategies.

With the person-centered approach we identified three distinct emotion profiles that reflected different emotional experiences during learning with MetaTutor. In line with our hypotheses and previous research, these profiles included a positive, negative, and neutral (referred to as low intensity in other studies; Robinson et al., 2017) emotion profile. However, it is important to note that the negative profile was not characterized by high levels of negative emotion intensities. It rather represented a group of students that had higher levels of negative emotions than the students belonging to the other profiles. An exception to this pattern was boredom, as the neutral profile showed comparable levels of boredom. This is in line with findings of previous studies emphasizing the distinct role of boredom during learning (Goetz et al., 2014). These findings were further supported through the variable-centered emotion patterns we identified in subsequent steps. Across six points of time throughout the learning session negative and positive emotions remained separate variable-centered patterns from boredom and neutral. This indicates that the separating features of our emotion profiles are related to a stable cluster structure of emotions. Moreover, our results indicated that the most profound difference in emotional experience between emotion profiles were found for the negative emotions ($\eta^2 = 0.48$ for the negative emotion cluster scores as compared to $\eta^2 = 0.09$ for other emotion cluster scores). In our profile solutions negative emotions were associated with one another regardless of their level of arousal. Interestingly, surprise was associated with the negative profile and negative emotions cluster. This finding corresponds with findings of a previous study that found a significant negative relation between surprise and the accuracy of metacognitive judgments indicating a potential negative impact on learning (Taub et al., 2019). However, the lack of differentiation of levels of arousal is likely caused by the imbalanced nature of arousal and valence in emotions measured in the present study (Robinson et al., 2017). Particularly, positive deactivating emotions were underrepresented in the EV. Nonetheless, across two different approaches we identified a theoretically supported and meaningful structure of emotions that centered around three levels of valence—i.e., positive, neutral, and negative.

The most striking feature across all profile solutions was the stability of the negative profile. More specifically, 26 of the 39 (67%) students in the negative profile were always assigned to the same profile regardless of the number of other profiles.[10] This indicates that the group of students with higher levels of negative emotions is most distinct from all other students (in regard to emotional experience). More importantly, comparisons of the learning outcomes for the profiles revealed that the negative profile performed significantly worse than at least one other profile at post-test in most profile solutions. In the three-profile solution presented in this paper, the negative profile was significantly outperformed by the neutral profile. This finding is well in line with previous studies using person-centered approaches, as multiple studies found that students with negative emotion profiles tend to learn less than those with neutral or positive profiles (Ganotice et al., 2016; Jarrell et al., 2017; Robinson et al., 2017; see **Table 2**). As opposed to variable-centered approaches that showed positive and negative effects of negative and positive emotions depending on the circumstances, person-centered approaches consistently found detrimental effects of negative emotions for learning. While under certain circumstances single negative (resolved) emotions can potentially benefit learning strategies and outcomes (e.g., D'Mello and Graesser, 2014; Taub et al., 2019), our data provided no support for beneficial effects of experiencing multiple negative emotions (e.g., students that belong to a negative emotion profile). It is important to note that while mixed effects of positive and negative emotions depending on the circumstances have been found in multiple studies, most studies indicate that positive emotions are typically beneficial and negative emotions are detrimental for learning (Boekaerts and Pekrun, 2015). Our results supported this general trend for negative emotions.

In addition to the question of which profiles do significantly differ in learning, we also investigated if and how variable-centered emotion patterns would predict learning. We found that positive emotions before the actual learning activity (EVs 1 and 2, see section Emotion Items) can predict learning outcomes beyond the explanatory effect of prior knowledge. During self-regulated learning with MetaTutor only negative emotions were significant predictors of learning, but not consistently (significant for EV3 and EV6, only marginally significant for EV4 and EV5). These findings indicate that predictive value of variable-centered emotion patterns for learning fluctuates over time and that negative emotions seem to play a predominant role during the learning activity. Furthermore, these finding reflect central approaches related to learning in digital learning environments – products and processes (Garcia-Martin and Garcia-Sanchez, 2018). More specifically, the profile analysis conducted in this study is primarily product focused as we first investigated differences in learning outcomes (i.e., product data) between emotion profiles. With subsequent analyses, we investigated the process nature of emotions by assessing how emotions form patterns over time and how linear developments in these patterns are related to learning.

We faced several challenges and identified limitations when applying the two clustering approaches to the present data. Our sampling approach was defined relative to the start and end of the session. In particular, we selected the first two EVs and the last two in the learning session. Of these questionnaires, only the first in the learning phase (EV3) and the very last before the posttest (EV6) were administered identically for all participants. The EVs in between these were identical relative to the start and end of the learning session, but slightly different in regard to learning time depending on the total number of EVs the participant completed (e.g., for participants with six EVs all questionnaires were in an actual sequence, while for participants with eight EVs the new sequence included the first four EVs and the last two EVs, leaving two EVs out and creating a spline which might not completely reflect the initial temporal trajectory). However, both profile analyses across all time points and the emotion clusters revealed that the selected clusters represented a stable, comparable selection of measures over time.

As a potential explanation for differences between emotion profiles we compared them in regard to emotion regulation and found significant differences in cognitive reappraisal, but not for expressive suppression between profiles. More specifically, the negative profile reported significantly lower habitual use of cognitive reappraisal than the positive profile, but not compared to the neutral profile. To back up these findings we compared the profiles in regard to variable-centered emotion pattern scores and their linear temporal trajectories. We found that emotion profiles did not only differ in averaged emotion pattern scores for all identified emotion patterns but also exhibited significantly different linear growth for negative emotions, positive emotions and boredom (see **Figure 4**). The most distinct differences lied in the negative emotion pattern as the negative profile displayed a linear increase in negative emotion pattern scores while the scores decreased/stagnated in the other profiles. This illustrates that the negative profile not only starts with higher values of negative emotions, but that this difference got larger over time. Taken together with our finding that the negative emotions cluster negatively predicted learning throughout the learning phase, this indicates that the issues of the negative

[10]This pattern was even stronger in the hierarchical cluster analyses as over 90% of students in that profile were consistently assigned to the same profile regardless of the number of other profiles.

emotion profile seem to arise over time and are linked to emotion regulation.

A potential explanation for the suboptimal performance of the negative emotion profile is the potential load on working memory imposed by negative emotions and emotion regulation (Curci et al., 2013). While positive emotions cannot enhance working memory beyond its natural capacity, multiple negative emotions may block valuable resources that are particularly required for mastering complex topics and completing challenging learning tasks. This phenomenon might be even more important in digital learning environments as they impose significant challenges to learners (e.g., for navigation through non-linear hyperlinked environments, coordinating multiple goals, integrate agent feedback, use sophisticated learning strategies; Opfermann et al., 2013). Future studies aiming to explain why negative emotions pose a detrimental effect on learning are needed, including cognitive load and its relation to working memory (Seufert, 2018; Anmarkrud et al., 2019).

Another limitation of the present study (and person-centered approaches in general) is the decontextualized nature of emotion measures used. Theories on affective dynamics stretch the importance of specific events or impasses that elicit emotions, however, the events preceding the measurement of emotions have not been considered yet. Specifically, given our data we cannot disentangle whether students learned less because they experienced negative emotions or if they experienced negative emotions because they were having difficulties during the learning process. Identifying if the elevated levels of negative emotions in negative profiles is related to characteristics of the learning task or the learning environment is crucial for both the understanding of the profiles and the development of adaptive systems that can support students and circumvent negative effects of negative emotions on learning though scaffolds. For instance, in our study we cannot rule out that the increase in negative emotion, especially in the negative emotions profile, was related participants being prompted to fill out self-reports to indicate their emotions repeatedly during the learning activity. Likewise, the precedents of emotional reactions during learning should be incorporated in future studies (e.g., by assessing which emotions specific prompts of pedagogical agents elicit). Taub et al. (2019) have shown that facially expressed emotions are associated with the accuracy of learning strategies. Identifying arising negative emotions and the learning processes they directly affect can bridge the gap between emotions and (meta)-cognitive processes. This goes hand in hand with another shortcoming of this line of inquiry – the sole reliance on self-reports to measure emotions. Models and research on emotions clearly state that emotions are multi-faceted processes and limiting our scope to the appraisal component (Scherer and Moors, 2019) is a significant limitation. Building multi-channel, multi-modal emotion profiles through the use of additional data channels can benefit person-centered research by refining profiles and by providing additional explanations how the profiles develop over time (e.g., through peaks in EDA). Lastly, personal predispositions (e.g., personality – narcissism as a predisposition for negative emotionality) is a general cause for differences in emotional experience and emotion regulation, and its effect on learning strategies could be very beneficial to deepen the understanding of emotions in self-regulated learning processes.

CONCLUSION

In conclusion, the results of our study highlight the importance of negative emotions during self-regulated learning with digital learning environments during complex learning. The present study adds to research in multiple ways. Methodologically, we have showcased how a person-centered and a novel variable-centered approach complement each other. Particularly identifying variable-centered emotion patterns in addition to emotion profiles enabled us to analyze temporal dynamics of multiple emotions simultaneously. A negative relation between negative emotions and learning outcomes was found with both approaches. This underlines the robustness of this finding and further shows that person-centered and variable-centered approaches can supplement each other. Moreover, clustering approaches offer the possibility to further connect findings from studies using different measures more easily (e.g., achievement emotions vs. learning-centered emotions). Through the combination of person-centered and variable-centered approaches, we have found that both the students with the highest levels of negative emotions overall and higher levels of negative emotions across all students showed a significant negative relation to learning. Furthermore, we have found that these detrimental effects are linked to lower (self-reported) emotion regulation. This indicates the need to identify when elevated levels of negative emotions arise, particularly for students who experience a multitude of negative emotions, for practitioners and researchers to intervene in a timely fashion before the detrimental effects of negative emotions settle in. Specifically, fostering students' emotion regulation as part of self-regulated learning activities with digital learning environments is a promising prospect to improve students' emotional experience and learning subsequently. Therefore, the design, development, and implementation of digital learning environments as well as educational interventions should incorporate emotions and emotion regulation as parts of (self-regulated) learning activities to maximize positive effects on students' learning.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

This study was approved the by North Carolina State University's IRB. All subjects gave written consent in accordance with the Declaration of Helsinki.

AUTHOR CONTRIBUTIONS

All authors contributed to the conception of the work and revised the final manuscript. RA and MT designed and conducted the study. FW conducted the statistical analyses. FW and MT wrote the first draft of the manuscript. RA and SN provided several rounds of edits on the manuscript.

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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.2019.02678/full#supplementary-material

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Improving Socio-Emotional Competencies Using a Staged Video-Based Learning Program? Results of Two Experimental Studies

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Relationship quality between teachers and their students is a critical aspect for well-being and effective learning in school. Accordingly, teacher training should promote competencies for creating and maintaining positive relationships in the classroom. The Helga Breuninger Foundation developed a video-based online training (Intus^3) that intends to focus on student teachers' interpersonal competencies by reflecting on staged videos. Although this training is well-designed, there is only little empirical evidence in general and so far no experimental research investigating the effects of Intus^3. Accordingly, we investigated whether this program is able to improve the capacities of student teachers' interpersonal competencies, affective well-being, and affective attitudes toward challenging students. We conducted two randomized experimental studies ($n1 = 132$, $n2 = 242$) within lectures in teacher education at the University of Potsdam, introducing the basics of inclusive education in two consecutive semesters. We compared groups first working with Intus^3 to waiting control groups that wrote an expository text based on empirical research discussing the relevance of teacher–student relationships with a longitudinal design with four measurement points. Latent change models showed that prior work with Intus^3 showed few effects but complex effects in comparison to the prior text work groups. In the larger and extended study 2, an increase of empathic concern was significant after the prior work with Intus^3. The results will be discussed with the perspective of the potential of further development of online training courses for affective learning for teachers and teacher students.

Keywords: affective learning, socio-emotional competencies, empathy, perspective taking, online training, digital

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INTRODUCTION

Since the study by Hattie (2010), there is ample evidence for us to assume that a good relationship between teachers and their students has a significant positive impact on productive schooling. In his international meta-meta-study, the teacher–student relationship was one of the most important factors predicting competency development in students. On a national basis, there is evidence that proves important effects. For example, in Germany, Aldrup et al. (2018) showed that teacher–student relationships play an important role in the development of teacher enthusiasm and exhaustion, which are in turn important factors that affect students' competency development (Kunter et al., 2013; Gegenfurtner et al., 2019).

A model that elaborates this assumption of the importance of the teacher–student relationships is the prosocial classroom model (Jennings and Greenberg, 2009). Taken together with the mentioned research, the current study is interested in learning more about ways of competency development in teachers and teacher students to enable them to establish beneficial relationships with their students.

STATE OF RESEARCH

An approach toward this goal can be derived from the prosocial classroom model (Jennings and Greenberg, 2009), namely focusing on teachers' social and emotional competencies (SEC) as prerequisites for their shaping teacher–student relationships. While there have been attempts to fill the gap of training of SEC and according to research for teachers internationally (e.g., Spilt et al., 2012), in Germany, there is still a lack of research and evidence-based programs, especially with regard to novice teacher students. Accordingly, it seems worthwhile to put more research effort into this endeavor. For our research at hand, we investigate an existing video-based online program that has been developed without our participation and compare it to text-based interventions in a lecture addressing large numbers of teacher students. First, we will elaborate on our conceptualization of SEC and sketch very briefly how it might be related to building productive teacher–student relationships. Subsequently, theory and evidence for interventions compared in the current study are presented before, finally, the investigated video-based program Intus[3] will be described in detail.

Socio-Emotional Competencies of Teachers and Productive Teacher–Student Relationship

SEC have been proposed to be of great significance for a healthy and productive work life of teachers. Jennings and Greenberg (2009) developed the prosocial classroom model that states with reference to a broad array of empirical evidence that teachers' SEC and their well-being influence healthy teacher–student relationships alongside an effective classroom management and an effective social and emotional learning (SEL) environment for students. Ultimately, the model assumes a positive influence on a healthy classroom climate and students' social, emotional, and academic outcomes. Rocchi and Pelletier (2018) showed accordingly that congruent positive beliefs of the relationship between coach and professional athletes were associated with higher psychological needs satisfaction. SEC consist of both emotional and social aspects. Both are important to create productive interpersonal relationships. However, given the current focus on the relationship between teachers and students, there is a stronger focus on social aspects while emotional aspects are mostly considered as affective components that are experienced in reference to these relationships. As such, both aspects are considered highly interdependent. However, theoretically, social aspects of SEC can be divided into cognitive and affective components. Such distinctions are rooted in social psychology (Davis, 1983a; Kanske et al., 2016), and two main facets can be described: (cognitive) perspective taking (PT) and (affective) empathic concern (EC). While PT describes the ability to assess situations from the perspective of that of another person, EC refers to a person's tendency to experience similar emotions as an observed person. As research indicates, PT and EC can be quite powerful, and they are distinct in their effects. For example, Vorauer and Quesnel (2016) showed in a study that if a member of a majority group shows high PT toward a member of a minority group, the latter reports more positive self-descriptions, but there is no such effect if the majority group shows higher levels of EC. There is also evidence for interactions between the constructs in such a way that higher EC can inhibit PT in affectively loaded situations (Kanske et al., 2016). Furthermore, there is initial evidence regarding teacher training that EC can be a positive predictor for developing higher teaching-specific self-efficacy (Krauskopf and Knigge, 2019). Accordingly, EC and PT seem to interact in rather complex ways in affective learning.

In inclusive settings, individualized planning (Richter and Pant, 2016) and relationship-sensitive teaching (Dumke, 1991) are customary instructional patterns. At the same time, teachers are specifically worried about establishing such patterns due to the challenges when facing more diverse emotional, social, and behavioral problems of students (de Boer et al., 2011). Accordingly, it can be assumed that SEC are especially important for the context of inclusive education (Krauskopf and Knigge, 2017). In line with this assumption, there is evidence that affective attitudes toward students with special needs might be of special interest as teachers' mental representations of their relationships with disruptive children are associated with negative affect (Spilt and Koomen, 2009). It has been found that such affect could lead to according behavior of teachers (Stuhlman and Pianta, 2002). Thus, it seems to be of importance to find ways to reflect on especially negative affective attitudes and the development of strategies to change or to deal with them for pre-service teachers starting with their university-based training (c.f. Pianta, 1999). In addition, such strategies show positive effects on student development as well as on the psychological functioning of teachers (Mashburn et al., 2006).

Interventions to Support the Development of Socio-Emotional Competencies of Teachers

While there are not many explicit programs focusing to support the development of SEC of teachers and/or accordingly the teacher–student relationships, Spilt et al. (2012) developed the "relationship-focused reflection program (RFRP) to promote teachers' relationships with behaviorally at-risk children" (p. 307). The core component of the program is a guided process for teachers to reflect on their positive and negative emotions toward their students in their daily work life. The objective is to increase teachers' SEC capacity to understand and deal with their affects and as a result change their own perspectives on the teacher–student relationship and the resulting behaviors. Narration and reflection have been used as tools in two blocks of two individual sessions in a 9-week-long time period. They found that closeness and sensitivity in the teacher–student relationships did rise during the duration of the program.

Besides the mentioned reflection sessions, a main component of the RFRP is an "Interpersonal Skills Training [. . .] based on the interpersonal communication model of Leary (1957)" (Spilt et al., 2012, p. 309). It is applied in a combination of a booklet and video examples of interactions between the teachers and the students. This is explicitly used to train the teachers to better understand their affects and cognitions and to use this knowledge to actively change their behavior. Explicit topics in the training are "in terms of the orthogonal dimensions affiliation (cooperation–opposition), and directivity (dominance–submission) and the complementarity principle (i.e., friendliness invites friendly behavior; dominance evokes submissive behavior)."

A German example for a structured and evidence-based intervention is a program applying guided supervision coaching groups for teachers across a time period of at least 6 weeks with 2 h/week (called Freiburg model; Braeuning et al., 2018). The objective of the Freiburg model is to increase teacher health. Nevertheless, in aiming at this goal, teacher–student relationships are a central content of the training. In dealing collaboratively with own cases of the teachers:

> "The intervention is conceptualized as a Balint-type group work based on a published manual [7]. It includes five modules dealing with the following issues: (1) basic knowledge of stress physiology and the effects on health parameters; (2) mental attitudes with a particular focus on mental health improvements in school teachers authenticity and identification; (3) competence in handling relationships with students; (4) competence in handling relationships with parents; (5) strengthening collegiality and social support among the staff. Since we have shown that participation in at least five sessions was sufficient for achieving the health benefit [2], the actual program has been shortened from originally 10 to currently six sessions." (p. 2/3)

Results on the evaluation of the Freiburg model work showed that the program is effective in improving teacher health. Nevertheless, SEC of the teachers have not been addressed in the evaluation accordingly; it is unclear if there are effects as intended. It is not investigated if teacher–student relationships improve after participation of the teachers.

The RFRP and the Freiburg model are very impressive programs and should be considered for broader establishment and further research. Nevertheless, the necessary resources to implement such intensive interventions are limited. Accordingly, it seems necessary to investigate less comprehensive alternatives that apply similar principles while being more economical.

The Online Program Intus³

The Helga Breuninger Foundation developed an online program intended to enhance SEC of teachers to improve their management of teacher–student-relationships, which is called Intus³ (online). The core element of this program are staged videos that show prototypic teacher–student interactions, which were developed iteratively in cooperation with teachers and the lay actor students themselves. Accompanied by expository videos and a pdf textbook, working through this video material is supposed to support teachers in reflecting on their initial emotions, thoughts, and behavioral impulses in order to create increasingly "resonant interactions." Such interactions are defined as "an expression of mindfulness and appreciation, is based on a resonant mindset." Intuition, in turn, is conceptualized as openness to one's own impressions and impulses and considered a central concept of the program (online).

The developers designed 40 staged videos in a cocreation process with students in a school in Tübingen, Germany. These short video clips show micro interactions that are supposed to provide prompts for practicing awareness, empathy, and reflection on spontaneous reactions. The expository videos and texts guide through step-by-step reflective processes, encouraging participants to come up with different possible spontaneous solutions in complex interactions of everyday life in the classroom.

Overall, the online training program is completed individually and organized in five modules. In our study, we applied only the first two modules. The first module *basic mindset* is supposed to support participants to "accept situations, understand scenes intuitively, empathically sensing needs, becoming aware of potentials," the second module *dialogic interventions* aims at "how to act proactively by acceptance, how to create productive atmospheres on intuition, how to solve conflicts sensing empathically the needs, how to act self-efficient focusing on potentials," and the third module deals with *body language* to "reading body language and intuitively recognize the significance of facial expressions [and] how to use 'body markers'" (Helga Breuninger Foundation)[1].

The Current Study

The goal of this study was to examine whether a video-based online training program can support the development of SEC as described above in samples of pre-service teachers still at the beginning of their training. Although the contribution of Jennings and Greenberg (2009) is now about 10 years old, their conclusions are still valid and guide the research questions of the current study:

"(a) Can interventions be developed to improve SEC?"

"(b) Do these interventions result in reduced teacher stress and burnout and increased well-being?"

The study at hand addresses the research questions (a) and (b) with regard to teacher student training. The hypotheses will be tested, if

- Regarding the immediate effect, the video-based Intus³ program shows different levels of affective and cognitive situational interest and amount of invested mental effort compared to a traditional academic writing task, with both—online program and writing task—focusing on teacher–student relationships.
- The implementation of the video-based Intus³ program shows larger effects over time on teacher students SEC,

[1]Helga-Breuninger-Foundation. Available online at: Intus3. www.intushochdrei.de/?lang=en (accessed January 31, 2019).

more concretely on their short-term development of EC, PT, affective attitudes toward students with Special Educational Needs (SEN), attitudes toward teacher–student relationships in general, and their psychological adjustment (emotional exhaustion) compared to a traditional academic writing task, with both—online program and writing task—focusing on teacher–student-relationships.

METHODS

Design and Sample

We conducted studies, both following a randomized control group design over the course of two consecutive semesters in 2018 and 2019. Participants attended an introductory lecture to the field of inclusive education (Study 1 $n = 114$; Study 2 $n = 209$). The lecture was comparable in content and structure across the semesters; however, they were held by different lecturers. In both studies, students answered an initial online questionnaire ($t1$) and were randomly assigned to one of two groups, subsequently. In order to ensure comparable learning opportunities for participating students in both conditions, we followed the rationale of a waiting control group. Participants in the intervention group *Online Program* First received an invitation to their personal Intus[3] workspace. There, they could access Module 1 (*mindset*) and 2 (*dialogic interventions*), which they were guided to complete over a 7-week period. The online platform and the research questionnaires were accessed via the same anonymous code sent to students at the beginning of the semester. This enabled us to include only participants who had completed both modules. The waiting control group *Textual Work First* started with a text-based task. Students were asked to complete a prototypic academic task during the same period of 7 weeks. They were instructed to write an expository text (2,500 characters) based on a systematic literature search on the topic of teacher–student relationships. Students were asked to base their writing on empirical research accessed through scientific databases and refer those in their texts explicitly. Students were provided two peer reviews. In Study 1, this peer-review process was supported by the online system *Tapaass* (Walter et al., 2017) and, in the Study 2, via the workshop module provided by Moodle. Both groups completed second online questionnaire after 7 weeks ($t2$). Thereafter, the waiting control group (Textual Work First) received access to the digital learning platform Intus[3], and the group (Online Program First) was assigned to complete the text-based task. After another period of 7 weeks, subsequent to all students completing the respective tasks, they filled in a third online questionnaire ($t3$). Finally, all participants completed the last questionnaire online at the end of the semesters ($t4$).

Regarding the online program, students in study 1 only completed the Intus[3] modules, whereas in study 2, students additionally wrote a short paper (1,500 characters) in which they reflected on their learning experience with this video-based online program.

In both studies, a subsample of students was additionally enrolled in a seminar accompanying an educational-psychological internship. Because the learning goals of the internship were associated with observing interactions in pedagogical environments, and thus pedagogical relationships, we controlled for seminar participation in the analyses presented below. We use the term *Treatment 1* to indicate group membership (Online Program First vs. Textual Work First) and *Treatment 2* to indicate additional seminar participation.

If students did not want to participate in the research, they were provided with an essay task on topics regarding inclusive education to gain all course credit. Students gave informed consent to their participation, and the regulations of the German data protection law (DGSVO) were followed.

Instruments

An array of empirically validated instruments was applied to measure the different aspects of SEC introduced above that were paralleled with the core constructs addressed by the online program Intus[3]. **Table 1** shows an overview of this selection with means, standard deviations, and Cronbach's alpha at $t1$. All scales showed sufficient internal consistency and will be shortly explained in the following subsections.

PT and EC

PT and EC were assessed by the respective subscales of the Interpersonal Reactivity Index developed by Davis (1983b) using an established German version by Paulus (2009). Regarding the conceptual framework of Intus[3], these constructs tap into participants' development toward an increasingly intuitive *understanding* of interpersonal scenes and conflicts from multiple perspectives (PT, four items, sample item: "I believe there are always two sides to a problem, and therefore try to consider both.") and *empathically sensing* the different needs and emotions of the different agents involved in an interpersonal conflict (EC, four items, sample item: "I experience warm feelings for persons less fortunate than myself"). Items were rated on a 5-point scale ($1 = never$, $5 = always$).

Affective Attitudes Toward Students With Special Needs

Affective attitudes are central to the conceptual framework of Intus[3], namely, the goals to foster *an overall accepting stance* and to increase *awareness of students*. Accordingly, a self-report measure based on the work of Avramidis et al. (2000), German version by Knigge and Rotter (2015) was applied in a brief version to assess participating pre-service teachers' affective attitude toward teaching in a classroom with a new student who displays (1) behavioral problems or (2) learning difficulties, respectively. Each scale consisted of adjectives describing emotions in the format of four semantic differentials (e.g., *positive* vs. *negative* on a 5-point scale) and a short situation description as item stem.

Emotional Exhaustion

If a person comes closer to the goals to *solve conflicts sensing empathically the needs [and ...] to act self-efficient focusing on potentials*, it can be assumed that emotional exhaustion is reduced due to an increase in effective coping mechanisms (c.f. Braeuning et al., 2018). To operationalize this conceptual foundation of the online program, we applied the emotional

TABLE 1 | Internal consistencies for the applied scales at the first time of measurement.

Variable	Study 1				Study 2			
	n	*M*	SD	α	*n*	*M*	SD	α
Affective attitude behavioral p	114	2.79	0.71	0.82	209	2.99	0.72	0.79
Affective attitude learning d	114	3.35	0.64	0.81	209	3.50	0.72	0.83
Empathic concern	114	3.78	0.61	0.69	209	3.73	0.66	0.72
Perspective taking	114	3.87	0.61	0.75	209	3.83	0.58	0.72
Emotional exhaustion	114	2.38	0.73	0.76	209	2.44	0.71	0.76
Goal student–teacher relationship	114	4.60	0.46	0.71	209	4.51	0.47	0.60

exhaustion subscale of a German measure by Enzmann and Kleiber (1989) based on the Maslach Burnout Inventory (Maslach et al., 1996). The scale consisted of four items using a 5-point Likert scale (sample item: I often feel exhausted during my studies").

Student–Teacher Relationship as a Personal Goal

As the enhancement of the quality of student–teacher relationships is an overarching goal of Intus[3], we assessed the degree to which students valued this as a professional goal for themselves. We used the respective subscale from a measure by Rüprich (2018) using a 5-point Likert scale (sample item: "I strive to become a teacher who develops a positive attitude toward my students.").

Measurements of the Perceptions of the Learning Experience

In addition to the measures tapping into the more distal constructs described above, we applied measures to assess the quality of the experience of the participating pre-service teachers while engaging with the video-based online program and the academic writing task, respectively. We chose to assess motivational aspects by measuring the cognitive and the affective dimension of situational interest. These constructs have been shown to be meaningful predictors for learning outcomes (e.g., Tsai et al., 2008). We used scales adapted from Deci et al. (1994) consisting of seven items for each scale (sample item cognitive: "I believe this activity could be of some value to me," sample item affective interest: "I enjoyed doing this activity very much"). Furthermore, we applied a more specific measure tapping into the cognitive processes associated with learning using video material vs. text material, namely, the amount of invested mental effort (AIME) introduced by Salomon (1984). This scale is an established indicator in research on comparing digital learning environments with regard to how deep the involvement with the presented content is perceived by participants. Thus, higher AIME scores are considered to point to a deeper content elaboration. We applied a validated German scale by Krell (2017) consisting of 12 items [sample item: "At the processing of the tasks, I haven't done my best particularly." (reversed)]. For all scales, a 7-point Likert scale was applied.

Statistical Analyses

Test for Measurement Invariance Over Time

As we were interested in changes over time in relation to an intervention, we computed latent change scores (LCS) for each time lag. LCS are a useful method to analyze latent change factors between different measurement times within longitudinal structural equation models (McArdle, 2009). To analyze LCS, the latent constructs must have an equal structure at the relevant measurement time. First, we checked if the data met the requirements for LCS.

First, the constructs of each study were checked for their factorial measurement invariance (Little, 2013). Since LCS are to be interpreted in this study, the model must have a strong measurement invariance (same factorial structure across time, factor loadings constrained to be equal across time, and intercepts constrained to be equal across time) (Widaman et al., 2010). The evaluation of the measurement invariance was based on the approach of van de Schoot et al. (2012). Confirmatory Factor Analysis (CFA) was specified to test the measurement invariance. Marsh et al. (1998) recommend to operationalize at least four indicators per construct for an adequate analyzing CFA models in small samples ($n = 100$). According to the suggestions of Marsh et al. (1998), the sample sizes of the two available studies (study 1 $n = 114$; study 2 $n = 209$) are sufficient with regard to validity, as in both studies, the constructs were operationalized by at least four indicators. The full information maximum likelihood (FIML) method was used, so that cases with missing values were also included in the analyses (Schafer and Graham, 2002). The χ^2 test, the Comparative Fit Index (CFI), and the Root Mean Square Error of Approximation (RMSEA) were used to evaluate the goodness of fit of the specified models. Since the χ^2 test is a sample-sensitive test procedure (Cheung and Rensvold, 2002), comparative and absolute fit indices are used in addition to the χ^2 test to check the model fitting (Beauducel and Wittmann, 2005). Within the framework of longitudinal studies, values >0.90 for the CFI indicate an acceptable model fit and values ≥ 0.95 indicate a good model fit. For the RMSEA, values ≤ 0.08–0.05 indicate an acceptable model fit, and values ≤ 0.05 indicate a good model fit (Little, 2013). To assess the level of factorial invariance, the conventions of Cheung and Rensvold (2002) were used. In this approach, the change in the model fit is evaluated by comparing the less restrictive model with the more restrictive one. As long as the ΔCFI does not decrease more than 0.01

TABLE 2 | Model fit statistics for testing of measurement invariance.

Model	Study 1								Study 2							
	χ^2	*df*	*p*	*CFI*	Δ *CFI*	*RMSEA*	Δ *RMSEA*	*RMSEA 90% CI*	χ^2	*df*	*p*	*CFI*	Δ *CFI*	*RMSEA*	Δ *RMSEA*	*RMSEA 90% CI*
Behavioral problem																
Configural	102.65	74	0.015	0.971		0.059		0.027; 0.086	147.56	74	0.000	0.958		0.071		0.054; 0.087
Metric	118.01	83	0.007	0.964	−0.007	0.062	0.003	0.033; 0.086	152.15	83	0.000	0.960	0.002	0.065	−0.006	0.048; 0.081
Scalar	125.62	92	0.011	0.966	0.002	0.057	−0.005	0.028; 0.081	177.18	92	0.000	0.951	−0.009	0.068	0.003	0.053; 0.083
Learning difficulties																
Configural	86.55	74	0.151	0.985		0.039		0.000; 0.069	144.65	74	0.000	0.954		0.070		0.053; 0.087
Metric	96.42	83	0.149	0.986	0.001	0.038	−0.001	0.000; 0.067	156.41	83	0.000	0.953	−0.001	0.068	−0.002	0.051; 0.084
Scalar	106.35	92	0.146	0.985	−0.001	0.037	−0.001	0.000; 0.065	162.35	92	0.000	0.955	0.002	0.063	−0.005	0.047; 0.078
Empathic concern																
Configural	107.44	74	0.007	0.962		0.060		0.032; 0.084	83.94	74	0.201	0.994		0.026		0.000; 0.050
Metric	117.85	83	0.007	0.959	−0.003	0.059	−0.001	0.031; 0.082	99.47	83	0.105	0.990	−0.004	0.032	0.006	0.000; 0.053
Scalar	137.02	92	0.002	0.947	−0.012	0.064	0.005	0.040; 0.085	113.92	92	0.060	0.987	−0.003	0.035	0.003	0.000; 0.054
Partial scalar	124.85	89	0.007	0.958	−0.001	0.057	−0.002	0.031; 0.080								
Perspective taking																
Configural	152.38	74	0.000	0.910		0.096		0.074; 0.118	163.19	74	0.000	0.943		0.078		0.062; 0.091
Metric	153.44	83	0.000	0.914	0.004	0.089	−0.007	0.067; 0.111	176.67	83	0.000	0.940	−0.003	0.076	−0.002	0.060; 0.091
Scalar	173.90	92	0.000	0.900	−0.014	0.091	0.002	0.070; 0.112	210.08	92	0.000	0.925	−0.015	0.081	0.005	0.066; 0.095
Partial scalar									188.06	89	0.000	0.937	−0.003	0.075	−0.001	0.060; 0.090
Emotional exhaustion																
Configural	197.84	134	0.000	0.958		0.067		0.046; 0.086	155.61	134	0.098	0.991		0.029		0.000; 0.045
Metric	213.03	146	0.000	0.956	−0.002	0.066	−0.001	0.045; 0.084	168.61	146	0.097	0.991	0.000	0.028	0.001	0.000; 0.045
Scalar	240.69	158	0.000	0.947	−0.009	0.070	0.004	0.051: 0.087	193.01	158	0.030	0.986	−0.005	0.033	0.005	0.011; 0.048
Student–teacher relationship																
Configural	97.55	74	0.035	0.960		0.059		0.037; 0.079	116.39	74	0.001	0.955		0.059		0.037; 0.079
Metric	112.38	83	0.018	0.953	−0.007	0.064	0.005	0.028; 0.093	120.39	83	0.005	0.958	0.003	0.054	−0.005	0.031; 0.074
Scalar	126.86	92	0.009	0.946	−0.007	0.065	0.001	0.034; 0.092	133.19	92	0.003	0.955	−0.003	0.053	−0.001	0.031; 0.072

Study 1 N = 114, study 2 N = 209.

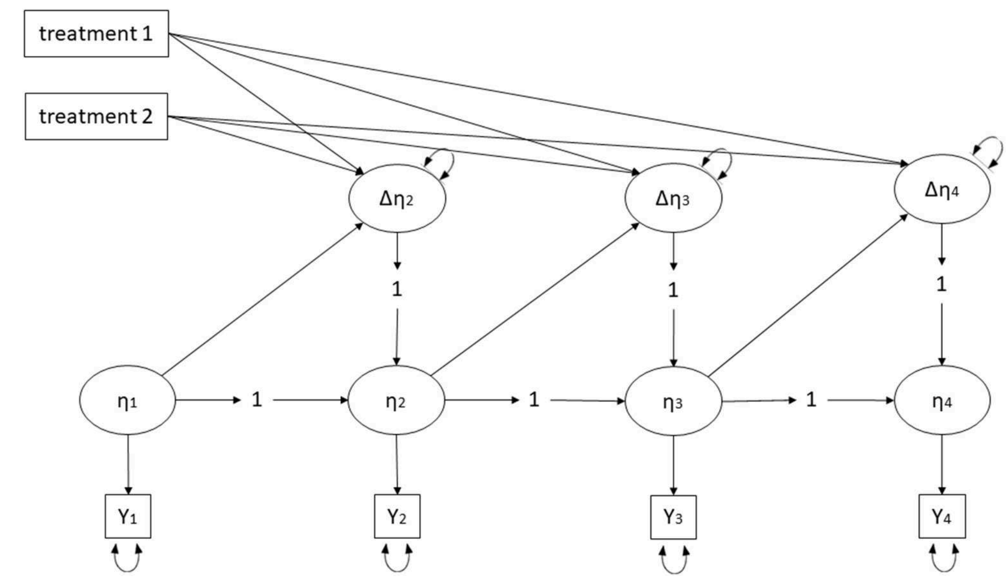

FIGURE 1 | Path diagram for a latent change score model. For the purpose of better clarity, the covariances are not shown.

units, the next higher level of invariance is assumed. For the ΔRMSEA, Chen (2007) assumes a significant deterioration of the model from a change in the model fit of 0.01 and higher. If the models showed a significant deterioration, it was investigated whether partial measurement invariance can be achieved by free-estimating parameters (Byrne et al., 1989).

In study 1, scalar measurement invariance could be verified for the constructs affective attitudes toward students with behavioral problems, importance of teacher–student relationships, and emotional exhaustion. EC showed partial scalar invariance across time. On the other hand, no scalar measurement invariance could be proven for PT (**Table 2**). In study 2, partial scalar measuring invariance was established for the construct PT. All other constructs reached scalar measurement invariance (**Table 2**). The statistical analyses were performed with the statistical software R (R Core Team, 2019) and the package lavaan (Rosseel, 2012).

LCS Models

We estimated LCS between different measurement times as indicated in **Figure 1** (McArdle, 2009).

We consider the parameter Δη2 the most relevant LCS to the present research because it displays the initial difference between treatment (1) and (waiting) control group. The following developments indicated by Δη3 and Δη4 include more complex learning experiences of students and are, therefore, more difficult to interpret.

RESULTS

Perceptions of the Learning Experience

Table 3 shows descriptive results, comparing how participants experienced the two online program and the text-based control task with regard to motivational and cognitive aspects. A clear picture arises that Intus[3] is experienced as cognitively and affectively more interesting, while the text-based task was rated higher on AIME. Overall, these results mirror prior findings that watching "TV" is more "easy," whereas textual work is perceived as more strenuous.

Latent Change Models

Longitudinal results showed few small results (**Tables 4**, **5**), which are rather inconsistent across both studies. The LCS considered most relevant here (Δη2), in study 1, there was only a negative effect, showing a less positive affective attitude toward students with learning disabilities. In study 2, Δη2 showed an increase in EC for those who worked on the Intus[3] modules first.

Additional significant effects were found for change scores referring to developments later in the semester. At Δη4, attending the reflective practice module of the additional seminar (Treatment 2) was related to a decrease in perceived emotional exhaustion in study 2. In study 1, students who first worked with Intus[3] reported less significance of their professional goal to aim for positive teacher–student relationships at the last measurement point.

DISCUSSION

The goal of the present research was to investigate whether a video-based online learning environment designed to reflect on difficult interactions between teachers and students in the classroom could function as a tool for promoting SEC in pre-service teachers. This endeavor was based on the research desideratum formulated by Jennings and Greenberg (2009). Based on basic research on differences between learning with text vs. learning with video, we expected a video-based online training program—compared to a traditional reading and writing assignment—to show greater impact on certain aspects of pre-service teachers' SEC, namely, their EC, PT, affective attitudes

TABLE 3 | Mean differences in cognitive interest, affective interest, and AIME between students working with a text and students working with an online tool for two measurement times.

	Time 1			Time 2		
	n	*M (SD)*	*d*	*n*	*M (SD)*	*d*
Study 1						
Cognitive interest						
Textual work	57	3.86 (1.39)	0.55	57	4.13 (1.47)	0.37
Online video environment	57	4.64 (1.43)		57	4.68 (1.54)	
Affective interest						
Textual work	57	3.54 (1.16)	0.80	57	3.83 (1.32)	0.43
Online video environment	57	4.53 (1.32)		57	4.46 (1.58)	
AIME						
Textual work	57	4.53 (0.83)	−0.82	57	4.57 (0.93)	−0.93
Online video environment	57	3.87 (0.78)		57	3.74 (0.86)	
Study 2						
Cognitive interest						
Textual work	97	4.43 (1.23)	0.46	112	4.58 (1.38)	0.16
Online video environment	112	5.02 (1.36)		97	4.80 (1.31)	
Affective interest						
Textual work	97	3.70 (1.14)	0.81	112	3.85 (1.26)	0.54
Online video environment	112	4.71 (1.34)		97	4.52 (1.22)	
AIME						
Textual work	97	4.32 (0.83)	−0.43	112	4.43 (0.84)	−0.66
Online video environment	112	3.99 (0.71)		97	3.89 (0.78)	

AIME, Amount of Invested Mental Effort; d, Cohen's d. Two-tailed test.

TABLE 4 | Results from LCS modeling (study 1).

Parameter	$\Delta\ \eta 2$			$\Delta\ \eta 3$			$\Delta\ \eta 4$		
	B	SE *(B)*	β	*B*	SE *(B)*	β	*B*	SE *(B)*	β
Behavioral problem									
Treatment 1	0.05	0.10	0.05	−0.01	0.10	-0.01	0.01	0.11	0.01
Treatment 2	−0.02	0.10	−0.02	0.12	0.11	0.11	−0.22	0.11	−0.19
Treatment 1	−0.28**	0.11	−0.23	0.19	0.11	0.17	0.05	0.12	0.04
Treatment 2	−0.05	0.11	−0.04	0.04	0.11	0.04	0.03	0.12	0.03
Empathic concern									
Treatment 1	−0.07	0.07	−0.08	0.04	0.08	0.05	0.09	0.08	0.10
Treatment 2	−0.08	0.07	−0.09	0.03	0.08	0.04	−0.03	0.08	−0.04
Perspective taking									
Treatment 1	−0.17	0.09	−0.17	0.15	0.08	0.17	−0.02	0.10	−0.02
Treatment 2	−0.02	0.09	−0.02	−0.18*	0.08	-0.20	0.13	0.10	0.13
Emotional exhaustion									
Treatment 1	0.00	0.10	0.00	−0.12	0.09	−0.12	0.05	0.13	0.04
Treatment 2	−0.01	0.10	−0.01	0.11	0.09	0.11	−0.10	0.13	−0.07
Student-teacher relationship									
Treatment 1	0.05	0.08	0.05	0.10	0.09	0.09	−0.26*	0.11	−0.22
Treatment 2	0.00	0.08	0.00	−0.03	0.09	−0.03	−0.01	0.11	0.01

*N = 114. Treatment 1 reference category = textual work first. Treatment 2 reference category = no seminar participation. *p < 0.05, **p < 0.01.*

toward students with special needs, and emotional exhaustion. As an extended manipulation check, we assessed affective and cognitive interest as well as participants' amount of mental effort with regard to learning with either task. Overall, we followed a waiting control group design to ensure that all participants were able to benefit from both assignments over the course

TABLE 5 | Results from LCS modeling (study 2).

Parameter	Δ η2			Δ η3			Δ η4		
	B	**SE (B)**	**β**	**B**	**SE (B)**	**β**	**B**	**SE (B)**	**β**
Behavioral problem									
Treatment 1	−0.01	0.07	−0.01	−0.07	0.08	−0.06	0.03	0.08	0.03
Treatment 2	−0.11	0.07	−0.09	0.06	0.08	0.05	−0.03	0.08	−0.02
Learning difficulties									
Treatment 1	0.01	0.07	0.01	−0.03	0.09	−0.02	0.00	0.08	0.00
Treatment 2	−0.05	0.07	−0.04	0.10	0.09	0.07	−0.05	0.08	−0.04
Empathic concern									
Treatment 1	0.13*	0.06	0.14	−0.04	0.07	−0.04	0.09	0.06	0.11
Treatment 2	−0.05	0.06	−0.05	0.04	0.07	0.04	−0.09	0.06	−0.11
Perspective taking									
Treatment 1	0.01	0.06	0.01	0.02	0.07	0.02	0.06	0.06	0.06
Treatment 2	−0.09	0.07	−0.09	−0.04	0.07	−0.04	0.04	0.07	0.04
Emotional exhaustion									
Treatment 1	−0.10	0.07	−0.09	0.10	0.08	0.09	0.02	0.09	0.01
Treatment 2	0.06	0.07	0.06	0.08	0.08	0.07	−0.20*	0.09	−0.16
Student-teacher relationship									
Treatment 1	−0.01	0.05	−0.01	0.05	0.06	0.05	0.05	0.06	0.05
Treatment 2	0.06	0.05	0.08	−0.05	0.06	−0.06	0.07	0.06	0.08

*$N = 209$. Treatment 1 reference category = textual work first. Treatment 2 reference category = no seminar participation. *$p < 0.05$.*

of a semester. To test the effects, we applied LCS modeling using data from four measurement points along the semester. In summary, the results of two studies with consecutive cohorts of pre-service secondary teachers yielded only few small effects, and across studies, there was no clear pattern. With regard to the immediate learning experiences, situational interest was consistently higher for working with the video-based online program; however, the amount of invested mental effort was higher for the writing assignment.

In study 1, we found that pre-service teachers who worked with the video-based online program Intus[3] showed less positive affective attitudes toward students with learning difficulties after 7 weeks compared to the waiting control group who was engaged in a writing assignment. This was an unexpected finding. A possible explanation could be Intus[3] creating a more realistic and immersive picture of how difficult interactions between teachers and students can be on the emotional level. In addition, in study 1, students were not asked to write a short reflection on their learning process (as they were in study 2). This could have left them with unresolved questions elicited by the video sequences. This, however, does not necessarily have to reflect a negative intervention effect as Spilt and Koomen (2009) have discussed for declines in desired outcomes (perceived relationship quality in their case). For example, a teacher could report more anxiety or less positive attitudes because of an increased awareness of his/her own negative emotions and interactions with the child. In this case, this could be an important first step to a positive change in classroom practices if the teacher training program can productively take up such developments subsequently.

