COGNITIVE AND AFFECTIVE FACTORS IN RELATION TO LEARNING

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COGNITIVE AND AFFECTIVE FACTORS IN RELATION TO LEARNING

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Table of Contents

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Editorial: Cognitive and affective factors in relations to learning

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Editorial on the Research Topic
Cognitive and affective factors in relations to learning

Both domain general (e.g., working memory, executive functions) and domain specific (e.g., number processing, phonological processing) cognitive factors have been found to predict learning in different age groups (e.g., Schneider et al., 2017; Peng et al., 2018). Likewise, research has shown that various affective factors such as different emotions (e.g., Camacho-Morles et al., 2021; Caviola et al., 2022) need to be considered when investigating individual differences in learning. However, less studies have investigated both cognitive and affective factors simultaneously in relation to learning. There is a lack of studies investigating the interplay (i.e., moderation and mediation) between cognitive and affective factors on learning.

The aim of this Research Topic is to deepen our knowledge on the cognitive and affective factors in relation to learning in different age groups. Providing a broad scope of emerging areas in research that simultaneously look at the interplay of these constructs related to academic learning, as well as longitudinally, the collection spans research methods and analyses, from innovative study designs to recent advances in methodology in this field. The volume comprises of two systematic reviews and 11 original research papers.

In their study, Koponen et al. show that educational interventions providing opportunities to practice and to perform successfully in math tasks, have positive effects on elementary school children's progress and change their belief about their own math skills, especially for children struggling with math. Thus, skill training math and teaching children to believe they can do and learn math is argued to enhance math development in general and specifically for low-performing children.

Zhang et al. combined the social cognitive career theory (SCCT) and the stimulus-organism-response (SOR) model and investigated university students' psychological cognition and attitudes in their learning. Their findings showed that self-efficacy and students' generic skills (e.g., self-management skills, learning and adaptability skills, problem-solving skills, concept, and analysis skills) had a mediating effect, when predicting learning satisfaction on either social support system or interaction relationship.

Moving to online learning, Wang Y. et al. conducted an online experimental study with 177 college students where they measured real-time emotions (joy and anxiety) with facial expressions and found that feelings of joy were positively related, and anxiety negatively related to students' self-reliance persistence. In other words, students that experienced joy were more persistently trying to solve the task while anxious students engaged in task-avoidance behavior.

The findings of Vanbecelaere et al. study increases our understanding on the dynamics of the home learning environment (HLE) and its impact on first grade children's cognitive and non-cognitive outcomes in math and reading. They showed a significant relation between parents' perceptions and their anxiety toward math and reading. A significant relation was also found between the parents' perceptions toward reading and the frequency of home reading activities, but not for math. Apart from socioeconomic status playing a role in children's digit comparison skills and math anxiety, no other HLE factors were found to have a relation to children's outcomes.

Shi and Qu article makes an important contribution concerning the mediating effect of overall positive mental state on cognitive ability and students' academic performance. Their study demonstrates that personality characteristics and psychology health play a partially mediating role between cognitive ability and English performance. The authors highlight the importance of environmental feedback to promote students' academic development and enhance their psychology health.

Jonsson et al. comparative study on the role of intrinsic cognitive motivation, analyses the effects of creative mathematical reasoning (CMR) and algorithmic reasoning (AR) on upper secondary students' conceptual understanding in math. Their study demonstrates that the CMR group outperformed the AR group. Need for cognition was a significant predictor of CMR's math performance, but not for the AR's. Further working memory capacity was a strong predictor, regardless of the group. From a school practice viewpoint, students should be offered time and struggle with constructing their own solution methods using CMR and supporting their conceptual understanding in math.

The two following reviews focus again on math anxiety. Finell et al. conducted a meta-analysis and investigated the link between math anxiety, working memory, and math performance. They found that (1) math anxiety was related to working memory, and that (2) working memory mediated the relation between math anxiety and performance. Their study lends support to the Attentional Control Theory as one possible mechanism underlying the math anxiety-performance relationship. In Balt et al. systematic review, math anxiety, and especially ways to reduce it, was investigated. Even if no clear picture could be found of what math anxiety interventions should look like for school-aged children, both mathematical intervention and cognitive-behavioral intervention approaches showed promising effects. Their conclusion calls for intervention research aiming to mitigate math anxiety among school-aged children.

The article by Wiklund-Hörnqvist et al. sheds light if retrieval practice in learning Swahili-Swedish word-pairs is influenced by individual differences in need for cognition. Using both behavioral and functional magnetic resonance imaging evidence, they concluded that retrieval practice is effective also for individuals with lower levels of need for cognition, in other words, those with low intrinsic motivation. This result thus supports the use of retrieval practice in schoolwork among upper-secondary school students.

Next, the contribution by Li et al. looks at the effect of class competition on academic achievement among primary school students, while considering their learning anxiety and engagement. The article illustrates how class competition was found to have a negative effect on academic achievement by increasing anxiety, but also a positive effect when promoting learning engagement. Thus, its role is important to acknowledge on academic achievement in relation to learning anxiety and engagement.

Dowker and Sheridan found math anxiety to be related to working memory, test anxiety, and math performance in a sample of 40 university undergraduate students. Female students experienced more math anxiety compared to males, but no gender differences were found in math performance. The authors argue that these findings lend support to the gender stereotype hypothesis postulating that gender differences in math emotions and motivation are mainly the result of students endorsing gender stereotypes like "boys are good at math".

Vilhunen et al. examined epistemic emotions and their relation to learning. Curiosity and enjoyment were positively associated with learning, whereas frustration and boredom negatively. When controlling for pretest performance, only boredom showed negative relation to posttest performance. The authors discuss the complexity of interplay between emotions and learning, for example from the state vs. trait nature of the emotions.

Finally, Wang H. et al. examined the relations between the gender differences in boredom and lexicon learning in Chinese. They demonstrated that females experienced less boredom and their word forgetting rate was lower compared to males. This warrants for future studies, such as how feeling of boredom could be reduced in language learning situations.