In study 2, participating pre-service teachers who worked with the video-based online training program displayed higher EC after 7 weeks compared to the waiting control group. We consider two aspects relevant for discussing this finding. First, in study 2, a systematical reflection process was implemented, that is, participants had to hand in a written reflection discussing their learning experiences with the online modules, which could also include critical points and questions that were left open to them. Considering the notion of reflective practice (Schön, 1983; Beauchamp, 2015), this additional intervention can be considered a necessary scaffold for producing this effect. Second, in study 2, we had a larger sample size, which could have produced a significant result according higher test power.

The few other significant effects were found at later measurement points. In study 2, there was a buffering effect toward the end of the semester (Δη4) of attending a reflection-oriented seminar accompanying an internship on perceived emotional exhaustion regarding the teacher training program. We consider this additional potential evidence that implementing learning opportunities for guided reflective practice might play an important role in the development of pre-service teachers SEC. In study 1, we found that other students who first worked with the video-based online training program lowered their goal intentions to aim for good teacher–student relationships at the last measurement point.

In summary, results for the scales tapping into pre-service teachers' SEC were inconsistent across studies, which limits the generalizability of the effects found. However, perceptions of the learning processes were consistent, with video being more interesting than text and text being more mentally effortful. These findings are in line with the early work by Salomon (1984) and need to be considered further in the future because mental effort is considered an important precursor for deeper elaboration of content. We did not assess participants' mastery of the content, that is, their declarative knowledge about teacher–student relationships acquired by the different tasks. This will be an important variable in future research to disentangle the differential effects of interest and invested mental effort. However, this rationale again strengthens our interpretation that writing a reflective text on their video-based learning might have added a deeper elaboration to the learning environment with regard to developing empathic competencies. With regard to future research, we would endeavor to investigate whether the lack of a guided reflection process could also be an explanation for negative effects of the video-based online training program on participants' affective attitudes toward students with learning difficulties and the goal to build good teacher–student relationships in study 1.

Furthermore, we consider the confirmation of the expected effects on EC in study 2 to indicate the potential effectiveness of the video-based online program as an exemplar for the development of social-emotional competencies of pre-service teachers in university-based teacher training. However, given that no similar result pattern was found in study 1, this interpretation will need to be supported by further empirical research.

An interesting result emerged from our efforts to control for the potential effects of a second treatment variable that was not in the focus of this study. In study 2, pre-service teachers who attended an additional seminar at the end of their internship where they guided to collaboratively reflect on interpersonal situations they had experienced during their internship felt less emotionally exhausted. On the one hand, this supports the assumption that collaborative case reflection could help reduce stress and, thus, emulate the effects of supervision. Similar results have been found in a study implementing the Freiburg model coaching program (Braeuning et al., 2018). On the other hand, there might be more complex statistical interaction effects at work that differ between study 1 and study 2, in addition to the different sample sizes. Maybe these different results are due to a three-partite interaction between participating in the collaborative case work and working with the video-based online program including the written reflection task. It could be an objective to test this *post-hoc* explanation in future research.

All these interpretations need to be considered with caution due to several limitations of our investigation. First, we only investigated short-term effects. The time lag of the most relevant intervention period was 7 weeks only, with a total time lag of 4 months for the whole investigation. It could make a difference if such an intervention study would be conducted over a longer period of time, including follow-up measures before the waiting group starts with the intervention. Second, we did not measure or observe behavior or tested participants' gain in declarative or procedural knowledge but only relied on self-report data. Although we applied established instruments, the answers could be subject to social desirability tendencies and other biases. Finally, we investigated pre-service teachers early on in their studies. If a video-based online program does not show all intended effects with this group does, this does not necessarily imply similar results with more experienced pre-service or even in-service teachers.

Besides all limitations mentioned, the research design chosen also has several strengths. First of all, the applied randomized waiting control group design provides a comparatively rigid research protocol regarding the internal validity while simultaneously working with field data. A field setting at the university can also be considered quite high in external validity. Subsequently, two independent yet comparable studies were conducted, and both could implement a longitudinal design with four measurement points using sophisticated statistical methods (LCS) based on established measurement invariance over time. By this waiting control group design, we were able to ensure that all students worked on meaningful tasks with a comparable content. Given the implementation into a regular (mandatory) university lecture, this was also done to avoid unfairness due to different tasks to fulfill within the class. Based on our interpretations, the most valid next step regarding empirical research would be to more explicitly focus on structured opportunities of reflective practice within the context of video-based online learning and SEC. One approach would be to compare different implementations of the Intus[3] program while varying the form and function of the written reflection. Another approach could be to observe SEC development using more nuanced measures and longer intervention lags. On the longer term, a sound intervention design with in-service teachers should be conducted as well, and behavioral measures and process data of the online application should be included. Finally, effects for the behavior in the classroom are an important aspect to investigate as it is always a very important question what interventions on teachers and teacher students finally mean for what is happening in the classroom.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

MK wrote the larger part of the manuscript, mainly aquised, designed, and coordinated the study. KK did co-acquise, co-design, and coordinated the study. He also wrote substantial parts of the manuscript and revised it fully. SW did almost all calculations and tables and wrote significant parts of the methods.

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Young Learners' Regulation of Practice Behavior in Adaptive Learning Technologies

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Although research indicates positive effects of Adaptive Learning Technologies (ALTs) on learning, we know little about young learners' regulation intentions in this context. Learners' intentions and self-evaluation determine the signals they deduce to drive self-regulated learning. This study had a twofold approach as it investigated the effect of feed-up and feed-forward reports on practice behavior and learning and explored learners' self-evaluation of goal-attainment, performance and accuracy. In the experimental condition, learners described their goals and self-evaluated their progress in feed-up and forward reports. We found no conclusive effects of the feed-up and forward reports on learners' regulation of practice behavior and learning. Furthermore, results indicated that young learners' self-evaluations of goal attainment and performance were biased. Contrary to other research, we found learners both over- and underestimated performance which was strongly associated with over- or underestimation of goal attainment. Hence the signals learners used to drive regulation were often incorrect, tending to induce over- or under-practicing. Similarly, we found a bias in self-evaluation of accuracy and accuracy attainment. Learners over- or underestimated their accuracy, which was associated with over- or underestimation of accuracy attainment, which may in turn have affected effort regulation. We concluded that goal setting and self-evaluation in feed-up and forward reports was not enough to deduce valid regulatory signals. Our results indicate that young learners needed performance feedback to support correct self-evaluation and to correctly drive regulatory actions in ATLs.

Keywords: self-regulated learning, Adaptive Learning Technologies, self-evaluation, calibration, primary education

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INTRODUCTION

Many learners in primary schools use Adaptive Learning Technologies (ALTs) in the Netherlands and around the globe (OECD iLibrary, 2016; Di Giacomo et al., 2016). These technologies allow learners to practice new mathematics, grammar and spelling skills on a tablet or Chromebook. ALTs are mostly used in blended classrooms, where alongside digital practice, teachers provide instruction and feedback (Molenaar and van Campen, 2016). Although ALTs have been found to improve learning (Aleven et al., 2016a; Faber et al., 2017), the question of how learners regulate their learning using these technologies remains largely unanswered. Great diversity in learners' behavior during practice has been found with respect to the number of problems solved as well as the accuracy of problem-solving (Molenaar et al., 2019a). In addition to differences in prior knowledge, this variation could originate from differences in how learners regulate their learning (Arroyo et al., 2007; Paans et al., 2019). Yet little is known about how learners regulate their learning in ALTs (Winne and Baker, 2013; Bannert et al., 2017).

Although trace data from ALTs provide detailed insights into practicing behavior which can be used to detect how learners learn over time (Greller and Drachsler, 2012; Gašević et al., 2015), their intentions cannot be deduced from the data trace. A way to examine learners' intentional regulation is to ask them to fill in feed-up and feed-forward reports (Hattie and Timperley, 2007), in which they set goals before a lesson and self-evaluate goal attainment after a practice session. This externally triggered goal setting and self-evaluation may influence learners' practice behavior and learning outcomes. This study had two goals therefore: (i) to examine the effects of feed-up and feed-forward reports on regulation of practice behavior and learning outcomes; and (ii) to investigate how learners set goals and self-evaluate goal attainment and how this could be associated with their practice behavior and performance.

This exploratory study contributes to the objectives of the special issue as it deepens our understanding of how regulation and learning interrelate and co-evolve in digital environments. Methodologically we combined the advantage of elaborate data traces to understand practice behavior with insights into learners' intentions measured by students' self-reports. First, we elaborate on how learners regulated learning while practicing in ALTs. Second, we discuss how feed-up and -forward reports provided insight into learners' intentions with regard to regulation and how it could affect learning as an external trigger for self-regulated learning.

Regulation and Affective States in ALTs

Adaptive Learning Technologies are widely used to practice arithmetic, spelling and grammar in primary education in the Netherlands (Molenaar et al., 2016; Faber et al., 2017) and around the world (Aleven et al., 2016b). These technologies are often integrated in blended learning contexts. Teachers provide instruction in new knowledge or skills, after which learners continue to practice on their own devices while teachers give individual learners feedback. There are three main advantages of ALTs over paper-based practice: (i) ALTs provide learners with direct feedback on answers given (Faber et al., 2017); (ii) ALTs adjust problems to the needs of learners by estimating their current knowledge and/or the probability that they will solve the problem correctly (Corbett and Anderson, 1995; Klinkenberg et al., 2011); and (iii) ALTs provide teachers with concurrent feedback about learners' performance in dashboards (Molenaar and Knoop-van Campen, 2018). Even though positive effects of ALTs on students' learning have been found compared to traditional learning environments (Aleven et al., 2016b; Molenaar and van Campen, 2016; Faber et al., 2017), few studies have addressed how students regulate practice behavior in ALTs and how this affects their learning.

In order to understand how learners regulate their learning in an ALT, we drew on the COPES model of self-regulated learning (Winne and Hadwin, 1998). This theory defines learning as a goal-oriented process in which learners make conscious choices working toward learning goals (Zimmerman, 2000; Winne and Hadwin, 2017). In order to reach these goals, learners engage in cognitive activities (read, practice, elaborate) to learn a new topic. Metacognitive activities (orientation, planning, monitoring, and evaluation) help learners to control and monitor their learning to ensure effective and efficient learning (Veenman, 2013; Molenaar et al., 2019a). Affective states motivate learners to put in an appropriate level of effort to progress toward their learning goals (Azevedo et al., 2008). In the COPES model (Winne and Hadwin, 1998; Winne, 2018) regulation unfolds in four loosely coupled phases: (i) the task definition phase in which learners generate an understanding of the task; (ii) the goal setting phase in which learners set their goals and plan their actions; (iii) the enactment phase in which learners execute their plans working toward their goals; and (iv) finally the adaption phase which is activated when progress toward the goals is not proceeding as planned and adjustments in strategies, actions or tactics are required. These phases occur in the context of task conditions and operations performed by learners that lead to new knowledge and skills.

At the same time, we know that learners often fail to regulate their learning effectively (Azevedo et al., 2008). It is well established that learners often face a utilization deficiency (Winne and Hadwin, 2013), which is the failure to adequately activate the monitor and control loop during learning. This loop is at the heart of the COPES model and is largely dependent on goals learners set. Only after learners have set goals, can they evaluate their performance and diagnose progress (Winne and Hadwin, 2017). Research has indicated that, even for students in higher education, it is difficult to set goals in a way that drives monitoring and control (McCardle et al., 2017). In the enactment phase, learners compare performance and goals in cognitive evaluation to determine the need for adaptations. Without objective performance information, students are dependent on their own self-evaluation (Panadero et al., 2018). Up till now few studies have investigated self-evaluation of goal attainment in real learning sessions (Nederhand, 2018). During practicing, the calibration between self-evaluation of goal attainment and goals set is important for signaling self-regulatory actions. These actions take the form of "If, Then Else" sequences (Winne, 2010). For example, *if* a learner judges their goal to be reached, *then* practice activities can cease, *else* practice is continued. *If* progress is lower than expected, *then* the student must increase effort to increase learning, *else* keep effort at the same level. Therefore, in order to understand students intentions with regard to regulation, we focused on the signals learners deduce and examined how self-evaluation of goal attainment related to learners' goals.

In this study, we examined calibration of goal attainment to understand the signals students deduce for regulation, whereas in most studies calibration refers to the alignment of a metacognitive judgment and a standard, most often test performance (Pieschl, 2009; Winne and Muis, 2011; Koriat, 2012). Most research investigates the "accuracy" of learners' judgments compared to real performance (Pieschl, 2009).

Although, as pointed out above, calibration of performance, i.e., how self-evaluation of goal attainment is related to actual performance, is not the signal that drives regulatory actions, it is important. It is a way to determine the validity of the signal students deduce from the calibration of goal attainment and the direction of possible inaccuracies. For example, *if* a student overestimates goal attainment, the signal used for regulatory actions indicates to stop practicing *and* calibration of performance indicates that the student has overestimated actual performance, *then* the student should continue to practice. In this case, the signal used for regulation is invalid and drives unwarranted adaptations. Especially when calibration of goal attainment and performance are biased in the same direction, over- or under-practicing is likely to occur. Although ample research has shown that young learners tend to overestimate their performance (Roebers, 2017), little is known about the standards they use to evaluate their performance nor about their ability to correctly self-evaluate goal attainment.

In addition to the emphasis on cognitive evaluation, the COPES model stresses that regulation is dependent on context (Winne and Hadwin, 2013). In ALTs learners mainly work on problems to further develop knowledge and skills on specific topics. Goal setting may help learners to evaluate progress and determine when to stop practicing or detect the need for adjustment. The ALTs' adaptivity also supports learners' regulation. Selected problems are adjusted to the student's current performance, so that the technology partially overtakes monitoring and control from learners (Molenaar et al., 2019b). Nevertheless an important element of regulation remains the task of the students, namely adjustment of effort to maintain accuracy (Winne, 2010; Hadwin, 2011). Accuracy is viewed as a function of knowledge and effort and learners can regulate accuracy by adjusting one or both of these elements (Molenaar et al., 2019a). ALTs often provide direct feedback indicating whether an answer is correct. Learners can use this feedback to estimate their accuracy over the whole practice session. For example, learners making many mistakes should increase their effort. As such ALTs' direct feedback has a function as a signal for adaptations. Direct feedback during practice provides explicit information to support regulation, but only when learners are able to process this information and translate it into meaningful adaptations. Even though some aspects of regulation are overtaken by the ALT, effort regulation remains the task of the student, which means that learners continue to control an important element of self-regulated learning.

To summarize, the control and monitoring loop in the COPES model explains how learners' internal feedback functions and drives how they regulate accuracy and effort during learning. When learners are effectively regulating their learning, they set goals which they use to evaluate the need for adaptations. Calibration of goal attainment provides an important signal for regulatory actions and in ALTs direct feedback can function as a signal for adjustments during practice. Even though part of the regulation is overtaken by the ALT, young learners still need to regulate their accuracy and invest sufficient effort to ensure progress toward their goals. Great diversity in practice behavior raises the question of how capable learners are in regulating their practice behavior and what their intentions are in these contexts.

How ALT Data and Interaction Influence Internal Regulation

Even though direct feedback available in an ALT may support cognitive evaluation, learners need to engage in this cognitive evaluation and translate the results into actions to actually impact their practice behavior. This is a complex process, especially for young learners. A failure to detect miscalibration will prevent the learner from making the right inferences and may lead to incorrect monitoring and trigger ineffective control actions. Further research into how learners set and self-evaluate goals, and how they interpret feedback as a signal, is essential to understand how learners regulate during learning in an ALT. Feed-up and feed-forward reports help learners set goals, self-evaluate goal attainment and explicitly formulate actions to improve their learning. These reports were originally developed as formative assessment tools and are known to support learning (Hattie and Timperley, 2007). Even though no explicit correlation with self-regulated learning has been found, recent discussions of SRL and formative assessment talk about the interaction between external and internal feedback (Panadero et al., 2018). A *feed-up report* is an external trigger to support learners to articulate *when* learning goals are reached (Hattie and Timberley, 2007). This helps them to set goals and standards for regulation. Standards help learners to set criteria that indicate *how* they can know when a learning goal has been reached. Consequently, feed-up reports are expected to support learners' cognitive evaluations in the enactment phase of the COPES model. A *feed-forward* report is an external signal to trigger cognitive evaluation, i.e., to compare the goals set with self-evaluated goal attainment to evaluate progress. When learners establish a difference between their self-evaluated goal attainment and the standards, they realize that their progress is not as expected and adaptation is needed. This may signal re-evaluation of effort or a change in strategies. Feed-forward supports learners to explicitly state estimated performance and determine the need for control actions based on that.

In addition to feedback that signals the level of accuracy to learners, *feed-up* and *feed-forward* reports can be an external trigger to help them to effectively monitor and control their learning. Integrating direct feedback with feed-up and feed-forward during learning can support a comprehensive approach to stimulate regulation by supporting learners to set standards, i.e., learning goals (feed-up) and verbalize progress toward their learning goals (feed-forward). This in turn may drive adaptation, which could support young learners to optimize their regulation. Various techniques e.g., prompts (Bannert et al., 2009), scaffolding (Azevedo et al., 2008), and intelligent tutor systems (Azevedo et al., 2016) have been used previously to assist learners' regulation in ALTs. Although these techniques are initially effective, they are less successful in sustaining regulation during learning in the absence of the tools. A drawback of these techniques is that they do not help learners to make explicit inferences about how their actions are related to progress toward their learning goals (Winne and Hadwin, 2013). The relation between performance, internal representations of the learning goals and goal attainment remains underspecified, making the contribution of practice to progress unclear.

PURPOSE OF THE STUDY

Although ALTs support learning, the question of how learners regulate their practice behavior in ALTs remains unanswered. Diversity in the number of problems and the accuracy achieved among learners in this context requires more insight into students' regulation. Trace data provide elaborate information about students' practice behavior, but fail to provide insight into learners' intentions. Goals learners set and their self-evaluation of goal attainment reflect those intentions and provide an important signal for regulatory actions. In addition, direct feedback may have a regulatory impact if learners have clear standards against which to evaluate their accuracy. In this study, we investigated how learners set goals and self-evaluate goal attainment using feed-up and feed-forward reports. These reports may function as external triggers to optimize learners' internal feedback loop, which in turn affects their regulation and learning. Hence this study had two goals: (i) to examine how feed-up and feed-forward reports may support learners' regulation and learning; and (ii) to investigate learners' regulatory intentions and the signals they use as input for regulatory actions. We used an exploratory experimental pre-test post-test design executed as a field study in group 7 (students aged 10–11) arithmetic classes in Dutch primary schools.

The following research questions are addressed:

1. How do the feed-up and feed-forward reports affect learners' effort, accuracy and learning?

   Based on earlier research, we expected the feed-up report to trigger learners to articulate goals which could be used as standards in cognitive evaluation. The feed-forward report is intended to support learners to self-evaluate their goal attainment. This external trigger to regulate is expected to improve practice behavior (effort and accuracy) and learning. We expected that learners in the experimental condition would make more effort (hypothesis 1), be more accurate (hypothesis 2) and consequently learn more (hypothesis 3).

2. What signals do learners deduce during self-evaluation and how is self-evaluation of goal attainment related to actual performance?

   Hardly any research has been done on self-evaluation of goal attainment, especially in young learners, and so we were unable to formulate any hypotheses. Previous research has indicated that young learners tend to overestimate their performance, which we also expected in this context.

3. What signals do learners pick up from direct feedback and how does self-evaluation of accuracy attainment relate to actual accuracy?

   This is an exploratory question as the signaling role of direct feedback on self-evaluation of accuracy has not been previously studied. A higher calibration on accuracy attainment compared to calibration of goal attainment could indicate a signaling role of direct feedback.

4. How are students' calibration values related to each other, to practice behavior (effort and accuracy) and to learning?

   We explored how calibration of goal attainment and performance are related to further understand learners' signals for regulatory action. We also explored whether and how calibration values are associated with practice behavior and learning.

MATERIALS AND METHODS

Participants

The participants in this study were 71 group 7 learners. The three participating schools were located in the east of the Netherlands and had a diverse population. The learners were between 10 and 12 years old with a mean age of 11.17 years and 33 boys (46%) and 38 girls (54%) participated in this study. Classes were randomly assigned to the experimental condition [two classes (n = 37)] and the control condition [two classes (n = 34)]. Learners had to participate in at least 3 out of 4 lessons. Based on that criterion, three learners were excluded from the sample. Furthermore, five learners missed the pre-test and four learners did not participate in the post-test.

Design

This study was conducted with a quasi-experimental pre-test – post-test design (see **Figure 1**).

Learners in the experimental condition were asked to fill in the feed-up and feed-forward reports in every lesson. They set goals prior to every lesson and self-evaluated their progress at the end of the lesson. Learners in the control condition did a puzzle prior to every lesson to keep the total time investment equal over the two conditions. Learners received instruction and practiced the three arithmetic skills during three lessons of 55 min each on three consecutive days. The design of each lesson followed the direct instruction model including teacher instruction, guided practice, class-wide practice and individual practice. The pre-test took place prior to the first lesson and learners did the post-test after completion of all the lessons. In the fourth lesson learners were instructed to practice the skills which they needed most practice in.

Materials

Feed-Up and Feed-Forward Reports

In the *feed-up* report, learners formulated their learning goals and standards to evaluate performance and progress. At the start of each lesson (first three lessons), learners in the experimental group were asked to answer four questions regarding their learning goals: (1) How skilled do you want to become at this particular subskill? (2) How many lessons do you need to reach

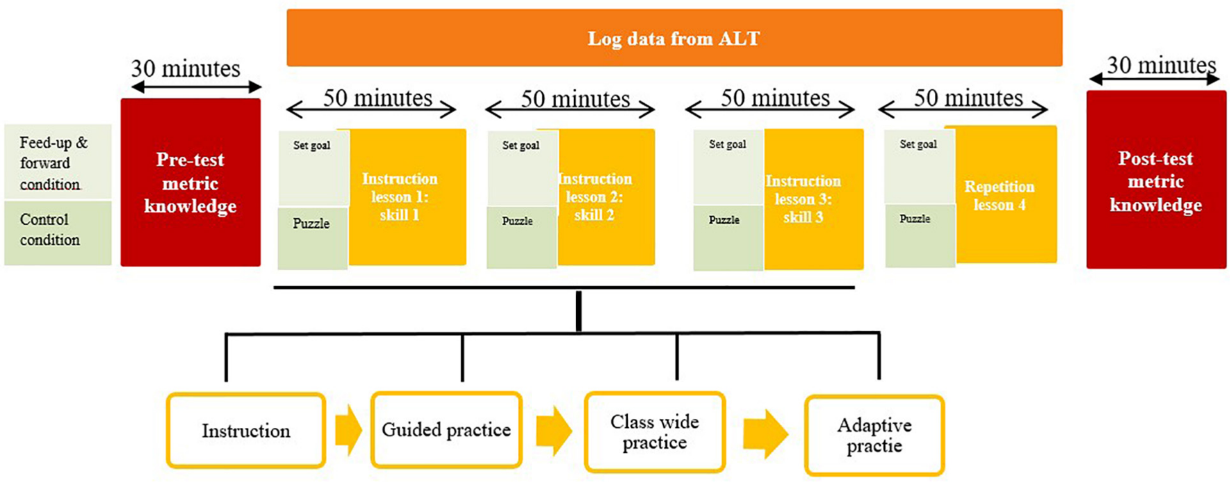


FIGURE 1 | Study design.

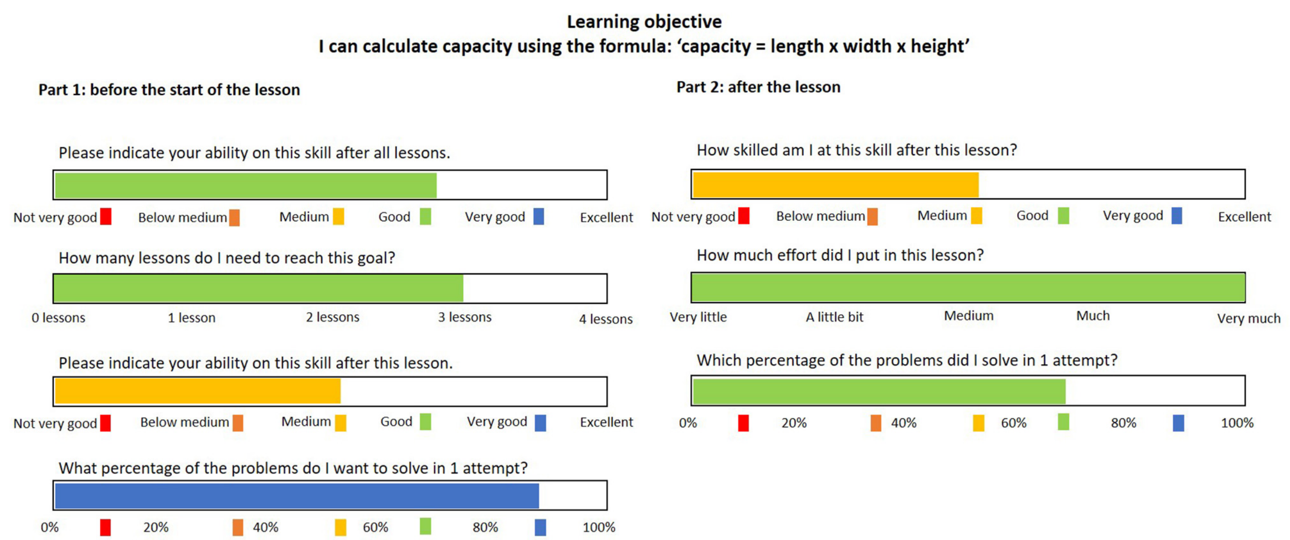


FIGURE 2 | The feed-up (part 1) and feed-forward (part 2) reports.

that goal? (3) How skilled do you want to become in this particular lesson? (goal for performance) (4) What percentage of problems will you solve correctly at the first attempt? (goal for accuracy). Learners answered all questions by sliding the bars below the questions (see the left side of **Figure 2**). The sliders represented a percentage the learners reached between 0 and 100. The chosen colors represented different ability levels which were also used in the teacher report on the ALT and learners were familiar with the color coding.

In the *feed-forward* report, learners were asked to self-evaluate goal attainment and progress toward their learning goal. After each lesson (first three lessons), they were asked to answer three questions: (1) What is your current ability level on the subskill studied today? (self-evaluation of goal attainment) (2) How much effort did you put into today's lesson? (3) What percentage of problems did you solve correctly in one attempt? (self-evaluation of accuracy attainment). Learners answered by sliding the bars below the questions (see the left side of **Figure 2**). Next, learners were asked to compare part 1 with part 2 to determine their *progress* and to see how far they were from reaching their goal. They were asked to indicate how often they received help from the teacher, whether they tried harder to solve a difficult problem, and whether they consulted hints in the ALT to solve the problem. They also had to indicate how satisfied they were with their learning during the lesson and what they would improve in the next lesson.

Before the fourth lesson (the rehearsal lesson), the learners were asked to indicate their ability on all three subskills, set goals for this last lesson and determine which subskill(s) they needed to work on in the rehearsal lesson. Again, learners indicated their ability scores at the end of the rehearsal lesson, evaluated their progress at the end of the lesson, explicitly indicated whether or not they had reached their goal, and explained their progress. This method meant that the feed-up, feed-forward cycle was repeated four times during the experiment.

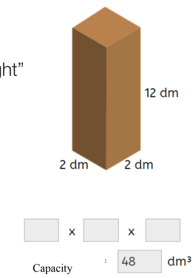
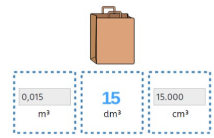
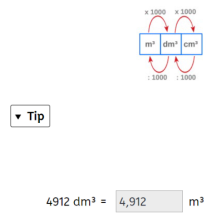
The Adaptive Learning Technology

The ALT used in this study is widely used for spelling and arithmetic education throughout the Netherlands. This technology is applied in blended classrooms in which the teacher gives instruction after which learners practice on their tablets. First, learners practiced in the class-wide practice stage on non-adaptive problems which were the same for each student in the class. Next, learners worked on adaptive problems, which were selected after each problem solved based on an estimate of the learner's knowledge called the ability score (Klinkenberg et al., 2011). This score was calculated by a derivative of the ELO algorithm (Elo, 1978). Based on the learner's ability score, the ALT selected problems with a probability of 75% that the learner would answer the problem correctly. After a learner had answered approximately 25 problems, the system had a reliable indicator: the ability score. This ability score was used as an indicator of performance. The difference between the previous ability score and the new score was used as an indicator of progress. Learners were also given direct feedback (correct or incorrect) after entering an answer to a problem and teachers could follow learners on teacher dashboards (Molenaar and Knoop-van Campen, 2018).

Subskills Learned

The three subskills all included different aspects of measurement of capacity (see **Table 1**). The Dutch metric system units for measuring capacity were used. The problems related to the first subskill "Calculate capacity using the formula: "capacity = length × width × height" were relatively easy because learners were given a formula to solve the problem. Examples were also used in this subskill to support learners" problem-solving. The problems related to the second subskill "Convert from common capacity units to cubic meters" (cm^3, dm^3, m^3) were of medium difficulty. Finally, problems within the third subskill "Convert cubic meter units (cm^3, dm^3, m^3) to liter units" (cl^3, dl^3, l^3) were hard, as learners were asked to do the conversion without a formula (see **Figure 3** for more examples).

TABLE 1 | Examples of problems for each subskill.

	Subskill	Example
Subskill 1	Calculate capacity using the formula: "capacity = length × width × height"	
Subskill 2	Convert from common capacity units to cubic meters (cm^3, dm^3, m^3)	
Subskill 3	Convert cubic meters units (cm^3, dm^3, m^3) to liter units (cl^3, dl^3, l^3)	

Measurements

Pre- and Post-test

The pre- and post-test consisted of 24 items, 8 items per subskill. The items in the pre- and post-test were structurally similar but different numbers were used. The difficulty level of the items, as indicated by the ALT, was used to balance both tests. **Figure 3** provides examples of the items for each subskill. The overall Cronbach's alpha for the whole pre-test was 0.93, with 0.94 for subskill 1, 0.93 for subskill 2, and 0.74 for subskill 3, respectively. The overall Cronbach's alpha for the post-test was 0.91, with 0.74 for subskill 1, 0.92 for subskill 2, and 0.78 for subskill 3, respectively. Learning gain was calculated as the difference between pre- and post-test. The values (given in the results section below) indicated that there was limited evidence for a ceiling effect, requiring a more complex measure of learning gain.

Measures From the ALT

The knowledge a student acquired on a subskill was expressed in the ability level as calculated by the ELO algorithm. This score was given as a number between 0 and 600. In order to compare this value with the students' goals, we translated the ability score into a percentage. The logs of the ALT stored data of the learners' practice activities, including a date and time stamp, student identifier, problem identifier, learning objective identifier, ability score after each problem and accuracy of the answer given. Based on this information indicators of effort and accuracy were calculated. Effort was measured by one indicator per subskill: the number of unique problems a student completed to practice this subskill. Accuracy was calculated by dividing the number of correctly answered problems by the total number of problems completed. **Table 2** provides an overview of all measures calculated and their definition.

Measures Taken From the Feed-Up and Feed-Forward Reports

A number of measures were taken from the feed-up and feed-forward reports used in the first three lessons (see **Table 3** for an overview). The feed-up report was used to measure the overall learning goal set per subskill, the lesson goal for each lesson and the goal for accuracy. The feed-forward report measured *self-evaluation of goal attainment* and *self-evaluation of accuracy attainment*. All these values were measured on a scale from 0 to 100%. Self-reported effort was measured on a scale from 1 to 5. The calibration values were calculated based on the values in the

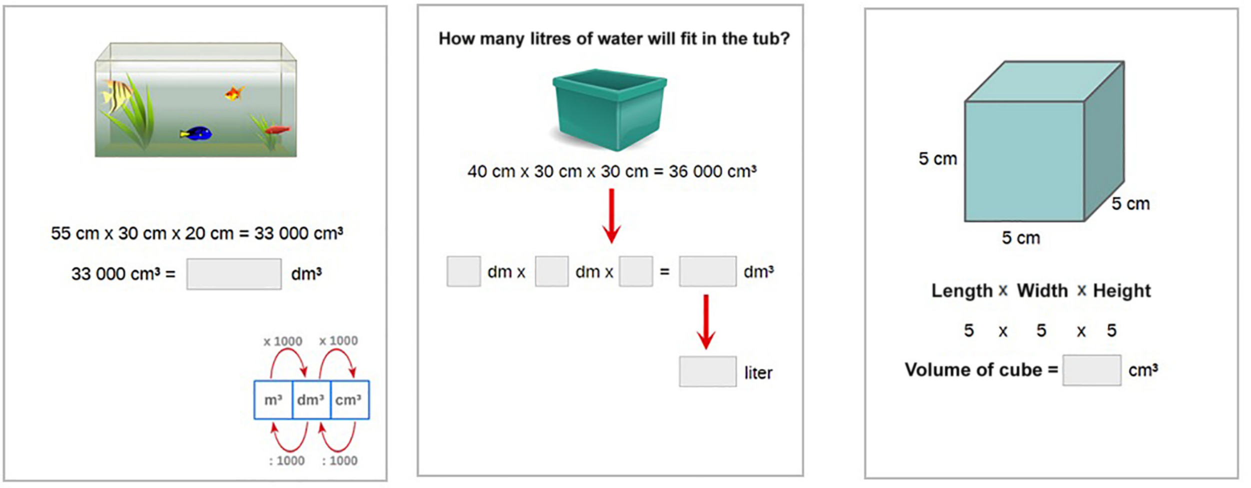


FIGURE 3 | Examples of items for the three subskills in the pre- and post-test.

TABLE 2 | Overview of learning, effort, and accuracy measures.

Learning measures	**Definition**
Prior knowledge	Pre-test, one per subskill
Post-knowledge	Post-test, one per subskill
Gain	Post-test/pre-test per subskill
Process measures	**Log file data**
Unique problems	Number of unique problems completed per subskill
Accuracy unique problems	Correct unique problems/total unique problems completed

feed-up and feed-forward reports. *Calibration of goal attainment* was calculated by deducting the goal set from the self-evaluation of goal attainment. *Calibration of performance* (typically referred to as calibration accuracy) was calculated by deducting the accuracy goal from the self-evaluation of accuracy attainment. These two values can be seen as signals for regulatory actions. In order to assess the correctness of these signals, *calibration of performance* was calculated by deducting actual performance from the self-evaluation of goal attainment and *calibration of accuracy* was calculated by deducting actual accuracy from self-evaluation of accuracy attainment.

Procedure

On the first day learners took the pre-test (30 min) after which the first instruction lesson of 45 min was given. The two other instruction lessons and the repetition lesson were given on separate consecutive days following the first lesson. On the fifth day learners took the post-test (30 min). Each instruction lesson started with 10-min instruction given by the teacher. This was standardized by using an instruction protocol. Afterward, the teacher practiced six to eight problems with the learners in guided practice. Then the learners continued to work on problems within that particular subskill. First, they completed a set of non-adaptive problems (15 problems) which were the same for all learners in the class. They then worked on adaptive problems for the remaining time in the lesson. In the fourth lesson the three subskills of the previous lessons were repeated and practiced with adaptive problems. Learners were instructed to select subskills depending on their learning goals.

Analysis

In order to assess how the feed-up and feed-forward intervention affected effort and accuracy, a MANOVA analysis was performed with effort on skill 1, skill 2, and skill 3 as within-subject factor and condition as between subject factor. A repeated measurement MANOVA was used to assess how the feed-up and forward intervention affected learning with the pre- and post-test scores (time) on skill 1, skill 2, and skill 3 (skill) as within-subject factor and condition as between subject factor.

This analysis consisted of three steps: (i) we addressed learners' *intentions regarding regulation*; (ii) we assessed the *signals learners deduced*; and (iii) we determined the *correctness of the signals*.

In order to understand learners' *intentions regarding regulation*, the goals they set, self-evaluation of goal attainment, accuracy goals set and self-evaluation of accuracy attainment from the students' feed-up report were reported. Next, to investigate the *signals learners' deduced* during cognitive evaluation, we analyzed the calibration of goal-attainment (self-evaluation of goal attainment – goals set). We calculated an absolute difference to understand the distance between the goals set and the learners' estimation of performance after the lesson. The relative difference was used to understand the bias learners have in their signals. Bias may be overestimation when learners assess their goal attainment to be higher than their goals set or underestimation when they assess goal attainment to be lower than their goals set. Finally, to determine *the correctness of the signals* the calibration of performance was calculated (self-evaluation of goal attainment – actual performance). Again, the

TABLE 3 | Measures taken from the feed-up and feed-forward reports.

	Description	Scale
Feed-up		
Overall goal set	The ability level the student ultimately wants to achieve for this subskill	0–100%
Lesson goal set	The ability level the student wants to achieve for the subskill during the first lesson	0–100%
Accuracy goal set	The percentage of problems a student wants get right at the first attempt	0–100%
Feed-forward		
Self-evaluation of goal attainment	The performance in ability level a student perceives to have achieved on the subskill during the lesson	0–100%
Self-evaluation of accuracy attainment	The percentage of problems a student perceived to have got right at the first attempt	0–100%
Self-reported effort	How hard the student worked during the lesson	Scale between 1 and 5
Calibration		
Calibration of goal attainment	Self-evaluation of goal attainment – lesson goal set	
Calibration of accuracy attainment	Self-evaluation of accuracy attainment – accuracy goal set	
Calibration performance	Self-evaluation of goal attainment – actual performance	
Calibration of accuracy	Self-evaluation of accuracy attainment – actual accuracy	

absolute and relative values were reported. We speak of overestimation when learners' self-evaluation of goal attainment was higher than actual performance and underestimation when it was lower than their goals set. The same logic in three steps was followed for calibration of accuracy and goal attainment. Finally, correlations were calculated in order to understand the relations between the calibration values.

RESULTS

Table 4 shows the descriptive statistics of the pre-test, post-test, gain, effort in the number of unique problems solved and accuracy while solving these problems.

Effect of Feed-Up and Feed-Forward Reports on Effort and Accuracy

For effort there was a significant main effect on skill $F(2, 67) = 5.41$, $p < 0.01$ indicating that learners showed different effort on the three subskills. There was no significant interaction between skill and condition $F(2, 67) = 0.41$, $p > 0.05$: in the experimental condition learners did not show more effort compared to learners in the control condition (hypothesis 1, rejected).

For accuracy there was a significant main effect on skill $F(2, 67) = 76.91$, $p < 0.01$ indicating that learners showed different accuracy on the three subskills. There was significant interaction between skill and condition $F(2, 67) = 0.3.13$, $p < 0.05$: in the experimental condition learners showed lower accuracy compared to learners in the control condition (hypothesis 2, rejected).

Effect of Feed-Up and Feed-Forward Reports on Learning Outcomes

There was a significant main effect of time $F(1, 67) = 109.45$, $p < 0.001$: learners scored higher on the post-test compared to the pre-test. There also was a main effect of condition $F(1, 67) = 1507.68$, $p < 0.001$: learners in the experimental group scored differently from learners in the control group; and a main effect of skill $F(2,67) = 404.89$, $p < 0.001$, learners scored differently on the three skills. In addition, there was an interaction effect between skill and condition, $F(2, 67) = 13.27$, $p < 0.025$, skill and time $F(2,67) = 61.71$, $p < 0.001$ and time and condition $F(1,67) = 20.95$, $p < 0.01$. Finally, there was a three-way interaction between skill, time and condition $F(2, 67) = 13.59$, $p < 0.01$. Follow-up analysis revealed that the experimental group scored lower on pre-test for subskills 2 and 3 compared to the control condition, whereas there were no differences at pre-test on subskill 1 (see **Figure 4**). The experimental group scored lower on post-test on subskill 1 compared to the control group, whereas for

TABLE 4 | Descriptive statistics.

	Subskill 1				Subskill 2				Subskill 3			
	Con		Exp		Con		Exp		Con		Exp	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Pre-test	7.36	1.45	6.92	1.99	5.58	2.83	2.69	2.81	3.55	2.17	2.33	1.84
Post-test	7.73	0.52	7.73	1.46	7.36	0.99	6.72	2.09	4.97	2.16	4.47	1.65
Gain	0.36	1.54	0.11	1.85	1.91	2.72	4.03	2.79	1.44	1.85	2.14	2.10
Effort	39.12	6.69	35.58	8.85	42.50	13.18	41.56	13.55	44.09	9.74	44.33	18.66
Accuracy	0.92	0.07	0.87	0.13	0.85	0.13	0.71	0.20	0.73	0.13	0.63	0.14

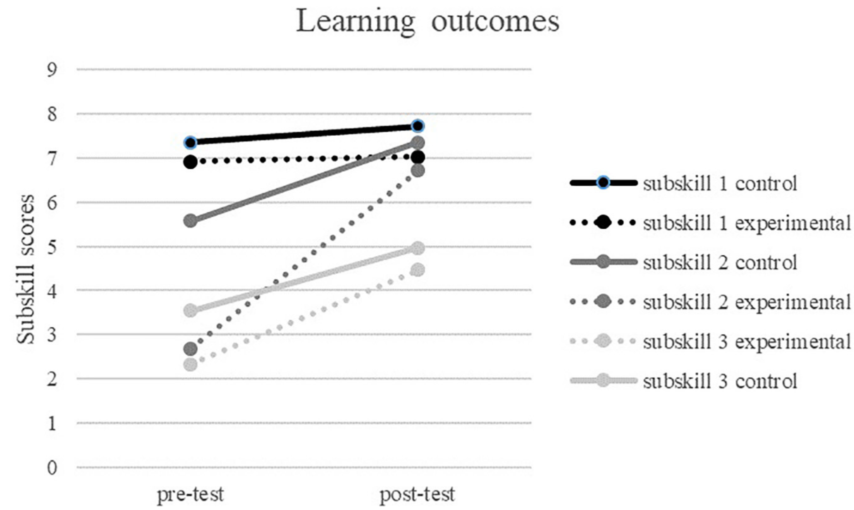


FIGURE 4 | Learning over the lessons per subskill indicating pre-test and post-test.

subskills 2 and 3 no significant differences were found. Finally, the experimental group showed a stronger growth over time for subskill 2 compared to the control group, whereas no differences in growth were found on subskills 1 and 3 (hypothesis 3, partially supported).

Relations Between Learners' Self-Evaluation of Goal Attainment and Actual Performance

The learners' intentions regarding regulation were entered in the feed-forward report. The lesson goals set by the students, their self-evaluations of goal attainment and their actual performance data are shown in **Table 5**. Before the lesson, the average goal set for a lesson was between 71% for lesson 1 and 76% for lesson 3. After the lesson, learners' self-evaluation of goal attainment was 76% on average which remained similar over the three lessons. Ability level, indicating actual performance, was available for 33 learners after lesson 1 but only for 6 learners after lesson 2 and 22 learners after lesson 3. The remaining 29 learners on skill 2 and 14 learners on skill 3 did not solve enough problems to calculate an accurate ability score. For skill 1 the average ability score was 80%, for skill 2 the average was 87% (6 learners) and for skill 3 the ability score was 83%.

TABLE 5 | Learners' *intentions regarding regulation*: lesson goals, self-evaluation of goal attainment, and actual performance after the lesson.

		Lesson goals set		Self-evaluation of goal attainment		Actual performance	
	n	***M***	**SD**	***M***	**SD**	***M***	**SD**
Lesson 1	35	71.71	19.01	75.14	19.15	80.24[1]	6.43
Lesson 2	36	73.16	16.42	77.36	17.01	87.67[2]	7.35
Lesson 3	36	76.95	16.57	76.67	20.14	83.86[3]	5.23

[1]*n = 33*, [2]*n = 6*, [3]*n = 23*.

The signals learners deduced to drive regulation in cognitive evaluation varied between self-evaluation of goal attainment and goals set which is called calibration of goal attainment. The average absolute goal attainment showed a 13% difference between learners' self-evaluation of goal attainment and goals set (see **Table 6**). This number was similar over the three lessons and indicates that learners on average were incorrect by 13%. With respect to bias in the goal attainment calibration, for lessons 1 and 2 the average relative calibration was positive. This indicates a trend toward overestimation of goal attainment, i.e., the self-evaluated goal attainment was higher than goals set. For lesson 3, this relative goal attainment value was approaching 0, indicating a trend toward calibration between self-evaluated goal attainment and goals set. When we further analyzed the bias in learners' goal attainment calibration, we found that the number of learners that perfectly calibrated increased over time from 11 in lesson 1–17 in lesson 3. The number of learners that overestimated their goal attainment remained similar at around 9 learners and the number that underestimated goal attainment reduced over time from 14 in lesson 1–9 in lesson 3.

Correctness of the signal was evaluated by calibration of performance. Overestimation of goal attainment can function as a regulatory signal to stop practicing, as according to the self-evaluation the goal has been achieved. This may be an erroneous signal when the self-evaluation and the actual performance are not aligned. For this reason, we examined calibration of performance, the relation between self-evaluated goal attainment and actual performance. This showed that on average learners were 13% inaccurate in their estimations. With respect to bias, the average relative goal attainment calibration was negative for all three lessons. This indicates a trend toward under-estimation (the self-evaluated goal attainment was lower than the actual ability level). On average learners estimated their performance lower than their actual ability level. When we further analyzed the bias

TABLE 6 | *Signals for regulation*: overview of absolute and relative calibration of goal attainment and performance per lesson.

		Absolute calibration goal attainment		Relative calibration goal attainment			Relative calibration performance		Relative calibration performance	
	n	*M*	SD	*M*	SD	*n*	*M*	SD	*M*	SD
Lesson 1	34	15.29	13.76	2.94	20.52	33	12.83	10.75	−4.47	16.27
Lesson 2	36	12.92	13.00	3.75	18.06	6	9.89	4.89	−2.67	11.52
Lesson 3	36	11.94	12.83	−0.28	17.65	22	14.69	15.61	−5.71	20.87

in learners' performance calibration, the majority of the learners, approximately 60%, underestimated their performance in lessons 1 and 3 and a smaller group, around 40%, overestimated their performance (see **Table A1** in the **Appendix**).

The combination of overestimation of goal attainment and performance is especially problematic as errors in both calibrations reinforce an unwarranted reduction in effort. Similarly, underestimation of goal attainment combined with an underestimation of performance underlie an unnecessary increase in effort. There was a significant positive correlation $(r_{\text{skill1}}) = 0.60$, $p < 0.01$ and $(r_{\text{skill3}}) = 0.75$, $p < 0.01$ between calibration of goal attainment and performance for lessons 1 and 3. This indicates that when learners over or underestimate goal attainment, they also tend to over or underestimate performance. This points toward a reinforcing effect that may induce an erroneous regulation of effort.

Relations Between Learners' Self-Evaluation of Accuracy and Actual Accuracy

The intentions of learners with regard to regulation of accuracy were also entered in the feed-forward report. Accuracy can function as a signal for learners to better understand their performance. **Table 7** provides the descriptive data on accuracy of goals set before the lesson, self-evaluation of accuracy after the lesson and actual accuracy. Before the lesson, the average of goal set for accuracy was 75%, which was similar for all three lessons. After the lesson, learners' self-evaluation of accuracy reduced over the three lessons from 84% in lesson 1–74% in lesson 3; this reduction was not significant F (32, 2) = 2.88, p = 0.07. This was in line with a significant reduction in actual accuracy $F(32, 2) = 42.82$, $p < 0.001$) over the lessons from 81% in lesson 1–73% in lesson 3.

TABLE 7 | Overview of the *intentions of learners for regulation*: accuracy of goals, self-evaluated accuracy, and actual accuracy per lesson.

		Accuracy of goals set before the lesson		Self-evaluated accuracy after the lesson		Actual accuracy	
	n	*M*	SD	*M*	SD	*M*	SD
Lesson 1	35	72.63	16.10	84.09	16.77	91.02	11.61
Lesson 2	36	77.63	17.01	80.39	18.88	82.77	19.47
Lesson 3	36	76.31	16.57	74.72	14.63	73.23	14.62

The signals learners deduced for regulation of accuracy: During practice learners received direct feedback which can be a signal for them to better understand their level of accuracy. The relation between accuracy of goal and self-evaluated accuracy is called the accuracy attainment calibration. Again, there is an absolute and a relative value. The average absolute accuracy attainment calibration was 13%, which indicates a difference between the accuracy set and self-evaluated accuracy (see **Table 8**). This number was similar over the three lessons. With respect to bias in the accuracy attainment calibration, in lessons 1 and 2 the average relative calibration was positive, indicating a trend toward overestimation of accuracy attainment. For lesson 3 this value was negative, indicating a trend toward underestimation of accuracy attainment. When we further analyzed the bias in learners' self-evaluation of accuracy, it appeared that the group of learners that perfectly calibrated increased over time from 8 in lesson 1–15 in lesson 3. This indicates that learners' estimates of their current level of accuracy were similar to their accuracy goals. The number of learners that underestimated their accuracy attainment reduced over the three lessons from 22 in lesson 1–8 in lesson 3. The number of learners that overestimated their accuracy attainment increased from 4 in lesson 1–13 lesson 3. Hence, the absolute calibration of accuracy attainment was comparable to the absolute calibration of goal attainment, but the relative calibration was somewhat higher for accuracy attainment. This shows little difference between the two calibration values which does not make the case for a signaling role of accuracy.

Correctness of the signals: Overestimation of accuracy attainment can function as a trigger to reduce effort as self-evaluation indicates the goal has been achieved. This may be an erroneous signal when the self-evaluation and the actual accuracy are not aligned. Calibration of accuracy shows that average absolute calibration of accuracy was 10% for lesson 1, increasing toward 15% for lesson 3 (see **Table A2** in the **Appendix**). With respect to bias, in lesson 1 the relative accuracy was negative, indicating a trend toward underestimation. Yet, for lessons 2 and 3 the relative accuracy was positive, indicating a trend toward overestimation. When we further analyzed the bias in learners' accuracy calibration, we found that about half of the learners underestimated their accuracy and the other half overestimated their accuracy in all three lessons.

The combination of overestimation of accuracy attainment and accuracy may be especially detrimental for learners as errors in calibration reinforce an unwarranted regulation of effort. Similarly, underestimation of accuracy attainment

TABLE 8 | *Correctness of the signals*: overview of absolute and relative calibration of accuracy attainment and accuracy per lesson.

		Absolute calibration accuracy attainment		Relative calibration accuracy attainment		Absolute calibration of accuracy		Relative calibration of accuracy	
	n	***M***	**SD**	***M***	**SD**	***M***	**SD**	***M***	**SD**
Lesson 1	35	14.15	12.05	10.91	15.12	9.89	10.83	−4.74	13.96
Lesson 2	36	12.19	11.92	3.03	16.90	12.40	12.68	1.60	17.78
Lesson 3	36	12.36	15.04	−4.58	19.03	14.93	12.46	3.73	19.27

combined with an underestimation of accuracy leads to an unnecessary increase in effort. There was a significant positive correlation (r_{skill1}) = 0.39, $p < 0.05$ and (r_{skill3}) = 0.35, $p < 0.05$ between calibration of accuracy attainment and accuracy for lessons 1 and 3. For lesson 2 the correlation was not significant (r_{skill1}) = 0.24, $p > 0.05$. This indicates that for skills 1 and 3, when learners under or overestimated accuracy attainment, they also tended to over or underestimate accuracy. This points toward a reinforcing effect that may induce an erroneous regulation of effort, but the association was lower than that between calibration of goal attainment and performance.

Relation Between Calibration and Practice Behavior and Learning Outcomes

First, we assessed the relationship between the calibration values. We found a significant positive correlation between calibration of goal attainment and calibration of accuracy attainment for lesson 1 (r_{skill1}) = 0.40, $p < 0.05$ and 2 (r_{skill2}) = 0.40, $p < 0.05$. This indicates that learners' bias in self-evaluation of performance and accuracy were linked. There was a significant positive correlation between calibration of accuracy and calibration performance for lesson 1 (r_{skill1}) = 0.60, $p < 0.01$. This indicates that self-evaluation, actual performance and accuracy were only related for the easy subskill but not for lesson 3.

Finally, we found a significant correlation between learners' accuracy (the percentage of correctly answered problems) and calibration of accuracy for subskill 2 (r_{skill2}) = 0.35, $p < 0.05$. This indicates that learners who show high accuracy tend to estimate their accuracy more correctly. We found a significant correlation between learners' effort (number of problems) and the calibration of accuracy, but only for skill 1 (r_{skill1}) = −0.43, $p < 0.05$. During lesson 1 when learners were more accurate, they solved more problems.

DISCUSSION

This study aimed to understand how learners regulate learning in ALTs. Next to trace data that provide insight into regulation of practice behavior, learners' intentions for regulation were examined using feed-up and feed-forward reports. These reports acted as an external trigger to elicit goal setting and self-evaluation and were therefore expected to affect internal regulation. We hypothesized that feed-up and forward reports would have positive effects on regulation of practice behavior and learning. Subsequently learners' intentions regarding regulation were further analyzed, examining how their evaluation of goal attainment functioned as a signal to drive regulatory actions. The correctness of this signal was assessed by examining the relation between self-evaluation and actual performance. We also examined the role of direct feedback as a signal for effort regulation. We investigated accuracy goals set to understand learners' intentions. The calibration of accuracy attainment was used to understand the signal learners deduced to regulate accuracy during learning. In order to understand the correctness of this signal the relation with actual accuracy was investigated. Hence, self-evaluation and calibration were assessed to understand how learners engaged in cognitive evaluation and made decisions for adaptation to guide their practice behavior and learning.

We found no conclusive evidence that the feed-up and forward reports affected learning. We did find that learners in the experimental condition showed more growth of knowledge during the lessons than the control group. However, these learners also had less prior knowledge than the control group, which may have induced these results. Moreover, we did not find any differences between the experimental and the control group with respect to effort these learners put in. We did find a significant difference between the conditions on accuracy: the experimental condition showed lower accuracy than the control condition. Again, less prior knowledge may underlie these differences. Due to initial differences on prior knowledge between the conditions, it is difficult to draw definite conclusions about the effect of the feed-up and feed-forward reports.

To further understand learners' intentions with regard to regulation, we investigated the goals learners set in the feed-up and feed-forward reports. The relation between these goals and learners' estimates of performance were the signals learners deduced during cognitive evaluation. We found that learners were inaccurate in their self-evaluation of goal attainment. The relative calibration of goal attainment showed a positive bias for lessons 1 and 2, which indicated that learners tended to overestimate their goal attainment, producing a signal "*stop practicing, the goal has been reached.*" For lesson 3, we found a negative relative calibration of goal attainment which indicated that learners set higher goals than they obtained according to self-evaluated performance. This signal was "*continue to practice the goal has not yet been reached.*" Overall, we saw an increase in calibration over the lessons, which means that learners more often believed they had reached their goal during a lesson. Still a quarter of the learners underestimated and believed they should continue to practice. Half of the learners for lesson 1 to one third of the learners for lesson 3 overestimated and believed they had reached their goal.

In order to understand the correctness of the signals, we continued to look at the relation between self-evaluation of goal attainment and actual performance. We could only perform this analysis for lessons 1 and 3, because for lesson 2 the ALT could only calculate a valid ability score for six learners. The calibration of performance showed that learners on average were inaccurate. The relative performance calibration was negative for all lessons, indicating a tendency for learners to underestimate their performance. Deeper exploration of the calibration values showed that in all three lessons approximately half of the learners underestimated and the other half overestimated their performance. This is surprising as most research indicates that young learners tend to overestimate their performance (van Loon et al., 2013; Roebers, 2017). This may indicate that the feed-up and feed-forward intervention did affect our learners' cognitive evaluation.

Calibration of goal attainment and performance were compared to understand how correct were the signals learners deduced. We found high positive correlations for lessons 1 and 3. Thus calibration of goal attainment and performance were highly related. When learners overestimated their goal attainment, which was the case for one third to half of the learners, they were also very likely to overestimate their performance. When translating this into "if then else" sequences, the signal "*stop practicing*" was most likely to occur when goals had not actually been reached. This error in the regulatory signal may have led to under-practicing. In a similar vein, when learners underestimated their goal attainment, which was one quarter of the learners, their actual performance was likely to be higher. In these cases, the signal "*continue to practice*" occurred when learners had in fact reached their goal leading to over-practicing. Hence, learners were likely to deduce inaccurate signals that drove their cognitive evaluation during the execution phase of the COPES model. This meant that learners were unable to accurately monitor their learning and consequently were likely to initiate incorrect control actions. Performance feedback could help learners to evaluate their progress more accurately and deduce valid signals to drive regulatory action (Panadero et al., 2018). Previous research has indicated that self-evaluation in feed-up and feed-forward reports supports learning, other studies have emphasized the need for performance feedback to actually affect regulation (Foster et al., 2017). The rationale is that in order to engage in cognitive evaluations learners need reliable, revealing, and relevant data in order to be able to draw valid inferences about their own learning process (Winne, 2010). Although the young learners in this study showed less inclination to overestimate compared to earlier research, the analysis above suggests that goal setting and cognitive evaluation alone were not enough to ensure learners deduced effective signals to drive regulation.

The role of direct feedback on learners' ability to assess accuracy during practice was examined to see if this would help them to deduce more accurate signals during learning. The average absolute calibration of accuracy attainment was inaccurate. The average relative calibration values were positive for lessons 1 and 2, indicating overestimation and signaling to learners to reduce effort, and negative for lesson 3, demonstrating underestimation eliciting increased effort. There was an increase in calibration over the lessons, which meant that learners more often indicated that they had reached accuracy goals during practice. This increase in calibration caused a decrease in underestimation from over half of the learners in lesson 1 to about one fifth in lesson 3. Overestimation went up from one tenth in lesson 1 to one third of the learners in lesson 3.

The relation with actual accuracy helped us understand the correctness of this signal. The average absolute calibration of accuracy was again 13%. The relative calibration of accuracy was negative for lesson 1, where learners underestimated their accuracy and positive for lessons 2 and 3, where learners overestimated their accuracy. Further analyses indicated that calibration was low and reduced over the lessons. Underestimation reduced over the lessons from half to one third of the learners and overestimation increased from one third to two thirds of the learners. This was in line with the increase in difficulty of the skills over the lessons. Once again, the results indicate that learners were unable to accurately monitor their effort, deduced wrong signals that, when translated into control actions during the execution phase, would not support effective regulation.

Next, we compared the calibration of accuracy attainment and accuracy to understand the correctness of the signals learners deduced. We found medium positive correlations for lessons 1 and 2, but not for lesson 3. Again, the signals learners deduced were directed in the same direction. Overestimation in accuracy attainment was related to overestimation of accuracy. Half of the learners deduced the signal to reduce effort when they should have increased effort and similarly the other half of the learners inferred that they should increase effort when they should have reduced effort. This again provides evidence of inaccurate use of signals even though learners had received explicit direct feedback during practice. The problem may lie in the fact that direct feedback provided information on the local level, i.e., per problem (Pieschl, 2009), whereas accuracy judgments were made on the global level, i.e., over a number of problems. It may be that young learners find it hard to translate information from the local to the global level. Yet the association between calibration values was less strong for accuracy than for performance. Based on this finding we speculate that direct feedback may indeed have helped the learners to evaluate their accuracy more effectively than their performance.

Finally, we addressed how calibration values were related to each other and we found that calibration of goal attainment and accuracy attainment were associated for lessons 1 and 2. This indicates that the signal learners deduced based on self-evaluation were related to each other.

For calibration of performance and accuracy, we only found a relation for lesson 1. This indicated that the bias between self-evaluated and actual performance and accuracy only existed for the easier subskill. Calibration values and practice behavior showed no association with respect to the number of problems solved nor with learning. We did find that accuracy and calibration of accuracy were related, indicating that learners with high accuracy tended to estimate their accuracy more correctly.

Limitations of this study were the fact that prior knowledge was different between the control and the experimental condition at the start of the experiment and so effects of the feed-up and feed-forward intervention could not be determined exclusively based on the experiment. However, the results of the in-depth analysis of learners' cognitive evaluations did provide us with clear evidence that feed-up and feed-forward reports without performance feedback did not support young learners to deduce correct signals for regulatory actions. Moreover, although the sample size of the experimental group was sufficient to obtain more insights into learners' regulation intentions, it was not large enough to engage in follow-up analysis of clusters of over and underestimating learners. Finally, for most students the actual performance (ability score) could not be determined by the ALT at the end of lesson 2 and, for lesson 3, there may have been a bias in the 22 students that did receive a score at the end of the lesson compared to the 13 students that did not receive an ability score. This research clearly emphasized the need for performance feedback during feed-forward interventions to increase the correctness of the regulatory signals that students deduce. Even direct feedback after each problem did not help students to correctly estimate their accuracy level during a lesson. Future research should investigate how learners benefit from performance feedback in a feed-forward report and if that influences practice behavior and learning. In addition to performance feedback, explicit information on their global accuracy level could be made available to students to support their regulation. Moreover, it would be interesting to assess in future studies how learners' intentions, the signals they deduce and correctness of those signals changes over time.

CONCLUSION

Although research has found evidence for positive effects of ALTs on learning, it has also found that the signals learners deduce to drive regulatory actions are mostly incorrect. We found no conclusive effects of the feed-up and feed-forward reports on learners' practice behavior and learning. Furthermore, we found that young learners' self-evaluations of goal attainment and performance were biased. Contrary to other research, we found that learners both over- and underestimated performance which was strongly associated with the over- or underestimation of goal attainment. Hence the signals learners used to drive regulation were often incorrect, which was likely to have induced over- or under-practicing. Similarly, we found a bias in self-evaluation of accuracy and accuracy attainment. Learners again over- or underestimated accuracy, which was associated with over- or underestimation of accuracy attainment, which may in turn have affected effort regulation. Yet the relation was less strong compared to performance, indicating that learners were supported by direct feedback in their accuracy judgment. We concluded that goal setting and self-evaluation in feed-up and feed-forward reports is not enough to deduce valid regulatory signals. Our results emphasize that young learners deduced inaccurate signals to drive their regulation and therefore needed performance feedback to support correct self-evaluation and to correctly drive regulatory actions in ALTs. This exploratory study has deepened our understanding of how regulation and learning interrelate and co-evolve in digital environments.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Ethics Committee Faculty of Social Sciences. Written informed consent from the participants' legal guardian/next of kin was not required to participate in this study in accordance with the national legislation and the institutional requirements.

AUTHOR CONTRIBUTIONS

IM wrote the sections "Introduction," "Results," and "Discussion." AH wrote the section "Materials and Methods," conducted the analysis, and edited the sections "Introduction" and "Discussion." RD performed the data science on the trace data, organized and extracted the data, and involved in editing all the sections of the manuscript.

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APPENDIX

TABLE A1 | Overview of number of learners that calibrated, over or underestimated on goal attainment and performance.

	Calibration goal attainment			Calibration performance		
	Calibrates	**Underestimate**	**Overestimate**	**Calibrates**	**Underestimate**	**Overestimate**
Lesson 1	11	9	14	0	19	4
Lesson 2	15	6	15	0	4	2
Lesson 3	17	10	9	2	13	7

TABLE A2 | *Correctness of the signals*: overview of number of learners that calibrated, under or overestimated on accuracy attainment and accuracy.

	Calibration accuracy attainment			Calibration actual accuracy		
	Calibrates	**Underestimate**	**Overestimate**	**Calibrates**	**Underestimate**	**Overestimate**
Lesson 1	8	22	4	5	17	13
Lesson 2	12	14	10	2	16	17
Lesson 3	15	8	13	1	13	19

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Online vs. Classroom Learning: Examining Motivational and Self-Regulated Learning Strategies Among Vocational Education and Training Students

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Numerous studies have been conducted to explore students' employment of motivational and self-regulated learning strategies (SRL). Research highlights the importance of having motivated students equipped with strategies that help them self-regulate their learning, this being highly important when learning is acquired through online learning programs. Nonetheless, such research has been scarce with Vocational Education and Training (VET) students; this is the gap in the literature this paper aims to address. The article analyzes the degree to which VET students employ motivational and SRL strategies by comparing them according to the learning mode chosen. To achieve this, a quantitative approach was adopted to carry out a cross-sectional study. A total of 577 first-year VET students responded to an online questionnaire based on some of the motivational and SRL strategies scale included in Pintrich's model. Statistical analyses were applied to test two hypotheses. Pintrich's model was validated through a confirmatory factor analysis considering its application to Catalan VET students for the first time. The results reveal significant differences between classroom and online students in terms of levels of metacognitive self-regulation and effort regulation when starting a VET program. However, this difference might not be entirely explained by the learning mode chosen. The findings of this study will provide VET researchers and practitioners with a greater understanding of their students' characteristics when starting the program and the means to develop strategies that ensure their engagement throughout the course.

Keywords: Vocational Education and Training, motivation, self-regulated learning strategies, online learning, learning mode

INTRODUCTION

There has been an international explosion of online learning and products in recent years, including the online delivery of Vocational Education and Training (VET) programs (Brennan et al., 2001). Online VET changes the relationship between educators and learners, interaction with the learning content, and among learners themselves, and contributes to alleviating time and space barriers.

Students enrolled on an online VET course have the freedom to acquire learning whenever and wherever they have the opportunity to. This situation allows students to control how they learn, the pace of their learning, and how to balance their daily tasks with the need to attend the course (Graham, 2006; Alkis and Taskaya, 2018). However, it is important to remember that in order "to succeed in autonomous online learning environments, it helps to be a highly motivated, self-regulated learner" (Artino and Stephens, 2009; Gegenfurtner et al., 2019).

This paper analyzes the degree to which students employ motivational and SRL strategies a few months after beginning a VET program. The aims of the study implemented to ascertain this were to provide VET researchers and practitioners with a greater understanding of their students' characteristics when starting the program and the means to develop strategies that ensure their engagement throughout the course.

Motivational and self-regulated learning (SRL) strategies employed by VET students have been underexplored in research, making it difficult to have a clear idea of what these might comprise (Savoie-Zajc et al., 2010). Various researchers (Cardinal, 2010; Cournoyer et al., 2015; Dubeau et al., 2017) have suggested that the low number of studies in this area could be related to the reputation that VET programs have of attracting less motivated students. Therefore, one reason for conducting this research is that to the best of our knowledge no studies have previously analyzed differences in students' motivational and SRL strategies with regard to the different types of VET learning available (traditional or online).

Much research has been conducted in education studies with regard to the role academic motivation plays in student success (e.g., Brackney and Karabenick, 1995; Credé and Phillips, 2011). Results show that the two variables are highly correlated (Müller, 2008; Park and Choi, 2009; Wang et al., 2013; Alkis and Taskaya, 2018). Indeed, Chen and Jang (2010) found high attrition rates to be negatively correlated with motivation in online learning environments. This can be linked to Rovai and Jordan's (2004) findings that online learning is not suitable for all students and that students succeeding in an online learning environment must be both highly motivated and able to regulate their own learning (Garrison, 2003; Artino and Stephens, 2009).

In the field of education, various motivational theories are employed in relation to academic motivation (Deci and Ryan, 1985; Berndt and Miller, 1990; Pintrich, 1991; Zimmerman et al., 1992; Meece and Holt, 1993), even if these do include common variables such as intrinsic motivation, extrinsic motivation, and self-efficacy, among others. Clark (1998) suggested that in order to obtain high commitment in a task, *task value* is the most important of the motivational factors, whereas Aristeidou et al. (2017) and Jung and Lee (2018) found task value to be associated with learning engagement and therefore learners' learning performance in online learning (Zhang and Liu, 2019). The concept of task value derives from expectancy-value theory (Eccles and Wigfield, 1995, 2002), understood as the extent to which tasks meet individual needs in pursuing a goal. In other words, how far students perceive the task they are doing is important and useful for their future plans or goals.

Studies on the concept of task value have obtained various results: if the task is of little value to students, they will not engage in it (Eccles and Wigfield, 1995; Neuville, 2004); high perceptions of task value positively correlate with course grades (Brackney and Karabenick, 1995; Linnenbrink and Pintrich, 2003; Liem et al., 2008; Najafi et al., 2018); and task value is a significant predictor of course completion (Pachlhofer and Vander Putten, 2014; Cho and Heron, 2015; Vanslambrouck et al., 2018). In a longitudinal study, Lee (2015) found that task value in online learning remained stable during an entire semester, showing that if students are helped to recognize the value of a task at the beginning of a course, they will stay engaged for the duration of it. However, in a study comparing blended learning with online learning, Alkis and Taskaya (2018) only found task value to be a significant predictor of academic success in the former.

In the context of VET, Radovan and Radovan (2015) found that task value increased among students when they were provided with realistic job-related tasks that put the learning they had acquired into practice. Therefore, when provided with powerful and meaningful learning environments, students perceive their learning tasks as being more valuable. Another study carried out with VET students by Dubeau et al. (2017) identified four patterns related to motivational and individual characteristics (exceptional, talented, low-achieving and drop-out), perception of task value being significantly higher among *exceptional students*.

Pintrich and DeGroot (1990) found not only motivational variables but also cognitive processes such as learning strategies to be important in explaining students' academic success, as stated by Martínez and Galán (2000). Specifically, in online environments, high levels of academic motivation and self-regulation were found to be due to the autonomous nature of online learning compared to traditional classroom contexts (Artino and Stephens, 2009). Despite its theoretical fuzziness, self-regulation is acknowledged as a multidimensional and process-oriented research construct coming from educational psychology (Kaplan, 2008; Prinz, 2019). Zimmerman (2000) regarded self-regulation as thoughts, feelings, and actions that are planned and modified to the fulfillment of personal goals. Hence, there is "no one set of cognitive, metacognitive, motivational, and behavioral strategies that constitutes the desirable mode of engagement in every setting and task" (Kaplan, 2008, 483).

Thus, the first hypothesis of this study is as follows.

H1. VET students employ motivational and SRL learning strategies in differing degrees according to the learning mode chosen (classroom or online). H1a for task value; H1b for metacognitive self-regulation strategies; and H1c for effort regulation strategies.

To be considered "self-regulated," students must be committed and efficiently control their own learning process (Zimmerman, 2015). However, learners' self-regulated learning is neither easy nor automatic (Pintrich, 1999). This translates into at least three important qualities: (1) self-observation (monitoring one's actions and thinking processes); (2) self-judgment (evaluating one's performance); and (3) self-reactions (one's response to performance outcomes) (Broadbent and Fuller-Tyszkiewicz, 2018). Other scholars add that holding positive motivational beliefs (positive attributions) regarding one's capabilities is also required for higher levels of self-efficacy (Boekaerts et al., 2000). In respect of this, SRL is a constructive process that develops with opportunities for self-directed practice over time. It is based on past experiences and personal, behavioral, and environmental factors (Pintrich, 2000; Zimmerman, 2015).

The phenomenon of self-regulation is complex and has been theorized in different ways. Most theories agree in highlighting behavioral, motivational, and cognitive processes as constitutive parts of SRL. First, behavior self-regulation includes students' control of resources, such as effort regulation, help seeking, and time/study management (Pintrich, 2004). Second, self-regulation of motivation and affect entails controlling and revising motivational beliefs, such as self-efficacy and goal orientation, to meet the demands of a task. And finally, self-regulation of cognition encompasses the control of deep processing strategies that lead to better learning and performance.

In addition, several models of SRL (Sitzmann and Ely, 2011) have recently been analyzed and compared by Panadero (2017). All models agree that SRL is cyclical and composed of different phases and subprocesses. However, the labels and processes in each phase differ from one model to another. Of such models, Pintrich's (2000). SRL model (2000) had a highly significant impact in the field and is widely known for its development of an instrument to measure SRL: the Motivated Strategies for Learning Questionnaire. The model classifies phases that other SRL models commonly share and areas for SRL (Lee et al., 2019), dividing SRL into the following four phases: (1) Forethought, planning and activation of prior knowledge of the task, the context, and the self in connection with the task; (2) Monitoring processes; (3) Control and regulation of different parts of the task, the context, and the self; and (4) Reaction and reflection on the task, the context, and the self – each also with four different areas for regulation: cognition, motivation and affect, behavior and context. The degree of student learning varies according to key self-regulatory processes. Pintrich (2004) stated that these SRL strategies were systematically directed toward the achievement of learning goals and divided them into three groups: (1) cognitive, (2) metacognitive, and (3) resource management. Cognitive strategies such as selective attention, decoding or structuring enable students to fuse new and existing information (Richardson et al., 2012). Metacognitive strategies refer to an awareness of learning procedures so as to be able to establish goals; thus, they are related to mentally representing learning goals, designing action plans, self-monitoring progress and evaluating goal achievement. Finally, resource management strategies require students to use social and their own resources to persist when confronted with a task (Richardson et al., 2012). Examples of students' regulatory strategies for controlling resources other than their cognition include managing their time, effort and study environment, as well as the use of peer, teacher, and other help-seeking learning strategies such as benefiting from a study group.

Within resource management strategies and SRL behavioral capacities (Pintrich, 2004), regulatory processes focus on how students best implement effort toward the accomplishment of academic tasks (Zeidner and Stoeger, 2019). In this sense, effort regulation occupies a key role in SRL and is understood as a learning strategy that entails self-managing motivation or persistence (Theus and Muldner, 2019). It is related to conscientiousness and academic self-efficacy.

Self-regulation also involves the transfer of self-regulation processes (knowledge, skills, and attitudes) to different learning situations and contexts, including work and leisure (Boekaerts, 1999, cited in Liveris and Cavanagh, 2012). In fact, through cyclical phases that explain the interrelation of the metacognitive and motivational processes involved in SRL at the individual level, students acquire what is known as self-regulatory competency (Zimmerman, 2000).

Due to the proliferation of digital environments, students now have more opportunities for interaction and practice, however, the design of digital learning contexts needs careful attention to ensure that the self-learning process is optimized (Ting and Chao, 2013). Likewise, there is a lack of evaluations measuring the impact of SRL on students in digital environments (Pérez-Álvarez et al., 2018). Moreover, the degree to which learners use SRL strategies may mediate the effects of dispositional characteristics and psychosocial contextual influences on academic performance in highly autonomous instructional settings. This has been understudied, however, and warrants further empirical investigation because it could have important educational implications for instructors (Artino and Stephens, 2009).

In summary, various studies have pointed out that online students need to employ motivational and SRL strategies more extensively in order to succeed academically. This raises a question regarding what variables -learning mode among them- explain differing degrees of motivational and SRL strategies employed by VET students when starting a program. Thus, the second hypothesis of our study is as follows.

H2. The learning mode chosen by VET students is a key variable when explaining the degree to which they employ motivational and SRL strategies when starting the program.

As mentioned, the general aim of this paper is to analyze the degree to which VET students employ motivational and SRL strategies a few months after beginning the program. In order to achieve this, the aim was divided into two specific goals: (1) to validate the adaptation of three scales measuring task value, effort regulation and metacognitive self-regulation; and (2) to identify differences in students' motivational and SRL strategies depending on the learning mode they have enrolled for (classroom or online). The results are presented in line with the aims outlined above.

MATERIALS AND METHODS

Design and Procedure

In order to respond to the research aims, a cross-sectional design was used. An on-line questionnaire was administered to a sample of classroom and online VET students during their first academic year, in two different ways.

For classroom VET students, the course coordinators or group tutors–henceforth tutors–were in charge of administration, which took place in the classroom, in a group setting, on a day and at a time agreed with the research team. Tutors provided their students with the link to the online questionnaire in class or *via* Moodle; students could either access the tool using their mobile phone or administration took place in the IT classroom if they were not allowed to bring their phones to school. Tutors were also responsible for reminding students that the questionnaire was completely anonymous and checking the last screen of the questionnaire to ensure the tool had been answered in full.

For online VET students, the school directors uploaded the links to the online questionnaire to the virtual learning environment–Moodle–and gave the students 2 weeks to respond to it. After a week, they sent a gentle reminder to all students in order to obtain more responses.

In both cases (classroom VET and online VET students) the scales were applied in the same order and through the same online platform. Response time varied largely, depending on question routes in the part regarding demographic information; but typically, it took 15 min to answer the entire questionnaire.

The Research Ethics Committee CER (FCES-2018-04) belonging to the International University of Catalonia (UIC Barcelona) approved the research design and implementation, including all consent procedures followed in the study. All participants were at least 16 years old and informed that they could refuse participation in the research or withdraw at any moment. The questionnaire was anonymous and participants' informed consent was implied through survey completion.

Participants

A purposive sampling technique was used to select potential participants. First, 10 VET programs were selected according to different criteria: the research team sought to include programs from both of the levels offered within the initial Spanish VET system (ISCED 3B and 5); all included programs had to be offered in both classroom and online modes and had to match the priority economic sectors, which were identified by experts in a previous phase of the research. It is important to clarify that although students were completely free to decide which learning mode they wanted to follow, this decision depended on many factors, such as the availability of the program in online mode, working while studying or family responsibilities.

Once the VET programs had been selected, we proceeded to select 39 public schools that ran these programs: these comprised four schools per program–one in each of the four Catalan provinces–except for one of the programs, which was only offered in two schools (leaving a total of 38 schools) plus one online school offering all the selected VET programs. Private schools were excluded from the sample because of the diversity of their VET teaching models, especially the online version.

The final sample was composed of 577 first-year VET students, out of a population of 92,125 pupils enrolled on VET programs in public schools in Catalonia (8,764 online students, 83,361 classroom VET students for the 2017–2018 school year), according to the latest public data available from the Catalan Education Department (Departament D'educació [DE], 2018). **Table 1** shows the main characteristics of the sample (valid cases).

Tools

The research tool comprised an *ad hoc* questionnaire in Catalan based on various validated scales. The decision to translate the questionnaire into Catalan was based on the language policy of Catalonia: as an autonomous region of Spain, Catalonia has some educational provisions particular to its region, including using Catalan as the language of instruction.

The questionnaire included a first part with questions asking for demographic information, mainly multiple-choice items (age, gender, school pathways, work experience), and a question about the main reason for enrolling on the VET program. The latter was a multiple-choice item with responses adapted from the Spanish version of the Vermunt Inventory of Learning Styles (Martínez-Fernández and Vermunt, 2013), specifically from the following learning orientations: personally oriented, certificate-oriented, self-test oriented, and vocation-oriented.

The second part of the instrument was composed of questions on cross-disciplinary skills (critical thinking, teamwork and communication), as well as the three variables related to motivational and SRL strategies: task value, effort regulation and metacognitive self-regulation. Lastly, students had to evaluate their accomplishment of five key technical/professional skills specifically related to their VET program.

All three scales related to motivational and SRL strategies -task value, effort regulation and metacognitive self-regulation- were

TABLE 1 | Description of the sample.

Variable	Distribution
Gender	42.5% females; 56.2% males; 1.4% other or do not want to answer.
Age	Mean 24.89 years (20.65 years for classroom VET; 37.96 for online VET); standard deviation 9.756 years (4.71 for classroom VET; 9.67 for online VET).
Type of program	75.4% classroom VET; 24.6% online VET.
Program	56.3% technology sector; 43.2% health and care sector; 0.5% other sectors.
ISCED level	42.3% level 3B; 57.2% level 5.
Prior work experience	29.8% no; 70.2% yes (among whom, 39.3% had work experience related to the VET program they were attending).
Main reason to enroll on VET program	28.8% personal interest; 25% to find a job in this sector; 24.3% to progress in my professional career; 9.7% to get a certificate; 7.5% other reasons; 4.9% to demonstrate to myself that I have the ability.

measured using our own adaptation of the corresponding factors taken from the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich, 1991). A selection of only some of the factors was required, since the questionnaire is very long and complex; furthermore, the MSLQ is modular, and it is very common for researchers to only use parts of it rather than the entire instrument (Holland et al., 2018). In order to choose the most relevant scales, we considered metacognitive self-regulation and effort regulation to be the strategies most related to the concept of "learning to learn," this emerging as one of the key competences for apprentices in a previous phase of the research based on interviews with stakeholders. In addition, task value was also included as it is one of the key motivational factors that can impact learning engagement (Aristeidou et al., 2017; Jung and Lee, 2018; Zhang and Liu, 2019), and therefore course completion (Pachlhofer and Vander Putten, 2014; Cho and Heron, 2015; Vanslambrouck et al., 2018). Since online courses generally have higher failed retention rates than classroom settings (Herbert, 2006; Smith, 2010; Bawa, 2016), the examination of this variable could be especially relevant for online VET students, who would probably need to employ a high degree of task value in order to successfully complete their studies.

To ensure the transferability of results, a backward translation procedure was followed. Two native Catalan speakers who are fluent in English translated the items into Catalan from the original English version and also adapted them to fit both the VET and online education contexts. A third native Catalan speaker checked and standardized both translations; when doubts arose, the Spanish version (Martínez and Galán, 2000) was consulted for the available items. In order to make the whole tool more uniform, the original response scale (a 7-point Likert scale from "Not at all true of me" to "Very true of me") was converted into a five-point frequency scale (from "Never" to "Always"). **Table 2** presents the three variables, with the number of items for each variable and an example item. Cronbach's Alphas are also reported for the original Pintrich (1991) scales.

According to Pintrich's (1991) model, task value is defined as students' evaluation of how interesting, how important, and how useful the task and the course material are. Effort regulation reflects a commitment to completing one's study goals, even when students encounter difficulties or distractions. Metacognitive self-regulation refers to exercising control over cognition and learning; it includes three general processes: planning, monitoring, and regulating.

Data Analysis

Since the original Pintrich (1991) scales had already been translated into Catalan and adapted to fit the VET context, their validation was required. In order to obtain evidence of validity based on the internal structure, a confirmatory factor analysis (CFA) was performed using the AMOS v.23 software. The original structure (Pintrich and DeGroot, 1990) was tested, with three correlated factors. After data depuration and inverting reversed items, a maximum likelihood estimation method was used (with regression imputation for missing values). Some readjustments were made to the final model by observing the regression weights and modification indexes.

Normality assumption of the factor scores was checked using the Kolmogorov-Smirnov test of normality, skewness and kurtosis intervals, visual inspection of normal and detrended Q-Q plots. The Kolmogorov-Smirnov tests showed none of the three variables to be normally distributed ($p < 0.0001$ for task value and effort regulation; $p = 0.011$ for metacognitive self-regulation). Task value and effort regulation distributions revealed negative asymmetry (skewness statistics −1.688 and −0.307, with standard error of 0.104); moreover, task value showed a leptokurtic distribution (kurtosis statistic 3.440, with standard error of 0.207). Also, the violation of normality for metacognitive self-regulation was due to multiple peaks and dips. **Table 2** presents the mean and standard error values for each of these variables.

In order to test H1, after checking the violation of normality assumption, Mann-Whitney U tests were performed. Finally, to test H2, three multiple regression models were performed, using the three motivational and SRL strategies as dependent variables; student profile and program type (classroom or online VET) were included. The stepwise method was used for each model. Independent variables (except for age) were encoded as dummy variables (0, 1). Following Lévy and Varela's (2003) recommendation, the multiple regression model analysis applied in this study did not aim to establish prediction, but to facilitate our understanding of which variables -

TABLE 2 | Analyzed variables, with number of items, example items and alpha coefficient.

Scale	Dimension	Variable	No items	Example item	Cronbach's Alpha	Mean (Standard Error)
Motivation scale	Value components	Task value	6	I think the course material in this class is useful for me to learn.	0.90	4.17 (0.78)
Learning strategies scale	Resource management strategies	Effort regulation	4	I often feel so lazy or bored when I study for this class that I quit before I finish what I planned to do (reversed).	0.69	3.71 (0.82)
	Cognitive and metacognitive strategies	Metacognitive self-regulation	12	I ask myself questions to make sure I understand the material I have been studying in this class.	0.79	3.33 (0.75)

learning mode among them- explain the different degrees of motivational and SRL strategy employed by VET students upon commencing the course.

RESULTS

Validation of Motivational and SRL Strategies Scales

After testing the first model, simulating Pintrich's (1990) original, the results suggested that the latent factor of metacognitive self-regulation had small regression weights on Items 1 and 8 (for Item 1, $\gamma = 0.159$ with $p < 0.0001$, and for Item 8, $\gamma = 0.066$ with $p = 0.151$). After analyzing item content and wording, we noticed that the two questions had a similar structure: both were reversed and had the word "often" in them. We therefore decided to eliminate these items from the analysis, since they did not have the same effect as the originals, possibly due to the translation into Catalan, which led to changes in the structure of the sentences.

Following this readjustment, the final model improved the χ^2 (from $\chi^2 = 921{,}387$ to $\chi^2 = 573.409$). Other fit indices appeared to be marginally acceptable (CMIN/DIF = 3.434; CFI = 0.910; TLI = 0.898; RMSEA = 0.065). **Figure 1** presents the standardized estimates and correlations among factors, and **Table 3** shows the non-standardized regression weights.

The analysis of the standardized residual covariances revealed some local misfits (by detecting some values |1.96|), particularly affecting the latent factor effort regulation. Likewise, the modification indexes suggested freeing the regression weights on effort regulation items from other factor items. These suggestions were not considered since the theoretical model did not support them, however, a revision of these items is highly recommended.

Finally, Cronbach's Alpha was $\alpha = 0.844$ for metacognitive self-regulation; $\alpha = 0.665$ for effort regulation; and $\alpha = 0.902$ for task value. Again, these results showed the need to improve the effort regulation scale, whereas the other two scales can be considered sufficiently reliable for group-level analysis.

The final instrument is available at https://ddd.uab.cat/record/215267.

Mean Differences Between Learning Modes Among Vocational Education and Training Students

H1 established that VET students employ different degrees of motivational and SRL learning strategies according to the learning mode chosen (classroom or online)–H1a, H1b, and H1c–. The results are presented below.

Perceptions of task value among online VET students (*Mdn* = 4.33) did not differ significantly from those of classroom VET students (*Mdn* = 4.33) at the beginning of the program, $U = 28674.50$, $z = -1.287$, $p = 0.198$, $r = -0.054$. This means that VET students enrolled on online learning programs have the same perception of task value as those students enrolled on classroom learning programs.

Metacognitive self-regulation levels among online VET students (*Mdn* = 3.50) differed significantly from those of classroom VET students (*Mdn* = 3.30) at the beginning of the program, $U = 24116.50$, $z = -2.244$, $p = 0.025$, $r = -0.095$. This means that at the beginning of a course, VET students enrolled on online learning programs perceive that they employ more highly developed metacognitive self-regulation strategies than those students enrolled on classroom learning programs. The data show a small effect size.

Effort regulation levels among online VET students (*Mdn* = 4.00) differed significantly from those of classroom VET students (*Mdn* = 3.50) at the beginning of the program, $U = 18745.50$, z = -5.623, $p < 0.001$, $r = -0.239$. This means that at the beginning of a course, VET students enrolled on online learning programs perceive that they employ more highly developed effort regulation strategies than those students enrolled on classroom learning programs. The data show a small effect size.

Considering the mean comparison, we refuted H1a and confirmed H1b and H1c.

Variables That Explain Degrees of Motivational and Self-Regulated Learning Strategies Employed by Vocational Education and Training Students

The study considered the second hypothesis: H2. The learning mode chosen by VET students is a key variable when explaining the degree to which they employ motivational and SRL strategies when starting the program. The statement was based on the idea that if online learners need to employ more motivational and SRL strategies in order to succeed academically, then it is important to determine which variables -learning mode among them- explain the different degree to which VET students employ motivational and SRL strategies at the beginning of the course.

To this end, we executed a multiple regression model using the motivational and SRL strategies as dependent variables. The independent variables were: student profile—age, male student, female student, pathways, having prior work experience, having prior work experience related to the VET program; classroom as learning mode; main reason for enrolling on VET program—personal interest, to find a job in this sector, to progress in my professional career, to get a certificate, to demonstrate to myself that I have the ability; and the other motivational and SRL strategies not used as dependent variables.

The first multiple regression model was executed using task value as the dependent variable. After five steps, the model obtained an adjusted R^2 of 0.138. This means that although metacognitive self-regulation, effort regulation, the motivation to progress in one's professional career, personal interest in the content of the VET program, and having professional experience (in general) were variables in the resulting model, they only explained 13.8% of perceived task value among VET students when starting a program. **Table 4** shows the coefficients of the resulting model, in which the chosen learning mode did not emerge as a significant factor

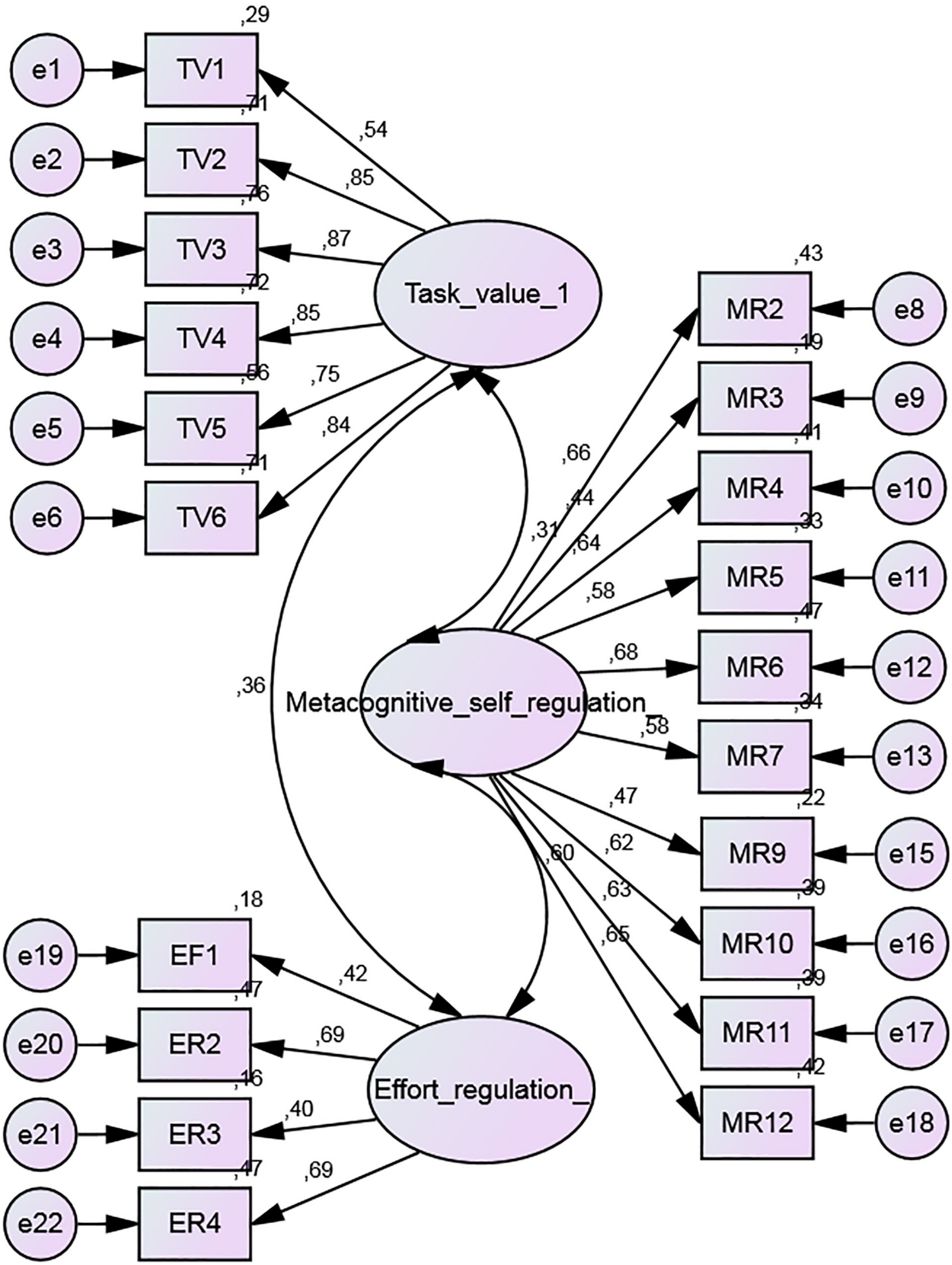

FIGURE 1 | Final CFA model (standardized estimates).