In conclusion, we hope the present Research Topic will help to shed light on these new research perspectives. We also believe that these novel themes, combining cognitive and affective factors in relation to learning, together with their methodological approaches, may be of great value for professionals and practitioners.

Author contributions

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

Conflict of interest

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

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References

Camacho-Morles, J., Slemp, G. R., Pekrun, R., Loderer, K., Hou, H., and Oades, L. G. (2021). Acitivity achievement emotions and academic performance: a meta-analysis. *Educ. Psychol. Rev.* 33, 10151–1095. doi: 10.1007/s10648-020-09585-3

Caviola, S., Toffalini, E., Giofré, D., Mercader Ruiz, J., Szücs, D., and Mammarella, I. (2022). Math performance and academic anxiety forms, from sociodemographic to cognitive aspecs: a meta-analysis on 906,311 participants. *Educ. Psychol. Rev.* 34, 363–399. doi: 10.1007/s10648-021-09618-5

Peng, P., Barnes, M., Wang, C., Wang, W., Li, S., Swanson, H. L., et al. (2018). A meta-analysis on the relation between reading and working memory. *Psychologic. Bull.* 144, 48–76. doi: 10.1037/bul0000124

Schneider, M., Beeres, K., Coban, L., Merz, S., Schmidt, S., Strickler, J., et al. (2017). Associations of non-symbolic and symbolic numerical magnitude processing with mathematical competence: a meta-analysis. *Develop. Sci.* 20, e12372. doi: 10.1111/desc.12372

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Benefits of Integrating an Explicit Self-Efficacy Intervention With Calculation Strategy Training for Low-Performing Elementary Students

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This study examined the malleability of math self-efficacy (SE) among children with poor calculation fluency via an intervention that targeted four sources of SE (mastery experiences, vicarious experiences, social persuasions, and emotional and physiological states). The effect of pure strategy training was contrasted with an intervention that integrated strategy training and explicit SE support. Moreover, the changes in SE source experiences and their relation with math SE, as well as the relation between math-SE profiles and calculation fluency development, were examined. In a quasi-experimental design, 60 Finnish children with calculation fluency problems in Grades 2 to 4 participated in strategy training (N = 38) or in an intervention that integrated SE support with strategy training ($N = 32$) for 12 weeks. The results showed that the explicit SE intervention integrated with strategy training enhanced math SE among children with poor calculation fluency and low SE (effect size, $r = 0.61$). Changes in mastery experiences and social persuasions were positively associated with changes in math SE among children who received the explicit SE intervention. An initially high math-SE profile and a profile indicating an increase from low to high math SE were related to growth in calculation fluency that approached the children's average age level during the interventions. In conclusion, an integrated approach that combined skill training and SE intervention was especially beneficial for children with poor calculation fluency and low math SE.

Keywords: self-efficacy, sources of self-efficacy, math, calculation fluency, low performance, intervention

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INTRODUCTION

Self-efficacy (SE) refers to people's judgments of their capabilities to organize and execute courses of action that are required to attain designated performances (Bandura, 1986). In an academic context, SE refers to the beliefs that students hold about their capability to perform and execute a learning task under specified conditions or to perform behaviors at desired levels (Bandura, 1986). SE has been proposed to be a meaningful determinant of learning because it affects the choice of activities, effort, and persistence in learning situations (Bandura, 1986, 1997). Students who hold a low level of SE for mastering a certain task, such as in mathematics, may avoid the task or give up easily, whereas those who believe they are capable work harder and persist longer. Dysfluency in arithmetic calculation, that is, difficulty in fact retrieval, is the most typical feature of math difficulties (Geary, 1993), and it has been shown to be rather persistent (Kaufmann et al., 2011). Children with dysfluency problems often rely on slow and error-prone counting strategies despite several years of schooling (Geary, 2004); therefore, these children need to work much harder in order to complete the same number of math tasks or the same amount of homework as their typically performing peers. In order to compensate for retrieval problems, teaching efficient calculation strategies is essential. It should be noted that not only are the level of basic numerical skills or conceptual understanding in arithmetic (e.g., Canobi, 2004) related to the use of efficient counting-based calculation strategies, but self-beliefs and emotions toward math have also been shown to affect calculation efficiency (Hoffman and Spatariu, 2008). Thus, in addition to providing targeted strategy training to improve the skills, it is essential to ensure that children believe that their calculation fluency can improve with practice and that they are able to learn and use more efficient strategies. Whether children's beliefs can be strengthened by providing positive efficacy-building experiences in math still needs to be researched.

Math Self-Efficacy and Its Relation With Math Performance

Meta-analytic studies (e.g., Richardson et al., 2012; Honicke and Broadbent, 2016) have provided empirical evidence that supports the theoretical claims of a positive correlation between academic SE and performance among middle school, high school, and college/university students. In the domain of math, several studies have shown the association between math SE and achievement among older students (e.g., Chen and Zimmerman, 2007; Ayotola and Adedeji, 2009; Kitsantas et al., 2011). There are fewer studies with younger children, but the existing literature supports the view that math SE is already related to performance in earlier stages of schooling (e.g., Pajares et al., 2007; Joët et al., 2011). In addition, most of the previous studies have focused on cross-sectional relations between math SE and math skills, and fewer studies have focused on longitudinal relations. Longitudinal studies among older students have found positive effects of math SE on later mathematics achievement (Grigg et al., 2018), an association between the growth of both constructs (Soland, 2019), and a reciprocal relation between mathematics achievement and math SE (Hannula et al., 2014; Arens et al., 2020). The few existing studies among elementary school children show more inconsistent findings. For example, Pajares and Graham (1999) found that the level of math SE predicted math performance both at the start and end of the sixth grade after taking into account motivational and emotional factors, such as self-concept and anxiety. Similarly, Galla et al. (2014) found that a higher level of academic SE was related to a faster rate of growth in math across elementary school. However, in a recent study among 4th graders (Kaskens et al., 2020) math SE did not predict the arithmetic skills in the end of 4th grade after taking into account self-concept, anxiety, and initial arithmetic skill level in the beginning of 4th grade.