TABLE 3 | Final CFA model (non-standardized regression weights).

Item	Latent factor	Estimate	S.E.	C.R.
TV6	Task value	0.964***	0.037	26.198
TV5	Task value	0.856***	0.040	21.483
TV4	Task value	0.960***	0.036	26.597
TV3	Task value	1.000		
TV2	Task value	0.910***	0.034	26.403
TV1	Task value	0.627***	0.046	13.740
MR2	Metacognitive self-regulation	0.984***	0.082	11.984
MR3	Metacognitive self-regulation	0.610***	0.069	8.876
MR4	Metacognitive self-regulation	0.978***	0.083	11.782
MR5	Metacognitive self-regulation	1.000		
MR6	Metacognitive self-regulation	1.086***	0.088	12.315
MR7	Metacognitive self-regulation	0.870***	0.079	11.047
MR9	Metacognitive self-regulation	0.643***	0.069	9.347
MR10	Metacognitive self-regulation	0.844***	0.073	11.565
MR11	Metacognitive self-regulation	1.019***	0.088	11.612
MR12	Metacognitive self-regulation	0.988***	0.083	11.917
ER4	Effort regulation	1.591***	0.205	7.763
ER3	Effort regulation	1.000		
ER2	Effort regulation	1.672***	0.216	7.756
ER1	Effort regulation	1.154***	0.180	6.421

****p* < 0.0001.

TABLE 4 | Multiple regression model coefficients, using Task value as the dependent variable.

	B	*SE B*	β
Step 1			
Constant	3.16	0.18	
Metacognitive self-regulation	0.31	0.05	0.29**
Step 2			
Constant	2.82	0.21	
Metacognitive self-regulation	0.24	0.06	0.23**
Effort regulation	0.15	0.05	0.16*
Step 3			
Constant	2.84	0.21	
Metacognitive self-regulation	0.22	0.06	0.21**
Effort regulation	0.15	0.05	0.16*
Reason to enroll: To progress in my professional career	0.21	0.09	0.12*
Step 4			
Constant	2.69	0.21	
Metacognitive self-regulation	0.23	0.06	0.22**
Effort regulation	0.15	0.05	0.16*
Reason to enroll: To progress in my professional career	0.30	0.09	0.16*
Reason to enroll: Personal interest	0.24	0.09	0.14*
Step 5			
Constant	1.49	0.55	
Metacognitive self-regulation	0.23	0.06	0.22**
Effort regulation	0.15	0.05	0.16*
Reason to enroll: To progress in my professional career	0.29	0.09	0.16*
Reason to enroll: Personal interest	0.24	0.09	0.14*
I have professional experience (in general)	1.21	0.52	0.11*

Adjusted $R^2 = 0.083$ *for Step 1,* $\Delta R^2 = 0.019$ *for Step 2 (*$p = 0.003$*),* $\Delta R^2 = 0.011$ *for Step 3 (*$p = 0.015$*),* $\Delta R^2 = 0.014$ *for Step 4 (*$p = 0.007$*),* $\Delta R^2 = 0.010$ *for Step 5 (*$p = 0.019$*), ***$p < 0.001$ ***$p < 0.05$.

in explaining perceived task value among VET students when starting a program.

When using metacognitive self-regulation as a dependent variable, four steps were needed to obtain an adjusted R^2 of 0.228. The variables effort regulation, task value, not having a personal interest in the content of the VET program (negative correlation) and being female were key variables that only explained 22.8% of perceived metacognitive self-regulation in VET students. Again, the chosen learning mode was not one of the significant variables in the model. **Table 5** presents the coefficients of this model.

The last regression model took effort regulation as the dependent variable. The resulting model obtained an adjusted R^2 of 0.246 in only three steps. This model comprised metacognitive self-regulation, student age, and task value. These three independent variables were able to explain 24.6% of the variance in the effort regulation variable, a higher percentage than the other three models. **Table 6** offers the coefficients of the model obtained. Again, the chosen learning mode was not a key variable in this model.

The results from all three models refuted the second hypothesis (H2).

DISCUSSION

The evidence suggests that motivation and SRL strategies are important in determining academic success in any educational stage and process, including in VET studies (Wang et al., 2013; Alkis and Taskaya, 2018). Online learning environments open up new avenues for VET students because they are not seen merely as tools to support learning, but as dynamic settings that are flexible, attractive and interactive, and make lifelong learning possible in any professional field (Brennan et al., 2001). Yet, not all students succeed in online VET. Studies have evidenced that they must be highly motivated and able to regulate their own learning (Garrison, 2003; Artino and Stephens, 2009). Our research aimed to analyze the degree to which VET students employ motivational and SRL strategies, focusing on the two VET modes, online and classroom, in order to understand how students' characteristics are related to their engagement in the course.

Validating Task Value, Effort Regulation and Metacognitive Self-Regulation Scales in New Contexts

Regarding the first aim of the research, some evidence of construct validity was obtained for the translated and adapted version of Pintrich's (1991) scales for analyzing metacognitive self-regulation, task value, and effort regulation among VET students in Catalan.

Our results showed that correlations among factors were quite similar as with the original model constructed by Pintrich (1991). This means that Pintrich's model is also suitable for analyzing motivational and SRL strategies used by VET students both online and on classroom programs.

Despite the similarities with Pintrich's (1991) original findings, the results for validity and reliability indicated that a revision of

TABLE 5 | Multiple regression model coefficients, using Metacognitive self-regulation as the dependent variable.

	B	*SE B*	β
Step 1			
Constant	1.973	0.161	
Effort regulation	0.366	0.042	0.408**
Step 2			
Constant	1.341	0.215	
Effort regulation	0.320	0.042	0.357**
Task value	0.192	0.044	0.203**
Step 3			
Constant	1.411	0.214	
Effort regulation	0.304	0.042	0.338**
Task value	0.199	0.044	0.211**
Reason to enroll: Personal interest	−0.253	0.074	−0.153*
Step 4			
Constant	1.444	0.213	
Effort regulation	0.293	0.042	0.326**
Task value	0.195	0.044	0.206**
Reason to enroll: Personal interest	−0.254	0.074	−0.154*
Female	0.134	0.067	0.090*

*Adjusted R^2 = 0.164 for Step 1, ΔR^2 = 0.037 for Step 2 (p < 0.001), ΔR^2 = 0.021 for Step 3 (p = 0.001), ΔR^2 = 0.006 for Step 4 (p = 0.047), **p < 0.001 *p < 0.05.*

TABLE 6 | Multiple regression model coefficients, using Effort regulation as the dependent variable.

	B	*SE B*	β
Step 1			
Constant	2.252	0.177	
Metacognitive self-regulation	0.454	0.052	0.408**
Step 2			
Constant	1.837	0.183	
Metacognitive self-regulation	0.402	0.050	0.361**
Age (in years)	0.022	0.004	0.275**
Step 3			
Constant	1.465	0.233	
Metacognitive self-regulation	0.366	0.052	0.329**
Age (in years)	0.021	0.004	0.263**
Task value	0.124	0.049	0.117*

*Adjusted R^2 = 0.164 for Step 1, ΔR^2 = 0.072 for Step 2 (p < 0.001), ΔR^2 = 0.011 for Step 3 (p < 0.001), **p < 0.001 *p < 0.05.*

the effort regulation scale is needed. Dunn et al. (2012) faced similar problems when conducting the statistical revaluation of effort regulation and metacognitive self-regulation scales. Thus, more analyses are required to confirm the goodness of fit of SRL scales among VET students in Catalonia, since difficulty and discrimination parameters may have changed. It is crucial that more data are gathered to validate the model in a new context like the current one. In addition, a revision of the translation and adaptation of Items 1 and 8 is required in order to improve them and include them in the model, which would make the results of the Catalan version of the scale more comparable with the original.

Despite the limitations mentioned, this step forward in the validation of scales in itself represents an important achievement that has not been reported previously, because it enables Catalan educational institutions to apply the model to all types of VET studies. This will provide VET instructors with the tools to evaluate the motivational and SRL strategies employed by their students and better adapt their teaching methodology to them.

Identifying Differences Between Learning Modes

In relation to the second aim of the study, namely, to identify differences in students' motivational and SRL strategies depending on the learning mode they enrolled on (classroom or online), the results of the Mann-Whitney test were relevant.

Our findings pointed to the fact that VET students enrolled on online learning programs perceived they have more highly developed metacognitive self-regulation and effort regulation strategies than those enrolled on classroom learning programs. This aligns with the results of other studies (Martínez and Galán, 2000; Artino and Stephens, 2009), which showed how important SRL strategies are in explaining students academic success, specifically in online learning (Triquet et al., 2017). Thus, having these strategies when starting a VET program in online mode becomes essential to their success. The last meta-analysis study published by Lee et al. (2019) showed an alignment between of our results and those of several studies on online learners' success factors and the importance of self-efficacy and SRL strategies. In respect of this, Magen-Nagar and Cohen's (2017) study proved that learning strategy was a significant mediator for motivation and academic achievement among online high-school students, which constitutes an important contribution to understanding the implications of our results.

Despite what we might have expected, no differences were found between online and classroom VET students when it came to perception of task value. This indicates that online and classroom VET students perceived the value of the task -the course they enrolled on- to be equally important, even though task value has been proven to be one of the most important motivational factors, it being associated with learning engagement and success (Aristeidou et al., 2017; Zhang and Liu, 2019) and a significant predictor of course completion (Cho and Heron, 2015; Vanslambrouck et al., 2018). As Cents-Boonstra et al. (2018) showed, VET students with a higher level of motivation also have a higher level of self-efficacy, which is strongly linked to learning success.

Considering these results, H1a was refuted and H1b and H1c were confirmed. In other words, there were no differences in perception of task value between online and classroom learning VET students, which refuted H1a; but there were differences in perceptions of the metacognitive self-regulation and effort regulation learning strategies employed between these two groups, which confirmed H1b and H1c, online learning VET students perceiving their self-regulated learning strategies to be more developed.

The fact that there were no differences in task value perception between online and classroom VET students reveals an important area for improvement for educational institutions. We expected online students to have a higher perception of task value than classroom students because their learning process is based on a more student-centered and autonomous model and they therefore need more self-motivation. Furthermore, online course satisfaction and its connection with student motivation were also found to be related to academic success in this study (Herbert, 2006), while Lee et al. (2019) review showed that task value and SRL strategies positively affect a sense of academic achievement, motivation and learner behaviors. Online VET instructors and course designers could use this knowledge to improve their programs and thereby foster motivation and success among VET students. Indeed, increasing online VET students' perception of task value by providing meaningful learning environments could improve students' motivation and academic success (Radovan and Radovan, 2015; Dubeau et al., 2017).

Approaching these differences by applying multiple regression models that use the factors posited by Pintrich as dependent variables, our findings suggest that more than 75% of the variance of all three models still remains unexplained with the profile variables included. Thus, the regression models obtained do not include all of the variables we need to help us understand which motivational and SRL strategies play an important role when selecting the mode of VET learning. One way to acquire fully explained models could be to use Pintrich's (1991) complete model; while others could be to measure other profile variables -such as time spent studying course materials, family responsibilities- and cognitive variablessuch as working memory (Torrano and González Torres, 2004), and designing longitudinal studies such as the work done by Lee (2015) using mixed-methods to gain more in-depth knowledge of the reasons behind the results obtained.

It is also interesting to note that the independent variable learning mode classroom or online that students enrolled on for the VET program was not significant in explaining the degree of motivational and SRL strategies employed by these students. Results from the two models allow us to refute our second hypothesis (H2), because we were not able to find any evidence to support the idea that the learning mode chosen by VET students was a key variable when explaining the degree to which they employ motivational and SRL strategies.

This means that even though there were significant differences between these type of students classroom and online in the degree to which they employed metacognitive self-regulation and effort regulation when beginning a VET program, this difference might not be entirely explained by their choice of learning mode. This idea can only be tested by conducting longitudinal studies during their learning period in VET programs similar to the work done previously by Lee (2015) or Throndsen (2011); using various methodological approaches may cover qualitative aspects of their responses that quantitative methodology cannot capture.

Limitations and Future Directions

Some limitations were identified when considering the implications of this study. The fact that the research was conducted in the Catalan VET context and the tool we applied was in the Catalan language can be seen as a limitation, considering the small size of the Catalan-speaking community. However, given the similarity of the VET system implemented in all Spanish regions—and also in some Latin-American countries—the results could be interesting for other Spanish communities, and the validated tool could easily be adapted to their context. Nevertheless, the specific context of the study generated one important limitation: the difficulty of comparing these results with other studies in the field. Another limitation is related to the non-random study sample, which, despite having an adequate number of participants, meant caution was required when attempting to generalize the results. A further limitation was the validation indices for the scales, which were acceptable but not optimal; more research will be needed to improve the scales.

Due to the little available research on VET students' motivation and the SRL strategies they employ (Savoie-Zajc et al., 2010), our findings could make an interesting contribution to the field.

Several researchers have suggested (e.g., Cardinal, 2010; Cents-Boonstra et al., 2018; Dubeau et al., 2017; Biemans et al., 2019) that VET programs attract less motivated students, and studies on VET motivational and SRL strategies are therefore not priority areas for exploration. To us, this opens a door to new research, which might focus on the Catalan context using the preliminary validated scales to compare motivation levels and SRL strategies between VET and high-school or university students—these being similar in age but differing in levels of motivation (Martin, 2008).

This article presents only one measurement of motivation and SRL strategies, which could be viewed as a limitation in terms of how far our results contribute to VET research. That said, however, we strongly believe that longitudinal studies are also a missing piece of the puzzle we have started to construct in here. Hence the project extending beyond this paper and including the collection of the same measures over the entire 2-year program; other qualitative techniques will be added to gather as much information as possible to obtain a clearer picture of VET students' motivation and SRL strategies. Our aim is to determine whether our results are maintained over time, as Lee's (2015) study did using a longitudinal sample.

In line with this, Lee (2015) has already pointed out that "when measurement on students' motivation is available in the early stages of a semester, some interventions can be implemented to foster their motivations, thus preventing their dropping out of class" (p.63). Knowing for a fact that this is also the case with Catalan VET students (both in classroom and online learning mode), educators can design and implement advanced tasks that engage students from the very first, since students' extensive employment of motivational and SRL strategies ensures a high probability of course completion and therefore academic success (Cho and Heron, 2015; Vanslambrouck et al., 2018).

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Universitat Internacional de Catalunya. Written informed consent from the participants' legal guardian/next of kin was not required to participate in this study in accordance with the national legislation and the institutional requirements.

AUTHOR CONTRIBUTIONS

CQ-P and AC-C contributed conception and design of the study and performed the statistical analysis. AC-C organized the database. CQ-P and AS-M wrote the first draft of the manuscript. CQ-P, AS-M, AC-C, and PP-H wrote sections of the manuscript. All authors wrote sections of the manuscript, contributed to the manuscript revision, read, and approved the submitted version.

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Affect in Peer Group Learning During Virtual Science Inquiry: Insights From Self-Reports and Video Observations

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The purpose of this study was to explore affect in small groups learning together face-to-face in a virtual learning environment. The specific aims of the study were to establish how affect within groups (valence, intensity) related to the quality of group outcome (high, average, low), and to capture individual differences within the groups by using a multimethod approach. Participants were six groups of three high school students (N = 18) who achieved distinct outcome levels. Students' self-reports of their affect and observed affect (researcher-coded selected segments from videos) were used to examine affect during three phases of interdisciplinary science inquiry, namely, planning the experiment, experimenting in the virtual laboratory, and concluding and preparing a joint group presentation. The overall results showed that positive affect was prevalent in both self-reports and researcher-coded observations across all phases. However, while self-reports displayed a strong dominance of positive affect, there was more variation in observed affect. Furthermore, the intensity of affect was higher in self-reports than in observations, for both positive and negative affect. Nonetheless, no effect of affect on group outcome was found. Finally, while within-group consistency in affect was evident in the extreme groups (high, low performance), it was more ambivalent in the groups that achieved an average performance. The results are discussed in light of the literature, and directions for future research on affect in collaborative learning are proposed.

Keywords: affect, group work, collaboration, science learning, CSCL, virtual learning environment

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INTRODUCTION

As evidenced in the literature, science learning is affected by attitudes, interest, and motivation, and the lack of interest toward science domains has been repeatedly remarked in recent decades (Ramsden, 1998; Alsop and Watts, 2003; Ainley and Ainley, 2011). This concern is still present, as interest, motivation, and engagement in science learning are continuously declining (Schneider et al., 2016). To enhance motivation and quality of learning in STEM (science, technology, engineering, and mathematics) subjects, new, engaging learning environments based on technology-supported inquiry and collaboration have been developed (de Jong, 2019). However, findings of the success of collaborative inquiry learning are diverse. Many studies have shown that new learning environments have positive effects on learning and motivation (see review by de Jong, 2019), but other research summaries have questioned the superior effects of inquiry learning (Stockard et al., 2018). In addition, the study of Chang et al. (2017) showed that working in collaborative groups in an inquiry-based environment is not engaging for all students (Chang et al., 2017).

The above described diverse findings of the effects of inquiry learning heighten the importance of studying the role of affect when developing novel learning environments in STEM domains (see also Gegenfurtner et al., 2019). The importance of affect in supporting students' interest, engagement, achievement, and experiences of science is widely acknowledged (Lin et al., 2012; Sinatra et al., 2014; King et al., 2015). In particular, positive affect has an especially significant impact on science activities (Laukenmann et al., 2003) and achievement (Ahmed et al., 2013; Liu et al., 2014). Students are more likely to feel positive (happy, confident, and successful), and perceive science as important to them if they are appropriately challenged according to their skills (Schneider et al., 2016).

During the last decades, many studies have dealt with affects and emotions in collaborative and technology-supported learning environments (e.g., Järvelä and Hadwin, 2013; Miller and Hadwin, 2015). Computer-supported collaborative (CSCL) inquiry environments have many features that differ from traditional teacher-centered classroom situations (e.g., Roschelle et al., 2011), and studies have shown that there are unique sources and directions of emotions in these environments (Järvenoja and Järvelä, 2005; Wosnitza and Volet, 2005). The unique features of these learning environments mean that the findings of studies focused on affect in traditional classroom contexts mainly emphasizing students' interpretations of teacher expectations and feedback (e.g., Salonen et al., 1998) are not necessarily directly applicable in the CSCL inquiry environments, which are still rarely used in science teaching in schools. This study focuses on the group, and individual level affects when students study demanding science tasks in a computer simulation-based collaborative inquiry environment. The main aim is to study what kind of affects appear in differently achieving student groups across different phases of inquiry processes by using a multimethod approach.

Collaborative learning environments based on CSCL inquiry consist of many features, which are specific for the appraisal and arousal of affects (Prince, 2004; de Jong, 2019). For example, these environments are assumed to provide students with engaging opportunities for learning by performing meaningful activities, such as modifying or elaborating the content they are studying. Working in these environments also requires reflection of students' ideas and discussing them with others. In addition, in CSCL inquiry, there is more freedom for the students' ideas and approaches than in direct teaching. These affordances and requirements of collaborative and technology-supported learning environments can arouse positive affects in some students but could also arouse anxiety and negative affect in others (Chang et al., 2017).

According to Wosnitza and Volet (2005), in technology-supported social learning activities, emotions are typically directed to self, other(s), the task, and the technology; thus, the understanding of affect in technology-enhanced collaborative settings is ambiguous. Thus, some of the emotions are task-related and can be called epistemic emotions (Pekrun et al., 2017), whereas others are focused on social and other aspects of the environments. Emotions are a crucial part of collaborative learning, but it is complicated how they enhance productive engagement (Polo et al., 2016). Collaborative conditions can arouse positive affects, but can also result in conflicts and tension, leading to negative affect (Baker et al., 2013). Social interaction, as an element of a learning environment can create strong emotional responses (Do and Schallert, 2004), which shows that social interaction, and the social context in general, may trigger students' positive or negative affective reactions and have a strong effect on their engagement (Zschocke et al., 2016).

Many of the studies on collaborative learning in science education have highlighted the positive effects of collaboration and small group work in science learning (e.g., Springer et al., 1999; Shibley and Zimmaro, 2002). Previous research has emphasized the importance of affective experiences during computer-supported science learning. In particular, studies highlight the interplay between affect and interaction and the significance of positive affect in social interaction on performance. For example, affect and engagement during upper-elementary school collaborative mathematics tasks in small groups showed that positive affect (happy, calm) was related to positive group interactions, while negative affect (tired, tense) was connected to disengagement and social loafing (Linnenbrink-Garcia et al., 2011).

Technology-based inquiry environments can be demanding and require novel ways to deal with the tasks and cope with the requirements of the environments, which highlights the affects directed at the different features of learning environments (Wosnitza and Volet, 2005). Baker et al. (2011) found that the most common affective states for undergraduate pairs in a virtual laboratory for chemistry were engaged concentration and confusion. Graesser et al. (2014) found a larger variety of important learning-centered emotions when students were using advanced learning technologies in computer science, mathematics, physics, and biology topics. Emotions the students found included frustration, boredom, confusion, and engagement/flow as well as moments of happiness, sadness, curiosity, surprise, delight, and anxiety.

Task-related emotions pertain to all learning situations (Wosnitza and Volet, 2005), but are particularly important in learning STEM concepts, which are characterized by varying beliefs about difficulty, anxiety, and lack of control (Pino-Pasternak and Volet, 2018). However, science topics can also arouse positive affect. For example, in a study by Tomas et al. (2016), positive emotions dominated the experiences and perceptions of students when studying socio-scientific issues. In that study, students were able to regulate their negative emotions during the group work to complete the task successfully.

King et al. (2017) studied ninth-grade students' discrete emotions during science activities in chemistry and found that learning new chemistry concepts resulted in frustration but was resolved by revisiting the concepts and through interaction with peers and the teacher.

Inquiry learning processes typically have different phases that can be distinguished from each other. There are different descriptions of the inquiry phases, which—at least partly—reflect the emphasis of deductive or inductive approaches (Pedaste et al., 2015). In their recent review, Pedaste et al. (2015) concluded that a typical inquiry includes phases, such as orientation, conceptualization, hypothesis generation, planning, investigation or experimentation, conclusion, and discussion. These phases have different demands and affordances and require different regulative processes (de Jong and van Joolingen, 1998) that may also arouse different epistemic emotions such as curiosity, joy, confusion, anxiety, frustration, and boredom (Pekrun et al., 2017) but also various social emotions (Wosnitza and Volet, 2005). Although qualitatively different working phases are a fundamental feature of inquiry learning, only a few studies have dealt with affects and motivation during these different phases. Several studies have studied temporal changes in motivation during STEM task performance, but have not specifically analyzed affects and motivation within different phases of inquiry (e.g., Tapola et al., 2013; Rodriguez-Aflecht et al., 2018). An exception is a study by Näykki et al. (2017) in which they organized a collaborative inquiry process into three phases (orientation, intermediate, and reflection) with a script (guiding students' activities) that included prompts for cognitive and emotional monitoring during the phases (e.g., 'What kinds of feelings does the task arouse?'). The results showed that student groups expressed more emotional monitoring during the orientation phase than during the two subsequent phases. However, socio-emotional support was provided equally during all phases.

In-depth analyses of discourses in collaborative learning contexts refer to the importance of emotions on the quality of discussion (e.g., exploratory talk, as described by Wegerif and Mercer, 1997) in collaborative groups. High-quality group interaction is possible in groups where participants behave politely and where students feel no shame in expressing ill-structured ideas. In this kind of environment, it is possible to change one's mind, and there is no aggressive criticism of others' views. Students do not feel sadness if their initial ideas are not accepted but rather are happy that the collective process led to stronger conclusions that were better justified (Polo et al., 2016). High quality group interaction is, however, not enough if it does not result in successful learning. There is empirical evidence that positive learning and achievement-related emotions predict academic performance (Niculescu et al., 2015). According to recent findings, students' emotions have an impact on their self-regulated learning and motivation, which for their part effect on students' academic achievement. However, these findings are focused on individual emotions and learning and are not necessarily directly applicable when collaborative learning in small groups is concerned. Researchers have argued that the role of affects can be dissimilar in situations based on the negotiation of meaning, and require mutual engagement and high levels of social interaction (Linnenbrink-Garcia et al., 2011; Zschocke et al., 2016). Linnenbrink-Garcia et al. (2011) indicated that both neutral and positive affects could facilitate constructive group interactions, while negative affect seemed to hinder productive group interactions.

Study groups consist of individuals and social relations between them. Thus, both individual and social processes require attention, while students jointly regulate motivation and engagement in collaborative learning (Järvelä et al., 2010). Individual group members' affects can vary because they interpret the cognitive benefits of collaborative work and the organizational-structural group processes and task characteristics differently (Zschocke et al., 2016). The role of individual differences in a group context, as well as the group's working practices, need consideration to understand better the divergence in group activity and performance (Summers and Volet, 2010). It is possible to analyze the affective tone of interaction on an individual and collective level (e.g., Polo et al., 2016). The aggregated effects of individuals' affects in groups can be positive or negative, and the way that aggregated affect activates the group work can be high or low (Linnenbrink-Garcia et al., 2011). Many features of the participant's affective behavior can cause problems for collaborative learning. Individual participating students may be unmotivated or dissatisfied with the tasks (Zschocke et al., 2016), can harm the quality of discussion by aggressive behavior (Polo et al., 2016), or present derogatory remarks about other students (Baker et al., 2013). However, individual participants can also play an important positive affective role in group work: for example, by providing socio-emotional support (Näykki et al., 2017).

According to a common view, affects have different interrelated components, including physiological reactions, subjective experience, and expressive behavior (Gross and Levenson, 1993). This manifold nature of affect highlights the importance of a multimethod approach in studying affects and emotions related to learning. There is a large variety of methods developed and used in studying affects in individual and collaborative learning processes. Methods can be based on snapshots (e.g., questionnaires) before and after learning episodes or measures during learning processes (e.g., observation; Wosnitza and Volet, 2005). Meyer and Turner (2006) have emphasized the importance of comparing and integrating self-reports and observations in the research of classroom practices.

The overall aim of the present study was to contribute to a better understanding of affect in small groups by using a multimethod approach and scrutinizing how group members' affects and behaviors contributed to the entire group's collective outcome. Four research questions were generated:

(1) To what extent is affect within a group (valence, intensity) similar at three distinct phases of their collaborative learning activity? In light of limited prior studies of affect within a group at different phases, stages, or

different aspects of an activity, the research questions are exploratory in nature.

(2) How is affect within a group (valence, intensity) related to group outcome (high, average, low)? It would be reasonable to expect that group interactions leading to high performance would generate positive affect within the group and the opposite for a group that achieved low performance. However, some studies (e.g., Tomas et al., 2016) have found that fun, collaborative science activities can generate positive emotions that interfere with learning and, in turn, with performance.

(3) What is the degree of within-group consistency in individuals' affect (valence, intensity) across phases? How does individual affect play out in extreme performing groups and a group displaying within-group diversity and change in individual affect? Previous studies indicate that similar positive affect among individual students would increase collaborative engagement with the task, and vice versa (Linnenbrink-Garcia et al., 2011). There are indications in prior research focused on other types of group processes (such as regulation or roles as indicators of engagement) that individual students have an impact on other group members, thus positively or negatively influencing the group effort, e.g., in terms of initiating and sustaining conceptual talk (Volet et al., 2019; see also, Rogat and Linnenbrink-Garcia, 2011).

(4) How consistent is self-reported affect and observed (researcher-coded) affect at both the group and individual levels? Since self-reports have been considered to serve an overly narrow view of affect (Wosnitza and Volet, 2005), the present study adopted a multimethod approach. In the case of affect, combining self-report data with researchers' observations of affect during students' actual collaborative learning processes was expected to provide complementary insight, and therefore a more reliable and richer understanding of affect in a small group regardless of whether the findings concurred or not. Complementarity was expected on the basis that, on the one hand, emotions could be concealed, and thus are not always observable from an external vantage point. While on the other hand, self-assessments can be biased for a range of reasons (e.g., social desirability, weak self-awareness) or affected by a recency effect (assessments were done after each whole session), therefore not providing an adequate account. This fourth question, related to the degree of consistency between self-reported affect and observed affect, was addressed systematically in each of the first three research questions.

MATERIALS AND METHODS

Learning Environment and Research Design

A web-based learning environment, Virtual Baltic Sea Explorer (ViBSE), was designed to offer a realistic context for learning both key science concepts and knowledge integrating biology and chemistry and cultivating scientific practice and reasoning skills (Kinnunen et al., 2018; see also, Vauras et al., 2019). The group activity involved running an experiment on the effects of fast pH changes in very important phytoplankton and certain species of copepods in the Baltic Sea's food chain, using a dominating science language, i.e., English. ViBSE offered a rich set of tools for students, such as a library of key constructs and phenomena, photos, interviews, and mini-lectures by the crew and researchers of the real research vessel Aranda, laboratory tasks, and links to external web pages concerning the news and state of the Baltic Sea. Thus, during their virtual exploration, the students became acquainted with scientific work, characterized by experimental methods, such as forming hypotheses, simulation of the research design, running experiments, and interpreting and concluding the outcomes. All data underlying the experiments were based on studies by real marine biologists in published articles (see, Bonaglia et al., 2013; Engeström-Öst et al., 2014). During the learning in the virtual learning environment (VLE), students were choosing the topic (in this study they were studying the effects of pH changes on the reproduction of copepods), making hypotheses and study designs and proceeding to the laboratory tasks (choosing the number of sea water bottles, eggs, pH and time). Laboratory tasks consisted of collecting the data, making analyses (e.g., counting the eggs and calculating basic statistics), and concluding and interpreting results. Small group collaborative inquiry, in the role of partners in the marine research team of a real environmental research vessel, was intended to elicit deep-level learning through genuine scientific dialogue and argument. Thus, ViBSE was designed to provide a bridge between the school and science worlds by positioning students as researchers and fostering their adoption of the practices, goals, and methods that guide the authentic research of professional scientists. Since the VLE was new to students and thus challenging for the students in a regular classroom, teacher assistance was further offered when needed (see Koretsky et al., 2019; Vauras et al., 2019).

The learning context for using the VLE were high schools, where students ($N = 120$) worked together in small peer groups ($N = 39$) during their regular science courses at an advanced level, and earned course credits for their participation. The students were between 16 and 19 years ($M = 17.27$; $SD = 0.68$) and over half of them were girls (65%). This gender distribution was related to the course topic, i.e., biology. The teacher assigned students to small peer groups in advance to level the disciplinary knowledge and English language competence within groups. All students were familiar with each other since they studied together in the course. The research team informed and guided teachers in using the VLE and in turn, teachers gave instructions to the students. The students were instructed to collaborate as a team, while the teacher's role was primarily to scaffold the groups. The small peer groups worked in their own space by their table with a shared laptop, during three sessions lasting 75–95 min each. The three working sessions followed the phases of scientific research: (1) planning: reading materials, generating a hypothesis, and experiment planning; (2) experimentation: including analysis of the results; and (3) conclusions: preparing a group presentation to the class, followed by discussion. All students in the class were asked to complete a paper-and-pencil questionnaire eliciting their affect at the end of each working session to avoid interruptions in the groups' learning process. This questionnaire was completed individually at all three measurement points, using the same procedure. Participation of both students and teachers was voluntary, and written permission for video recording the groups' interactions was obtained from all students (and guardians if students were under 18 years of age).

Participants for the Present Study

Altogether, six intact groups, totaling 18 students (4 boys and 14 girls) were chosen for close analysis out of 39 groups. The decision to select a small number of groups was necessary due to the exploratory nature of the study and, in particular, to allow an in-depth, detailed analysis of each group. These six groups were selected based on their group outcome (two Low, two Average, and two High). Selection criteria for the groups was that they were intact groups of the same three students during the entire process (three working sessions). The outcome measure was the group presentation at the very end of the three working sessions. Two qualified science professionals in biology and chemistry evaluated the overall quality of the groups' presentations, taking into account the research plan, hypotheses, understanding of the task and presentation structure, actual presentation, conclusions, and quality of the scientific language used in the presentation. The groups were divided into three performance levels based on the quality of their group presentation (1 = low−, 2 = low+, 3 = average−, 4 = average+, 5 = high−, 6 = high+). The number of distinct productive outcome groups was 6 high (13 girls, 3 boys), 14 average (28 girls, 14 boys) and 19 low (34 girls, 22 boys) groups. In this paper, pseudonyms are used to address individual students within the groups.

Data and Data Analyses

Self-Reported Affect

Students were asked to evaluate their affect individually on a systematic affect scale based on the valence of positive and negative affect on a 10-point bipolar Likert scale from the orthogonal positive and negative affective states (e.g., excited-tired, confident-insecure) (Pietarinen et al., 2019). A circumplex model of affect was applied to capture activating and deactivating affects as well as valence (e.g., Feldman Barrett and Russell, 1998; Linnenbrink-Garcia et al., 2011; see also, Scherer, 2005). The selection of affective states for the scale was based on the findings of previous studies and learning-related emotions in advanced learning technologies, as described by Graesser et al. (2014). Each student assessed 12 items altogether, representing 24 affective states (proud-ashamed; enthusiastic-bored; excited-tired; delighted-disappointed; interested-uninterested; confident-insecure; happy-unhappy; glad-angry; pleased-annoyed; satisfied-frustrated; relaxed-anxious; calm-tense). Students' affect during the group task was measured at the end of each working session, based on their perceptions of the affective states they experienced in each preceding working phase. Aggregated individual reports by a particular group were used in all group-level analyses. For frequency analyses, values ranging from one to four were classified as negative, from five to six as neutral, and from seven to ten as positive. For this study, neutral (total of approximately 22–25% of all self-ratings; see Pietarinen et al., 2019) were excluded from these analyses since the focus was on comparing, specifically, valence and arousal in relation to two different data collection methods (self-reports and observations) and to ensure comparable data for this purpose.

Observed Affect

The video segments for the in-depth analyses of observed affect were chosen from the total video footage from each group. These segments represented meaningful and continuous verbal interaction (i.e., collaboration) within the group and featured each of the working phases, namely, Planning, Experimentation, and Conclusions, following the steps of scientific research (see Tsovaltzi et al., 2010). Data for coding was thus restricted to these meaningful segments to ensure manageable coding and comparable observation for all groups through all working phases. Because the groups varied in terms of the length of their conversations and activity completion rates, the selected video segments were of unequal length (approximately 10–16 min). Therefore, the group analyses were based on observations appropriate for science learning (see Derry et al., 2010), and two independent coders coded them, using the Observer XT 12. The coding scheme was modified from earlier research on affect dimensions (Scherer, 2005; Linnenbrink-Garcia et al., 2011) and group processes (Vauras et al., 2008; Linnenbrink-Garcia et al., 2011; Rogat and Linnenbrink-Garcia, 2011). Consistent with these prior studies, the researchers' observations considered both verbal and non-verbal interaction, and paralanguage (sighing, yawning) to capture all possible indicators of affect, i.e., valence and activation. The coding was undertaken first at the episode level (a chain of [verbal] interaction) to define the sequences for turn-level analyses, and then at the turn level (a word, sentence, talk or noticeable gesture of one person) to gain greater insight into the groups' affect-related interactions. The coding protocol is shown in **Figure 1**. The total amount of turns across the selected segments was 6390, and 1542 turns (24%) contained the observed affect. The inter-coder agreement was calculated from all turns within randomly selected episodes. **Table 1** presents the indicators and examples for diverse levels of valence and intensity.

First, the two coders viewed the selected video segments independently and detected all episodes with observed affect (i.e., verbal interaction between at least two of the three students when affective behavior could be detected). All neutral episodes were excluded from subsequent analyses at the turn level. While the starting and end turns of the episodes identified by the two coders were not always the same, the episodes themselves were located in the same timeframe. The inter-coder agreement initially varied between 64 and 94%, and after discussion, the agreement ranged between 87 and 97%.

Second, both coders coded a random sample of episodes from each group and phase (approximately 30%) independently at the turn level, and agreement for valence and intensity agreement varied between 64 and 92%. All disagreements were minor, concerning mainly differences in intensity (high, low)

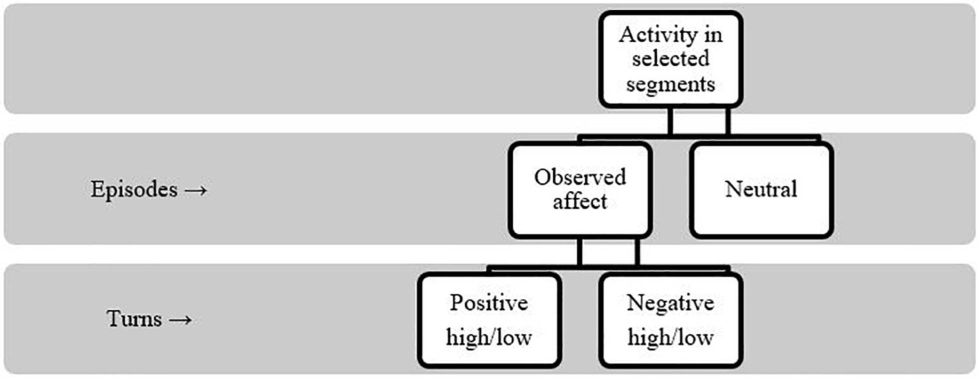

FIGURE 1 | The coding protocol.

and occasionally related to valence when sarcasm played a role. After discussion, the agreement varied between 82 and 96%, and the range of Cohen's kappa-values for all groups and phases (κ = 0.722 – 0.938) were substantial or almost perfect (see Landis and Koch, 1977).

RESULTS

The results are organized around the first three research questions. The first result addressed the extent of similarities and differences in affect (valence, intensity) in the groups in the three phases of the collaborative learning activity. The second result examined the issue of the relationship between group outcome and affect within groups (valence, intensity), and the third addressed the degree of within-group consistency in individual students' affect (reported, observed; valence, intensity) across phases. The data used to answer the third research question is complemented by an in-depth narrative analysis of individual affect in three groups: the two extreme performing groups and one group that displayed within-group variation and change in individual affect over the three phases. The fourth question, related to the degree of consistency between self-reported affect and observed affect, is addressed in each of these three questions.

Similarities and Differences in Affect Within a Group at Three Phases of Their Collaborative Learning Activity (Research Question 1)

Self-reported affect within groups (aggregated individual reports) and observed affect within groups (researcher-coded) overall were examined in turn, in terms of valence and intensity. The distribution of self-reported affect by valence and intensity (arousal) across the three phases is presented in **Table 2**, and the distribution is illustrated in **Figure 2A**. Further, the distribution of observed affect by valence and intensity (high and low) across the three phases is presented in **Table 3**, and illustrated in **Figure 2B**.

TABLE 1 | Affective behavior coding categories and examples.

Valence	Intensity	Indicators	Examples
Positive	High	Clear and intense positive gestures, body language or facial expression or specific statement expressing high positive affect, high tone of voice, laughing, and joking while laughing.	Paula: "*Fine, I knew so much*" and laughs, touching her hair. Joel jokes: "*Very reliable research result*" and laughs: "*Somewhere in the university, it is 30 pages.*"
	Low	Clear and light positive gestures, body language, or facial expression or specific statement expressing positive affect, positive tone of voice, smiling, joking with a calm face. Also, an expression of surprise.	Hanna jokes: "*I was maybe avoiding a bit,*" smiling. Anna says: "*Here is a dictionary,*" looking surprised
Negative	High	Clear and intense negative gestures, body language or facial expression, or specific statements expressing high negative affect, high tone of voice.	Isabel says: "*It irritates me when this is in English; everything irritates me now*" (whining) Anna looks irritated: "*What the heck. we have done these slowly*", turning around
	Low	Clear and light negative gestures, body language, or facial expression or specific statement expressing negative affect, negative tone of voice. Turning away from other(s) with a negative expression in reaction to others or the task. Also, sighing and yawning.	Jesse answers Elias's comment: "*Some weird organism*" and looks uninterested and amused, watching his mobile phone. Laura says: "*I don't know*" and yawns.

TABLE 2 | Distribution of self-reported affect overall by valence and intensity (arousal) across the three phases.

Valence	Arousal	Planning	Experimentation	Conclusions
Positive	Activating	77 (46%)	47 (31%)	85 (51%)
	Deactivating	70 (42%)	54 (36%)	66 (39%)
	Deactivating	12 (7%)	31 (20%)	10 (6%)
Negative	Activating	9 (5%)	20 (13%)	7 (4%)
Total		168 (100%)	152 (100%)	168 (100%)

The findings were interpreted according to percentages because the total number of self-reports of affect was not the same across all phases (168 for Planning and Conclusions, and 152 for Experimentation). As documented in **Table 2** and illustrated in **Figure 2A**, there was a dominance of positive over negative affect overall (high and low arousal combined) in each of the three phases, but the pattern was less salient in the Experimentation phase (67%) than in the Planning phase (88%) and the Conclusions phase (90%). The pattern of self-reported affect in the Experimentation phase differed from the other phases, with one third (33%) being negative, compared to only 12% in the Planning phase and 10% in the Conclusion phase. The relatively high proportion of negative affect during the Experimentation phase may indicate that the task and collaboration with peers were particularly stressful during that phase. It is important to note that students' self-reported assessment of their affective states at the end of each phase applied to the entire working session and, therefore, while these self-reports reflected their affective state at this particular stage of the task, it may have also reflected their overall mood during that session.

In respect to observed affect and as reported in the method section, 24% of the video data selected for analysis (1542/6390 turns) was identified as containing affect-related behaviors, with the rest considered neutral. This percentage differed only slightly across phases, with 28% (622/2,208 turns) in the Planning phase, 19% (351/1804 turns) in the Experimentation phase, and 24% (569/2,383 turns) in the Conclusions phase.

Overall, the coded observations of students' affect revealed some similarities and some differences, as found in the self-report data. **Table 3** shows the distribution of observed affect overall, by valence and intensity across the three phases; this distribution is illustrated in **Figure 2B**.

Similar to the self-report data, positive affect was dominant in all phases (over 70%, when combining high and low intensity), but the positive affect in the Conclusions phase was not as salient when based on the observations rather than the self-reports. Furthermore, the positive affect observed in the video data was dominant in low intensity, whereas a high proportion of the self-report data featured positive affect, representing activating rather than deactivating arousal. With regard to the observed negative affect, the percentage was relatively similar to the self-report data for the Planning phase (12% vs. 14%) and the Experimentation phase (33% vs. 29%), but the percentage of observed negative affect was higher than the self-report data for the Conclusions phase (10% vs. 25%).

Relationship Between Affect Within a Group and Group Outcome (Research Question 2)

The relationship between affect within a group (valence and intensity) and group outcome was examined by comparing group self-reported (aggregated individual reports) and observed affect (researcher-coded) across the six groups that differed in terms of their group outcome. The distribution of self-reported and observed affect by valence and intensity across the six distinct outcome groups and the three phases, respectively, is presented in **Tables 4**, **5**, and illustrated in **Figure 3**.

Overall, as displayed in **Table 4** and illustrated in **Figure 3**, all six outcome groups reported dominantly positive arousal (activating/deactivating combined) for all phases, with two exceptions: Average_4 for the Planning phase (only 48%), and Low_1 for the Experimentation phase (only 22%). The two extreme groups, High_6 and Low_1, were strikingly different in their self-reported affect; as the highest performing group, High_6 systematically reported positive arousal (activating/deactivating combined) for each phase (100%), whereas the lowest performing group, Low_1, reported a substantial proportion of negative arousal (activating/deactivating combined) for each phase (Planning 33%, Experimentation 78%, and Conclusions 46%).

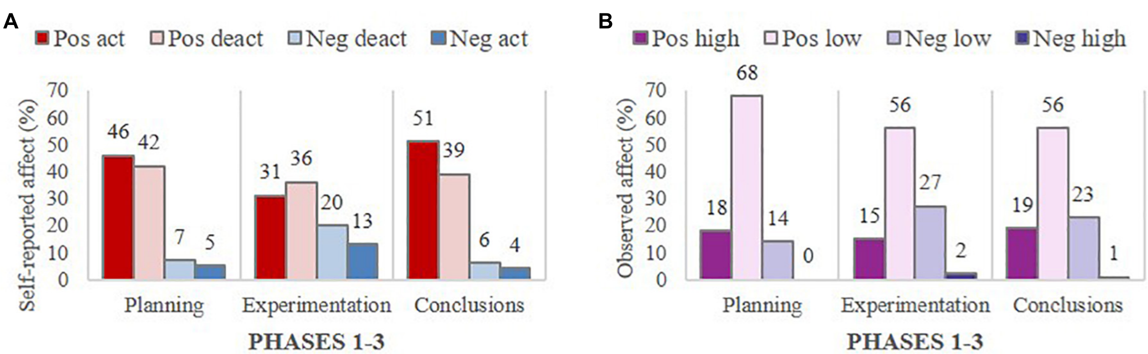

FIGURE 2 | Self-reported **(A)** and observed affect **(B)** overall by valence and intensity (arousal) across three phases.

TABLE 3 | Distribution of observed affect overall by valence and intensity (high and low) across the three phases.

Valence	Intensity	Planning	Experimentation	Conclusions
Positive	High	113 (18%)	52 (15%)	109 (19%)
	Low	422 (68%)	198 (56%)	320 (56%)
	Low	87 (14%)	93 (27%)	133 (23%)
Negative	High	0 (0%)	8 (2%)	7 (1%)
Total		622 (100%)	351 (100%)	569 (100%)

This contrasting pattern of findings is consistent with the performance-related differences between these groups. The pattern is also consistent with anecdotal statements made by members of group Low_1, who repeatedly expressed uncertainty regarding the task and their performance. Furthermore, it was noteworthy that all high and average performing groups reported strictly positive arousal (100%) for the Conclusions phase, whereas the two lowest performing groups, Low_1 and Low_2, reported considerably high negative arousal (activating/deactivating combined) for the Conclusions phase (Low_2 39%; Low_1 46%). Apart from the two extreme groups, the group Average_4 attracted the researchers' attention and further examination [see Section Degree of Within-Group Consistency in Individual Affect Across Phases: Insights From Three Illustrative Groups? (Research Question 3)], since this group reported a substantial proportion of negative arousal (activating/deactivating combined) for the Planning phase (42%) and the Experimentation phase (40%), but no negative arousal for the Conclusions phase (0%).

In respect to the findings on observed affect, as shown in **Table 5** and illustrated in **Figure 3**, positive intensity (high and low combined) was also dominant across groups and for all phases but for one exception, Average_3 for Experimentation (only 25%). In contrast to the self-reports, this group displayed 75% negative affect (although of low intensity) during the Experimentation phase, while their self-reports showed only 20% negative affect. Overall, and despite the dominantly positive observed affect, some negative affect was also observed in all groups, irrespective of the group outcome. However, it is important to note that only a few groups displayed high intensity negative affect; most groups' observed negative affect was of low intensity.

Interestingly, the two extreme groups' (High_6 and Low_1) self-reported and observed affect revealed similar within-group differences. Furthermore, the two extreme groups' differences in observed affect were not as striking as the differences in their self-reported affect. Specifically, while High 6 reported exclusively positive affect, the coded observations of their interactions displayed some negative affect, though of low intensity and ranging only from 11 to 21%. In contrast, Low_1 displayed predominantly positive affect (from 55 to 68%) and very little negative affect of high intensity (only 0 to 7%). Altogether, regarding the lowest performing group (Low_1), the proportion of observed negative affect was remarkably similar to their self-reported affects for both the Planning phase (self-reported affect 33%; observed affect 32%) and the Conclusions phase (self-reported affect 46%; observed affect 48%). The intensity of negative affect, however, appeared lower in the observed affect data than the self-reported data. For the Experimentation phase, the proportion of negative affect was higher and of higher intensity in the self-report than in the observed data (self-reported affect 78%; observed affect 35%).

Alongside the extreme groups and considering their observed affect, Average_4 continued to represent a group of interest, as their observed negative affect was not as noticeably high (20 and 37%, respectively) as their self-reported negative affect for Planning and Experimentation (52 and 40%, respectively). Although there were observations of negative affect in the Conclusions phase, only positive affect was self-reported at that phase. Exploring further at the individual level why this group may have reported predominantly positive affect in the Conclusions phase when a third of their turns (32%) in the segment selected for analysis displayed some negative affect seemed warranted and is reported in Section "Degree of Within-Group Consistency in Individual Affect Across Phases: Insights From Three Illustrative Groups? (Research Question 3)."

All in all, the general finding regarding self-reported and observed affect within groups indicates that positive and negative affect appeared to be of lower intensity in the observations than in the self-reports. However, the observations revealed negative (low intensity) affect in many instances where it was not reported in self-assessments. These general findings, obtained by applying two distinct methods, will be discussed later. Before that, the investigation of affect within a group will be further deepened through illustrations of self-reported and observed affect at the individual level within three distinct outcome groups (High_6, Low_1, and Average_4).

Degree of Within-Group Consistency in Individual Affect Across Phases: Insights From Three Illustrative Groups? (Research Question 3)

To gain insight into the within-group dynamics of affect, a glance at the degree of homogeneity in individual self-reported and observed affect within groups revealed rather consistent affect patterns among members in the two extreme groups, but not in the Average_4 group. The self-reported affect and the observed affect of individuals within their respective groups are presented in **Figures 4–6**, followed by excerpts from their verbal interactions related to the task and science content.

In the highest performing group (High_6), the reported and observed affect of all individual students were predominantly positive, and in the lowest performing group (Low_1), all students reported and were observed to display a substantial degree of negative affect. In the group of interest, Average_4, the patterns appeared more complex and varied. Each group is presented in turn below.

It is important to note that when coding observed affect, high and low positive intensity was determined based on a composite of smiling, laughing, and joking about the activity, content, or technical issues, and sometimes the attitudes, interest,

TABLE 4 | Distribution of self-reported affect in distinct outcome groups across the three phases.

			Planning		Experimentation		Conclusions	
Group	**Valence**	**Arousal**	***Number of turns***	***% of turns for group***	***Number of turns***	***% of turns for group***	***Number of turns***	***% of turns for group***
$High_6$	Positive	Activating	19	56	14	58	13	59
		Deactivating	15	44	10	42	9	41
		Deactivating	0	0	0	0	0	0
	Negative	Activating	0	0	0	0	0	0
$High_5$	Positive	Activating	18	55	9	28	20	57
		Deactivating	14	42	12	38	15	43
		Deactivating	0	0	8	25	0	0
	Negative	Activating	1	3	3	9	0	0
$Average_4$	Positive	Activating	2	11	6	24	20	57
		Deactivating	7	37	9	36	15	43
		Deactivating	6	32	5	20	0	0
	Negative	Activating	4	20	5	20	0	0
$Average_3$	Positive	Activating	17	52	9	36	21	58
		Deactivating	14	42	11	44	15	42
		Deactivating	1	3	2	8	0	0
	Negative	Activating	1	3	3	12	0	0
Low_2	Positive	Activating	12	48	7	30	5	28
		Deactivating	13	52	9	40	6	33
		Deactivating	0	0	4	17	3	17
	Negative	Activating	0	0	3	13	4	22
Low_1	Positive	Activating	9	38	2	9	6	27
		Deactivating	7	29	3	13	6	27
		Deactivating	5	21	12	52	7	32
	Negative	Activating	3	12	6	26	3	14

and level of content knowledge could be detected from students' comments. In respect to the high and low levels of negative intensity, there was a greater variety of indicators, for example, irritation, bitterness, tiredness, frustration, and boredom, which occurred alongside negative gestures and facial expressions (such as sighing or yawning). One challenge was to code sarcastic comments, as the intended meaning was often found to be ambiguous.

Group $High_6$ (Ella, Robin, Sara): Students in this group reported mainly positive affect and hardly any negative affect. Only Ella reported tiredness (low negative arousal) at the Conclusions phase. However, this exception is unlikely to have had any impact on group outcome. In contrast, some negative affect was observed in each video segment selected for coding. It is noteworthy that high intensity negative affect was totally absent in both self-reports and observations, as shown in **Figure 4**. Positive affect (high and low intensity combined) was dominant in the observations of all students; for Ella, it ranged between 84 and 95% (M = 89%), for Sara 73–83% (M = 77%), and Robin 77–94% (M = 86%), indicating that Ella displayed the most positive affect across the three phases (see **Figure 4**). Remarkably, humor and laughter were present seamlessly in all the conversations related to the scientific content of the task, as illustrated in the verbal interaction example of positive (high and low intensity combined) affect at the Conclusions phase. The group was writing the interpretation of the results and searching for information about the effects of pH on copepods and changes in the food chain from the internet:

> Ella: "It depends on the species"…"We cannot know what species there should be"
> Sara [whispers]: "Nauplius … here!" smiling, surprised, and delighted: "The larva of the crustacean," smiling and looking at Ella, then laughing with her
> Ella: [with a higher voice] "Yes, wonderful!" looking satisfied
> Ella: "And now when it translated it in Finnish it was just right," laughing

Students in group $High_6$ demonstrated high levels of concentration and a determination to complete the task. They focused mainly on the task, and when off-task behavior occurred, it ended quickly, and the group returned to the task. Robin was absent twice during the working periods, and assessed his affect only once, but he was present twice in the selected segments for observations because the group proceeded quickly to the Experimentation phase in the first working period. Robin's attention was often focused on the technical details connected to experimentation in the virtual laboratory, but despite some skeptical questioning, he managed to keep his tone humorous and thus positive, as the following example at experimentation phase of positive low intensity affect demonstrates. The teacher was helping the group to build the experimental design of the study, the number of water bottles, selecting the pH, selecting the time for egg development, and calculating the number of eggs:

> Robin: "The number of bottles . . . what's the point of that?" smiling and amused
> Ella and Sara are looking at Robin and smiling
> Sara: "Shall we put here the number of the bottles too?"
> Ella and Robin are still smiling
> Robin: "Why does it matter how many bottles there are?" smiling
> Sara: "I don't know," shaking her head and laughing

In respect to Robin's lack of self-reported data, and based on the finding of relatively equally distributed positive affect within this group, it is reasonable to assume that his absence had minimal impact on the group outcome and the overall affect within the group. From the very beginning of the collaboration, individual participation appeared equal, and the group atmosphere was very open and positive, thus inviting anyone to join the conversation. Interactions were mainly polite and respectful, without any rude or disrespectful comments to other group members. The few negative comments were mainly directed at the task, the content or technical issues concerning the learning environment, which means that the positive tone of the verbal interaction was maintained, as seen in the following example of low negative intensity affect at the experimentation phase. The students had problems to understand what to do with the experimental design, and then the teacher arrived:

> Sara: "Umm, difficult to find this kind of pH value. . ."
> Robin: "It is something like six and a half," frowning
> Then, everyone is smiling

Group Average$_4$ (Hanna, Heidi, Laura): In contrast to group High$_6$, the group Average$_4$ appeared to lack interest and motivation for the task and achieving good performance, even though they displayed continued concentration throughout the activity. In support of this claim was the substantially high proportion of negative affect reported by each student in the Planning and Experimentation phases: Heidi, 43 and 33%; Laura, 57 and 20%; Hanna, 60 and 67% (see **Figure 5**). Markedly, the important negativity emerging from these self-reports disappeared in the Conclusions phase, since all students reported dominantly positive affect and no negative affect. Comparing students' self-reports of affect with the researchers' observed affect revealed a more complex and diverse picture of affect within this group. Contrary to students' self-reports, the observed affect showed evidence of the dominance of positive affect for all students across the three phases. Specifically, as

TABLE 5 | Distribution of observed affect in distinct outcome groups across the three phases.

Group	Valence	Arousal	Planning: *Number of turns*	Planning: *% of turns for group*	Experimentation: *Number of turns*	Experimentation: *% of turns for group*	Conclusions: *Number of turns*	Conclusions: *% of turns for group*
High$_6$	Positive	High	14	19	15	15	19	21
		Low	45	60	74	74	56	61
		Low	16	21	11	11	16	18
	Negative	High	0	0	0	0	0	0
High$_5$	Positive	High	6	12	7	13	18	20
		Low	34	68	22	40	51	59
		Low	10	20	23	42	17	19
	Negative	High	0	0	3	5	2	2
Average$_4$	Positive	High	3	5	7	14	10	23
		Low	41	75	24	49	20	45
		Low	11	20	18	37	14	32
	Negative	High	0	0	0	0	0	0
Average$_3$	Positive	High	49	25	0	0	15	13
		Low	135	70	3	25	61	53
		Low	10	5	9	75	39	34
	Negative	High	0	0	0	0	1	1
Low$_2$	Positive	High	35	20	10	14	44	26
		Low	121	71	45	65	104	61
		Low	15	9	11	17	22	13
	Negative	High	0	0	3	4	0	0
Low$_1$	Positive	High	6	8	13	20	3	5
		Low	46	60	30	45	28	47
		Low	25	32	21	32	25	41
	Negative	High	0	0	2	3	4	7

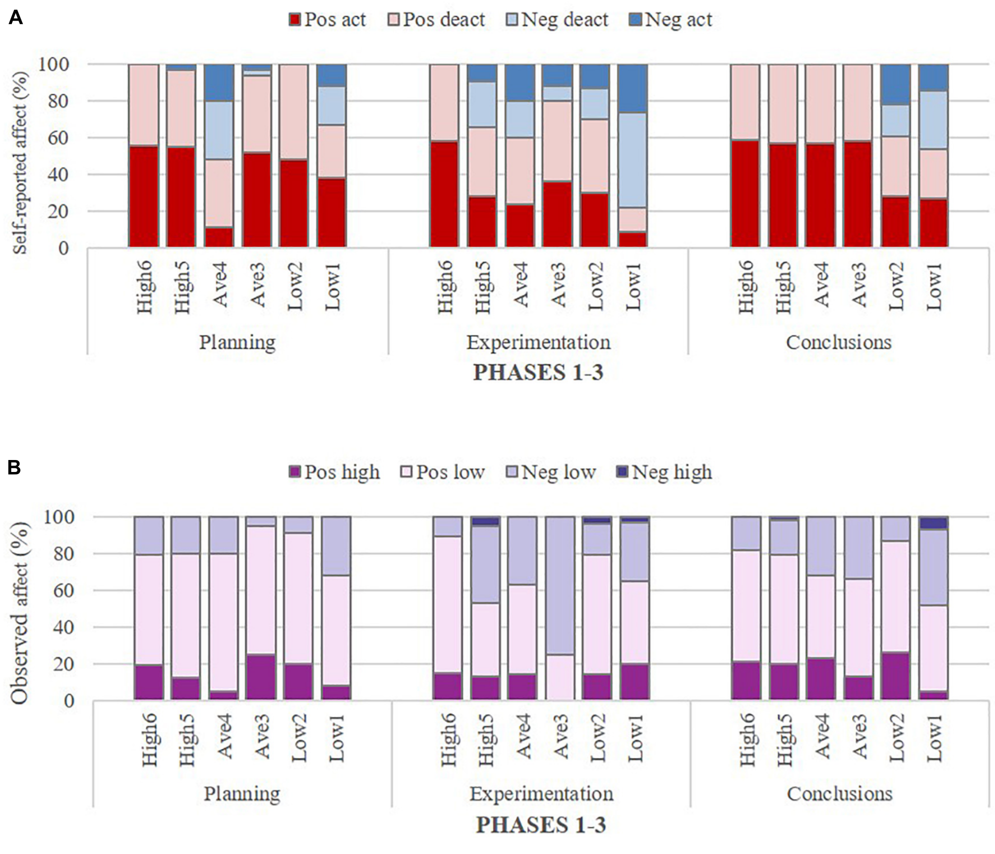

FIGURE 3 | Self-reported **(A)** and observed **(B)** affect across three phases in six distinct outcome groups.

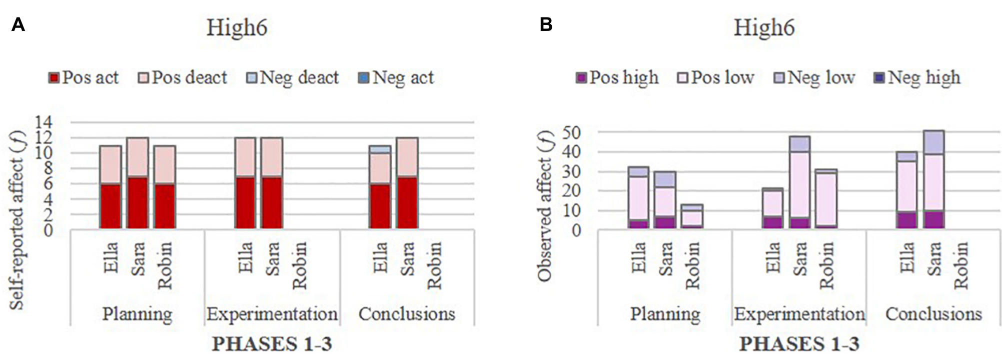

FIGURE 4 | Self-reported affect **(A)** and observed **(B)** affect in the group High$_6$.

illustrated in **Figure 5**, for Heidi, positive affect (low intensity) varied between 89 and 100% (M = 93%), for Laura between 50 and 72% (M = 60%) and for Hanna between 56 and 89% (M = 68%). There were only a few exceptions where negative affect was dominant for Laura, such as self-report at the Planning phase and observations in the Experimentation phase, and for Hanna, self-report at the Planning and Experimentation phases. One possible explanation may be that the task was perceived as not interesting or challenging enough. The following excerpt illustrates the visibility of the negative tone in the comments related to the positive (high and low intensity combined) affect in the group's verbal interaction at the conclusions phase, when the students were discussing and writing the interpretation of the results, and making the presentation:

> Laura: "Yes, yes . . . what should I put here now?" smiling and laughing
> Hanna: "A wild guess," laughing with Heidi
> Laura: "It stays there, closely," laughing, "Well. . . hmm," smiling

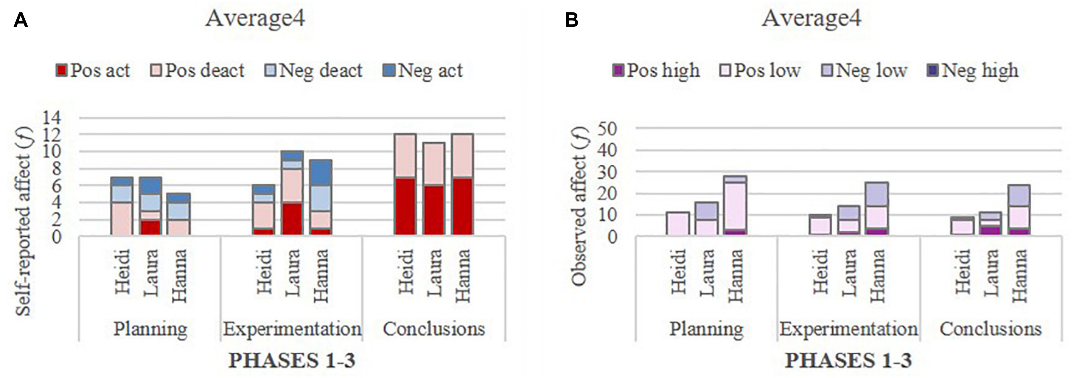

FIGURE 5 | Self-reported **(A)** and observed **(B)** affect in the group Average$_4$.

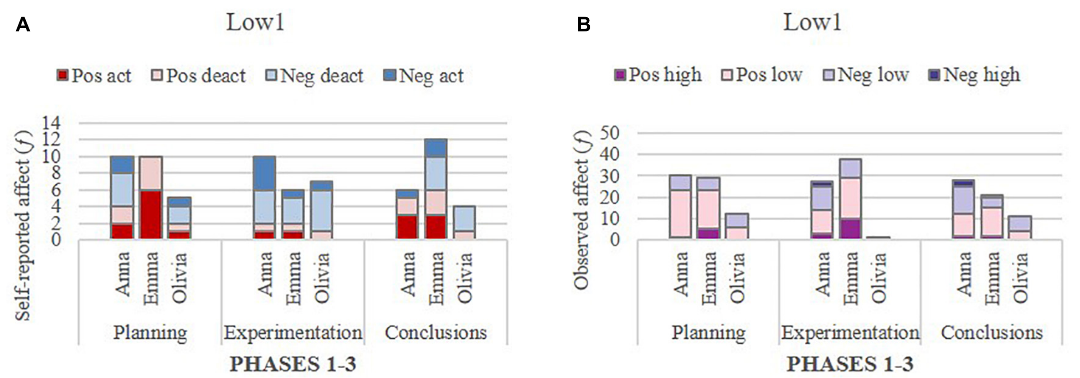

FIGURE 6 | Self-reported **(A)** and observed **(B)** affect in the group Low$_1$.

> Hanna: "I don't know, figure out something better," smiling
> Laura: "I think that was good," laughing
> All three are laughing

The negative tone was visible in the comments related to the positive (high and low intensity combined) affect in the group's verbal interaction at the experimentation phase as well, while the students were discussing how to start the experiment and proceed:

> Heidi: "Do we study everything now?" smiling
> Hanna: "Everything," laughing
> Heidi [continues]: "Like eggs, hatching . . . Do we study everything?" smiling
> Laura: "Umm," smiling

In respect to negative affect, and contrast to students' self-reports for the Planning and Experimentation phases, there was no observable high intensity negative affect. The self-reports highlighted mainly tiredness and frustration, but also insecurity (Heidi and Laura) as well as anger and annoyance (Hanna). Despite some negative tone of affect in the observations, participation in the group appeared equal, the students were friendly and kind to each other, and humor and joking was mainly directed at the task or the technology but not at other students in the group. The following excerpt at the Conclusions phase is a conversation where the students were commenting on the task (low negative intensity affect), illustrating how low motivation and attitude may have contributed to the average performance of this group when the students were writing the interpretation of the results and making the presentation:

> Laura is sighing [loudly]
> Hanna: "I don't get why we have to write these here," looking tired and bored, leaning into her hand, sighing
> Heidi: "Yeah"
> Hanna is sighing [loudly]

Group Low$_1$ (Anna, Emma, Olivia). In contrast to groups High$_6$ and Average$_4$, where self-reported and observed affect were not entirely consistent, group Low$_1$ reported a dominance of negative affect (high and low intensity combined) across all three phases, and the same finding was obtained in the analyses of their interactions. Positive affect was therefore limited within this group; specifically, Anna reported 20–83% (M = 48%) positive affect (high and low intensity combined), Emma 33–100% (M = 61%) (high and low intensity combined), and Olivia 14–40% (M = 26%) (low intensity). In respect to the observations, a more positive picture of affect emerged compared to self-report. For example, the observations of Anna revealed 43–77% (M = 57%) positive affect (high and low intensity combined), of Emma 71–80% (M = 76%) positive affect (high and low intensity combined), and of Olivia 36–100% (M = 62%) positive affect (low intensity). Based on the video observations, negative communication within the group was visible, as illustrated in **Figure 6**. As can be seen, Olivia displayed the lowest proportion of positive affect in this group, but she also had the smallest number of turns, since during the selected episodes representing meaningful and continuous verbal interaction (see Section Materials and Methods), she did not participate much in the verbal interactions and often sat quietly, looking at the screen.

In comparison to groups $High_6$ and $Average_4$, where all group members participated relatively equally, in group Low_1 it was Anna, the weakest student (based on a rather weak grade in the science course) who led the group; thus, members' participation was not equal. It was evident that Anna and Emma were ignoring Olivia, possibly because she was, voluntarily or not, quiet most of the time in the segments selected for observation. Moreover, although students in this group concentrated on the task, they did not seem to understand what had to be done. Overall, students in this group appeared to be passive, confused, and worried. Confusion and helplessness were visible even when the conversation displayed positive (high and low intensity combined) affect, as shown in the following excerpt at the planning phase when the group was searching information about the Nauplii from the internet:

> Anna: "What is this?" looking at the screen
> Emma: "I don't know, click there so we can get away from here," laughing
> Anna and Olivia are smiling
> Anna: "Let's do so," smiling
> Emma: "So you did click then," laughing [widely] and looking at Anna
> Anna: "Yeah," smiling

Initially, the group appeared to work on the task from a positive position but as the phases evolved, affect changed from positive to a more negative tone. At the end of the first phase, their self-reports displayed interest and calmness, but only calmness was sustained in the next two phases. The observed affect was more directed at themselves than at the task or the technology like the other groups, and they did not appear to know where they should be heading. Details and irrelevant matters captured their attention, and they often lost a sense of direction. Finally, nobody in the group appeared interested in completing the task, as illustrated in the positive low intensity affect example at the conclusions phase, when the group was making their presentation and accidentally clicking a new tab:

> Anna: "Here is a dictionary," looking surprised
> Emma: "What the damn is this? You don't say...," smiling

Furthermore, the negative affect increased over time within this group as students appeared to realize the inevitable failure of their assignment. They reported a wide array of negative affective states, such as tiredness, boredom, frustration, disinterest, disappointment, and insecurity. One noticeable observation in this group compared to the other groups is that two students, Emma and Olivia, reported feeling ashamed in the Conclusions phase, as they realized that they failed the task. As the weakest student, Anna did not report being ashamed, but one may speculate that she was perhaps used to failing and thus accepted the poor group outcome at the end. Eventually, this group asked for help from the teacher because they were not able to proceed with the task any more. However, they did not understand the teacher's instruction and failed to complete the task, as reflected in the negative affect (high and low intensity combined) example presented below at the experimentation phase, while examining the questions concerning the design of the study:

> Anna: "What the heck ... we have done these slowly," turning around and looking at the other groups
> Emma: "You don't say," smiling and waving her hands

The negative affect (high and low intensity combined) was present in the group discussion concerning the main variables in the study as well as the rules of scientific reasoning at the experimentation phase:

> Anna: "I don't understand this at all," shaking her head, looking worried
> Emma is smiling and mumbling something [uncodable]
> Anna [leaning forward on the table]: "I don't understand," looking desperate
> Emma: "I don't understand either," laughing

DISCUSSION

Similarities and Differences in Affect Within Groups at Three Phases of Their Collaborative Learning Activity

Examining affect in collaborating groups in three working sessions showed how positive affect was prevalent across all three learning phases, as evidenced by both methods, self-reports, and observations (RQ1). Positive affect was dominant even though the students worked with a challenging science task in an unfamiliar, web-based VLE. This pattern of finding was obtained using two distinct methods of data collection and analysis, self-reports, and video observations. This finding is in line with other studies that reported the dominance of positive emotions in students' experiences and perceptions of science learning, corroborated by self-reports, video observations, and interviews (Linnenbrink and Pintrich, 2004; Tomas et al., 2016).

In addition, the patterns of self-reported affect in the Experimentation phase were found to differ from the other phases by showing a relatively high proportion of negative affect. This pattern may indicate a more stressful and demanding phase in students' process of science learning. In this particular activity, handling the experimentation was quite different from the simple, hands-on laboratory tasks students had performed earlier in their studies. An opposite pattern was noticed in the last phase, Conclusions, where self-reports displayed overriding positive affect but observed affect not to this extent. This outcome is consistent with the study by King et al. (2017), as they found that in respect of the challenges when students were able to work with the science content, they displayed positive emotions. It is also plausible to assume that in this instance, the selection of the analyzed video segments may have played a role. The observations were made when students were in the process of completing the initial work on the content of the presentation (outcome), whereas self-reports elicited students' affect experienced throughout the whole session (preparing, writing, and presenting). Thus, it is possible that self-reports of positive affect at the Conclusions stage captured students' relief that they had completed this challenging collaborative group assignment.

Relationship Between Affect in the Groups and the Group Outcome

The relationship between affect within groups and group outcome proved to be more complicated than indicated by earlier literature emphasizing the impact of positive affect on science activities (e.g., Laukenmann et al., 2003) and achievement (Ahmed et al., 2013; Liu et al., 2014). This expected effect of positive vs. negative affect on performance was only evident in extreme groups, with the highest performing group showing consistent and dominant positive affect and the lowest performing group, to a noticeable degree, negative affect. The finding concerning these extreme groups is consistent with Linnenbrink-Garcia et al.'s (2011) study, which found that positive group interactions were associated with positive affect and negative affect resulted in disengagement and social loafing. Overall, however, the outcomes resonated with the multimethod study in mathematics in which the students of distinct outcome groups (high, moderate, low) experienced both positive and negative emotions, regardless of the difficulty level of tasks (Ahmed et al., 2013).

Furthermore, findings from the groups other than the extreme groups of the present study revealed that the proportion of affect was not systematically related to the groups' performance. Positive affect probably did not always stem from engagement with the task and scientific content, but also from students' social interactions with their peers or superficial features of the technology (see also, Wosnitza and Volet, 2005). This finding leads to a tentative conclusion that experiencing positive or negative affect may not always be directly related to performance or learning quality (process or product); this outcome has been reported in previous studies (Tomas et al., 2016; see also, Fredrickson, 1998). For example, Tomas et al. (2016) found that fun-related emotions are not conducive to productive learning because they interfered. Although Pietarinen et al. (2019) showed that joviality, indicating, e.g., joy, interest, and enthusiasm, positively related to the level of group outcome and mediated by aiming for scientific understanding, their findings highlighted strongly the role of more clearly task-oriented affect, namely self-assurance, which is composed of confidence and pride. In future research, the source of fun-related or joy-related emotions and their relationship to the quality of learning should be investigated.

Degree of Within-Group Consistency in Individual Affect (Valence, Intensity) Across Phases

Although the degree of participation of individual group members varied, their affect echoed rather well with each other. Three groups of interest (two extreme groups and one average group with an evolving affect pattern) were brought under great scrutiny to deepen our understanding of how individual group members play a role in collaborative work. In the highest performing group, all students reported only positive and displayed positive and very little (low intensity) affect. Sustained positive tone in this group signposted the importance of shared affect and therefore can be interpreted in terms of the mutual provision of socio-emotional support (Näykki et al., 2017; see also, Pietarinen et al., 2019). In the lowest performing group, although all students experienced and displayed both positive and negative affect, the degree of negative affect was notable. The discourse illustrations from this group indicate that the students struggled with the task demands; one strong indication of their struggle was their expressed feelings of shame and their inability to benefit from teacher support. Their observed affect, though, indicated a more positive tone, and it is possible that it was their social interactions, not the challenging and possibly frustrating task, that triggered their positive emotional behavior, whereas their reported mood after the whole session was more negatively clouded. This interpretation would be consistent with earlier outcomes showing that if students are appropriately challenged according to their skills, they will more likely feel positive (Schneider et al., 2016), whereas unresolved obstacles may ultimately lead to boredom and disengagement (D'Mello and Graesser, 2012).

Interestingly, all individual students in the average performing group that were examined closely showed some movement, from stating varying degrees of negative affect in the first two sessions to reporting overriding positive affect in the last one. Although a hint of negativity was evident in the researchers' observations of their last session, their self-reported affect at the end was very positive for all of them. Illustrations from their discourse indicate frustration and boredom with the task, but not with their social interactions as such. One can only speculate that their positive experiences at the end captured a feeling of relief after ending the task or their satisfaction that they were eventually able to complete the task. The patterns of affect displayed within this group throughout a challenging collaborative activity raise the complex issue of the relationship between affect, engagement, and learning. Since these types of more or less average performing groups are the most typical in educational settings, future research should go beyond comparisons of extreme performing groups and try to unveil the affective processes and their effect on learning of the most typical, often very diverse, groups.

CONCLUSION

This study analyzed the affective tone of interactions at both group and individual level (see, Polo et al., 2016) by comparing and integrating self-reports and observation as emphasized by Meyer and Turner (2006). Further, following Linnenbrink-Garcia et al. (2011), positive and negative affect, i.e., valence, as well as the intensity of affect in terms of high and low were assessed and analyzed from both individuals' separate and group-level aggregated affects.

Overall, the two methods resulted in highly corroborated outcomes, but the intensity of affect appeared stronger in self-reports than in observations. This result seems to concur with the premise of invisible emotions stated in the research questions. As the students in this study were not young children, the social expectations for adult-like, task-oriented behaviors are presumably influencing their interaction in formal learning contexts. In particular, the influence of age is supported in the observed data showing that neutral, non-affective interaction and behavior was prevailing. It further needs to be kept in mind that the observations focused on visible affective behavior *in situ* in the restricted context of meaningful task-related episodes, whereas self-reports covered the whole session retrospectively and could be based on more salient or recent feelings and memories. From this viewpoint, the matching outcomes concerning the valence of affect strengthen the reliability and consistency of outcomes. Thus, self-reports and observations in this study show that they can be used as measures of students' affect in learning situations, either separately or in combination. Both measures showed similar results underlining the dominance of positive affect in all phases regardless of the measurement point or instrument. Also, in combination, these measures can supplement the scope of the analyses by presenting a more comprehensive understanding of the phenomenon under study.

Finally, caution with generalizations is warranted, since the focus of this study was in high school students and particularly in six groups of science education students, which limits the generalizability of the results. However, despite this limitation, the outcomes of this study at the group and individual level also raise challenges for future studies by pointing out the complex dynamics of affect, task engagement, and achievement in average groups. Prior research has strongly focused on extreme groups, which also in this study showed the least complicated associations between these factors.

Since learning, whether in traditional or novel (e.g., virtual) environments, is rarely solely student-led at school contexts, the role of the teacher, as a resource for scientific inquiry in providing not only cognitive but importantly also affective support, should be investigated (see also, Vauras et al., 2019). Although this was outside the scope of the present study, the discourse examples revealed that stronger teacher support would have been needed, particularly in facing task challenges and in the case of struggling groups where students probably lack confidence in science (see also, Volet et al., 2019).

DATA AVAILABILITY STATEMENT

The datasets for this manuscript are not publicly available because the participants are identifiable in the video data. Requests to access the datasets should be directed to MV, Vauras@utu.fi.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by The Ethics Committee of the University of Turku. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin. Written informed consent was obtained from the individual(s), and minor(s)' legal guardian/next of kin, for the publication of any potentially identifiable images or data included in this article.

AUTHOR CONTRIBUTIONS

TP was responsible for data acquisition and analysis, and drafted the preliminary version of the manuscript. MV, SV, and EL contributed to the writing. All the authors were involved in editing of the manuscript and approved the final manuscript.

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Sensor Measures of Affective Leaning

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The aim of this study was to predict self-report data for self-regulated learning with sensor data. In a longitudinal study multichannel data were collected: self-report data with questionnaires and embedded experience samples as well as sensor data like electrodermal activity (EDA) and electroencephalography (EEG). 100 students from a private university in Germany performed a learning experiment followed by final measures of intrinsic motivation, self-efficacy and gained knowledge. During the learning experiment psychophysiological data like EEG were combined with embedded experience sampling measuring motivational states like affect and interest every 270 s. Results of machine learning models show that consumer grade wearables for EEG and EDA failed to predict embedded experience sampling. EDA failed to predict outcome measures as well. This gap can be explained by some major technical difficulties, especially by lower quality of the electrodes. Nevertheless, an average activation of all EEG bands at T7 (left-hemispheric, lateral) can predict lower intrinsic motivation as outcome measure. This is in line with the personality system interactions (PSI) theory of Julius Kuhl. With more advanced sensor measures it might be possible to track affective learning in an unobtrusive way and support micro-adaptation in a digital learning environment.

Keywords: sensor measures, process measures, affect, emotion, motivation, EEG, affective learning, self-regulated learning

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INTRODUCTION

That emotion and motivation play a crucial role for all kinds of learning processes is proven in various empirical works, for example the impact of positive emotions (Estrada et al., 1994; Ashby et al., 1999; Isen, 2000; Konradt et al., 2003; Efklides and Petkaki, 2005; Bye et al., 2007; Nadler et al., 2010; Huang, 2011; Um et al., 2012; Plass et al., 2014; Pekrun, 2016). And it is quite difficult to compare the various results because they are built on different theories and different measures. Of course measures, underlying theories and even analytical methods are intertwined with each other forming typical research paradigms. A very prominent research paradigm is self-regulated learning (Pintrich and De Groot, 1990; Zimmerman, 1990; Winne and Hadwin, 1998).

Self-regulated learning emphasizes cognitive and metacognitive processes (e.g., Winne and Hadwin, 1998; Winne, 2018). Even if affective and motivational processes are explicitly mentioned they are reduced to a helping function for the primary cognitive and metacognitive processes (Wolters, 2003; Schwinger et al., 2012). This might be caused by the dominant view of the teacher on learning processes (teaching-learning short circuit – see Holzkamp, 1993; see also Holzkamp, 2015). Moreover, most data gathering techniques are not able to cover affective processes fully because they rely mostly on verbal (self-report) data (see also Veenman, 2011).

Because of the holistic nature of emotional processes (Kuhl, 2000a) a verbal report is a simplified representation of emotions.

To lay out a brief theoretical foundation for the process measures used in this study, three major aspects of learning are emphasized here:

1. Learning is always a process over time.

2. Learning is always an internalization process with various degrees. The learning subjects transform themselves for future interaction with the (learning) environment.

3. Affect, emotions, and motivations play a crucial role for learning as an internalization process over time. A higher degree of internalization leads to a number of positive effects: e.g., less perceived effort, higher achievement, more effective use of learning time (Metzger et al., 2012).

Internalization processes go along with positive affect as well as with the dampening of negative affect. Positive affect fosters intuitive learning processes that can be sustained over a long time without any effort (Csikszentmihalyi, 1990). Dampened negative affect supports connecting the inner self as well as self-schemata with the learning topic (as provided by specific learning environments including digital environments) (Kuhl, 2000a,b).

Negative affect as well as the dampening of positive affect stop or at least pause internalization processes of learning. Negative affect usually goes along with analyzing incongruent features of the learning topic that might be threatening (Kuhl, 2000b). Dampening of positive affect freezes the ongoing learning activity and initiates a shift toward more reflective processes of learning like thinking and problem solving (Kuhl, 2000b). So, according to the personality system interactions (PSI) theory (Kuhl, 2000a; Kuhl et al., 2015) it can be assumed that positive and negative affect as well as the dampening of these two are associated with specific processes of self-regulated learning. A sustained negative affect should hinder processes of internalization that could result in processes of intrinsic motivation. Derived from magnetic resonance imaging (MRI) studies negative affect is associated with activities of the left amygdala (Schneider et al., 1995, 1997; Sanchez et al., 2015) and may also result in a higher parietal left-hemispheric activation. There is also some evidence that negative mood is associated with frontal left hemispheric electroencephalographic activity (for an overview see Palmiero and Piccardi, 2017), but empirical results are built on induced emotions and not directly comparable to this study.

Internalization processes initiate processes of deep learning. Especially, resulting knowledge is associated with self-schemata (important aspects of the inner self). The interconnectedness with important aspects of the inner self helps to prevent knowledge from becoming inert (see Renkl et al., 1996). By charging the gained knowledge with personal affect and emotions the recall in various future situations will be much easier. By increasing the chance for recall this will also foster long term memorization, also because every recall in itself is a new association.

Associated with these deep learning processes is the development of a stable interest (e.g., Krapp, 2005). First, often weak associations between learning topics and the inner self could be described as new situated interested (Bernacki and Walkington, 2018). And in the long run as the associations with the inner self become stronger this might lead to stable interest and in the end to an enduring individual interest (see also Hidi and Renninger, 2006).

So far, affective and motivational states within the learning process have been dominantly conceptualized on a meso level time frame, like the postulated impact of positive affect on internalization. Investigations on a micro level time frame like Bosch and D'Mello (2017) will be much more common in the future. Besides methodological challenges how to combine and triangulate data sources from different time levels (see Järvelä et al., 2019), theoretical problems arise. Especially, micro level theories like the cognitive disequilibrium model (D'Mello and Graesser, 2010) has to be interconnected and integrated into higher level models of self-regulated learning (e.g., Winne and Hadwin, 1998, 2008). It can be assumed that the positive effects of affective learning, especially the internalization process cannot be fully supported by digital learning environments. In person-to-person learning situations the teaching person can react to the emotions of the learning person and adapt the learning process accordingly to personal needs. Typically, a person has two main ways for providing affective learning support:

(1) Emotional support, e.g., by soothing someone.

(2) Adaptation of the learning situation, e.g., by providing individualized feedback.

So far, direct emotional social support must be provided by a human being. So we will explore how a digital learning environment can be adapted to individual needs that change during the learning process. Micro-Adaptation (for an overview see Park and Lee, 2003) is working on the premise that interactions between learner and learning environment lead to adaptation. The learner provides a "signal" and the learning environment reacts with a specific adaptation. Whereas the actions of teachers might be intuitive and to some degree undefined, the algorithms of a learning environments must be exactly defined. At first, motivational or emotional states must be measured and identified subsequently. Secondly, adaptive reactions to these identified states must be defined.

For the purpose of micro adaptation in a learning environment it is important to gather information during the learning process (Panadero et al., 2016). A simple way for doing so is embedded experience sampling (Larson and Csikszentmihalyi, 1983; Csikszentmihalyi and Larson, 1987; Hektner et al., 2007). Embedded Experience sampling is usually based on short questionnaires that will be presented in defined time intervals or event related. Clearly, embedded experience sampling is able to track the process character of learning. But two pitfalls will remain: these are still self-reports who will only reflect emotional and motivational states that can be verbally expressed. In this way, rather unconscious processes cannot be reported (at least for a part of people who cannot access their feelings easily). In sum, embedded experience sampling can only convey the verbally expressed motivations and emotions which reflect cognitive thoughts rather than pure motivations or emotions. The second pitfall is that embedded experience sampling as a specific form of self-report will always disturb the learning process. Therefore, additional measures are required that can unobtrusively measure processes of affective learning.

RESEARCH QUESTIONS

So, in this study we want to measure processes of affective learning unobtrusively with physiological data. Two types of data will be used for prediction: electrodermal activity (EDA) and electroencephalography (EEG). Two types of predicted data will be reported: online or process measures (experience sampling) and outcome measures for self-regulated learning.

MATERIALS AND METHODS

Participants

Subjects participated in an 1-h long learning experiment. Learning material was taken from a course in a higher semester. Individuals who had already attended these courses were excluded from participating in the study.

Data were gathered in two cohorts (see **Table 1**). The first cohort consisted of 65 students of Psychology and was tested between October 2016 and February 2017. One subject pulled out of the study due to self-reported headache caused by the EEG headset, reducing the number of participants in the first cohort to 64 (n = 14 male). Subjects in the first cohort were between 19 and 38 years of age (M = 22.59, SD = 3.23). The second cohort consisted of 36 students of Psychology (n = 13 male). Here, data were collected in February and March of 2018 and age ranged between 18 and 32 (M = 22.14, SD = 3.66). The experiment was identical in both cohorts. Cohorts only differed in the wearable devices employed for data collection. In the first cohort, 31 subjects used the Emotiv Insight EEG headset, and 32 the InterAxon Muse EEG headset. Data of the Muse headset had to be discarded due to technical problems with data collection. Data were collected on smartphones (companion devices) with the use of Apps programmed specifically for the experiment. Technical problems with the Muse headset were only observed using a third generation Motorola Moto G running Android 6.0.1. There were no issues when using an alternative device (LG Nexus 5× running Android 6.0.1), nor with the Emotiv Insight and any companion device. The second cohort was scheduled to compensate for the lost data. In the second cohort only the Emotiv Insight headset was used. 24 complete EEG datasets exist for the first cohort, and 30 for the second. In addition to the headsets, the wrist-worn wearable device AngelSensor was used in the first cohort. It was worn by the subjects on the dominant hand (i.e., right hand for right-handed individuals). Data were discarded due to problems with handling the device. In both cohorts, subjects wore the Microsoft Band 2 (MSB2) on their non-dominant hand (i.e., left hand for right-handed individuals). 47 complete MSB2 datasets exist for the first cohort, and 26 for the second. Complete datasets for both EEG and MSB2 exist for 21 subjects in the first cohort, and 22 in the second.

TABLE 1 | Sample sizes.

	n	EEG (Emotiv Insight)	EDA (MSB2)	EEG ∩ EDA
Cohort I	64	24	47	21
Cohort II	36	30	26	22
Σ	100	54	73	43

Procedure

The experiment took place in a soundproof experimental booth. Before the learning experiment, subjects were asked to put on the wearables themselves. Good fit was ensured by the test supervisor. They were then given the experimental instruction. After the first set of questionnaires, the subjects were shown a demo item of the parsimonious questionnaire to familiarize them with the scales. The subjects were then handed the learning material and the learning session started. During these 60 min of learning, participants were interrupted every 4.5 min with a vibration alarm, and asked to fill out the parsimonious questionnaire concerning their motivational state on a smartphone. Sensor data from the wearable devices were collected throughout the learning session. The learning session was terminated after 60 min and the subjects filled out the second set of questionnaires including the Multiple-Choice-Test. Retrospective questionnaires were presented before the Multiple Choice-Test.

Learning Material

Participants were given study material from a higher semester of educational psychology. The material consisted of a nine-page excerpt about intrinsic and extrinsic motivation from a German textbook on pedagogical psychology (Schiefele and Köller, 1998), as well as two case studies. Each case study describes a university student with motivational struggles. Subjects were asked to explain the problems using the theory provided in the textbook excerpt, and to make recommendations regarding possible courses of action.

Process Measures (Experience Sampling)

To assess subjects' affective states during the learning task, a parsimonious questionnaire was devised and implemented (see **Figure 1**). It was presented on a smartphone, and subjects used their fingers as input on the touchscreen to complete it. Subjects were alerted to fill out the questionnaire every 270 s (4.5 min) via a vibration alarm lasting 1 s, for a total of 13 experience samples. To our knowledge, no recommendations exist for determining the frequency of such a high-frequency experience sampling. The 270 s were therefore determined in informal pre-tests to be the minimum amount of time before the experience sampling was perceived as annoying and intrusive. The instruction asked participants to state how they were feeling prior to being interrupted by the vibration alarm. Answers had to be given within 60 s to be processed as valid data The questionnaire was designed to be completed in as little time as possible. Responding time averaged 16.36 s (SD = 7.36, Median = 14.64), meaning participants spent about 4 min of the 60-min learning session answering the questionnaire (6%).