Moreover, changes in academic SE (Galla et al., 2014) or in math SE (Phan, 2012b) have not been found to be related to later achievement in math, although such a relation has been found in other academic domains, such as reading (Hornstra et al., 2013; Galla et al., 2014), language (Hornstra et al., 2016), and science (Phan, 2012b). These findings from longitudinal studies raise questions regarding to what extent math SE is malleable and whether learning in math can be improved by supporting math SE in addition to skill training. To the best of our knowledge, no previous controlled intervention study has investigated the effectiveness of explicit SE intervention on math SE and math achievement.

Finally, although academic SE has been shown to be especially relevant when students encounter academic difficulties (Multon et al., 1991; Klassen, 2002), studies on math SE and math performance among elementary school children have mostly been conducted with typically achieving children, or the level of academic skills was not considered. In a meta-analysis conducted by Multon et al. (1991), the association between SE and academic performance was stronger among low-achieving students than among typically achieving students. Children with learning difficulties have also been shown to report lower general academic SE as well as lower SE in math, writing, and reading (Klassen, 2002). As low SE is assumed to decrease a student's persistence to work hard, especially when facing difficulties (Bandura, 1997), it can be especially harmful for children with learning difficulties, who need to practice harder than their typically learning peers in order to achieve required academic skills.

Sources of Self-Efficacy

Social-cognitive theory (Bandura, 1997) hypothesizes that SE is developed and modified as children interpret information from four sources: past experiences (mastery experience), feedback and evaluative information received from others (social persuasion), models seen in reference groups (vicarious experience), and feelings and emotions experienced while engaged in or thinking about an activity or performance (physiological and affective states). However, so far there have been only a few studies that have used longitudinal or experimental designs, and thus, little understanding of the developmental dynamics between the hypothesized sources and SE.

According to Bandura (1997), the most powerful source, *mastery experiences*, stems from one's interpretations of earlier performances. For example, academic SE in a certain domain is developed and modified based on how one interprets and evaluates information about one's academic accomplishments in previous similar learning situations; experiences of success raise SE, and failures lower it. Findings from cross-sectional studies among elementary school children suggest that children rely strongly on mastery experiences when building their academic SE in different scholastic domains (see Britner and Pajares, 2006; Pajares et al., 2007; Usher and Pajares, 2008, 2009; Joët et al., 2011). However, the few existing longitudinal studies in math provide a different picture; mastery experiences have been shown to be only weakly associated with the level of math SE (Phan, 2012a,b), negatively associated (Phan, 2012a), or not at all associated (Phan, 2012b) with the growth of math SE among elementary school children when three other sources of SE were included in the same model.

The development of SE is not assumed to be dependent solely on personal interpretations of one's success in past performances but is also affected by how one experiences the feedback and support provided by others (Bandura, 1986, 1997). That is, *social persuasions* and evaluative feedback from teachers, parents, and peers influence one's SE. Younger students, in particular, have been found to depend on such feedback and have been suggested as being the most open to what others tell them, especially when learning new skills and lacking previous experience with the academic task at hand (Bandura, 1986, 1997). In particular, SE has been found to increase when students are provided with frequent and immediate feedback (Schunk, 1983). In a longitudinal study among elementary school children, social persuasions were found to be associated with the initial level of math SE but not with its growth among third and fourth graders (Phan, 2012a), whereas an opposite trend was found among fifth and sixth graders; social persuasions were associated with growth but not with the initial level of math SE. In a longitudinal study on reading SE, those students from second to fifth grade who experienced little feedback and support from teacher, parents, and peers and, more importantly, experienced loss of this social persuasion became less confident of their skills over time (Peura et al., 2021).

Moreover, learners acquire SE information through observations of models and social comparisons, that is, through v*icarious experiences.* Observing the actions of other people, such as peers and classmates, informs learners of their own capabilities (Bandura, 1997). Students who observe peers mastering a task are likely to feel more efficacious because they believe that they are also capable of accomplishing it (Schunk, 1989). Students' vicarious experiences in math can be improved by giving them the opportunity to observe their friends, who they consider to be similar to them with respect to performance level, succeed in solving problems. However, the findings from longitudinal studies are contradictory. On the one hand, a rather strong association between vicarious experiences and math SE has been found for the initial level of SE in math (Phan, 2012a), and on the other hand, no association was found with the initial level or growth of SE (Phan, 2012b). This may be partly related to the age of the children because the association was found among third and fourth graders but not among fifth and sixth graders. It has been suggested that vicarious models may play different roles as a source of math SE in different developmental stages (Ahn et al., 2017).

Students also acquire efficacy by acquiring information from their *emotional and physiological states* (e.g., anxiety, heart rate, sweating), and according to Bandura (1997), they tend to interpret physiological states as indicators of their academic competence as they evaluate their performance. A high level of negative arousal has been found to be related to lower SE in math among middle school students (Klassen, 2004) and among elementary school children (Joët et al., 2011; Phan, 2012b; Lau et al., 2018). Negative emotional states have also been shown to be negatively associated with the growth of math SE among elementary school children (Phan, 2012a,b).

A lower SE in students with learning difficulties (or learning disabilities) has been explained by them having less access to efficacy-building experiences (i.e., sources of SE) needed to develop and shape their SE (Hampton and Mason, 2003). Unfortunately, students with difficulties in learning may have fewer opportunities to experience success than their peers (Hampton and Mason, 2003; Usher and Pajares, 2006, 2008; Arslan, 2013). This would suggest that in order to boost SE among students with learning difficulties/disabilities, special attention should be placed both on the challenge level of the tasks and support in skill training as well as on feedback and activities, ensuring that they have access to all four sources of SE. Currently, there is a lack of knowledge about whether SE can be supported by providing positive source experiences, and especially so among children with learning difficulties/disabilities.

From Theory and Empirical Evidence to Intervention

Despite the strong theoretical framework of socio-cognitive learning and some empirical evidence that supports the association between SE and its four sources, few intervention studies have aimed to enhance SE by enabling positive source experiences and examining the influence of SE level and its changes on the development of academic skills. Interventions among children with learning difficulties have mainly focused on providing training for the compromised skill itself or the cognitive skills assumed to underlie the academic difficulties (Kearns and Fuchs, 2013). The intervention studies that have aimed to enhance participants' SE in math have focused on strategies and goal-setting instructions (Schunk, 1985) together with social comparative information (e.g., Schunk, 1983) and peer models (Schunk and Hanson, 1985). To the best of our knowledge, there are no previous SE intervention studies among poor-performing children in the context of math that explicitly target all four sources of SE, even though the social-cognitive theory hypothesizes that SE beliefs are developed and modified as children interpret information from the four sources. In addition, it has been shown that intervention effects on SE become larger as the number of sources included in the intervention increase (Unrau et al., 2017). Covering all four sources in the interventions is further supported by findings that indicate that at the individual level, students may rely on different sources of information in varying combinations (Chen and Usher, 2013). Furthermore, students with learning difficulties are assumed to have less access to sources of efficacy information (Hampton and Mason, 2003), and low-performing students have been shown to lose source experiences over time, and this has been found to relate to their decreasing self-efficacy (Peura et al., 2021). Thus, if we assume that exposure to sources of SE enhances SE and thereby positively influences effort and persistence in learning situations and consequently learning, it would be of utmost importance to provide positive source experiences, especially for students with learning difficulties or low performance.

To our knowledge, only two intervention studies have targeted all four sources of SE (mastery experiences, social persuasions, vicarious experiences, and the psychological and affective state) among elementary school children with learning difficulties or low achievement. One focused on writing skills (García and de Caso, 2006), and the other focused on reading fluency (Aro et al., 2018). The findings of these two studies have been encouraging. García and de Caso (2006) found that writing skills can be improved by enhancing children's writing SE with the establishment of a positive psychological and affective climate, created by providing social persuasions, explicating mastery, and providing vicarious experiences. Aro et al. (2018), in turn, found that intervention resulted in a greater positive change in reading SE in the group that was provided explicit SE support in addition to reading fluency training than in the group that was only provided reading fluency training. Moreover, a change in reading SE was positively associated with a change in reading fluency only within the group that received explicit SE support. In the target skill itself, reading fluency, the two intervention groups showed equal improvement.

Present Study

The purpose of the present study was to fill existing gaps in the field of math-SE research and examine to what extent explicit SE support that incorporated targeted skill training supports SE, as compared to targeted skill training only.

The present study had three aims. The first aim was to examine the changes in math SE among two calculation strategy training groups, one with (*the SE group*) and another without (*the skill group*) explicit SE intervention, and their controls. The second aim was to examine the changes in the source experiences of SE during the intervention among children participating in two interventions (the SE and skill groups) and the relation between the changes in the source experiences of SE and math SE. The third aim was to examine the association between different SE profiles formed on the basis of the level and change in math SE during the intervention (i.e., high SE, low-to-high SE, low SE, and low-increasing SE) and improvement in calculation fluency during the intervention.

In the present study, we extended a recent study with the same participants, which focused on reporting the effectiveness of calculation strategy training on calculation fluency among second to fifth graders who used immature counting-based strategies in basic addition despite formal schooling for several years (Koponen et al., 2018). In that study, strategy training was shown to be effective in supporting calculation fluency; both intervention groups receiving the identical strategy training (with and without SE intervention, SE and skill groups) showed improvements in calculation fluency during the intervention, outperforming the control groups that received either the corresponding intervention in reading (children with low reading fluency) or business-as-usual support for math at schools. However, in that study, the changes in math SE or source experiences were not examined. In the present study, the following specific research questions were addressed:

Math Self-Efficacy

a) *To what extent does explicit calculation strategy training with or without additional explicit math-SE intervention enhance math SE?* Changes in math-SE were compared between the two intervention groups (SE and skill) and with the business-as-usual controls.
b) *To what extent does explicit calculation strategy training with and without explicit math-SE intervention enhance math SE among children with an initially low math SE?* Children reporting a low pre-intervention math SE were included in these analyses in order to study the influence of the intervention conditions among children in most need of support for math SE.

Source Experiences and SE in Math

a) *To what extent does explicit calculation strategy training with and without explicit math SE enhance source experiences?*
b) *Are the changes in sources related to changes in math SE during the interventions?*

Self-Efficacy and Skill Development

a) *Are the level and changes in math SE related to improvement in calculation fluency, that is, are there differences between children with different SE profiles (i.e., high SE, low-to-high SE, low-increasing SE, and low SE) in calculation fluency change?*

METHOD

Participants

This study was part of a longitudinal research project (Self-efficacy and Learning Disability Intervention (SELDI; 201396-2015)) that focuses on elementary school children's self-beliefs, motivation, and reading and math fluency skills. The data for the present study were collected over two consecutive autumn terms, with the first measurement point in November and the last one in October of the next school year.

A total of 20 schools in urban and semi-urban areas in Central and Eastern Finland volunteered to participate, from which the classes and children were recruited for this study to implement calculation or reading fluency interventions. Ten of the schools provided calculation fluency interventions. Written consent was obtained from the guardians of the participants. The research procedure was evaluated by the University of (Jyväskylä) Ethical Committee.