The questionnaire consists of five bipolar sliding scales (sliders) ranging between two endpoints marked with affective words (end items). Sliding scales differ from rating scales (e.g., Likert scales) in that subjects are free to choose any

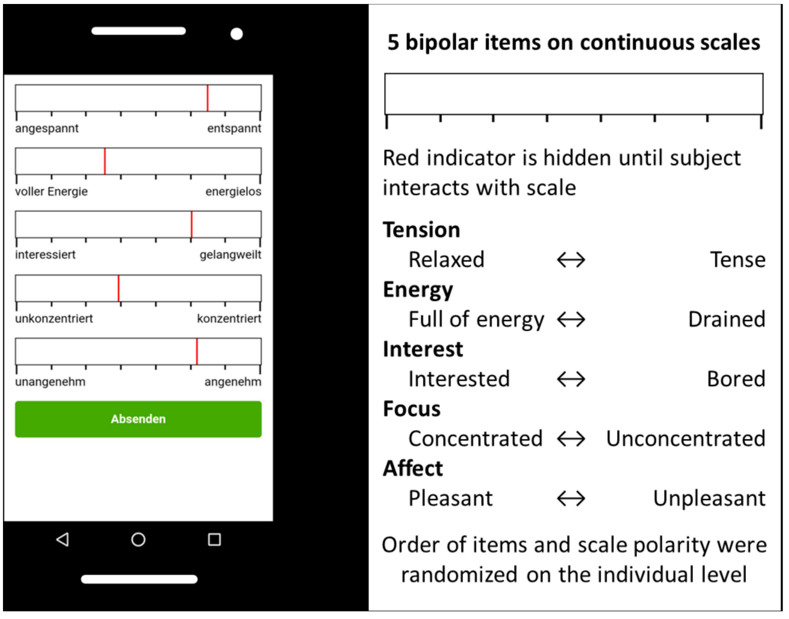

FIGURE 1 | Experience sampling with a parsimonious questionnaire.

value between the arbitrarily set end values of −4000 to +4000. The scales are marked with eight tick marks to provide orientation to the subjects, visually mimicking an eight-point Likert scale. Sliders have been shown to yield comparable results to ordinary categorical response formats in online surveys (Roster et al., 2015). The five bipolar sliding scales used are interest, energy, valence, focus, and tension. They range between the end items bored – interested [gelangweilt – interessiert] (interest), without energy – full of energy [energielos – voller Energie] (energy), unpleasant – pleasant [unangenehm – angenehm] (valence), focused – not focused [unkonzentriert – konzentriert] (concentration), and relaxed – tense [entspannt – angespannt] (tension). Similar or identical items have been used in the past to assess affective states in other longitudinal designs (Triemer and Rau, 2001; Wilhelm and Schoebi, 2007). Items were chosen to ensure a short response time (resulting in 16 s response time in average). Intervals between measurements are typically measured in hours, while in our current study we used a much higher measurement frequency of only minutes (high-frequency experience sampling). Order and polarity of the scales were fully randomized, but kept consistent for each subject. On each experience sample, the indicators on the sliders were hidden until subjects first interacted with the scale. Subjects were therefore not able to see which point on the continuum they had previously selected.

Outcome Measures

Prior to the learning session, subjects gave their demographic data. At the end of the learning session, learning outcome was measured with a multiple choice test, and subjects gave retrospective self-reports regarding their motivational and affective states across the whole learning session. Subjects filled out part I and II of Dundee Stress State Questionnaire (DSSQ Matthews et al., 1999). Part I is the Mood and Affect portion and is equivalent to the UWIST Mood Adjective Checklist (Matthews et al., 1990). It consists of 29 affective adjectives on the four subscales Energetic Arousal, Tense Arousal, Hedonic Tone, and Anger/Frustration. Subjects are asked to state to which degree they felt the given affective state over the course of the learning session. Part II of the DSSQ concerns motivation and consists of the Intrinsic Motivation and Workload subscales, the latter of which is the NASA-TLX questionnaire in modified form (Hart and Staveland, 1988). In addition, we presented a more finely grained measure of retrospective regulation derived from Self-Determination Theory (Ryan and Decy, 2000). It distinguishes between Amotivation, External Motivation, Introjected Motivation, Identified Motivation, Intrinsic Motivation, and Interest (Prenzel and Drechsel, 1996). Additional questionnaires that measure the Integrated Model of Learning and Action (Martens, 2012) will not be reported in this article.

Electrodermal Activity

Microsoft Band 2 (MSB2) was used to collect Skin Resistance measurements at the wrist of the subjects' off-hand. Galvanic Skin Resistance (GSR) is the inverse of Skin Conductance and a measure of EDA. The MSB2 samples GSR at 5 Hz. Electrode contact was ensured by tightening the strap of the MSB2 around the subjects' wrists. No gel was used.

Electroencephalography

Wireless, wearable Headsets were used to collect EEG measures. Approximately half of the first cohort tested

FIGURE 2 | The asymmetric Emotiv Insight Headset. Reproduced with permission.

donned the Emotiv Insight (see **Figure 2**) and the other half the InterAxon Muse EEG Headsets. Data of the Muse Headset had to be discarded due to problems with data collection. We opted to test a second cohort using the Emotiv Insight to systematically increase the sample size.

The Emotiv Insight uses five dry electrodes to measure EEG on the scalp. The electrode positions are roughly equivalent to the standardized electrode positions AF3, AF4, T7, T8, and Pz according to the modified combinatorial nomenclature (MCN). The Emotiv Insight is an asymmetrical headset with the electronics, battery, and reference electrodes on the left side of the device. It is fixated over and behind the left ear, where the T7 electrode and two reference electrodes make firm contact with the head. The Emotiv Insight uses two common mode sense (CMS)/driven right leg (DRL) reference electrodes on left mastoid process. The remaining electrodes are attached to non-adjustable plastic arms that wrap around the skull. The headset sits tight on the head, although positions of the remaining four electrodes vary somewhat from subject to subject.

The Emotiv Insight does not expose the raw EEG data stream out-of-the-box, although licensing options exist. By default, the Emotiv Insight returns precomputed power values for the theta (4–8 Hz), alpha (8–12 Hz), lower beta (12–16 Hz), upper beta (16–25 Hz), and gamma (25–45 Hz) bands for each of the five electrode positions. According to the FAQ[1], the Insight samples at 2048 Hz, which is then downsampled to 128 Hz. Documentation about probable additional filtering is non-existent. Band power data are computed via Fast-Fourier-Transformation and returned at 8 Hz, employing a 2 s Hanning window with a step size of 125 samples.

[1]https://www.emotiv.com/knowledge-base/what-is-the-sampling-rate-for-the-emotiv-insight-and-why-has-it-been-designed-this-way/

Data Analysis

Complete datasets for EEG and EDA combined existed for 45 subjects, we therefore opted to attempt prediction using EDA and EEG data separately. This maximizes predictive power for each sensor measure, while disallowing direct comparisons of predictive power between the sensor measures.

Reports of statistical analysis and results are split in two. First, we attempt to predict all 13 experience samples on each of the 5 scales employed. Here, data from the 270 s preceding each experience sample were used. From this time interval, physiological data where subjects were busy answering the parsimonious questionnaire were removed. With this procedure approximately 6% of the data were discarded. The resulting time varies from person to person and from sample to sample, the metrics we computed and explained below are therefore based on varying amounts of data. Secondly, we attempt to predict the data gathered from retrospective questionnaires. For this, we used sensor data gathered across the whole learning session, minus times when subjects were busy answering the parsimonious questionnaire.

We estimate predictive potential of measured sensor data by using and evaluating two machine learning regression algorithms. All complete datasets were included in the analysis.

Preparation of Physiological Data

Each sensor outputs a sequence of sensor data for proband *i* during an experiment. In order to predict questionnaire values, the raw data measured by each sensor are transformed to a set of features that describe the sensor data sequence. Features for the machine learning process are generated by splitting sensor data into 13 segments corresponding to the intervals for experience sampling. The following features were generated for EDA: mean, median, standard deviation, maximum, minimum, difference between maximum and minimum value, difference between medians of first 30 s and last 30 s (denoted tendency in the evaluation). The same features as for EDA were calculated for the EEG for each electrode position and precomputed power band (theta, alpha, low beta, high beta, gamma). In addition, we computed several indices of brain activity: low beta divided by alpha for all sites (denoted BLA), beta divided by the sum of theta and alpha (denoted NASA). Furthermore, anterior and temporal laterality indices were used comparing activity at left hemispheric sites across all bands with activity at right hemispheric sites across all bands. Lateral T is computed as the difference between T7 and T8 for all frequency bands and Lateral AF as the difference between AF3 and AF4.

Machine Learning

Two different machine learning models were employed to evaluate predictive potential of sensor data, one linear (Ridge Regression) and one non-linear model (Gradient Boosting with the XGBoost algorithm). Training the respective models is done by a model-specific training procedure that adjusts the parameters of the model to training data and an evaluation procedure that predicts target values for a set of features. The machine learning models learn functions that map sets of features

x_i to questionnaire values y_i by minimizing a loss function that depends on the machine learning model. The models are trained on training data that consist of feature-label pairs (x_i, y_i) of probands.

Ridge Regression (Hoerl and Kennard, 1970) is a l2-regularized linear regression model. The regularization parameter penalizes large weights of the model. Gradient Boosting (Friedman, 2001) is a more complex non-linear model that has shown impressive results on a large variety of regression and classification problems (Chen and Guestrin, 2016). The model uses several hyperparameters to control the complexity of the learned model. In our experiments we use the XGBoost algorithm of Chen and Guestrin (2016).

The data structure determines the validation procedure. For the purpose of cross-validation one data point is systematically left out. For predicting a single outcome measure the leave-on-out (LOO) cross-validation method was used. For predicting the 13 data points nested within an individual during the learning experiment the leave-one-proband-out (LOPO) cross-validation method was used. Both forms of cross-validation are very similar and iteratively assign a part of the data set to be validation data that cannot be used for training, but they differ in regard to the underlying data structure. Especially, the subsequent analytical steps are similar for both procedures.

The LOPO cross-validation simulates a prediction based on observed sensor data of previously unseen probands. To this end, let $X_i = \{(x_i{}^1, y_i{}^1), \ldots, (x_i{}^{13}, y_i{}^{13})\}$ be a set of 13 feature-label pairs of process outcomes of proband i. Let $D = \{X_1, X_2, \ldots, X_n\}$ be the set of all those feature-label sets of probands $I = \{1, 2, \ldots, n\}$. We iteratively choose proband $i = 1, \ldots, n$ and remove its data subset X_i from the pool of training data D. The resulting data set D_{-i} is used to train the machine learning regressor which is then evaluated on the remaining set X_i using any of the error functions of the last paragraph. The final outcome of LOPO-CV is computed by averaging over all probands.

The LOO cross-validation instead only removes a single feature-label pair. Let $D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$ be the set of all feature-label pairs corresponding to probands $I = \{1, 2, \ldots, n\}$. We iteratively choose proband $i = 1, \ldots, n$ and remove its feature-label pair (x_i, y_i) from the pool of training data D. The resulting data set D_{-i} is again used to train the machine learning regressor which is then evaluated on the remaining pair (x_i, yi) using any of the error functions of the last paragraph. Both Ridge Regression and XGBoost use hyperparameters that help to avoid overfitting by adjusting the complexity of the learned model. Parameters are tuned on each LOPO or LOO training set D_{-i} separately. The hyperopt-library (Bergstra et al., 2013) was used to perform parameter tuning with a threefold cross-validation on D_{-i}.

Features were selected on each LOPO or LOO training set D_{-i} separately, whenever stated. The recursive feature elimination with cross-validation (RFECV) algorithm (Guyon et al., 2002) was used.

For evaluating predictions two error functions were used, namely root mean square error (RMSE) and mean absolute error (MAE). Additionally, Pearson correlation coefficients between predictions and real values were computed.

The baseline method for questionnaires predicts the questionnaire values of proband i to be the mean value of questionnaire values of all other probands. That is, $\hat{y}_i^{bl} = \text{mean}(\{y_1, \ldots, y_n\} \setminus \{y_i\})$ where \ denotes the relative complement of sets. This baseline does not take into account any sensor data but serves as a sensibility check for results achieved by the machine learning models. Analogously, the baseline method for experience sampling predicts the values for each sample as $\hat{y}_i^{bl,1} = \hat{y}_i^{bl,2} = \ldots = \hat{y}_i^{bl,13} = \text{mean}(\{y_1^1, y_1^2, \ldots, y_1^{13}, y_2^1, \ldots, y_n^{13}\} \setminus \{y_i^1, \ldots, y_i^{13}\})$. Meaningful predictions have to be better than the baseline method. In this way, general trends over time that are shared by all probands cannot be predicted significantly by the machine learning model.

RESULTS

Prediction results are presented compared to the corresponding baseline measure. Evaluation errors are compared to the baseline for significance using student's t-tests.

Prediction of Experience Sampling Using Electrodermal Activity (EDA)

No machine learning model was able to predict process measures from experience sampling significantly above baseline using median EDA (see **Table 2**).

TABLE 2 | Results for predicting experience sampling using electrodermal activity (EDA).

	RMSE	MAE	*r*	*p*	*d*
Interest					
Ridge	1645.2	1324.3+	0.003		
Boosting	1600.3+*	1291.2+*	0.171	0.092	0.20
Baseline	1636.9	1327.4	−0.813		
Energy					
Ridge	1590.0+	1292.4+	0.046		
Boosting	1586.9+	1299.6+	0.061		
Baseline	1596.0	1302.3	−0.815		
Focus					
Ridge	1630.0+	1339.4+	0.032		
Boosting	1610.8+	1320.3+	0.132	0.143	0.17
Baseline	1633.6	1347.5	−0.747		
Valence					
Ridge	1573.8	1280.3	−0.828		
Boosting	1577.6	1284.5	−0.146		
Baseline	1573.7	1280.3	−0.828		
Tension					
Ridge	1660.8	1372.6	−0.527		
Boosting	1659.5	1370.6	−0.675		
Baseline	1654.7	1367.2	−0.791		

+*improved performance over baseline.* **denotes significant improvement.*

TABLE 3 | Results for predicting experience sampling using electroencephalography (EEG).

	RMSE	MAE	*r*
Interest			
Ridge	1867.9	1529.1	−0.355
Boosting	1779.2	1427.8+	−0.061
Baseline	1761.9	1438.2	−0.835
Energy			
Ridge	1852.2	1545.0	−0.498
Boosting	1774.6	1469.8	−0.201
Baseline	1715.7	1433.8	−0.831
Focus			
Ridge	1818.0	1485.0	−0.018
Boosting	1850.3	1527.9	−0.166
Baseline	1783.9	1469.7	−0.791
Valence			
Ridge	1736.9	1401.5	−0.215
Boosting	1689.7	1365.3	−0.131
Baseline	1654.1	1340.2	−0.786
Tension			
Ridge	1738.5	1379.4	0.039
Boosting	1715.1	1389.9	−0.080
Baseline	1650.3	1341.6	−0.791

+: improved performance over baseline.

Prediction of Experience Sampling Using Electroencephalography (EEG)

The machine learning model was not able to predict process measures from experience sampling significantly above baseline using features of the Emotiv Insight (see **Table 3**).

Prediction of Outcome Measures Using Electroencephalography (EEG)

Out of the 12 outcome measures we employed, we were able to predict Intrinsic Motivation as measured by the DSSQ significantly above baseline using sensor data from the Emotiv Insight (see **Table 4**).

Table 4 shows the average prediction results with LOO cross-validation for outcome measures based on EEG sensor features. We compare predictive performance of ridge regression, XGBoost and the baseline method using RMSE and MAE as well as label-prediction correlation (LPC). As addional information we added the Reliability (REL) of the scales estimated with Cronbach's Alpha. Both ridge regressions as well as XGBoost significantly outperform the baseline method using a student's t-test with p-values of 0.004 and 0.069. The effect sizes are d = 0.58 and d = 0.35, resp. Label-prediction correlation is also visualized by **Figure 3** that plots real values of intrinsic motivation for all probands (x-axis) in comparison to the predicted values of XGBoost (y-axis).

In **Table 5** we show the features with highest average weights as learned by XGBoost and averaged over all cross-validation iterations. We like to note that the prediction performance can be a misleading quantity as XGBoost is a non-linear regression method that predicts based on non-linear combinations of features. Consequently, a high importance of a feature does not entail that the feature has large predictive power on its own. For comparison, the highest Pearson correlation coefficients between

TABLE 4 | Predicting outcome measures with EEG using leave-one-out cross validation (LOO-CV).

	REL	RMSE	MAE	*r*	*p*	*d*
Amotivation	0,68					
Ridge		0.535+	0.400+	−0.076		
Boosting		0.557	0.412	−0.099		
Baseline		0.538	0.408	−1.000		
External motivation	0,61					
Ridge		0.509	0.425	−0.066		
Boosting		0.529	0.408	−0.515		
Baseline		0.491	0.382	−1.000		
Introjected motivation	0,38					
Ridge		0.869	0.756	−0.207		
Boosting		0.789	0.649	−0.414		
Baseline		0.737	0.618	−1.000		
Identified motivation	0,60					
Ridge		0.960	0.757	−0.406		
Boosting		0.863	0.693	−0.468		
Baseline		0.801	0.642	−1.000		
Intrinsic motivation	0,69					
Ridge		0.804	0.653	−0.376		
Boosting		0.734+	0.609+	−0.119		
Baseline		0.739	0.610	−1.000		
Interest	0,80					
Ridge		0.985	0.857	−0.223		
Boosting		0.940	0.816	−0.409		
Baseline		0.838	0.701	−1.000		
DSSQ II intrinsic motivation	0,81					
Ridge		1.079+*	0.815+*	0.685	0.004	0.58
Boosting		1.406+*	1.115+*	0.335	0.069	0.35
Baseline		1.516	1.310	−1.000		
DSSQ II workload	0,37					
Ridge		1.236	0.990	−0.665		
Boosting		1.151 +	0.937+	0.290		
Baseline		1.231	0.979	−1.000		
DSSQ I tense arousal	0,89					
Ridge		0.623	0.517	−0.519		
Boosting		0.644	0.549	−0.318		
Baseline		0.621	0.512	−1.000		
DSSQ I anger/frustration	0,87					
Ridge		0.611	0.498	−0.591		
Boosting		0.591+	0.468+	0.144		
Baseline		0.610	0.492	−1.000		
DSSQ I energetic arousal	0,90					
Ridge		0.808	0.695	−0.252		
Boosting		0.753	0.628+	0.033		
Baseline		0.729	0.639	−1.000		
DSSQ I hedonic tone	0,88					
Ridge		0.597+	0.489	−0.366		
Boosting		0.611	0.492	0.133		
Baseline		0.598	0.486	−1.000		

*+improved performance over baseline. *denotes significant improvement.*

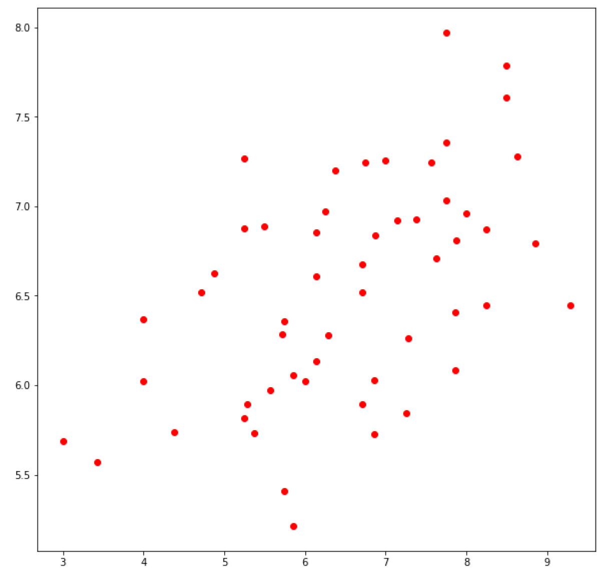

FIGURE 3 | Plot of real values for Intrinsic Motivation (*x*-axis) vs. predicted values via LOO procedure (*y*-axis).

TABLE 5 | Most important features according to the average weights of XGBoost.

Feature	Weight
T7 Nasa max	0.20
T7 BETA_LOW median	0.10
Pz BETA_HIGH tendency	0.10
T Lateral ALPHA maxmin	0.09
T7 BLA min	0.09
T8 BETA_LOW max	0.06
Pz GAMMA tendency	0.05
T8 BETA_HIGH mean	0.05
AF Lateral ALPHA min	0.03
T7 BETA_LOW mean	0.03
T7 THETA min	0.03

features and intrinsic motivation are listed in **Table 6**. If we only consider medians, **Table 7** shows the features predicting intrinsic motivation with highest correlations.

DISCUSSION

The effect that an average activation of all EEG bands at T7 (left-hemispheric, lateral) can predict lower intrinsic motivation as outcome measure after the learning effect is in line with assumptions of the PSI theory (Kuhl, 2000b, 2001). Kuhl (2000a, 2001) predicts that activating left hemispheric macro systems – especially object recognition – will inhibit right hemispheric macro systems – especially the extension memory. It can be derived that processes of intrinsic motivation need active right hemispheric activation. The extension memory is the bridge to all self-experiences and self-schemata and therefore a key system for internalization processes proposed by self-determination theory

TABLE 6 | Features with highest absolute Pearson correlation coefficients with intrinsic motivation.

Feature	Weight
T7 Nasa max	−0.53
T7 GAMMA median	−0.44
T7 BETA_HIGH median	−0.42
T7 THETA median	−0.38
T7 Nasa maxmin	−0.37
T Lateral THETA tendency	−0.36
T7 ALPHA median	−0.35
T8 BETA_LOW std	−0.35
T7 BETA_LOW std	−0.35
T7 BETA_LOW median	−0.34

TABLE 7 | Features with highest correlation with Intrinsic Motivation considering medians.

Feature	Weight
T7_GAMMA_median	−0.44
T7_BETA_HIGH_median	−0.42
T7_THETA_median	−0.38
T7_ALPHA_median	−0.35
T7_BETA_LOW_median	−0.34
nasa_AF4_median	−0.26
T8_GAMMA_median	−0.26
lateral_T_BETA_HIGH_median	−0.25
AF4_BETA_HIGH_median	−0.24
T8_BETA_HIGH_median	−0.24

(Ryan and Decy, 2000). Nevertheless, the data presented here must be interpreted very carefully. The direct measurement of right hemispheric activation could not be achieved in this study. This might be due asymmetric design of the head set: the delicate placing of the right electrode opposed to the tight grip of left electrode.

In this work consumer grade wearables for EEG and EDA with the selected features failed to predict emotions measured with short questionnaires (embedded experience sampling) that were repeatedly presented during the learning experiment. This gap can be explained by some major technical difficulties:

1. The grip of the consumer grade EEG is asymmetrical and not as tight as a professional EEG set. In addition, no liquids were used in the experiment to foster the electric flow. This argument can be repeated for the consumer grade measurement of EDA. The wrist band guarantees no tight pressure to the skin and was not supported by additional liquids.
2. Internal programs of the consumer grade electronics were not fully disclosed, so compression algorithms may have spoiled the data to some extent.
3. The general setting of this natural learning experiment might not invoke enough measurable arousal and especially not galvanic skin response. The learning situation used in this experiment was intentionally quite common for university student.

4. It cannot be fully excluded that embedded experience sampling might not measure the same processes as the EEG or the EDA. Experience sampling is still a form of verbal expression that reflects emotions. But of course, this expression might be distorted by the very same self-reflecting processes.

The fourth argument can – to some degree – be defused by the fact that this work can predict self-report data for the outcome variable intrinsic motivation.

OUTLOOK

Some of the major flaws in this study will be healed in the following study by using professional equipment for EDA and EEG. Furthermore, emotions will be measured by facial expressions. The authors still believe that unobtrusive measures of affective learning are very important for understanding learning processes. Subsequently, a theoretical and methodological coevolution will be needed that covers learning processes on micro as well as meso level and integrates affective and motivational regulation processes more deeply into theories of self-regulated learning. This will hopefully be the basis for successfully adapting digital learning environments.

DATA AVAILABILITY STATEMENT

The datasets generated for this study will not be made publicly available to maintain participants' confidentiality. Requests to access the datasets should be directed to the corresponding author.

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

TM and MN designed the experiments. TM, MN, and UD wrote the manuscript. MN executed the experiments. TM, MN, and UD analyzed the data.

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METHODS
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A Collaborative Learning Design for Promoting and Analyzing Adaptive Motivation and Emotion Regulation in the Science Classroom

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The aim of this paper is to introduce our current research design to study socially shared regulation processes in a science classroom where a collaborative learning design is implemented. The design is based on a self-regulated learning framework that provides opportunities and support for self-initiated regulation among individual learners and collaborative groups. It utilizes modern technology to structure and support regulated learning in the groups. The paper focuses on elaborating the research design, particularly from the perspective of motivation and emotion, by presenting the dual relationship between designing learning scenario that supports learners' motivation and emotion regulation with technology and researching the multifaceted role of motivation and emotion as they occur in collaborative learning. To do this, the paper first describes the entire collaborative learning design while paying attention to how technology can be utilized to support the awareness of motivation, emotion, and their regulation. Then, the focus shifts to considering the methodological principles and implementation of multimodal data gathered in relation to authentic collaborative learning tasks. A case example from a secondary school science classroom demonstrates possibilities for multimodal data use in analyzing motivation, emotion, and their regulation in collaborative learning. It also illustrates the dual role of the implemented technological 6Q support tool by showing how data collected from the students' use of the tool can be utilized in scientific analysis. The paper concludes by providing a short discussion about the current advancements of emerging technology in motivation and emotion research in the learning sciences highlighting the significance of sharing the theoretical premises of the research design as well as practical experiences from implementation of these designs for future research.

Keywords: collaborative learning, learning design, regulation support, emotion, motivation, SRL, socially shared regulation, multimodal methods

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INTRODUCTION

Collaboration-based instructional approaches promote learning techniques for active and agentic learning (Hmelo-Silver, 2004). They support socially coordinated inquiry, knowledge creation, and stimulate higher levels of cognitive processing (Griffin et al., 2012; Sawyer, 2014), which are essential for twenty-first-century learning needs. Collaborative learning's benefits have been demonstrated by many researchers (Miyake, 1986; Roschelle and Teasley, 1995; Webb et al., 1995), and it is an increasingly valued teaching and learning practice in education. Ideally, during collaborative inquiry, learners monitor their understanding collaboratively to discover gaps in their knowledge base and actively implement appropriate study tactics and resources to overcome these gaps in coordination between the group members (Hmelo-Silver et al., 2013).

Increasingly, emerging technologies have been used to enable, stimulate, organize, support collaboration, and collaborative learning processes. In the computer-supported collaborative learning (CSCL) field, the focus has been on understanding how collaborative interactions emerge and are constituted (Wise and Schwarz, 2017). These processes have been supported through scripting and prompting, which are often used to facilitate productive interaction [e.g., Wang et al. (2017), Schnaubert and Bodemer (2019)]. However, prompts can also be used to explicitly raise learner's awareness of their collaborative learning processes at the individual and group level (Chanel et al., 2016). While there is a large body of empirical evidence indicating that learners benefit from scripts, prompts, and awareness tools in the context of CSCL (Schnaubert and Bodemer, 2019), it is unclear how the tools affect learning outcomes. These tools focus on supporting learners' cognitive and metacognitive processes, and the role of motivation and emotion have been largely ignored (Belland et al., 2013).

Regardless of the considerable progress made in the CSCL research field, groups still struggle to succeed in their collaborative efforts and in finding the strategies that would allow them to invest group members' learning potential in the shared learning processes (Järvelä et al., 2013). Although CSCL approaches have proven beneficial to learning, they are often motivationally and emotionally demanding as students are assumed to engage in higher-level thinking and interaction while taking greater responsibility for and control over their own and the group's shared learning processes (Mäkitalo-Siegl and Fischer, 2013). Hence, a substantial portion of the challenges learners face is related to cognitive hurdles that have socioemotional and motivational origins (Järvenoja et al., 2013). It has been argued that there is a need to emphasize supporting motivation and emotion in groups while groups share and build common ground on which to develop collaboration (Ludvigsen, 2016). This is particularly the case with adolescent students who experience novel and more demanding academic situations the same time they are going through developmental changes causing emotional hurdles (Gómez-Ortiz et al., 2016; Hollenstein and Lanteigne, 2018).

It is evident that the role of motivation and emotion in collaborative learning is more complex than just whether the individuals are motivated or simply dislike social interaction or dependence on others (Järvelä and Renniger, 2014). Emotional reactions to learning can change the way people approach collaboration, feel about the task, or interpret the social learning situation. Without actively and explicitly maintaining and enhancing motivation during learning, initial interest, or curiosity may not be enough to overcome challenges, especially when the premises and attitudes are unfavorable for collaboration. Theories of motivation and emotion in learning aim to explain this multifaceted functioning and the relationship between learners' beliefs and feelings in relation to learning (Pekrun, 2016). These theories have been utilized to explain why and how learners pay attention to, concentrate on, invest effort in, and persist in their academic learning (Volet and Järvelä, 2001; Schutz and Pekrun, 2007), as well as the precise challenges faced when collaborative groups do not reach their potential regarding cognitive processing (Hadwin et al., 2018).

Motivation and emotion regulation has been characterized as a fundamental part of effective collaborative interactions in the learning mechanisms of collaborative groups (Hadwin et al., 2017).

By engaging in emotion regulation as a part of regulated learning, learners address emotions, and their expression in the learning context and the way they experience them (Gross, 1998; Boekaerts, 2011; Goetz et al., 2015) and furthermore, they attempt to adjust the situation to better support their emotional well-being and learning. Emotion regulation is composed of active employment of strategies to reach the above-mentioned goal. Motivation regulation aims also to maintain learning and commitment to learning but focuses particularly on building up, maintaining, or restoring motivation in the learning situation (Wolters and Benzon, 2013). Research on the socially shared regulation of learning (SSRL) that extends the self-regulated learning (SRL) theory to include regulation processes taking place between collaborating group members has provided promising prospects to understand the function and role of motivation and emotion in collaborative interactions (Järvenoja et al., 2015; Hadwin et al., 2017). Via socially shared emotion regulation, group members can collectively ensure an emotionally solid (social) base on which academic tasks can be completed (Boekaerts and Pekrun, 2015; Pekrun, 2016). That is, when engaging in the socially shared regulation of emotion, several group members collectively engage in regulatory interaction that aims to release negative affect, dissolve emotional tension, unravel emotional experiences, or reduce negative emotional responses to socio-emotionally challenging situations that could hamper the group's learning and collaboration. The socially shared regulation of motivation, in turn, aims to purposefully maintain and restore a favorable motivational state during a learning process to achieve the learning goals (Boekaerts and Pekrun, 2015). Motivation regulation can be directed, for example, at initiating, restoring, strengthening, or redirecting interest, motivational goals, or self-efficacy beliefs (Wolters and Benzon, 2013). What makes both motivation and emotion regulation socially shared is the group members' coordinated and complementary efforts, which contribute to regulating the groups' motivational and emotional state (Järvelä et al., 2017).

Awareness of emotional reactions, challenging situations, and motivational conditions is a premise for groups to activate regulation on a social plane (Diamond and Aspinwall, 2003; Op't Eynde and Turner, 2006; Järvenoja et al., 2015). However, research on SSRL focusing on emotions and motivation indicate that group members do not always recognize the need for regulation or display the need for it explicitly on a social plane, resulting in challenges for SSRL to emerge (Koivuniemi et al., 2017; Hadwin et al., 2018) Based on previous research, we claim that providing support for increasing awareness can foster the group members to jointly activate these processes (Bakhtiar et al., 2018; Järvenoja et al., 2018a).

While acknowledging the critical role of emotion and motivation in contemporary learning, the aim of this paper is to introduce our current research design which relies on our former process-oriented approach and aims at implementing empirical studies on socially shared regulation processes in a science classroom. The research design is implemented in relation to a collaborative learning design, which is also introduced in the paper. The collaborative learning scenario is designed to promote and support socially shared regulation processes in authentic collaborative learning settings. In this paper, we focus on students' motivation and emotion regulation, describe the dual relationship between supporting motivation and emotion regulation, and analyze the multifaceted role of motivation and emotion as they occur in collaborative learning. In the collaborative learning design, we implement the SRL framework (Zimmerman, 2000; Hadwin et al., 2017), which affords learners opportunities to take responsibility for their own learning and offers possibilities to support learners' emotion and motivation regulation with technology. We will first discuss the entire collaborative learning design while paying attention to pedagogical structures and how technology can be utilized to support the awareness of motivation, emotion, and their regulation. Then, we shift to considering the methodological principles that support the aim of studying regulated learning from multimodal data collected from authentic collaborative learning settings. To concretize these methodological principles, we conclude with a case illustration demonstrating the possible implementation of multimodal data in analyzing motivation, emotion, and their regulation in collaborative learning. The data used for the example were obtained from a secondary school science classroom where the collaborative learning design was implemented.

A COLLABORATIVE LEARNING DESIGN FOR PROMOTING MOTIVATION AND EMOTION REGULATION AS A PART OF COLLABORATIVE SCIENCE LEARNING

Motivation and emotion regulation do not emerge in isolation but are related to the individual group members' wider motivational structures, as well as context, situation, and cognitive processes (Weiner, 1985). Although the multifaceted function and role of motivation and emotion in collaborative learning are increasingly acknowledged (Lajoie et al., 2015; Hadwin et al., 2017; Järvenoja et al., 2018a; Winne, 2018), supporting motivation and emotion has not been emphasized when designing learning environments (Belland et al., 2013). However, some researchers [e.g., Janssen and Bodemer (2013)] have considered motivation and emotion as a part of the CSCL framework, focusing on increasing group members' awareness of cognitive and social processes. Other researchers, such as Bakhtiar et al. (2018), have been developing scripts that not only enhance group members' awareness of possible socio-emotional challenges but also prompt their awareness of possible strategies that could be used to overcome such challenges.

Järvelä and Renniger (2014) have stated that it is not enough to consider how to support motivation and emotional engagement of learners who have negative emotions and low motivation. They have argued that when designing collaborative learning tasks, deliberate attention should also be paid to on-going process and how those who are initially engaged or gradually building a situational interest can be encouraged to maintain their motivation and deepen their interest during the learning process. Continuous commitment to learning goes beyond the initial motivation to volitional attempts to maintain, strengthen, and direct motivation to circumstances where motivational and emotional commitment is confronted by situational circumstances (Corno and Kanfer, 1993). When designing formal learning settings, guiding principles should also consider how spaces to practice motivation and emotion regulation in action can be created (Järvelä et al., 2020). Proper and timely support for motivation and emotion regulation initiates opportunities for this. It also provides learners possibilities to internalize concrete techniques to implement during future learning when motivational and emotional commitment is jeopardized, but external support is not available (Fischer et al., 2013).

To follow this line of argument, we have created a collaborative learning design focusing on promoting and studying motivation and emotion regulation, along with a wider focus on the regulation of collaborative learning. To capture the dynamics of students' individual motivational and emotional factors during the learning process, we utilize an ecologically valid learning context and research design that enables us to assess authentic learning challenges and embedded processes of motivation, emotion, and their regulation. We implemented the design in a study of secondary school students (~13 years of age, $N = 94$, 36 male, 58 female) and their science teachers. All the participants were from a same comprehensive school located to an urban area in the Northern Finland and had an equal socio-economic background. The students' were participating in the study while they engaged in collaboratively studying wave motion and its various physical manifestations for a 7-weeks study period. The science topic was derived from the national physics curriculum and focused specifically on light and sound as elements of wave motion. Ninety-four students from five seventh-grade classes and four teachers volunteered to participate. The participating students were divided into 30 heterogeneous groups based on their previous science grade. Students who did not agree to participate in the research studied the topic following the same pedagogical structure but collaborated in separate groups and in a different classroom. During the data collection period, students participated in four collaborative learning sessions and completed one individual exam and one collaborative exam.

The collaborative learning design is built on the idea of a "flipped classroom." Recently, the flipped classroom concept has been gaining considerable attention due to its potential to facilitate the regulation of learning (Jovanovic et al., 2019). The use of a flipped classroom in collaborative learning creates a learning setting in which students are provided opportunities to take responsibility for their own learning by familiarizing themselves with the content knowledge beforehand to prepare for collaborative learning. Collaboration during school lessons, in turn, promotes interaction between students via sharing information, searching for meanings and solutions, and maintaining a shared understanding of the problem (Iiskala et al., 2011). Accordingly, a flipped classroom combines conventional face-to-face classroom learning with preparatory activities to optimize collaborative learning and knowledge construction. The role of the teacher is to design opportunities for independent learning and act as a facilitator supporting collaborative learning activities in face-to-face settings that are also supported with technology. However, how this type of learning setting challenges and promotes motivation, emotion, and their regulation is yet to be well-understood.

In our collaborative learning design, the flipped classroom structure and the collaborative work were coordinated by using a technology-based environment called Qridi®, which provided the main structure for the entire 7-weeks learning period, as well as for each lesson. Students used the Qridi® platform (https://kokoa.io/products/qridi) with tablets to structure their collaboration and increase awareness of the regulation of learning in each lesson. In the Qridi® environment, they were able to check, for example, the phase of the lesson. Qridi® offers tools for formative evaluation, an environment in which learners can perform self, peer, and group evaluations and where teachers can also evaluate students' learning. In our learning design, Qridi® was tailored to switch the focus from the evaluation of learning to structure and increase students' awareness of the collaborative learning task phases in general and, specifically, supporting their awareness of the regulation of learning.

The structure of each lesson was purposefully designed to follow the same structure (**Figure 1**), although the focus and nature of the exercises varied as the students' understanding of the subject deepened. With the help of the Qridi®, the structure was visible for the students from the very beginning, which provided them possibilities to prepare, control, and coordinate their collaboration not only within but also across the lessons. The first basic principle was that based on flipped classroom principles, the students independently studied the upcoming topic in their science textbook prior to each lesson. When students entered the classroom, the teacher first introduced the new topic to the students and ensured that each student had enough knowledge about the topic to engage in collaborative learning. Second, the students were prompted to prepare for the collaborative work by responding to a situated 6Q tool in the Qridi® environment (see chapter 3.1. for more detailed description of the 6Q tool). As regulation of learning requires meta-level consciousness of the current situation and the need for regulation (Hadwin et al., 2017), the 6Q tool targets to increase the students' awareness of their current motivational and emotional state. This can help students to create meta-level consciousness of the motivational and emotional aspects calling for regulation in that particular lesson. For example, identifying a negative emotional state can make the student realize that "something is wrong" and needs regulating. Third, to emphasize and make explicit the planning and goal setting phase of regulated learning, the students were prompted to discuss and commit to shared goals and plans for their collaborative learning for that lesson (*What is the goal for your collaboration? What will you do to achieve your goals?*). Shared plans and goals were written down in Qridi®. Altogether, these three activities formed an initiation phase for each lesson and prepared the students for the collaborative work.

After the initiation phase, most of the lesson time was devoted to collaborative work. When designing learning contexts that promote regulation and, in particular, motivation and emotion regulation, it is crucial that both the structure and the content of the planned tasks optimally challenge the students (Perry, 1998). From the collaborative learning perspective, tasks that call for multiple perspectives and where the meaning needs to be negotiated through interactions with others have been developed for decades (Von Glasersfeld, 1998). In the current collaborative learning design, the implementation of the flipped classroom structure aimed to provide independence and room for collaborative groups to plan and coordinate their joint working whilst still ensuring individual learning. Each collaborative learning task consisted of mathematical calculations and hands-on scientific experiments. The content and exercises of the tasks were designed with assistance from science teachers to ensure they covered the required subjects and content, and the researchers ensured that the tasks provided possibilities for the regulation of learning. In one learning task, for example, the task was to do experiments on the light and sight. The groups were provided with four different main themes for investigation (1. Investigate illumination by changing the distance of the light, 2. Investigate intensity of light, 3. Investigate propagation of light, and 4. Investigate how reflection is related to sight). A flashlight, a set of experiments and related materials as well as guiding questions and instructions were provided to the groups. The groups planned and executed the experiments related to overall task by implementing each group member's prior knowledge. This knowledge was gained in the preparatory homework activity in which the group members independently studied the factual knowledge on light and sight. During the collaborative working individual understanding was shared to co-construct more profound and shared understanding of the topic.

When the collaborative working time was over, the students returned to the Qridi® to test their individual knowledge by completing a multiple-choice questionnaire about the key concepts of the day's topic and repeated the 6Q tool reflection structure in the reverse order. First, the students together discussed the group's goal achievement (*How did you achieve your goals for collaboration? Why?*) and second, filled in their individual reflections on their motivational and emotional state. Each lesson ended with teacher-led discussions and conclusions and the provision of homework, which, according to flipped classroom principles, was always the new topic for the next lesson. Finally, from the regulated learning perspective, we have argued that the learning tasks and projects should be long enough to provide a genuine need for taking control over their own learning processes. Hence, in our collaborative learning design, the students were engaged in a several-week learning period, and each collaborative learning session lasted for 90 min to

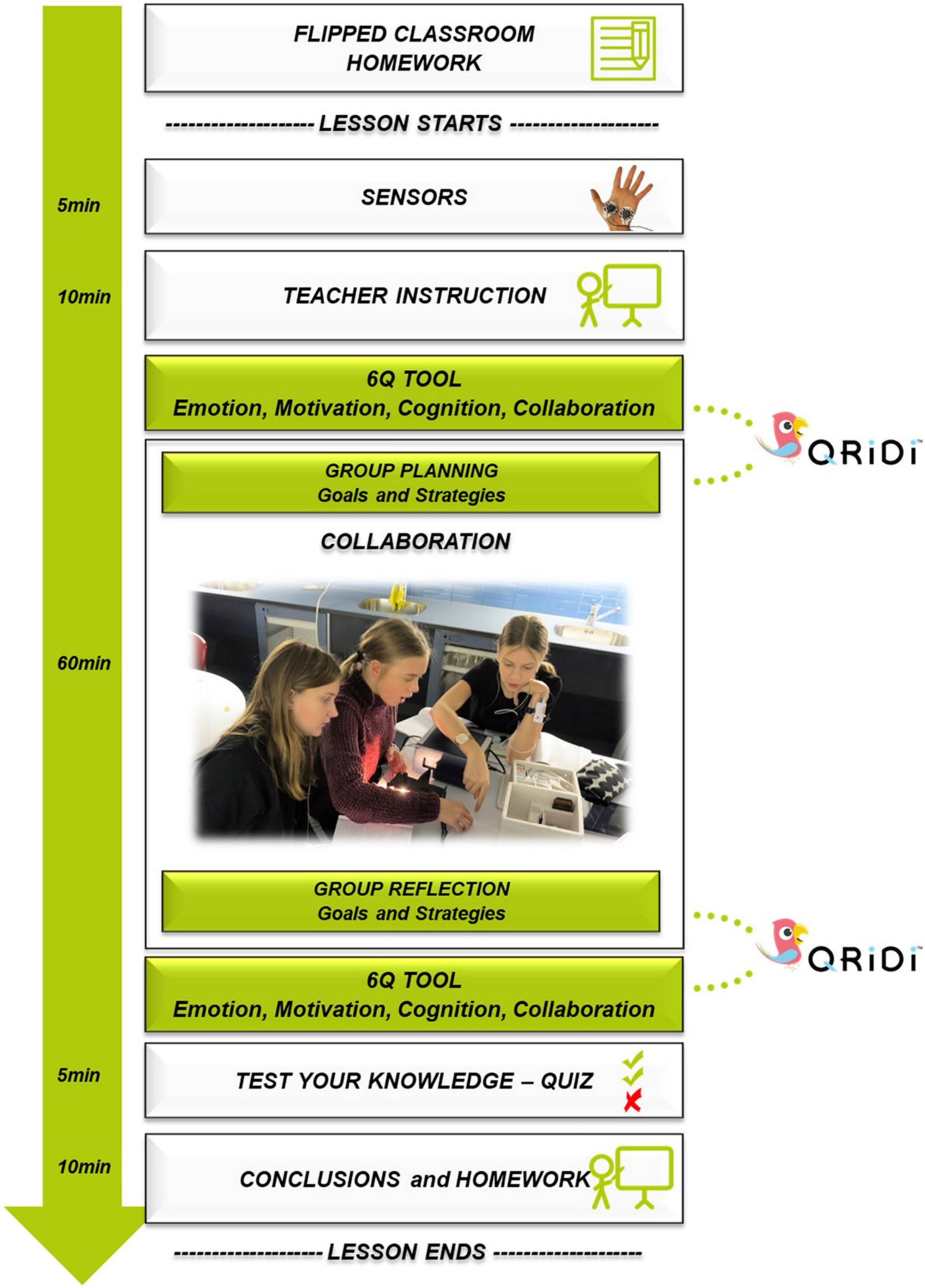

FIGURE 1 | Outline of the collaborative learning design.

provide enough possibilities for regulation within and across the lessons.

The collaborative learning design aligns closely with the principles of SRL theory regarding the independence of the learner and the length and nature of the learning tasks. In practice, the alignment of the learning design and SRL theory is realized, for example, in how the responsibility of the learning is switch to the learner by assuming that they study the content knowledge prior to the collaborative learning sessions. Each session is structured according to the regulated learning cycle (planning, monitoring, evaluating) (Hadwin et al., 2017), and this cycle was also explained to the students in the beginning of the 7-weeks study period. The students were also familiarized with the idea of "taking charge of own learning" and explained how regulation of learning encompasses motivation and emotion regulation in addition to the regulation of cognition (Järvelä et al., 2016). The regulated learning cycle is related to the complete study period but was visible also in the sub-structures of the design. This is, the regulated learning cycle was present in the structure of each collaborative learning session, in individual working and in the use of 6Q tool. The students were explained that emotions and motivation can be regulated in any phase of the regulated learning cycle. To ensure the accurate comprehension of the 6Q tool items, each single item used was explained to the students and the meanings of the items were elaborated carefully. Also, it was emphasized that there are no right or wrong answers and the students' responses for the 6Q tool are not going to influence their physics grades.

To summarize, the design provides a framework for teachers and researchers to structure collaborative learning in a meaningful way that also considers the role of motivation and emotion in the learning process. The long-term design and unvarying overall structure, with varying but related content and exercises, allows the study of fluctuating emotional processes and the role of motivation integrally with the context and the learning process. Real-life learning situations enable grasping the multiple layers of motivation and emotion that are realized in the regulatory actions in situ (Volet et al., 2009; Järvenoja et al., 2015). However, we were also interested in reaching the students' own situation-specific appraisals and interpretations as they are essential to understanding the reasons for certain observable activities. The presented learning design provides a relevant opportunity for this as the students repeatedly evaluated their situational motivation and emotion in relation to learning and collaboration. In the next chapter, we elaborate on the role of awareness in collaborative groups' motivation and emotion regulation and pinpoint how the students' evaluations of their motivational and emotional state, as well as their cognitive abilities and collaboration, gathered with the 6Q tool, served as a support tool for regulation.