The original sample consisted of 1,327 children (638 girls, 689 boys) from Grades 2 to 5. Of this sample, 178 (13.41% of the original sample) were second graders (M_{age} = 8.35 years, SD = 0.32 years), 471 (35.49%) were third graders (M_{age} = 9.34 years; SD = 0.31 years), 383 (28.86%) were fourth graders (M_{age} = 10.40 years; SD = 0.35 years), and 295 (22.23%) were fifth graders (M_{age} = 11.39 years; SD = 0.36 years). After screening this larger sample using at or below the 20th percentile as a criterion for poor performance, 240 children were screened for individual assessment in calculation fluency; after which, 69 children were selected to participate in calculation strategy training (see the description of the screening process below) with (SE group) or without (skill group) an explicit self-efficacy intervention. In addition to the confirmed weakness in calculation fluency (use of counting-based strategies), the project's parallel reading interventions and available resources for special education defined the number of final intervention groups, and thus, the number of children participating in the calculation fluency intervention. Intervention was provided mainly for children from second to fourth grades, but some fifth graders were included as well. To form a control group ($N = 69$), one child from the class of each participant in the math intervention was selected based on having the next-lowest calculation fluency score. Classmate controls were matched for gender (when possible), and they received business-as-usual support, including any special education usually provided in the school. Controls who came from the same classes as the children in the SE group did not differ from those controls that came from the same classes as children in the skill group in the improvement of self-efficacy or calculation fluency during the intervention period ($p > 0.05$), and thus, they were combined to form one control group. The two intervention groups and the control group did not differ in age or non-verbal reasoning (Raven's Matrices test, $p > 0.05$). The two intervention groups were matched with the initial level of calculation fluency, and they did not differ in the initial level of math SE ($p > 0.05$).

A quasi-experimental design was applied. The schools, classes, and teachers volunteered to participate, and the caregivers gave written consent for participation. The study was carried out at the participating schools and during regular school hours. Screening was conducted with regard to both reading and calculation fluency, and the volunteering schools selected for calculation interventions were randomized to have the calculation strategy training either with or without specific SE intervention. This was done in order to avoid treatment contamination, which could happen if the programs were provided in the same school. Approximately half of the children participating in the calculation intervention received SE intervention following a manual-based intervention program, and the other half participated in groups in which the teachers were not explicitly instructed with regard to SE but were provided a manual-based strategy training program. This design insured that the groups had identical strategy training. There were no differences between the two intervention groups in terms of calculation fluency in the pre-intervention assessments.

Screening Procedure for Intervention

Screening for inclusion in the calculation strategy intervention was carried out in two steps. First, all participants from the original sample were assessed in terms of their calculation fluency using group-administered timed calculation tasks. Children from Grades 2 to 4 whose performance was at or below the 20th percentile in the calculation fluency task (compared to their grade level) were selected for individual assessment, which included 20 single-digit addition items (e.g., 2+8, 5+4, 9+6, 7+3) presented one by one in a game-like context. The children were asked to respond as quickly as possible to each item. A point was given for correct responses within 3 s. Inclusion criteria for the intervention were that the children showed dysfluency, both in the group-administered calculation fluency task (i.e., performance at or below the 20th percentile) and in the individual assessment situation that required fast fact retrieval or the efficient use of back-up strategies (slow or incorrect responses on at least 30% of the simple addition items). Out of the 240 children who in the group administered calculation fluency task showed calculation fluency below the 20th percentile, two children had missing data, and in the individual assessment situations, 154 children also showed use of immature calculation strategies. Eight of these children with dysfluency in reading also participated in the reading intervention. Altogether, 69 of the children who met the criteria and were from those schools implementing calculation intervention were included in the present study (77 children were from schools and classes where math intervention was not implemented). Additionally, six children with low calculation fluency but who did not meet the selection criteria participated in the calculation intervention for practical reasons (i.e., to be able to form a group at the school) and were not included in the analyses. The number of children receiving SE intervention embedded in strategy training was 31 (SE group), and 38 children received just strategy training (skill group). The final groups for this study were composed of the children for whom there were complete SE data from all four assessment points: 28 children in the SE group and 32 in the skill group. Children who had missing data did not differ from those children who had full data in the initial level of calculation fluency. The main reasons for missing data were absences from school on assessment days or moving to another school.

Intervention Design and Procedure

We applied an intervention design with two pre-assessments, one post-assessment, and one follow-up assessment as a part of a larger longitudinal follow-up study. Pre-intervention assessments were conducted in November and January. The 12-week interventions started at the end of January. A post-intervention assessment was conducted after the intervention ended in April, and a follow-up assessment was performed 5 months after the intervention, at the end of September or the beginning of October. At the second pre-intervention assessment, a shortened assessment battery, including addition and subtraction fluency tasks, was administered during one group assessment session. The group assessment was administered before the individual assessment at each time point.

Measures

Calculation Fluency Measure

Basic addition fluency was assessed using a group-administered paper-and-pencil test with 120 items and a 2-min time limit (Koponen and Mononen, 2010). The addends had values of 10 or smaller. One point was given for all items answered correctly within the time limit, and the total score was calculated. Correlations with other calculation fluency tasks (subtraction and arithmetic tasks with multiple operations) varied from 0.74 to 0.85.

An individually administered addition fluency task was used for screening children with low calculation fluency (at or below the 20th percentile) to confirm that the dysfluency in calculation was real and not due to other factors that were not possible to detect in the group assessment (for details, see Koponen et al., 2018). The individual game-like assessment used a *no-choice technique* to assess addition fluency. The children were shown a card with an addition problem on it and were required to answer correctly within 3 s to win the card. One point was given for all items answered correctly within the time limit, and the total score was calculated.

Math SE

The group-administered questionnaire specifically targeting math-SE was developed based on the guidelines outlined by Bandura (2006). Researchers with expertise in self-efficacy, math development and learning difficulties were consulted in item formulation. Two different specificity levels of self-efficacy for arithmetic were assessed: intermediate, and general level. Items targeted arithmetic skills, learning and applying the skills in daily settings, and thus were appropriate and concrete for primary school children (see **Appendix A**). The children completed the questionnaire before the calculation fluency assessment. Trained research assistants gave pre-written instructions and read aloud all the questionnaire items one by one to ensure that everyone could answer them regardless of their reading skill. The items began with the question "*How certain are you that you can...,*" and the children rated the strength of their confidence using a seven-point scale ranging from "*I'm totally certain I can't...*" (1) to "*I'm totally certain I can...*" (7). The questionnaire covered seven self-efficacy items that were related to calculation skill: beliefs on one's current ability in calculation (two items), one's ability to learn to be more fluent/accurate (two items), and one's ability to apply calculation skills in daily life (three items). The items are presented in **Appendix A**. Cronbach's alpha for the self-efficacy scale was 0.71.

To examine the association between SE and fluency improvement during the intervention (RQ3), all the intervention children were classified into four groups according to their ratings on the SE questionnaire before and after the intervention. The cut-off score for the low SE group (at or below 42 points) was based on the whole sample using the median score for math SE for the low-performing children (at or below the 20th percentile in addition fluency; $N = 263$). The high SE group ($N = 15$) included children whose total SE score was above 42 before and after the intervention. The low-to-high SE group ($N = 16$) included children whose SE score was at or below 42 but was above 42 after the intervention. The low-increasing SE group ($N = 9$) scored at or below 42 both before and after the intervention but showed SE enhancement during the intervention. The low SE group ($N = 18$) included the rest of the children with an SE score at or below 42 both before and after the intervention and without enhancement in SE.

SE Source

Sources of math SE were assessed using 12 items, adapted from a questionnaire previously validated by Usher and Pajares (2009). Children rated their mastery experience (three items, e.g., "I do well in math"), social persuasions (three items, e.g., "My teacher has often told me that I am getting better in math"), vicarious experience (three items, e.g., "I admire adults who are good in math"), and physiological and emotional state (three items, e.g., "I feel tension when I have to do math"*)* using a 7-point Likert scale (1, *not true,* to 7, *true*). The items are presented in **Appendix B**. Higher scores for mastery experience, social persuasions, and vicarious experience referred to positive experiences, whereas higher scores on the physiological and emotional state subscale represented experiencing more adverse physiological arousal and emotional states (reverse scoring was used in the total score). Cronbach's alphas for the source experience scales were 0.86 at pre-assessment 2 and 0.77 at post-assessment.

Intervention Programs

Calculation Strategy Training

In the present intervention study, both intervention groups received a similar type of calculation strategy training implemented based on a shortened version of the SELKIS intervention program (Koponen et al., 2011). This program focuses on derived fact strategy training and aims at helping children to discover more efficient calculation strategies using their existing knowledge of number sequences, number concepts, and arithmetical facts (conceptual knowledge). Addition fluency was selected for the training context in math because it forms a ground for other arithmetic operations, such as subtraction and multiplication, which are even more difficult and laborious to solve using only counting-based strategies. Children participated in the strategy training group sessions twice a week for 45 min at a time. The number of participants in the groups varied between four and six. In addition, they had two short weekly gaming sessions for practicing basic addition skills by playing math games and received a worksheet for homework that included similar types of addition problems practiced during strategy sessions (for details, see *Authors*).

SE Intervention

The intervention elements (see **Table 1**) aimed at enhancing math SE explicitly targeted the four sources of SE (Bandura, 1997). *Mastery experiences* were provided by using individually challenging but accessible tasks. This element was also present in the skill program, but in the SE program only, several forms of feedback and practice were provided to insure that each individual's progress became visible, thus assuring mastery experiences. First, positive, explicit, and concrete feedback was provided on improvements in calculation fluency and on shifts toward using more efficient calculation strategies. During the 12-week intervention, children practiced four sets of addition problems, and before and after training on each set of problems, they carried out a 1-min calculation fluency task. Based on the results (the sum of correctly solved problems), they were allowed to color the corresponding number of floors on a tower. Attention was paid to each individual's improvement. Second, twice a week, the children participated in short game sessions in which they practiced calculation strategies by playing math games. The sessions were guided by a school assistant (or class teacher). In the SE program, school assistants were trained to give feedback related to a child's improvement compared to his/her previous performance or the effort she/he showed during the game session. In both intervention programs, children received a sticker or stamp after each game session indicating attendance. To provide children with *social persuasions*, the teachers in the SE group explained and verbally praised the children's efforts in practicing and improvement. Particular attention was paid

TABLE 1 | Intervention structure: Weekly SELKIS-intervention sessions and game sessions and elements of the SE-program to foster self-efficacy.

	SKILL-program	SE-program
Time used	**Game sessions**	
15 min two times per week	Math games guided and attendance marked by school assistant or regular class teacher	Math games guided and SE feedback given by school assistant or regular class teacher
Time used	**Weekly SELKIS-intervention sessions**	
5 min	Welcome and orienting	Welcome, orienting, and emotion checklist
5 min	Checking homework	Sharing feedback from the last game session, checking homework, and giving SE feedback
25–30 min two times per week	SELKIS-strategy training	SELKIS-strategy training integrated with SE intervention (feedback on effort, personal progress, and use of fluent strategies, encouraging peers, stories and discussion related to learning, emotion, and SE)
5 min	Cleaning up, homework	Cleaning up, homework, emotion checklist
	Sources of self-efficacy provided during the weekly group sessions	
Mastery experience	• Reachable challenges with exercises adapted to each child's skills	• Reachable challenges with exercises adapted to each child's skills • Individual concrete visual feedback on progress in calculation fluency (e.g., calculation fluency towers, • Individual concrete feedback on improvement in the use of efficient calculation strategies (e.g., stairs describing the development of calculation strategies) • Individual concrete feedback on working habits and effort during and after each group session, game session, and homework (e.g., discussions)
Vicarious experience	• Exercises in a peer group with similar skill levels	• Exercises in a peer group with similar skill levels • Mastery models observing peers and focusing on good performance and improvement of the peers
Verbal persuasion		• Systematic feedback on development and effort verbalized by teacher • Encouraging feedback from peers • Directing child's attention to his/her own improvement and recognizing it
Affective reactions		• Naming of affective state, discussions on emotions concerning learning and self-ratings of willingness to practice • Stories and discussion about the relation between emotion, thoughts, behavior, and learning • Mistakes and setbacks accepted and allowed in a positive atmosphere • Filling in the emotional checklist at the beginning and at the end of the session

to the children's development and effort, but the reasons for temporary setbacks were also discussed. In the SE group, the teacher started each intervention session by providing verbal feedback related to the homework tasks (reminding them of the importance of training and effort, etc.), and each child shared with the teacher the feedback he/she received from the school assistant in the game session, which was written on a game pass. In the skill group, the teacher was instructed to check homework regularly. Moreover, during the SE intervention, teachers had private discussions with each child that focused on what types of strategies she/he used before the training and how the distribution and frequency of the strategies changed during the training. The teacher demonstrated to each child his/her progress in applying more efficient calculation strategies using a picture of stairs to visualize the strategy development. In addition to the social persuasions from the teachers and school assistants, the children were also encouraged to provide positive feedback for each other related to the use of fluent calculation strategies or signs of improvement.