SUPPORTING COLLABORATIVE GROUPS' REGULATED LEARNING WITH TECHNOLOGICAL TOOLS

Collaboration skills are important to achieving successful learning, but they tend to be neglected and undermined when collaborative learning is implemented (Mullins et al., 2011; Baker, 2015; Kuhn, 2015; Kirschner et al., 2018). Neglecting these skills has contributed to computer-based learning environments and technological learning tools not reaching their full educational potential. Prior research clearly indicates that many students are unable or unwilling to regulate their learning (Shapiro and Niederhauser, 2004; Azevedo, 2005). Although different types of tools and technologies are widely used in the field of CSCL, students and teachers do not always recognize the opportunities they provide for (practicing) the regulation of collaborative learning processes (DiDonato, 2013; Järvelä et al., 2013). This has led SRL researchers to emphasize that supporting regulation is fundamental to effective individual learning (Cohen, 1994; Azevedo, 2015), as well as collaborative groups (Järvelä et al., 2016). For example, Wang et al. (2017) showed how adaptable collaboration scripts can be effective for regulation activities. They found that an adaptable script increased the students' use of monitoring and reflection activities, but it did not have an effect on planning. They concluded that adaptable collaboration scripts decrease the need for planning but provide more opportunities for monitoring task progress. Their results show that an adaptable script facilitates learners' use of self-regulation through the promotion of co-regulation processes. Similarly, Schnaubert and Bodemer (2019) incorporated metacognitive group awareness information into CSCL to help build students' confidence in their ability to regulate the collaborative process. They found that support provided in the form of visualizations has positive effects on joint regulation but not on the learning outcomes.

Following research-based evidence, researchers have developed technological tools from different premises to prompt and support regulation explicitly (Azevedo and Witherspoon, 2009; Miller and Hadwin, 2015). For example, some of the technological platforms are designed based on the principles of a certain pedagogical structure, such as inquiry learning, but include elements that support regulation, such as WeSpot (Mikroyannidis et al., 2013), which can be tailored to support the regulation of learning. Some other learning platforms are more general in their basic principles but allow researchers or course instructors to use and modify the tools available to create regulation support according to the specific purpose and context. For example, in their study of higher education students' regulation during a semester-long undergraduate course, Bakhtiar et al. (2018) modified the Moodle environment, which was used as an online environment for the coursework, to script motivation and emotion regulation. Their version of the Moodle included forms for students to plan collaboration activities, as well as consciously consider what type of emotional challenges they anticipated in relation to their collaboration. Some technologies, such as nStudy (Winne and Hadwin, 2013), integrate SRL theory principles, and hence, regulation support is embedded in their structures. Finally, the technological tool can be designed to support regulation, for example, the S-REG tool, which provides targeted support for groups' SSRL based on the motivational, emotional, and cognitive challenges the individual group members become aware of with the help of the tool (Järvelä et al., 2016).

In complex learning settings that emphasize students' individual responsibility and the regulation of learning, students could benefit from the explicit support of motivation and emotion that exceeds the overall regulated learning support. The hallmark for the successful regulation of learning is that the learner becomes aware of the need for regulation. This awareness is followed by an accurate recognition of the target of regulation, whether it is related to cognitive aspects or originates from emotional challenges, motivational issues, or both (Malmberg et al., 2015). Only then can the learner reliably choose and apply proper regulation strategies and eventually adapt the SRL process and take charge of the learning process. Regardless of the form of technology or tool aiming to support motivation and emotion, the main principle of this support can, hence, be simplified into two main principles: increasing learners' awareness of the need for motivation and emotion regulation and accurately recognizing how they can regulate the situation (Järvenoja et al., 2018b; Järvelä et al., 2020).

6Q Tool for Motivation and Emotion Regulation Support

Motivation and emotion do not function in isolation in collaborative learning. Rather, cognitive, social, emotional, motivational, and contextual variables interact with each other in a multifaceted, dynamic manner (Thompson and Fine, 1999). Targeted support for motivation and emotion regulation provides situated support for motivation and emotion during collaborative inquiries but in relation to cognitive processes (Järvenoja et al., 2017). Hence, in the current collaborative learning design, we targeted explicitly prompting students' awareness of their situational motivation and emotion simultaneously with the awareness of cognitive interpretations with the 6Q tool. The development of the 6Q tool was based on prior research on supporting awareness of different regulation targets (see Järvelä et al., 2016).

The guiding idea of the 6Q tool was to promote students' awareness of targets that potentially could call for active regulation. This was done with repeated evaluations of their emotional state and level of motivation simultaneously with cognitive ability evaluations and an appraisal of the current collaboration. Hence, 6Q prompts students' awareness of all the possible targets for regulation in parallel but explicitly recognizes each target to avoid the possibility of one undermining the others. In practice, the 6Q tool consists of six 0–100 slider-scale questions where students estimate their task understanding (Schraw and Dennison, 1994), perceived task difficulty (Efklides et al., 1998), emotional activation and valence (Pekrun et al., 2007), situational interest (Tapola et al., 2013), and perceptions of group work (Volet, 2001). In terms of motivation and emotion, **Figure 2** shows how, at the beginning and the end of the group work, the students are instructed to individually evaluate their emotional state and level of motivation: *how they are currently feeling* (positive–neutral–negative and deactivated–neutral–activated) and *how the task seems to them* (boring–neutral–interesting and difficult–neutral–easy).

Technological support tools often require becoming familiar with the tool and learning how to use it to achieve the intended supportive effect it can provide (Mayer and Moreno, 1998). Also, there is a risk of the tool being so "heavy" that it can even move the target away from the actual learning situation it is aiming to support. The 6Q tool implements a single-item approach for each variable to prevent the tool from being unnecessarily intrusive. By selecting a single-item measure approach, we balance between the dual purposes of the tool use; the 6Q tool supports self-awareness but avoids unnecessary intrusiveness by keeping the focus on the collaborative learning task. As for data validity, Goetz et al. (2016) argue for single item measures, particularly when measuring state-like situation-specific and varying motivational experiences. Single-item measures have been found to be reliable and useful in several SRL studies conducted during learning [e.g., Ainley et al. (2002), Ainley and Patrick (2006)] even if psychometric attributes are weaker compared to traditional multi-item questionnaires where the reliability and validity test between the items within a scale can be computed with common statistical analyses. When the measures are related to a specific situation or task, and the measure is used by a participant more than once, a questionnaire needs to be simple enough to diminish the effects of the questionnaire itself, so it more reliably measures the actual attitudes of the participants. In addition, as the Qridi® environment was already familiar to the students, the 6Q tool did not require too much effort from the students to use it. Accordingly, a slider scale and a single-item solution appeared to be the most functional and valid solution as it worked well with the Qridi® design and were easy and fast to use. This solution enabled a repeated use of the 6Q during the classroom lessons without intrusiveness and decrease in reliable responding. Finally, the single-item solution allowed to capture the situational variation in motivational and emotional states within a person.

COLLECTING AND ANALYZING MULTICHANNEL DATA WHEN UTILIZING THE COLLABORATIVE LEARNING DESIGN—ZOOMING ON MOTIVATION AND EMOTION

In this chapter, we move from the learners' perspective to a research perspective to illustrate what types of data related to motivation and emotion we gain by implementing the collaborative learning design. In the following, we focus on presenting examples of the possible use of different data sources instead of reporting detailed results. In the examples, we consider the multi-componential and multi-faceted nature of motivation and emotion, such as the variation and fluctuation in emotional states within and across individuals, and the relationship between affective experiences and motivational or cognitive aspects and provide analytical ideas for further research [e.g., Bakhtiar et al. (2018), Goetz et al. (2016), Ketonen et al. (2018), Moeller et al. (2018)]. Instead of focusing solely on individuals, we are particularly interested in group-level processes; depicting how *socially shared motivation and emotion regulation* function and fluctuate during collaborative learning situations. Considering how motivation, emotion, and their regulation are situated and embedded in subjective appraisals, contexts, and cognitive processing,

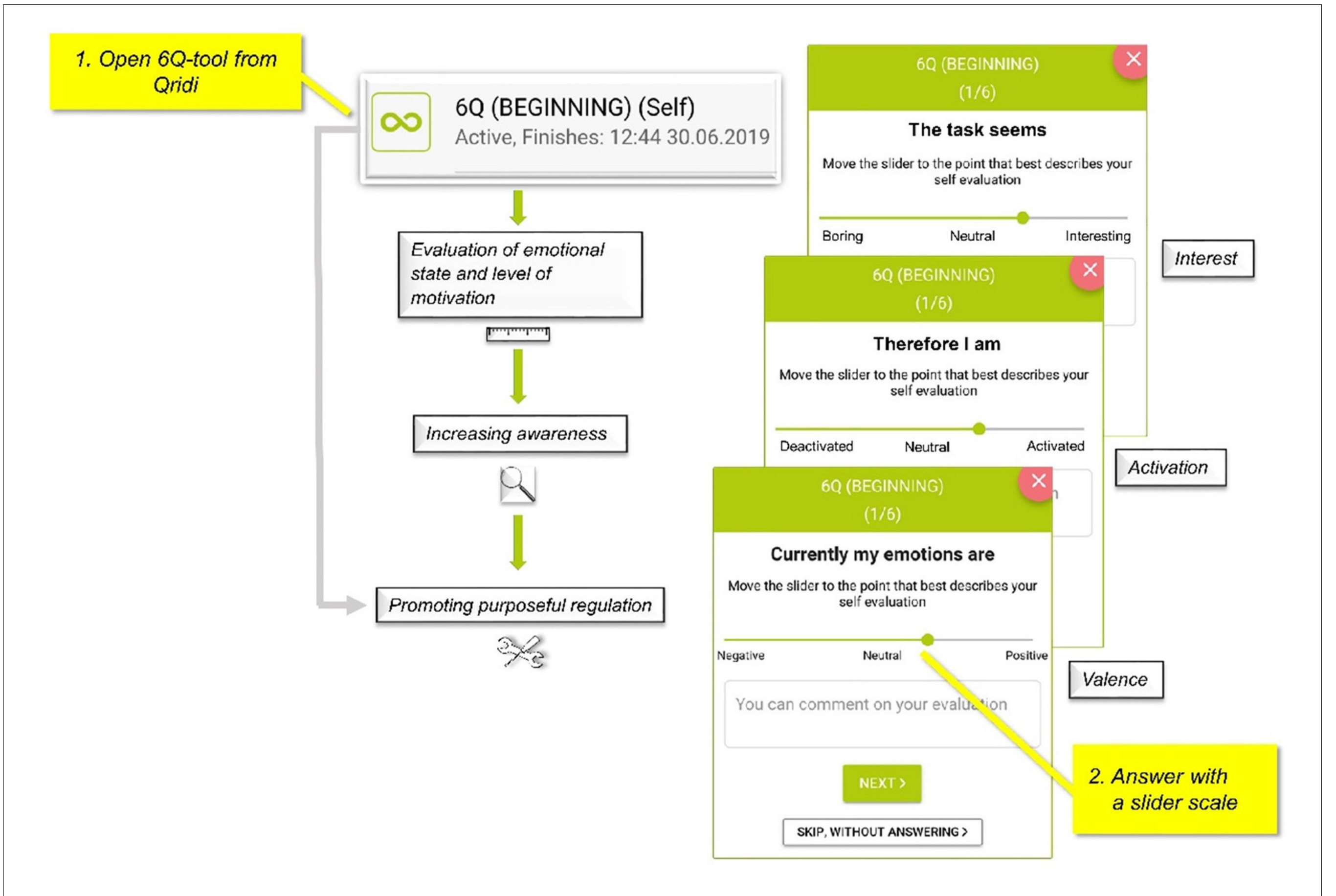

FIGURE 2 | An example of the 6Q tool's structure in terms of its motivational and emotional aspects. By increasing students' awareness of their situational emotional and motivational state, the 6Q tool prompts students' to actualize motivation, and emotion regulation when needed.

research designs that capture the variety of meaningful indicators are needed.

As the students study according to our collaborative learning design, multiple data sources produce a multimodal data corpus that encompasses data on motivational, emotional, and cognitive aspects on the individual and group level. Prior to beginning the study, the participating students responded to trait-type self-reports about their SRL strategies and task interest (Cleary, 2006), metacognitive awareness (Schraw and Dennison, 1994), self-efficacy (Usher and Pajares, 2008), and group assignment appraisals (Volet, 2001), each validated and used extensively in earlier research (see **Table 1** for the different measures utilized and their features). The purpose of these measures was to gain an overall understanding of the students' motivational traits and emotional and regulatory underpinnings. The motivational and emotional appraisals, expectancies, values, beliefs, and goals collectively form the (pre)conditions for motivation and emotion regulation and regulated learning (Pekrun, 2016; Winne, 2019). The learning situations were constituted based on these conditions, indicating that the learner's approaches and decision-making processes were personalized by prior experiences and events over time, but they were also shaped in the course of action, making them sensible for the situation (Hadwin et al., 2017).

During the 7-weeks multichannel data collection process, students' collaborative work was followed by video recordings and individual-level physiological measures. To capture the learning activity in its natural setting and obtain multimodal process data related to the different cognitive, emotional, and motivational components, the learning session was recorded using four Insta360 Pro video cameras placed in the classroom and separate microphones placed in front of each group. Video data provides contextualized data through different channels (i.e., voice, facial expressions, and interactions) from the different operations shaping the groups' shared and individual motivational and emotional states. Operations that can be tracked from video data cover verbal and nonverbal emotional expressions, socioemotional interactions, actualized motivation, and emotion regulation. To capture students' covert physiological reactions during the learning situation, such as students' physiological reactions related to emotional activation, their electrodermal activity (EDA) and heart rate (HR) were recorded via Shimmer3 GSR + devices (**Figure 3**). The GSR+ electrodes were attached on the palm of the non-dominant

TABLE 1 | Self-report data collected prior to the 7-weeks science learning period.

Theoretical focus	Specific construct	Data source	Sample *N*
Self-regulation	SRL strategies	Questionnaire Cleary, 2006	94
Metacognition	Awareness	Questionnaire Schraw and Dennison, 1994	94
Motivation	Task interest	Questionnaire Cleary, 2006	93
Motivation	Self-efficacy	Questionnaire Usher and Pajares, 2008	93
Collaboration	Appraisals of collaborative working	Questionnaire Volet, 2001	93
Outcome	Individual performance	Physics exam designed by teachers	94
Outcome	Group performance	Collaborative exam task designed with teachers	30* (groups)

**Due to absences of students from the group exam, some group compositions were adapted from the original.*

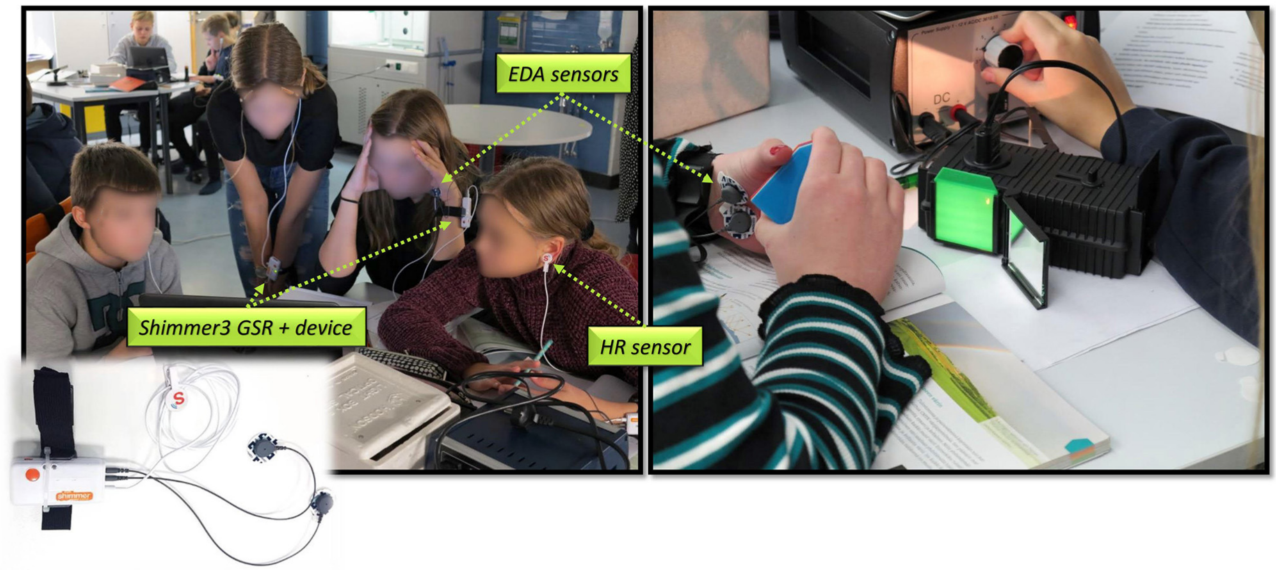

FIGURE 3 | An illustration how the students wore the Shimmer3 GSR+ devices in the classroom during collaborative learning.

hand and measured the students' EDA. HR was measured with an optical pulse sensor placed on the ear lobe. According to the students' experiences and field observations, the sensors did not restrict students' required motoric actions during the lessons. Hence, in our experience, the Shimmer3 is a functional and relatively unobtrusive device to collect continuous, high granularity process data on physiological activity in classroom contexts. The EDA measures, for example, have already been used to track students' general physiological activation level during learning sessions (Pijeira-Díaz et al., 2018). It has been implemented also in studies on learners' short-term emotional responses (Dawson et al., 2007). Combined with video data, EDA data enables to track physiological emotional reactions in relation to the regulatory interactions. Though certain challenges remain, EDA and HR provide intensive temporal data about physiological activity that can be related to data on motivational, emotional, and cognitive processes during task execution (Pecchinenda and Smith, 1996; Kreibig and Gendolla, 2014; Efklides et al., 2018), and have potential as a new data channel when learning processes are studies in authentic contexts. Altogether, the collaborative learning design produced a versatile data corpus, which is presented in **Table 2**. All the required equipment was brought to the school and installed in the science classrooms to capture the learning activity in its natural setting (**Table 2**). In addition, after the learning period, we measured the students' learning outcomes at both the group and the individual level.

As one of the multiple data sources, we used the 6Q tool to collect students' situation-specific motivational, emotional, and cognitive experiences related to each collaborative session before and after the collaborative work (**Table 3**). With 6Q tool data, we can capture group members' varying subjective motivational and emotional experiences that are impossible to capture with other process data modalities. Particularly, 6Q tool data provide a possibility to explore situational variations in individuals' motivational state and the valence-activation space (Pekrun, 2016; Törmänen et al., 2020). From the motivational perspective, the 6Q tool taps situational variation in self-efficacy beliefs and interest. Of particular interest, however, are measures

TABLE 2 | Process data collected during the science learning period.

Theoretical focus	Specific construct	Data source	Sample *N*
Emotions Motivation Cognition Collaboration	For example: socio-emotional interaction, socially shared motivation, and emotion regulation	Video (Insta360 Pro camera, separate microphones)	7 sessions × 90 min × 30 groups = 212 h
Emotions	Physiological arousal and activation	Electrodermal activity (Shimmer3 GSR+)	7 sessions × 90 min × 84 students = 582 h
Outcome	Content knowledge	Fact test (Qridi)	7 × 94 = 289/376 responses*

Due to individual students' occasional absences from the lessons, the sum of the responses is lower than expected.

tapping emotional dimensions, as the 6Q tool guides the students to evaluate, in addition to the current emotional valence, how deactivating vs. activating they interpret the current emotional state. By providing data from two modalities of the emotional experience, the valence that separates positive emotions from negative ones, and the activation that relates emotions to physiological arousal and learning activity (Ben-Eliyahu and Linnenbrink-Garcia, 2013; Boekaerts and Pekrun, 2015), the 6Q tool establishes a mediating data source that connects and combines the other data sources to study the relationships between motivation, emotional states, and actualized motivation and emotion regulation in collaborative learning (Linnenbrink-Garcia et al., 2016).

To summarize, all the data modalities presented in **Tables 1–3** provide data that can be considered to contribute to motivation and emotion regulation in the context of collaborative learning, but they follow different theoretical, conceptual, and methodological assumptions, as well as differences in the granularity of the analysis unit or differences in temporal nature. While we have argued that multimodal data collected in an authentic context are needed to capture motivation, emotion, and their regulation in their natural environment, another question that arises is *how can we proceed with the varying data modalities*. The following case example demonstrates how we have begun to combine different data modalities with 6Q tool data and how they can be triangulated to obtain profound information related to the students' motivational and emotional conditions and variations throughout the learning session.

Figure 4 illustrates, with one learning session of a case group consisting of three students (one male, two female), how the general self-report data provide a means to understand students' trait-like motivational conditions (i.e., science interest and self-efficacy) that are present when they enter the collaborative learning situation, while the 6Q tool produces cumulative data on students' situation-specific experiences. In the case example, the group members' motivational conditions are heterogeneous; Student 1 self-reports her interest and self-efficacy regarding science to be high with means of 4.0 and 4.1, respectively, on a Likert scale from one to five, while Student 2 indicates they are low ($M = 1.8$ and 2.4, respectively), and Student 3 places himself on medium level ($M = 3.2$ and 3.3, respectively). Hence, motivational conditions for the case group's collaborative learning and socially shared regulation of motivation and emotion are different than if all the group members, for example, shared the same interest and efficacy level.

TABLE 3 | 6Q tool data components.

Theoretical focus	Specific construct	Data source	Sample *N*
Cognition	Task understanding and perceived task difficulty	6Q tool	7 sessions × 2 times/session × 94 students = 801/940 responses*
Emotion	Valence and activation	6Q tool	
Motivation	Situational interest	6Q tool	
Collaboration	perceptions of group work	6Q tool	

Due to individual students' occasional absences from the lessons, the sum of the responses is lower than expected.

Situated 6Q tool data capture students' situational emotional experiences (valence and activation) and task interest with a slider scale from 0–100. Thus, it not only sheds light on the situational motivational and emotional preconditions prior to each collaborative learning session but also reveals how these modalities change in the course of collaboration. In the case example, the students' situational emotional experiences and interest seem to correspond to their general motivational conditions regarding science learning at the beginning of the collaborative work. This is shown in their evaluations of emotional valence and activation, as well as interest, which are illustrated in **Figure 4**. Student 1, for example, seems to maintain the same positive evaluation in the situational level as she initially indicated in self-reports; her emotional state is fairly positive (64) and she is also fairly interested and activated (64 and 62, respectively). In turn, Students 2 and 3 are indicating negative valence (8 and 35, respectively) with medium level of activation (46 and 48, respectively) and interest (51 and 50, respectively). However, towards the end of the learning session, group members begin to evidence more variation, indicating that the collaborative work and interaction start to gradually influence their situational motivational and emotional interpretations (**Figure 4**). At the end of the collaboration, Student 1 indicates even more positive valence (87) with fairly high levels of activation (73) and interest (80). Student 2 shows a slight increase

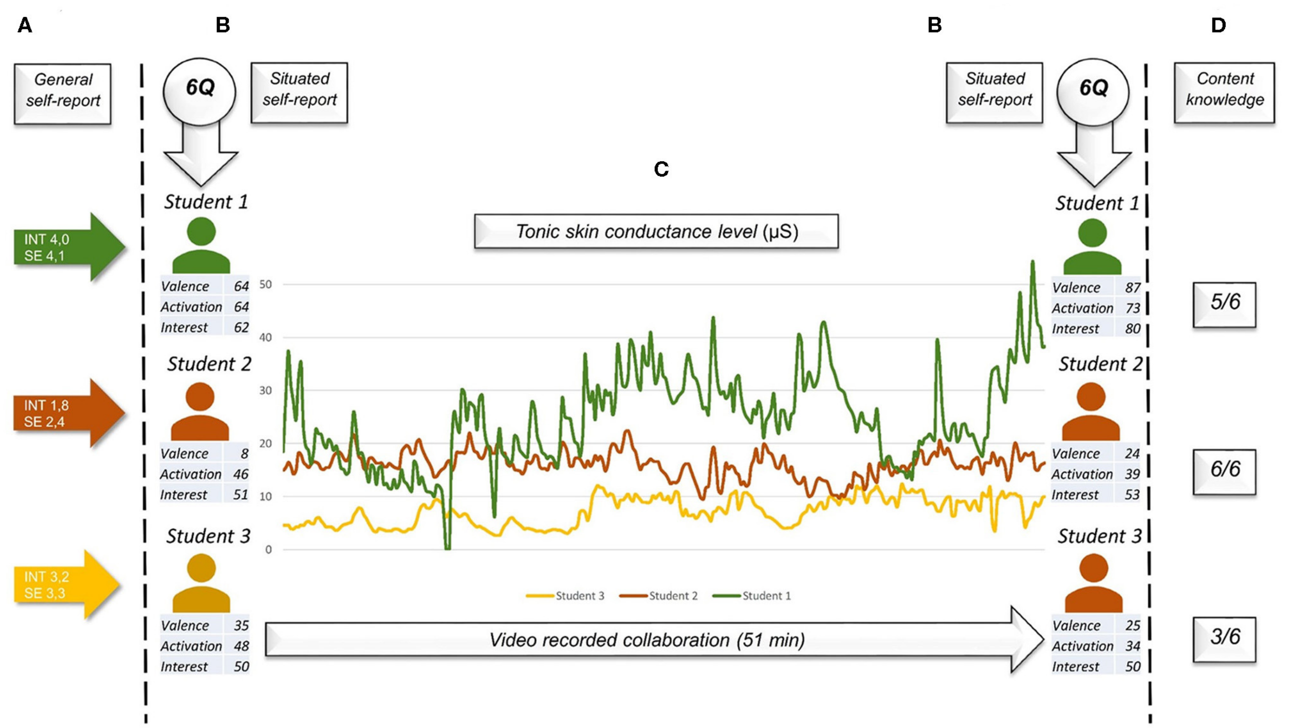

FIGURE 4 | A case example to illustrate how to combine data from different sources. The visualization includes students' **(A)** self-reported general science interest (INT) and self-efficacy (SE), **(B)** situated self-report data (6Q) of their emotional state (valence and activation) and task interest, **(C)** tonic skin conductance level during collaboration traced from EDA data, and **(D)** scores from the knowledge quiz completed after the lesson.

in valence from 8 to 24, whereas Student 3 has a slight decrease from 35 to 25, and both students remain in the medium levels of activation and interest. Thus, when aiming to understand and explain emotional and motivational effects on learning, more fine-grained process data are needed to capture contextual factors and situational variation during the learning process.

Next, the case example adds physiological data from each group member with their subjective general and situational appraisals. To obtain temporal online process data with high granularity, the students' emotional activation was measured with EDA. EDA data can be analyzed on both the individual and the group level, which provides possibilities for analyzing the socio-emotional aspects of collaborative learning. One dimension of the EDA measurement is the participants' slowly varying tonic skin conductance level (SCL) (Dawson et al., 2007; Boucsein, 2012). In the case example, EDA data during 51-min period of collaborative learning is presented for each student. The tonic SCL level of each student measured during collaboration is visible in colored lines in **Figure 4**. The example data was processed using MATLAB based software Ledalab (http://www.ledalab.de/). As the Shimmer3 GSR+ sensors produce data with the sampling rate of 128 Hz, the data was first down sampled into 16 Hz. The raw data was then decomposed into tonic and phasic components using continuous decomposition analysis (Benedek and Kaernbach, 2010b). The example shows that Student 1, who indicates a higher level of interest on the trait-type self-report and a high, increasing activation level related to her emotional state in 6Q, shows both a high maximum level of SCL (54 μS) and high variation in SCL within the session. The two other students' SCL range, however, follows the degree of variation defined as normal in prior research (2–20 μS; Dawson et al., 2007).

Another way to define students' arousal level is through the phasic short-term skin conductance response (SCR) peaks visualized in **Figure 5** by the green, yellow, and red boxes under the SCL lines. SCR peaks are strongly associated with emotional responses caused by an external stimulus and are more reactive to variation than SCL (Dawson et al., 2007; Christopoulos et al., 2016). In situations with continuous stimuli, such as collaborative learning, the frequency of SCRs can be used as an indicator of the current arousal state (Dawson et al., 2007; Blascovich et al., 2011; Braithwaite et al., 2013). In the case example, the data was first smoothed out using an adaptive Gaussian filter and SCRs were then detected using the classical trough-to-peak technique (Benedek and Kaernbach, 2010a). Next, the number of peaks in each 1-min segment was calculated to define student's level of arousal in each minute: at rest, a frequency of 1–3 peaks/min occurs (Dawson et al., 2007), and frequencies higher than 20 peaks/min are considered as high arousal (Boucsein, 2012). While the students' SCL level could be used to follow individual group members' physiological arousal (in relation to other members), the SCR peaks could be beneficial in, for example, locating emotionally relevant, short-term high-arousal

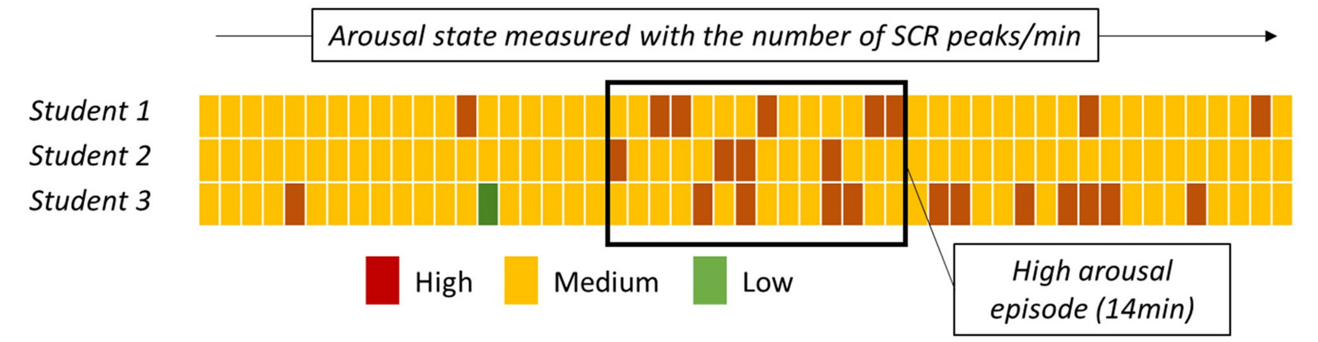

FIGURE 5 | The physiological arousal state (high, medium, low) of each student measured with the number of SCR peaks/min during the case example session. Each segment in the visualization corresponds to one minute of collaboration.

situations on a group level to be further investigated with qualitative data sources, such as video data, particularly when operating with a large amount of data. For example, in the case example, we would be interested in targeting the 14-min high-arousal episode to explore socioemotional interactions and possible challenges that could lead to the need for regulation and, further, actualized co- and socially shared motivation or emotion regulation.

To conclude, when studying motivation and emotion regulation via multimodal process data, each modality reveals a different motivational and emotional aspect influencing and shaping actualized motivation and emotion regulation, which is illustrated in **Figure 4**. The multimodal dataset can be used to explore the groups' learning process within one session as was mainly the case with the current example, but the real potential lies in the possibility to zoom in and out in terms of granularity, temporality, and cyclicity (Järvelä et al., 2019). Thus, multimodal (process) data afford opportunities to study emotion, motivation, and their regulation both within and across learning sessions, individuals, and collaborative groups. Individual learning patterns and paths can be cross-analyzed with their peers to unravel the role of different motivational and emotional factors in relation to social interaction, time, and other learning variables. Finally, multimodal data provide systematic ways to combine quantitative datasets with qualitative ones to profoundly analyze motivation, emotion, and their regulation as context- and situation-specific and as a part of the wider process of regulated learning.

DISCUSSION

Learning in technology-supported collaborative learning environments involves intricate, complex interactions among cognitive, metacognitive, motivational, affective, and social processes across specific tasks, topics, or domains, and learning contexts (Baker et al., 2013; Ludvigsen, 2016). Motivational and emotional hurdles seem to be particularly challenging to tackle in this complicated combination. Regardless of the profound advancement in theoretical understanding, many open questions concerning the multifaceted and situated function of "non-cognitive" aspects in collaborative groups' regulated learning remain unanswered (Järvenoja et al., 2018a). Emerging technologies offer opportunities to make these mental processes, such as the subjective experiences of affective reactions or motivational underpinnings or non-verbal emotional reactions, "visible" and, further, guide and support learners in becoming more conscious of the non-cognitive factors influencing their learning. As the possibilities of technology contribute to the understanding of the functioning of motivation and emotion in collaborative learning, more possibilities for technological tools to prompt and support the motivation and emotion regulation of collaborative learning also become available [e.g., Järvelä et al. (2015)].

In this paper, we have argued that an advanced understanding, particularly of motivation and emotion regulation and its various factors, is essential to harness the benefits of technology in supporting these processes in collaborative learning. Especially adolescent students who are yet developing abilities to function in the more demanding academic and social world (Gómez-Ortiz et al., 2016; Hollenstein and Lanteigne, 2018) can benefit from this type of support in learning situations. The dual aim of embedding the support of learning and regulation and data collection methods providing data on the fluctuating process of learning and interaction becomes concrete in the presented collaborative learning design. Our recommendation is to take both sides into account by providing support for learners while simultaneously collecting data on motivational and emotional aspects contributing to socially shared regulation processes. Accordingly, we highlight that both aspects should be addressed explicitly in the learning and research designs. From the research perspective, this provides possibilities for data collection that corresponds to educational change and, particularly, to a need for ecologically valid analyses and results related to regulation in collaborative learning (Belland et al., 2013; Wise and Schwarz, 2017; Järvenoja et al., 2018a). From the learner-support perspective it is essential to share the understanding of the role of regulation for collaborative learning with schools and teachers. The teachers are in a key role in implementing the collaborative learning designs and support in practice (Van Leeuwen and Janssen, 2019). To do that, they need information that is built on prior research evidence and justified theoretical assumptions focusing on the implementation of the collaborative learning designs. To build up premises for collaboration between researchers and teachers, we stress the importance of introducing descriptions of research designs and justifications behind the certain (practical) choices, as we have done in this article. Interdisciplinary regulated learning research is currently progressing (Azevedo and Gašević, 2019), and along with this progress, opportunities for understanding and promoting adaptive motivation and emotion develops. The use of multimodal learning process data could become new "channels" for identifying processes that have been impossible to achieve with conventional educational psychology research methods (Azevedo, 2015). For example, Dindar et al. (2019) studied regulation processes in the collaborative learning of physics through situated self-reports, physiological signals, and academic achievement. Their study showed that situated measures of motivation regulation predict academic achievement. Also, the between student concordance in self-reports of motivation, cognition, and behavior was found to be related to concordance in physiological signals. The results demonstrate the complexity of the relationships between SRL variables and show the potential value of physiological measures when studying learning processes. Similarly, a study conducted by Taub et al. (2019) demonstrates how multimodality can reveal the connections between emotions and the metacognitive aspects of regulation processes when students learn with the assistance of a hypermedia-based intelligent tutoring system. In their study, students' emotions were traced through automatic facial expression analysis and investigated in relation to the accuracy of students' self-reported monitoring judgments. The results of these and related studies increase the understanding of the value of emotions in the learning process. Also, Harley et al. (2019) gathered multimodal data covering the experiential and physiological components of medical students' emotions during a diagnostic reasoning task. In their study, they examined the relationships between students' self-reported habitual emotion regulation strategies, physiological activation measured through electrodermal activity (EDA), self-reported emotions and appraisals, and academic achievement. They found that the students' skin conductance level (SCL) positively predicted anxiety and shame, whereas skin conductance response (SCR) was associated with higher academic achievement. Furthermore, emotion regulation tendencies predicted physiological arousal during the learning situation.

Today, physiological devices are mostly used to track, for example, health-related information, but all of the abovementioned studies are examples of how researchers have used multimodal data to relate motivational and emotional process data to other learning components. While prominent empirical research exploring the possibilities of different types of data channels is emerging, [e.g., Haataja et al. (2018), Malmberg et al. (2019)], we are still in the process of discovering the relevant combinations of different data sources and proper ways to combine data from different channels to track learning. To trace motivation and emotion regulation from process data and to explain the conditions and products to which it is bound (Bakhtiar et al., 2018), we need data from different aspects of collaborative learning process and from individuals participating in collaboration in their natural learning environments. While multimodal and process-oriented approaches have started to emerge also in the field of learning sciences, researchers are faced with various challenges that come along. These challenges span from designing and conducting complex research design to the issues in analyzing complex, nested and time-bound data, which varies in granularity and source. In the field of learning science and among researchers engaged in process-oriented learning research, there is an on-going discussion on the need to share not only the successful results from empirical studies, but also to share in more detail the research designs and ideas for analyses (Harteis et al., 2018; Winne, 2019). To progress as a field, it is essential to share the premises of these researches, practical experiences, and overall designs that are all built on prior research evidence and justified theoretical assumptions. In addition, more extensive and interdisciplinary efforts are needed in basic research on emotion and motivation to reach the full potential of the available emerging technology and digitalization for human learning. If we manage to share our understanding more comprehensively, we can reach the potential of the unobtrusive multimodal data channels and transfer their power to tools that provide learners "on the fly" support when needed.

DATA AVAILABILITY STATEMENT

The datasets generated for this study will not be made publicly available. The dataset includes personalized data from minor participants. The research permission approved by the ethics committee delimits the use of data to the research group members.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Ethics Committee of Human Sciences, University of Oulu (https://www.oulu.fi/eudaimonia/node/19813). Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin. Written informed consent was obtained from the minor(s)' legal guardian/next of kin for the publication of any potentially identifiable images or data included in this article.

AUTHOR CONTRIBUTIONS

HJ, JM, and SJ were responsible for the theoretical, research-based aims of the research project, scientific design principles of the collaborative learning design, and data collection. They also hold the main funding of the research. KM, TT, EH, and SA were responsible for running the design and collecting the data. HJ was primarily responsible for structuring the manuscript, while TT was primarily responsible for the case example. All authors contributed to writing and editing, participated in designing the learning design, and planning the data collection process.

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Taking Affective Learning in Digital Education One Step Further: Trainees' Affective Characteristics Predicting Multicontextual Pre-training Transfer Intention

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The past decades have shown an accelerated development of technology-enhanced or digital education. Although an important and recognized precondition for study success, still little attention has been paid to examining how an affective learning climate can be fostered in online training programs. Besides gaining insight into the dynamics of affective learning itself it is of vital importance to know what predicts trainees' intention to transfer new knowledge and skills to other contexts. The present study investigated the influence of five affective learner characteristics from the transfer literature (learner readiness, motivation to learn, expected positive outcomes, expected negative outcomes, personal capacity) on trainees' pre-training transfer intention. Participants were 366 adult students enrolled in an online course in information literacy in a distance learning environment. As information literacy is a generic competence, applicable in various contexts, we developed a novel multicontextual transfer perspective and investigated within one single study the influence of the abovementioned variables on pre-training transfer intention for both the students' Study and Work contexts. The hypothesized model has been tested using structural equation modeling. The results showed that motivation to learn, expected positive personal outcomes, and learner readiness were the strongest predictors. Results also indicated the benefits of gaining pre-training insight into the specific characteristics of multiple transfer contexts, especially when education in generic competences is involved. Instructional designers might enhance study success by taking affective transfer elements and multicontextuality into account when designing digital education.

Keywords: affective learning, distance education, training, transfer of learning, multicontextual transfer, intention to transfer, information literacy

INTRODUCTION

This study, that took place within a distance learning environment, investigated to what extent five affective trainee characteristics influenced the students' pre-training intention to transfer new learning from an information literacy course to two contexts: their study and their work.

One of the major developments in the field of education over the last decades has been the digitization of education. Due to the development of educational technologies, we have witnessed the emergence of a variety of forms of, and tools for interactive, collaborative and personalized learning. Terms that are used to describe these new environments are, amongst others, web-based, blended, digital, online, and distance learning environments. This development not only offers opportunities to widen access to education but also to design new learning spaces and develop and use new digital and interactive tools to optimize the educational experience and effectiveness. To optimally use and take advantage of these achievements a deeper insight into the learning processes and learners' experiences within these digital environments is needed.

Our study was situated at the open university in the Netherlands, an institute that evolved from distance learning with paper study materials in the 1980s to an educational institute with personalized and activating online education. According to the hierarchy of Brindley et al. (2004) *online learning* is considered a subset of the overarching concept of *distance education*, characterized by the geographical separation between teachers and learners. As this gap was gradually regarded as a pedagogic shortcoming, the potential of online media to support and transform both teaching and learning in a variety of ways offered a means to bridge this separation (Bernard et al., 2004; Cunningham, 2017). Distance education distinguishes two major forms of instruction namely synchronous and asynchronous, although various blends exist also with face-to-face instruction. Synchronous means that students in a group are engaged in learning at the same time, much like the traditional face-to-face classroom, but not necessarily at the same place. Asynchronous education, having its roots in the traditional correspondence education, is individually based and time, place, and group independent. Respondents in our study, interchangeably referred to as students, learners, or trainees, participated in asynchronous learning with no direct physical or electronic contact with fellow students and mainly mail contact with their lecturers about their training assignments and results.

A recognized tool to design effective learning is Bloom's Taxonomy. It offers a hierarchical set of learning objectives in three domains: the cognitive domain including mental skills or knowledge, the sensory domain encompassing manual or physical skills, and the affective domain referring to feelings, attitudes, and emotions. In this study we have focused on the affective domain reflecting the learner's attitude toward the educational experience. This includes individual psychological aspects like attitudes, feelings, motivations, emotions, and values (Krathwohl et al., 1964). To facilitate learning in a face-to-face but also in an online learning environment it is considered important to foster a positive and motivating affective learning climate (Mazer et al., 2007) resulting in positive attitudes toward the training content, and lecturers and students who are feeling ready, able and motivated to participate in and successfully complete training. This also accounts for the subsequent step in the learning process namely the transfer of learning. Often interchangeably used with transfer of training, in this study it is more generally defined as the application of what has been learned to new situations (Testers et al., 2019). It has been studied for more than a century and is considered the *raison d'être* of education and an important indicator of the quality and success of the instructional design. On the other hand, research suggests that transfer of learning, especially in formal educational settings, is not self-evident. This paradox, also known as the transfer problem (Baldwin and Ford, 1988; Haskell, 2001), not only affects the quality of the education but also offers a poor return on investments in education. Baldwin and Ford (1988) have distinguished three domains of variables that might affect the transfer process: learner characteristics, training characteristics, and the organizational environment. A number of variables in the learner domain, including the ones that are used in our study, have an affective character and correspond with the individual aspects in the affective domain in Bloom's Taxonomy: motivation or willingness to learn, expectations about the outcomes of the learning process and the personal capacity, and psychological readiness to participate. While research on transfer recognizes the importance of affective learner characteristics for the transfer process (Huang et al., 2015; Leberman and McDonald, 2016) little is known about how to foster affective learning (Boelens et al., 2017; Gegenfurtner et al., 2019) and an affective transfer climate in distance education environments. And even less information exists about affective predictors of the learners' intention to transfer new learning and how to enhance their positive influence on the transfer process. Grounded in conceptual models in the transfer of training literature (Noe, 1986; Baldwin and Ford, 1988; Holton, 1996; Quesada-Pallarès and Gegenfurtner, 2015), this study intends to contribute to filling this gap and associate with a call for more research on the trainees' perception of the learning context and their personal experiences (Baldwin et al., 2017). It investigated to what extent the students' pre-training intention to transfer learning was influenced by five affective trainee characteristics.

Intention to Transfer

The best way to investigate the effect of a specific variable on the transfer process would be to look at the resulting transfer. Besides the fact that there is no consensus on when to speak of a successful transfer, certain circumstances might hamper this assessment. One can think of transfer of so-called *open skills*, as opposed to closed skills, of which the application is not uniform and depends largely on the specific context and needs, and the learners' creativity. Information literacy, the course the participants in this study were about to take, consisted of such open, complex higher-order cognitive skills (Brand-Gruwel et al., 2005; Reece, 2007). Furthermore, monitoring transfer might be problematic when it involves relative autonomous workers like the participants in this study. For these reasons, this study investigated the influence of five variables not on actual transfer, but on the students' pre-training intention to transfer.

Although often used interchangeably, in this study the concepts motivation and intention are considered successive steps in a motivational process (Al-Eisa et al., 2009; Quesada-Pallarès and Gegenfurtner, 2015) where the intention to transfer intermediates between motivation to transfer and transfer itself. Motives explain why people act in a specific way while Ajzen in his Theory of Planned Behavior Ajzen (1991) considers intentions to capture these motives and subsequently indicate 'how hard people are willing to try, how much of an effort they are planning to exert to perform the behavior. As a general rule, the stronger the intention to engage in a behavior, the more likely should be its performance' (Ajzen, 1991, p. 181). According to Gollwitzer (1993, p. 147) "forming intentions is functional in the sense that it helps to achieve respective outcomes and to perform relevant behaviors." Also the Goal-Setting Theory (Locke and Latham, 1990) and the Theory of Interpersonal Behavior (Triandis, 1980) consider intention a reliable predictor of behavior, including the transfer of training (Hutchins et al., 2013). Literature reviews show that the relationship between transfer variables and the intention to transfer new learning is largely missing from the literature (Cheng and Hampson, 2008; Hutchins et al., 2013). This study aims at contributing to filling this gap by investigating the influence of five independent variables on the dependent variable intention to transfer: learner readiness to transfer, motivation to learn, expected positive personal outcomes, expected negative personal outcomes, and personal capacity. It offers initial suggestions on how to enhance a positive affective transfer climate as an impetus to the design of strategies that are attuned to the specific study and work related conditions of their trainees.

Learner Readiness

Learner or intervention readiness can be defined as the extent to which trainees are psychologically ready to enter and participate in training. As a rule, one can say that a positive pre-training perception of the program will enhance the learner's preparedness to participate.