To assure *vicarious experiences*, the children worked in groups with similar levels of calculation fluency. The participants in the SE program were also encouraged by the teacher to observe the improvements of their peers and share these with the group to provide vicarious experiences. For example, participants were encouraged to point out efficient strategies used within a group at any time during the sessions. After identifying an efficient strategy, they colored one circle of a strategy chain that was visible in the classroom during the intervention sessions to demonstrate concretely that they were making progress as a group. Moreover, they played a card game in which each participant had a pile of cards with addition problems; they had to solve as many problems as possible within 1 min and mark down their score. Other participants provided encouragement (*social persuasions*). After the first round, all the scores were totaled for the team score. The aim for the second round was to beat one's own first score and together with the other participants to help obtain a better team score, reflecting progress and success as a group.

To think about and discuss the *emotions related to learning and practicing*, the participants filled in an emotional checklist indicating how eager they were to practice. These self-ratings were completed at the beginning and at the end of each session to enable discussions about learning-related emotions and to provide an opportunity to express feelings about the strategy training. The SE program included stories related to emotions, beliefs, choice of actions, and consequences in learning that were read by the teacher and discussed together with the children. Using the self-ratings and discussions, the aim of the SE program was to enhance awareness as well as self-knowledge of how emotions and beliefs influence one's behavior in learning situations and learning outcomes.

Teacher Training and Fidelity

Before the intervention, the researchers instructed all the participating teachers on how to implement the program for the calculation strategy training. Moreover, the teachers who conducted the strategy training with self-efficacy feedback were shown how to provide feedback and implement group activities aimed at supporting self-efficacy in math. All the teachers in both groups received group-specific, detailed session-by-session manuals. Two 3-h training sessions were organized, which included the theory of calculation fluency development and how to implement intervention in practice using the program manual.

A number of methods were used to ensure the fidelity of the interventions. First, the teachers were trained in small groups so the instructions for the interventions could be delivered separately for each intervention program. Second, the teachers were provided with session-by-session manuals and materials. Third, meetings and telephone conversations were arranged to monitor adherence to the intervention protocols; after the third intervention session, researchers called each teacher to ensure that the manuals were followed and that the main principals of the programs were understood. Moreover, two meetings were arranged during the interventions to share experiences and ensure that all teachers understood the key elements of the intervention. Fourth, teachers were given a checklist of the feedback to provide for each child on improvement, the amount of work done, effort, and persistence during the practice. The teachers also completed a checklist diary, marking the completed intervention sessions and noting any exceptions in intervention activities or the attendance of participants. Finally, at the end of the intervention, a questionnaire was completed by the participating children in order to check that their experiences with the practices within the interventions corresponded to the intended content. The questionnaire consisted of 28 items with a four-point scale ranging from "*Always…*" (1) to "*Never*" (4). The questions asked about the feedback and evaluations the child felt she/he had received from the teacher on his/her improvement compared to his/her performance at the beginning (making the progress visible to children; mastery experience), social persuasions and feedback given by teacher on training and trying hard (social persuasions), social persuasions and feedback given by other group members (social persuasions), observing the improvement of others in the group (vicarious experience), discussions on emotions and thoughts regarding learning (emotions/thoughts), and questions about more general issues concerning the intervention atmosphere and content (general). Total scores were calculated for each scale. The skill and SE groups differed significantly on all the scales concerning SE-specific content (the Mann-Whitney U test showed significant *p*-values that varied from 0.029 to 0.001), as the SE children reported more SE-related source experiences. In contrast, no difference was detected in the general scale ($p > 0.05$). These differences imply that the interventions were perceived differently by the children in all aspects relevant to explicit SE support in math.

There were 128 activities within 24 intervention sessions (introduction of strategies, games/exercises, starting and closing activities), and the average proportion of activities completed by teachers without exceptions (e.g., did not have time enough) was 97%. The attendance percentage of individual children typically varied between 92 and 100% in a group, meaning that in most of the groups, a child was absent for no more than two of the 24 intervention sessions. However, there were four children who missed four out of 24 intervention sessions, one missed five sessions, and one missed seven sessions. All of these children were included in the analyses.

Data Analyses

Due to the relatively small sample sizes and non-normally distributed SE variables (Kolmogorov-Smirnov, $p < 0.05$), non-parametric analyses were used for the first research question. To analyze the intervention effects on SE, the within-group changes in SE over the three time periods (baseline, intervention, and follow-up) were analyzed separately for the two intervention groups and the control group by using a non-parametric Friedman test, and for the *post-hoc* analysis, the Wilcoxon signed-rank test with Bonferroni correction was used. In addition, comparisons of the SE gain scores during the intervention were conducted using the Kruskal-Wallis test and pairwise comparisons using the Bonferroni approach. Moreover, the same analyses were rerun with only the children who had low SE before the intervention (cut-off score for low SE at or below 42 points).

Second, analyses related to changes in source experiences during the intervention and association with SE were conducted for the two intervention groups. The source variables were mainly normally distributed (Kolmogorov-Smirnov, $p > 0.05$), and parametric analyses were used. However, for two source variables (vicarious experiences and emotional and psychological states) with non-normal distributions, additional analyses were conducted using non-parametric methods. The development during intervention was analyzed by using repeated measures ANOVA and the Friedman test. The comparison of the gain scores during the intervention was tested by using an independent sample *t*-test and Mann-Whitney U test. The association between changes in source scores and SE were analyzed by using Spearman's rank-order correlation coefficient.