Research shows that learner readiness is a significant predictor of transfer of training and task performance (Ryman and Biersner, 1975; Hicks and Klimoski, 1987; Baldwin and Magjuka, 1991; Tannenbaum et al., 1991; Bates et al., 2007; Devos et al., 2007; Kulik et al., 2007; Bhatti et al., 2013). There is also evidence that learner readiness indirectly predicts transfer of training via its influence on the trainee's motivation to learn (Sanders and Yanouzas, 1983; Holton, 1996; Knowles et al., 1998).

Previous studies on transfer suggest various affective individual characteristics that may enhance or impede the learners' readiness and subsequently their transfer of training. It is for example important that a training program meets the learners' individual needs and expectations and is relevant to their performance. Other aspects that are mentioned are for example training reputation and the expectations about its quality. Maurer et al. (2003) noticed that prior participation in training was a predictor of the trainees' intention to participate in training.

Looking at these aspects learner readiness might be enhanced by involving learners already before the training in the instructional design process, for example by assessing their specific expectations and needs. This becomes more relevant but also more challenging in a globalizing world (Gegenfurtner et al., 2009) with the internationalization of education, and a tendency toward the personalization of learning in blended learning environments. This not only refers to the learners' diverse backgrounds or learning preferences. Baharim (2008) for example found that learner readiness significantly differed across age, where older trainees (>41 years.) showed more readiness to participate in training than younger ones. He suggested that they might target the training more toward their career development requirements than younger trainees. Pre-training framing might not only prove a useful tool to enhance the trainees' readiness to learn (Bates and Holton, 2004; Tai, 2006) but indirectly also their motivation to transfer (Ruona et al., 2002; Kirwan and Birchall, 2006; Devos et al., 2007). Instructional designers might, for example, offer a realistic preview of the training design, content end requirements and give learners a realistic impression of how the training will benefit their performance, in this case in their study and work context. Baldwin and Magjuka (1991) concluded that this, amongst others, leads to learners who have greater intentions to transfer and apply what they have learned back to their respective job settings.

In our study, the construct learner readiness has been operationalized in terms of the degree to which trainees are familiar with the training content, know how the training will improve their skills, and how it relates to their educational and professional development.

Motivation to Learn

The most important precondition for transfer of training is actual learning; without learning there will be nothing to apply. This makes the motivation to learn, also referred to as pre-training motivation, not only an important aspect of affective learning but also a pre-condition for transfer. In the literature motivation to learn may refer to a general desire to enrich one's knowledge and skills, and the consecutive aspiration to attend specific training. With a focus on the latter, we have defined motivation to learn as "the direction, intensity, and persistence of learning-directed behavior in training contexts" (Kanfer, 1991).

Extended research confirms that a learner's motivation preceding training is a critical precursor not only to cognitive and skill-based training outcomes but also to transfer motivation and to transfer itself (Noe, 1986; Tannenbaum et al., 1991; Facteau et al., 1995; Quinones, 1995; Chiaburu and Marinova, 2005; Tziner et al., 2007). Various intrinsic and extrinsic individual and situational characteristics have been mentioned as predictors of training motivation, for example, self-efficacy, job involvement, learner readiness, familiarity with the training content and expected outcomes and utility (Jackson, 2014), age and work environment (Noe and Schmitt, 1986; Baldwin and Magjuka, 1991; Mathieu et al., 1992; Facteau et al., 1995; Kontoghiorghes, 2002). Also, the status of training is considered an important predictor. Although we learn from previous studies that attending on their own volition enhances the trainees' motivation to learn (Hicks and Klimoski, 1987; Baldwin and Magjuka, 1991; Mathieu et al., 1992; Clark et al., 1993) also a mandatory training might increase training motivation (Baldwin and Magjuka, 1991; Rynes and Rosen, 1995; Cotterchio et al., 1998; Tsai and Tai, 2003; Gegenfurtner et al., 2016) when mandatory is considered an expression of the relative importance of the training to an organization or if attitudes toward the training, based on pre-training hearsay or personal experiences (Facteau et al., 1995), are very favorable. Additionally, Baldwin and Magjuka (1991) point to the degree of choice of training content as an important variable, rather than the choice of attending.

In our survey, we have measured the students' pre-training motivation to participate in the training by asking them to what extent they consider this training important for their study and work, if they expect that the training will improve their performance in both contexts, and if not attending would feel like a missed opportunity.

Expected Positive and Negative Personal Outcomes

Personal outcomes are the personal consequences of specific behavior, in this case, the application of new knowledge and skills to new situations. These outcomes can be positive as well as negative. Building on Rouiller and Goldstein (1993) and Vroom (1964) effort-performance and performance-outcome perceptions as causes of behavior Holton et al. (1997, 2000) defined positive personal outcomes as "the degree to which applying training on the job leads to outcomes that are positive to the individual." These outcomes may include intrinsic and extrinsic incentives like increased personal satisfaction and growth opportunities (Facteau et al., 1995), increased productivity and work effectiveness, additional respect, salary increase or other rewards, the opportunity to further career development or to advance in the organization (Bates et al., 2012), verbal praise and bonuses (Xiao, 1996), higher performance evaluations (Facteau et al., 1995), and increased job security (Cheng, 2000). Positive personal outcomes are considered a significant predictor of perceived training transfer (Clarke, 2002; Ruona et al., 2002; Bates et al., 2007), of the learners' motivation to learn (Noe, 1986; Facteau et al., 1995; Cheng, 2000), and of their motivation to transfer (Ruona et al., 2002; Nijman, 2004). According to Holton et al. (2000) supervisor support "serves as a reward to employees by signaling to them that their learning application efforts are viewed positively." Perceiving appraisal support by supervisors and also peers before and after training, be it informational, instrumental or emotional, will enhance a belief in the relevance and applicability of the training and in the opportunities to apply new learning which, in turn, might lead to higher transfer outcomes (Nijman, 2004). In our pre-training study, we asked students if they think they should receive positive reactions when applying new learning, and if this should lead to rewards and positive performance evaluations, both in their study and work context.

Negative personal outcomes are the negative consequences for trainees of using (Rouiller and Goldstein, 1993) or not using learned knowledge and skills. In our study, we have focused on the latter and defined negative outcomes as the extent to which individuals believe that not applying skills and knowledge learned in training will lead to negative outcomes (Holton et al., 2000). These negative consequences, by Rouiller and Goldstein (1993) labeled as punishment and negative or no feedback, might include reprimands when not using new knowledge or skills on the job, penalties, peer resentment, reassignment to undesirable jobs, or reduced opportunities for a further job or career development or salary raises (Khasawneh et al., 2006). The limited research that is available on this construct (Nijman, 2004; Katsioloudes, 2015) shows that peer and supervisor support can be strong predictors of negative personal outcomes; the stronger the pre- and post-training support by peers and supervisors, the stronger their negative reactions for not using new learning (Nijman, 2004). While at the same time these negative reactions by peers or supervisors may increase the learners' motivation to transfer (Ruona et al., 2002). In our survey, we have asked students if they think that not applying new learning will result in negative responses, negative performance evaluations, and criticism.

Personal Capacity

In their Learning Transfer System Inventory (LTSI) Holton et al. (2000) address the ability to apply learning to the job by two elements: personal capacity and opportunity to use. Personal capacity is defined as the "extent to which individuals have the time, energy and mental space in their work lives to make changes required to transfer learning to the job" (Holton et al., 2000, p. 344). Studies using the LTSI model suggest that this construct is a significant predictor of transfer of training (Bates et al., 2007; Frash et al., 2010). This model also indicates an indirect influence on the transfer of training via motivation to transfer. Kirwan and Birchall (2006) underline the importance of both personal capacity and motivation for the realization of two key characteristics of transfer namely generalization and maintenance.

Looking at attributes associated with personal capacity a lack of time has been found to inhibit the transfer of new learning (Awoniyi et al., 2002; Clarke, 2002; Cromwell and Kolb, 2004; Gilpin-Jackson and Bushe, 2007) while low workload pressure was positively correlated to transfer (Awoniyi et al., 2002). Aspects of personal capacity may have been labeled differently for example as workload (Russ-Eft, 2002), work schedule, personal energy, and stress level (Bates and Holton, 2004), self-management (Richman-Hirsch, 2001), and dealing with situational constraints (Olivero et al., 1997). Also, variables at an individual level like age and gender may affect personal capacity (Velada et al., 2009).

Not surprisingly there is a strong relationship between personal capacity and the given opportunity to perform or apply new learning within a specific educational or organizational context in terms of "adequate equipment, information, human and financial resources, materials, and supplies" (Holton et al., 2007, p. 394). Within our study we have operationalized personal capacity by asking learners to what extent they had other obligations or life events that might prevent them from attending the training as intended, and to what extent they expected that work pressure and a lack of time might prevent them from practicing their newly gained competences. In the pre-training context of our study no learning and therefore no actual transfer had yet taken place. Research however shows that during and after learning personal capacity, that is closely related to Ajzen's perceived behavioral control, may not only influence transfer via intention but can also mediate the relationship between intention and actual transfer.

In our study transfer of training, and thereby also the development of the intention to transfer, is considered a process that does not only takes place during a post-training test but that starts already before and also continues after an intervention (Baldwin et al., 2009; Sitzmann and Weinhardt, 2018). Education typically focuses on transfer at one point in time, mostly directly after training when the students' knowledge, comprehension, and retention are tested (Blume et al., 2010). Educational designers also tend to concentrate predominantly on the training program when designing training for transfer. Research, however, shows that already before entering training specific conditions might enhance or inhibit the students' transfer of training (Holton et al., 2000; Naquin and Holton, 2003). To complement previous research this study has asked students which affective trainee characteristics from the transfer literature already before the course influenced their intention to transfer prospective learning.

Furthermore, transfer of learning is generally measured within one specific context, mostly education or work. The distance learning students who participated in this research were studying beside their educational work and were starting a course in information literacy. This generic competence is not only useful in the context of their study but also in their educational work context. Our study, therefore, extends previous research by investigating the students' intention to transfer to both their study and work context in one study.

RESEARCH QUESTION AND HYPOTHESES

This study aimed at supporting the design of digital educational interventions that enhance the transfer of learning to multiple contexts by estimating the extent to which five affective learner characteristics predicted intention to transfer: learner readiness, motivation to learn, expected positive personal outcomes, expected negative personal outcomes, and personal capacity. Complementing previous literature (Testers et al., 2019) the present study adds a new aspect to transfer research by comparing two different transfer contexts within one single study: Study and Work.

This resulted in the central question: How are affective learner characteristics from the transfer literature associated with the intention to transfer training to the participants' study and work contexts? We hypothesized positive relationships of learner readiness (Hypothesis 1), motivation to learn (Hypothesis 2), positive personal outcomes (Hypothesis 3), negative personal outcomes (Hypothesis 4), and personal capacity (Hypothesis 5) on the intention to transfer. No hypotheses were formulated on the expected differences in these relationships for the Study and the Work contexts as very limited previous research exists on multicontextual transfer.

MATERIALS AND METHODS

Participants

In this study, we have questioned 366 adult students in their first year of the premaster Learning Sciences at the Open University of the Netherlands. Most of the students were teaching in primary, secondary and higher education and studied at the Open University beside their work. **Table 1** shows the demographic characteristics of the participants, more specifically their gender, age, years of work experience, and work type. Differences in variable scores between female and male participants were statistically non-significant ($p > 0.05$).

Training Program and Procedure

To prepare them for their study, the participants were about to start a mandatory web-based course *Information Literacy for Social Scientists* (4,3 ECTS) (Wopereis et al., 2016). This training program was based on the Four-Component Instructional Design (4C/ID) model (Van Merriënboer and Kirschner, 2018), which included five authentic tasks each with varying a level of support (Brand-Gruwel et al., 2009), and performance feedback. One of the tasks was: "Write a blog post of about 400 words about the article that you have critically studied. Write a summary of 200 words and a critical examination of 200 words. In doing so use the guidelines for paraphrasing, citing, and referring correctly." After the students were informed about the aim and content of the program but before they started with their first task, students

TABLE 1 | Demographic characteristics of the study participants.

Variable	Frequency	Percentage
Gender		
Female	284	77.60
Male	82	22.40
Age		
<25 years	70	19.13
25–35 years	119	32.51
36–45 years	100	27.32
46–55 years	64	17.49
56–65 years	13	3.55
Work experience		
<2 years	61	16.67
2–5 years	76	20.77
6–10 years	100	27.32
>10 years	129	35.25
Work type		
Permanent position	277	75.68
Temporary position	47	12.84
Temporary employment agency	18	4.92
Freelancer	14	3.83
Voluntary work	10	2.73

Total sample size is N = 366.

filled out a questionnaire that was integrated into the electronic course as Task 0. Before taking the survey all students were informed that their responses would be used exclusively for this research and that their personal data and responses would be treated confidentially and with utmost care.

Measures

A multi-item web-based online survey was used to collect the data. The authors used a novel design in which each question was related to both the participants' Study and Work environment (Testers et al., 2019). The questionnaire used a 7-point Likert scale, ranging from 1 (*do not agree at all*) to 7 (*totally agree*). The dependent variable was the intention to transfer while the five independent variables were learner readiness, motivation to learn, positive personal outcomes, negative personal outcomes, and personal capacity. For reasons of comparability, the same number of variables and items were used for both the Study and Work context. **Table 2** shows per scale the number of items, the reliability coefficient (Cronbach's Alpha), and an example item for both the Study and the Work context.

Data Analysis

Initial screening of the data (cf. Kline, 2015) showed linearity, heteroscedasticity, univariate and multivariate normality, and no multivariate outliers. Missing data appeared to be missing at random and was treated with EM imputation (Allison, 2003). With several exploratory factor analyses (ML extraction, Oblimin rotation) the structure of the items of all six constructs was investigated separately for the Study and Work context. To achieve a clear and unambiguous structure several items from the original item set were removed (cf. Thurstone, 1947). **Tables 3**, **4** show the final results with the same six factors for both transfer contexts. In both contexts, the total variance explained confirms the utility of the model: 76.01% for the Study context and 76.52% for the Work context.

Structural Equation Modeling (EQS version 6.3) was used to test the model of **Figure 1**. For both the Study and Work context a "hybrid MRA model" was used, incorporating a confirmatory factor analysis, and a MRA model for measuring direct causal effects. To measure to what extent the hypothesized model fitted the research data five goodness-of-fit indices were used: χ^2 to measure absolute fit, Comparative Fit Index (CFI), Incremental Fit Index (IFI), Standardized Root-Mean Square Residual (SRMR), and the Root-Mean Square Error of Approximation (RMSEA). In line with the recommendations of Hu and Bentler (1999) the cut-off criteria for acceptable model fit were: CFI >0.95, IFI >0.95, SRMR <0.08, and RMSEA <0.06.

RESULTS

The study intended to investigate to what extent the trainees' pre-training intention to transfer was influenced by learner readiness (Hypothesis 1), motivation to learn (Hypothesis 2), positive personal outcomes (Hypothesis 3), negative personal outcomes (Hypothesis 4), and personal capacity (Hypothesis 5) in both their Study and Work context. **Table 5** presents the means, standard deviations, reliability estimates, and intercorrelations amongst all six constructs.

In both contexts the six-factor model generated an acceptable fit. **Table 6** shows the psychometric properties. In the Study context the X^2 was 207.69 (df = 120), CFI = 0.97, IFI = 0.97, SRMR = 0.05, and RMSEA = 0.05 (90% CI = 0.04, 0.06). In the transfer context Work, the X^2 was 252.34 (df = 120), CFI = 0.96, IFI = 0.96, SRMR = 0.05, and RMSEA = 0.06 (90% CI = 0.05, 0.07). These estimates suggest an acceptable and comparable model fit for both contexts.

TABLE 2 | Number of items, reliability estimates, and example items of all scales.

Scales	Items	α	Example
Dependent variable			
Intention to transfer	3 (study)	0.94 (study)	I intend to apply the newly gained competences in my study
	3 (work)	0.96 (work)	I intend to apply the newly gained competences in my work
Independent variables			
Learner readiness	3 (study)	0.79 (study)	Prior to this course I know how the program is supposed to affect my information literacy in my study
	3 (work)	0.81 (work)	Prior to this course I know how the program is supposed to affect my information literacy in my work
Motivation to learn	3 (study)	0.82 (study)	I attend the course because I think it will improve my performance in my study
	3 (work)	0.77 (work)	I attend the course because I think it will improve my performance in my work
Personal outcomes pos.	3 (study)	0.73 (study)	I should receive positive reactions if I apply the newly gained competences from this course in my study
	3 (work)	0.83 (work)	I should receive positive reactions if I apply the newly gained competences from this course in my work
Personal outcomes neg.	3 (study)	0.82 (study)	I expect to be criticized if I do not utilize the newly gained competences in my study
	3 (work)	0.84 (work)	I expect to be criticized if I do not utilize the newly gained competences in my work
Personal capacity	3 (study)	0.87 (study)	At the moment there are other commitments or events in my life that prevent me from doing this course the way it should be done.
	3 (work)	0.92 (work)	

TABLE 3 | Factor loadings of all scales in the transfer contexts *Study* and *Work*.

	Transfer context: *Study*						Transfer context: *Work*					
	Factor 1	**Factor 2**	**Factor 3**	**Factor 4**	**Factor 5**	**Factor 6**	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**	**Factor 5**	**Factor 6**
Learner readiness	−0.014	0.023	0.708	0.037	−0.002	−0.053	0.038	−0.021	0.033	0.662	−0.161	0.013
	−0.029	−0.040	0.862	−0.034	−0.002	0.057	−0.038	−0.003	−0.006	0.824	0.155	−0.026
	0.120	0.009	0.623	0.065	0.104	−0.020	0.104	0.037	−0.055	0.711	0.167	0.053
Motivation to learn	0.019	−0.028	0.037	0.015	0.759	−0.016	0.090	−0.019	0.027	0.070	0.804	0.072
	−0.053	0.029	−0.001	−0.041	0.800	−0.014	0.159	0.017	−0.080	0.173	0.706	0.085
	0.103	−0.014	0.052	0.056	0.680	0.059	−0.013	−0.019	0.071	−0.064	0.501	0.008
Personal outcomes positive	−0.069	0.009	0.036	−0.046	−0.041	0.801	−0.076	0.060	−0.007	0.012	−0.027	0.804
	0.089	0.000	−0.091	0.167	0.205	0.460	0.084	−0.001	0.003	0.023	0.160	0.704
	0.108	0.023	−0.038	0.070	0.010	0.646	0.071	0.005	0.125	−0.007	0.004	0.721
Personal outcomes negative	−0.013	0.035	−0.010	0.785	0.034	−0.065	0.061	0.036	0.833	0.023	0.032	−0.028
	0.008	0.016	0.020	0.843	−0.059	0.115	0.072	0.062	0.888	−0.032	0.036	−0.030
	−0.003	−0.044	0.044	0.698	0.008	0.011	−0.032	−0.090	0.579	0.008	−0.015	0.155
Personal capacity	−0.022	0.612	0.135	−0.090	0.003	0.084	−0.147	0.412	0.142	0.076	0.087	−0.072
	0.006	0.905	−0.061	0.064	−0.005	−0.019	0.035	0.896	−0.076	−0.014	−0.057	0.123
	0.004	0.884	−0.095	0.042	0.003	−0.054	0.114	0.944	−0.064	−0.075	−0.073	0.056
Transfer intentions	0.960	−0.011	0.046	0.018	−0.045	−0.033	0.905	−0.033	0.067	0.079	0.031	−0.017
	0.819	−0.047	−0.057	−0.039	0.125	0.054	0.861	0.001	0.031	−0.047	0.115	0.059
	0.965	0.030	0.036	−0.004	−0.042	0.003	0.919	0.004	0.016	0.064	−0.016	−0.006

TABLE 4 | Explained total variance of factors in the transfer contexts *Study* and *Work*.

	Transfer context					
	Study			*Work*		
Factor	**Eigenvalue**	**% of variance**	**Cumulated%**	**Eigenvalue**	**% of variance**	**Cumulated %**
1	5.19	28.81	28.81	5.71	28.90	28.90
2	2.59	14.38	43.19	2.43	11.14	40.03
3	2.13	11.82	55.01	2.01	11.09	51.13
4	1.50	8.33	63.34	1.71	7.76	58.89
5	1.16	6.45	69.79	1.17	4.40	63.29
6	1.12	6.22	76.01	0.95	4.23	76.52

The model parameter estimates of the structural relations among factors for the Study and Work contexts are presented in **Figures 2**, **3**. In the transfer context Study, intention to transfer was positively predicted by motivation to learn ($\beta = 0.48$, $p < 0.01$), personal outcomes positive ($\beta = 0.13$, $p < 0.01$), personal outcomes negative ($\beta = 0.13$, $p < 0.01$), and learner readiness ($\beta = 0.10$, $p < 0.01$); the relationship between personal capacity and intention to transfer ($\beta = -0.15$) was statistically non-significant. In the transfer context Work, intention to transfer was predicted by motivation to learn ($\beta = 0.34$, $p < 0.01$), personal outcomes positive ($\beta = 0.30$, $p < 0.01$), and learner readiness ($\beta = 0.30$, $p < 0.01$); the relationship of intention to transfer with personal capacity ($\beta = 0.02$) and personal outcomes negative ($\beta = -0.11$) were statistically non-significant.

A comparison between the two transfer contexts Study and Work showed different model parameter estimates between the independent and dependent variables. **Table 7** presents the differences between beta coefficients for all variables. The highest difference emerged for Personal Outcomes Negative (Study context: $\beta = 0.13$, Work context: $\beta = -0.11$, $\Delta = 0.24$) followed by Learner Readiness (Study context: $\beta = 0.10$, Work context: $\beta = 0.30$, $\Delta = 0.20$), Personal Capacity (Study context: $\beta = -0.15$, Work context: $\beta = 0.02$, $\Delta = 0.17$) and Personal Outcomes Positive (Study context: $\beta = 0.13$, Work context: $\beta = 0.30$, $\Delta = 0.17$), and finally Motivation to Learn (Study context: $\beta = 0.48$, Work context: $\beta = 0.34$, $\Delta = 0.14$). These analyses tend to indicate the benefits of examining multiple transfer contexts when estimating learners' characteristics predictors of intention to transfer.

DISCUSSION

This study has explored learning processes in digital education, more specifically how to foster an affective learning climate in a distance education environment that enhances the learners' intention to transfer new learning We consider the transfer or application of new learning a key aspect of learning processes

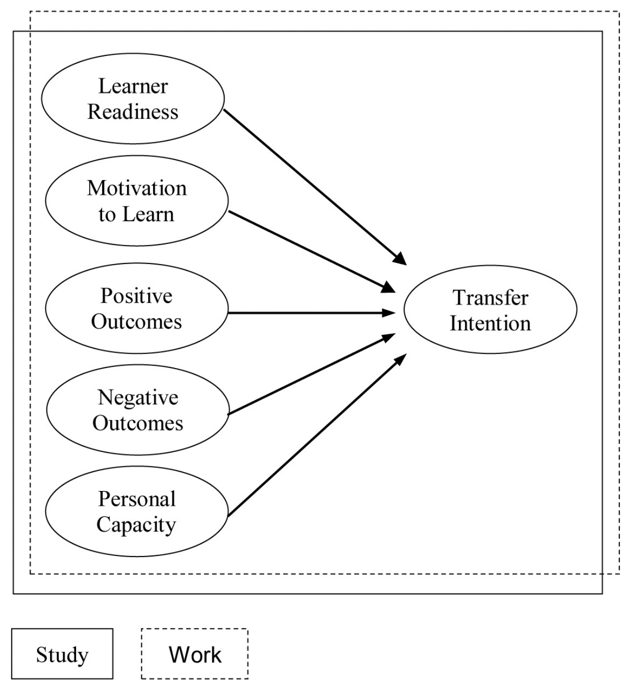

FIGURE 1 | Hypothesized relationships in the transfer contexts *Study* and *Work*.

and an essential indicator of study success. Complementing sparse research on the intention to transfer learning within distance education settings we have investigated trainees' pre-training perceptions of the importance of five affective trainee characteristics for their intention to transfer new learning to their Study and their Work context.

Previous literature indicates that transfer of learning in educational settings is not only happening during post-training tests. It is a process that is influenced by a variety of factors not only during but also before and after a training program. The first finding of our pre-training study confirms that already before the actual training several variables, in this case, five affective learner characteristics may influence the learners' intention to transfer new learning. Educational designers might take this into account when creating affective learning climates that facilitate the transfer of new learning.

The second finding of our study is that there is a difference between the beta coefficients for both transfer contexts. This indicates that a multicontextual perspective might be appropriate when designing education of generic competences for transfer. Looking at the relative importance of the five variables to the trainees' intention to transfer new learning we noticed that in the Study context motivation to learn (β = 0.48, Hypothesis 2), personal outcomes positive (β = 0.13, Hypothesis 3), personal outcomes negative (β = 0.13, Hypothesis 4), and learner readiness (β = 0.10, Hypothesis 1) positively predicted transfer intention while its relationship with personal capacity (β = −0.15, Hypothesis 5) was non-significant. In the transfer context Work we found that intention to transfer was significantly predicted by motivation to learn (β = 0.34, Hypothesis 2), personal outcomes positive (β = 0.30, Hypothesis 3), and learner readiness (β = 0.30, Hypothesis 1) while personal capacity (β = 0.02, Hypothesis 5), and personal outcomes negative

TABLE 6 | Goodness-of-fit indices of the structural models in the transfer contexts *Study* and *Work*.

	Transfer context	
	Study	***Work***
X^2 (df)	207.96 (120)	252.34 (120)
CFI	0.97	0.96
IFI	0.97	0.96
SRMR	0.05	0.05
RMSEA (90% CI)	0.05 (0.04; 0.06)	0.06 (0.05; 0.07)

TABLE 5 | Correlation matrix of all variables.

	M	SD	1	2	3	4	5	6	7	8	9	10	11	12
Transfer context: *Study*														
1. Learner readiness	4.75	1.48	(0.79)											
2. Motivation to learn	5.70	1.26	0.44**	(0.82)										
3. Personal outcomes positive	5.15	1.51	−0.03	0.35**	(0.73)									
4. Personal outcomes negative	4.86	1.87	0.12*	0.42**	0.45**	(0.82)								
5. Personal capacity	2.89	1.65	−0.53	−0.06**	0.11*	0.00	(0.82)							
6. Transfer intention	6.53	0.84	0.24**	0.57**	0.36**	0.42**	−0.21**	(0.94)						
Transfer context: *Work*														
7. Learner readiness	4.19	1.48	0.79**	0.34**	−0.05	0.09	−0.02*	0.15*	(0.81)					
8. Motivation to learn	3.91	1.83	−0.12*	−0.46**	−0.13*	−0.07	0.01	−0.1**	−0.32**	(0.77)				
9. Personal outcomes positive	4.23	1.82	0.05	0.27**	0.47**	0.19**	0.10	0.17**	0.18**	−0.47**	(0.83)			
10. Personal outcomes negative	2.30	1.45	0.03	0.15*	0.23**	0.20**	0.16**	−0.04	0.11*	−0.46**	0.44**	(0.84)		
11. Personal capacity	3.24	1.84	0.07	0.13*	0.17**	0.14*	0.61**	−0.05	0.04	0.03*	0.24**	0.11	(0.78)	
12. Transfer intention	4.96	1.77	0.27**	0.36**	0.06	0.04	−0.06	0.31**	0.47**	−0.45**	0.55**	0.16**	0.08	(0.96)

*Cronbach's alpha estimates in brackets on the diagonal. *p < 0.05, **p < 0.01.*

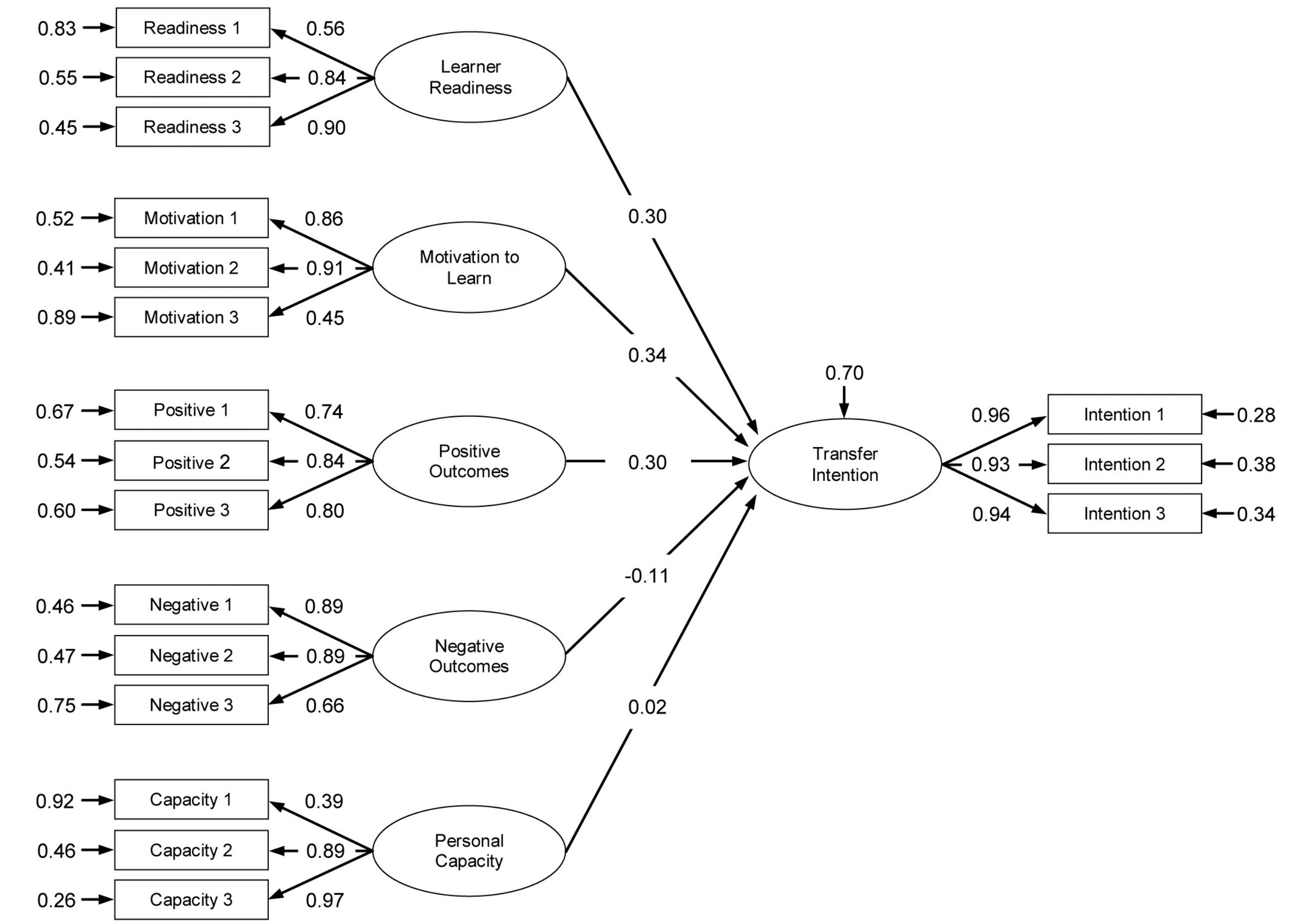

FIGURE 2 | Measurement and structural model parameter estimates of transfer context: Study.

($\beta = -0.11$, Hypothesis 4) were statistically non-significant. These findings indicate that transfer enhancing or impeding conditions within these contexts may differ and that it might prove beneficial for educational designers to adopt a multicontextual perspective, especially when it involves generic competences like information literacy that can be used in, or are specifically meant for multiple transfer contexts. Course designers might inventory and discuss these context-specific transfer conditions during the training and stimulate trainees' reflections on how to create and foster their personal optimal affective transfer climate.

Looking at the results in more detail we see that motivation to learn was the strongest predictor of transfer intention in both contexts, although stronger in the Study than the Work context. This might not come as a surprise as the framing of the training, mandatory and given at the very beginning of the premaster, might be considered an indication that this training must be important to the students' study success, which in turn will enhance their motivation to learn. The results also confirm findings from previous studies where the learners' pre-training motivation to learn is considered a critical precursor not only of cognitive and skills-related learning outcomes but also of transfer motivation and in effect of transfer itself (Noe, 1986; Tannenbaum et al., 1991; Facteau et al., 1995; Quinones, 1995; Chiaburu and Marinova, 2005; Tziner et al., 2007). Without initial learning, there will be nothing to transfer. This makes the enhancement of this affective learner characteristic all the more important. From the literature, we learn that various intrinsic and extrinsic individual and situational factors may influence the trainees' pre-training motivation to learn and to transfer, including age and work environment (Noe and Schmitt, 1986; Baldwin and Magjuka, 1991; Mathieu et al., 1992; Facteau et al., 1995; Kontoghiorghes, 2002; Jackson, 2014). In our study motivation to learn referred to the trainees' motivation to participate in and learn from the specific training in information literacy they were about to take, not to their motivation to learn in general. To support the motivation process educational designers might involve trainees when designing the training content, for example by offering the opportunity for students to use cases from their daily practice for their assignments. It is also important to communicate before the start of the training the content and expected outcomes and their utility for contexts relevant to the students. This appears to be more important for adult learners, the participants in our research. Training that meets their specific

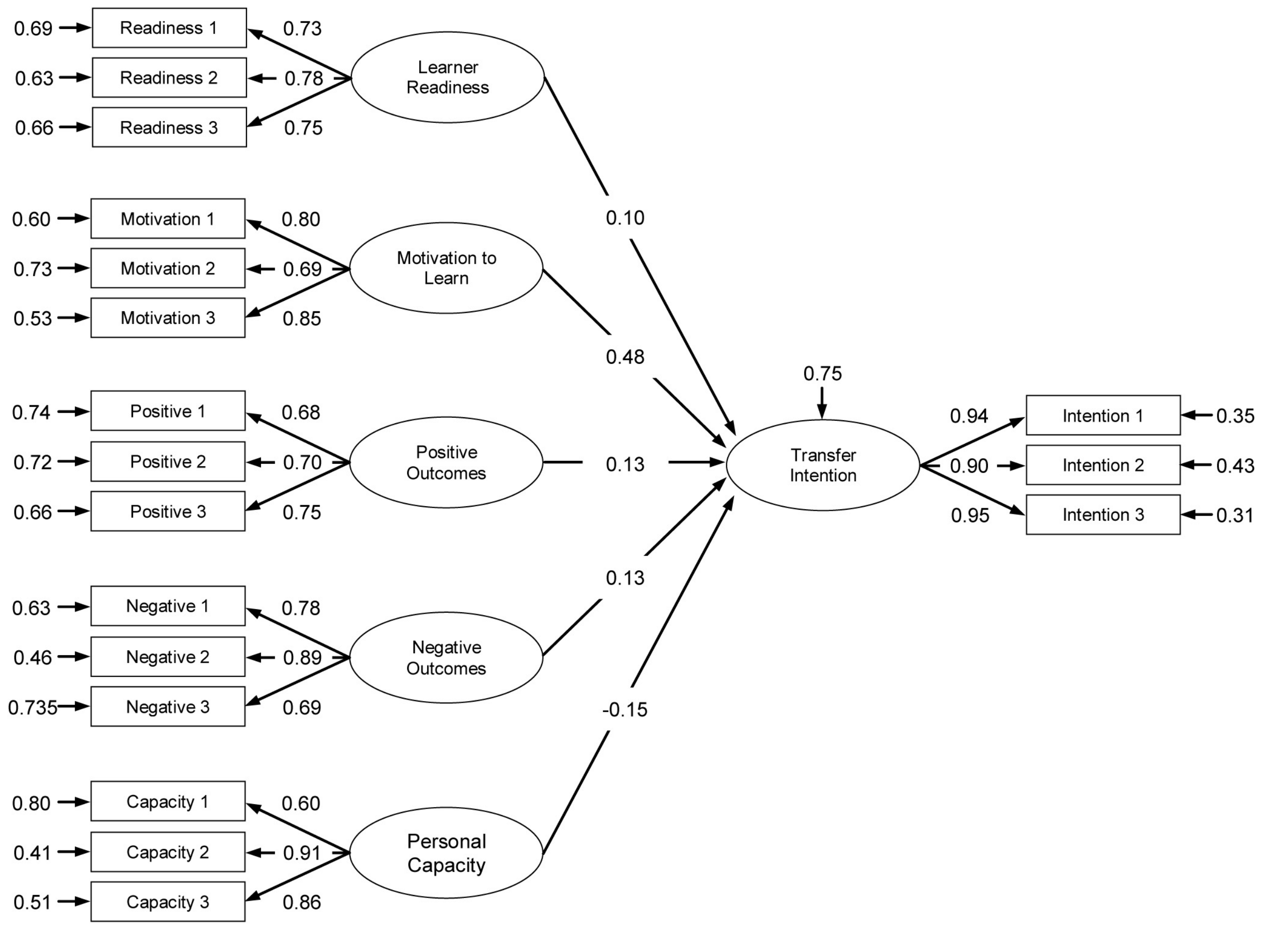

FIGURE 3 | Measurement and structural model parameter estimates of transfer context: Work.

needs for practical applicability not only predicts learning, as confirmed by adult learning theories (Wlodkowski and Ginsberg, 2017) but also transfer of learning (Leberman et al., 2006; Nafukho et al., 2017). The fact that this training is mandatory and situated at the very beginning of the trainees' pre-master Learning Sciences could be presented as indicators of its importance. Future research might complement existing studies on the effect of voluntary and mandatory training participation on the transfer process (Gegenfurtner et al., 2016), including on motivation to learn and on the intention to transfer. Also, learner readiness, another affective learner characteristic from this study, proved to be a significant predictor of transfer intention, although more in the Work than in the Study context. This might be explained by the fact that in the Study context learner readiness should not be an issue as students who started the training were, or at least were supposed to be, ready to apply new learning in their assignments. In the Work context application of new learning was not self-evident or immediately required but more a personal choice, which would make feeling ready more relevant. Previous research shows that learner readiness might indirectly affect the actual transfer of training via its influence on motivation to learn (Holton, 1996; Sanders and Yanouzas, 1983; Knowles et al., 1998). Already before the actual start of the training learner readiness, and consequently transfer itself, can be enhanced in various ways. Training might focus on more generalizable principles that can be customized according to specific context requirements. Trainees can for example also be involved in the instructional design process, offering them opportunities to express their specific needs and expectations before and during the training. This would be in line with the contemporary attention for the learner's uniqueness, resulting in a more personalized way of teaching and learning. Another way to enhance learner readiness, and also their motivation to learn and intention to transfer, would be pre-training framing. A positive pre-training perception of the program will enhance the trainees' preparedness to attend the training. This can be achieved by offering a realistic preview of the training, for example by communicating what can be expected in terms of content, quality, and relevance to the trainees' transfer contexts. Knowing what to expect and how they will be supported during the training might enhance the learners' self-efficacy and thereby indirectly their readiness to attend the training.

Previous studies on transfer show that also expected positive and negative personal transfer outcomes may predict the trainees' motivation to learn (Noe, 1986; Facteau et al., 1995; Cheng, 2000),

TABLE 7 | Comparison of beta coefficients between the two transfer contexts *Study and Work*.

Influence on intention to transfer	Transfer context		
	Study	**Work**	**Δ**
Learner readiness	0.10	0.30	0.20
Motivation to learn	0.48	0.34	0.14
Personal outcomes positive	0.13	0.30	0.17
Personal outcomes negative	0.13	-0.11	0.24
Personal capacity	-0.15	0.02	0.17

as well as their motivation to transfer (Ruona et al., 2002; Nijman, 2004) and actual transfer (Clarke, 2002; Ruona et al., 2002; Bates et al., 2007). The respondents in our study considered expected positive personal outcomes relevant for their intention to transfer new learning in both their Study and Work context. This can be expected for their Study context as the proper use of new learning will lead to increased effectiveness and positive performance evaluations. But trainees considered positive outcomes more relevant in their Work context. This despite the fact that they worked relatively autonomous and that using new learning from this one specific training in their work might not be noticed by peers and supervisors. One explanation might be that, working mainly as lecturers and tutors, newly gained information literacy competencies might be considered useful for their educational activities as well as for their personal development, for example when searching for high-quality information to stay up-to-date in their profession. The effect of expected negative outcomes on the trainees' intention to transfer was only significant in the trainees' Study context. This seems obvious as not using new learning during the training will inevitably lead to negative feedback from lecturers or lower grades for assignments. Not applying new learning in the Work context will probably go unnoticed and will not lead to negative consequences like peer or supervisor resentment.

Finally, the variable personal capacity appeared to be not significant in both transfer contexts, indicating that the trainees didn't expect that their intention to transfer new learning to their Study and Work contexts would be hampered by other obligations or a lack of time and energy to practice.

The initial recommendations in our study to facilitate a positive and motivating affective transfer climate in a distance learning environment are in line with general recommendations on how to enhance affective learning. They can be used as an impetus for complementary strategies aligned to the specific conditions of the training and the trainees. When designing a training program instructional designers might for example stimulate the trainees' willingness or motivation to learn by giving them opportunities before and during the training to express their personal preferences and specific needs for their transfer context(s), by communicating the quality, relevance, and gains of attending the training, by encouraging, and by building self-efficacy. Literature confirms that peers and supervisors are important actors in building and maintaining an encouraging, inspiring and productive learning and transfer climate, not only during but also before the actual start of the training. During our research, the a-synchronous training the participants were about to take was characterized by the absence of physical and online contact between students while contact between students and lecturers was limited to reviewing and advising on the assignments. Social presence (Spears, 2012) and social interaction (Jung et al., 2002; Swan, 2003; Yang et al., 2010) are considered to be two important preconditions for successful online and affective learning (Sun and Chen, 2016; Richardson et al., 2017). After our study, the format of the training has been altered and now includes more synchronous interaction between students through collaborative group assignments. This however also requires more time and planning of the adult trainees who often have a multitude of obligations besides their study. Future research within this altered setting but also in more traditional face-to-face environments might show in what way social presence and social interaction influence the relationship between affective learner characteristics like learner readiness and motivation to learn, and the intention to transfer.

This study contributes to the conceptual development of affective learning by complementing limited previous research on variables that might enhance or impede an affective transfer climate in distance education environments. It also adds a new aspect to transfer theories by adopting a multicontextual perspective on transfer, investigating the transfer process to two application contexts within one sample. Results confirm the value of this new perspective and of the importance of affective learner characteristics to the transfer process in distance education.

The practical relevance of our study is that it advises educational designers on how to create and maintain an affective learning climate that enhances the transfer of new learning. They might, for example, take into account that transfer is not only the application of new learning during a post-training test but a process that is influenced by a multitude of variables already before the actual start of training. Our study more specifically underlines the importance of affective learner characteristics to the transfer process. Involving trainees in the program design and proper framing might enhance training transfer. It might also be useful to realize that if transfer, especially when it involves generic competences, is meant or suitable for use in multiple contexts these may each have their specific transfer enhancing or impeding conditions. Gaining insight into these contexts and discussing them during training might prove profitable to the transfer process.

There are several limitations to this study. The first limitation is the use of only a self-report survey for collecting the data. Although there are legitimate arguments against the use of only this one source, including the risk of common method bias, specific conditions might prevent the use of additional data sources like observation, interviews, psychological signal measurements, or actual transfer measurements. In our study, respondents were distance learners studying from home and working relatively autonomous at various locations throughout the Netherlands. Also, new learning from the training consisted of so-called open higher-order thinking skills that can be executed in a variety of ways. This makes monitoring and measuring the transfer process, including the development of transfer intention of the individual participants near to impossible. For future research, however, we would opt for triangulation of the data when circumstances allow. Furthermore, this study took place in a very specific educational environment, namely distance adult education. Future research might be expanded to face-to-face or blended learning environments and to pre-adult learners. And finally, the participants in our study were predominantly female (77.6%). In general, research findings on the effect of gender on training related variables tend to be inconsistent (Powell, 1988; Bass and Stogdill, 1990). This may be the result of different research settings like field or laboratory (Dobbins and Platz, 1986), and the research focus. Looking at variables that predict training outcomes, for example, Tziner and Falbe (1993) observed that gender affected the motivation to transfer. Velada et al. (2009) concluded that male respondents had higher perceptions of several training variables from the Learning Transfer System Inventory, including "positive personal outcomes" and "personal capacity to transfer" than female respondents. The present study has been focused on the relationship between pre-training transfer intentions and five trainee-related variables. Results show that differences in variable scores between female and male participants were statistically non-significant ($p > 0.05$). Future research might look closer into the role of demographic characteristics on the transfer process and in what way these characteristics are influenced by, for example, specific research, cultural, work, or educational conditions.

We have tried to minimize undesirable bias by emphasizing in advance that responses would be treated anonymously and with the greatest care and that the electronic survey offered the possibility to answer the questions in private.

Our study intended to extend limited research on the influence of affective learner characteristics on transfer processes in a-synchronous online distance education by adopting a pre-training and multicontextual perspective. Results indicate that these perspectives and the constructs and items used in this study may offer educational designers practical tools to design educational interventions that will enhance the learners' intention to transfer new learning, and in the end transfer itself. We welcome future studies that confirm, challenge or complement the value of these perspectives for transfer research. In the next step of our research, we will investigate the temporal dimension of the transfer process by comparing the effects of individual, instructional and environmental predictors of intention to transfer before, directly after and 3 months after the training.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Before the participants started with their first task, students filled out a questionnaire that was integrated into the electronic course as Task 0. Before taking the survey all students were informed that their responses would be used exclusively for this research and that their personal data and responses would be treated confidentially and with utmost care.

AUTHOR CONTRIBUTIONS

LT was involved in the acquisition of the data. AG and LT performed data analysis and interpretation. SB-G and AG critically revised the manuscript. All authors contributed substantially to the design and execution of the study and approved the final version.

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