Third, in order to analyze the influence of the level and changes in SE on skill development, all children from the two intervention groups were classified into four SE profiles based on their SE ratings before and after the intervention (high SE, low-to-high SE, low SE, and low-increasing SE). The change in

TABLE 2 | Changes in self-efficacy among two intervention groups and controls (RQ1).

Group		Scores at each assessment points				Friedman test	Paired comparison		
		Pre1	Pre2	Post	Follow-up		Pre1 vs. Pre2	Pre2 vs. Post	Post vs. Follow-up
SE group	*Md*	42	41.5	44.5	44	16.95** (3, 28)	0.05	−2.85**	0.16
	min/max	*25/46*	*16/49*	*32/49*	*30/49*			(adj. *p* = 0.027)	
Skill group	*Md*	38.5	39.5	41.5	42	9.68* (3, 32)	−0.1	−2.23*	0.29
	min/max	*15/49*	*21/48*	*20/49*	*18/49*			(adj. *p* = 0.121)	
Controls	*Md*	44	45	46	46	9.11* (3, 51)	−1.38	−0.27	−1.15
	min/max	28/49	28/49	27/49	31/49				
SE $group_{low}$	Md	36	36	42	43	23.35*** (3,13)	−0.15	−3.11**	−0.3
	min/max	*30/42*	*16/42*	*32/49*	*36/49*			(adj. *P* = 0.011)	
Skill $group_{low}$	Md	31	37	37	40	8.09* (3,17)	0.18	−1.2	0.27
	min/max	*15/42*	*21/42*	*20/47*	*18/49*				
$Controls_{low}$	Md	37	33.5	37.5	36	4.55 (3, 12)	NA	NA	NA
	min/max	*29/42*	*28/40*	*27/48*	*31/49*				

**p < 0.05, **p < 0.01, ***p < 0.001. Low refers sub group of children having self-efficacy level at or below 42 points at pre assessments. Md, median score; min, minimum score; max, maximum score.*

TABLE 3 | Effect sizes for changes in self-efficacy (RQ1).

Group	*N*	Effect sizes (*r*)		
		Pre1 vs. Pre2	Pre2 vs. Post	Post vs. Follow-up
SE group	28	0.01	0.38	0.02
Skill group	32	0.01	0.28	0.04
Controls	51	0.14	0.03	0.11
SE $group_{low}$	13	0.03	**0.61**	0.06
Skill $group_{low}$	17	0.03	0.21	0.05
$Controls_{low}$	12	NA	NA	NA

Large effect sizes are written in bold. Following intervals for r were used according to Cohen (1988): no effect <0.1; small effect 0.1–0.3; intermediate effect 0.3–0.5; >0.5 large effect. Low refers sub group of children having self-efficacy level at or below 42 points at pre assessments.

calculation fluency was analyzed by using the Friedman test, and for the *post-hoc* analysis, the Wilcoxon signed-rank test with Bonferroni correction was used. In addition, a comparison of calculation fluency gain scores between the profile groups was conducted using the Kruskal-Wallis test.

Changes in the target variables (SE or calculation fluency) during all possible time periods between the four assessment points were analyzed in RQ1 and RQ3, and the Bonferroni correction took these multiple comparisons into account. However, here we report only the results from the periods that were relevant for the intervention design: between pre-assessments 1 and 2 (baseline), between pre-assessment 2 and the post-assessment (intervention), and between the post-assessment and follow-up assessment (follow-up).

Effect sizes, $r = Z/\sqrt{(N)}$, were computed from standardized test parameters (Field, 2013), and the partial eta squared was reported for the ANOVA models. The following intervals for *r* were used according to Cohen (1988): no effect, <0.1; small effect, 0.1–0.3; intermediate effect, 0.3–0.5; and large effect, >0.5. Corresponding intervals for the partial eta squared were as follows: no effect, <0.01; small effect, 0.01–0.09; intermediate effect, 0.09–0.25; large effect, >0.25. Effect sizes were used as a parallel source when considering the strength of the evidence, and unlike the *p*-value, it is independent of sample sizes.

RESULTS

RQ1: Effects of Calculation Strategy Training and Explicit SE Intervention on Math SE

First, we analyzed the within-group changes in math SE over the four assessment points (**Table 2**). Math SE was found to change in all three groups (SE, skill, and control). *Post-hoc* analysis revealed a significant increase in math SE among both intervention groups but not among the control group during the intervention. The effect size was intermediate in the SE group and small in the skill group (**Table 3**). After taking into account the Bonferroni correction, a significant adjusted *p*-value was found only for the SE group. None of the groups had significant changes in math SE during the baseline or follow-up period. A closer examination of the changes for those children who had low math SE before the intervention revealed that only in the SE group did the children with initially low math SE show improvements in their math SE during the intervention period. The effect size was large (**Table 3**).

Second, changes in math SE during the intervention (SE-gain score) were compared among all three groups. The Kruskal-Wallis test revealed significant differences among the groups (**Table 4**). Pairwise comparisons showed significant differences between the SE group and the controls as well as between the skill group and controls; the intervention groups had a larger increase in math SE during the intervention compared to the controls. After taking into account the Bonferroni correction

TABLE 4 | Comparison of gain scores in self-efficacy during intervention (RQ1).

	Groups									Test
	SE			Skill			Control			Kruskal Wallis Test
	M (sd)	Md	min/max	M (sd)	Md	min/max	M (sd)	Md	min/max	
Self-efficacy gain score (Post-Pre2)–all	4.86 (8.98)	2.50	−15/33	2.60 (4.56)	2.00	−7/15	0.53 (5.13)	0	−10/21	9.16** (2, 111); SE = Skill > controls
Self-efficacy gain score (Post-Pre2)–low	9.23 (9.82)	7.00	−3/33	2.58 (4.75)	1.00	−4/15	2.50 (6.02)	4.00	−8/15	5.39 (2, 42)

***p < 0.01. Low refers sub group of children having self-efficacy level at or below 42 points at pre assessments.*

for multiple tests, the adjusted p-value indicated significant differences between the SE group and the controls ($p = 0.02$) but not between the skill group and the controls ($p = 0.08$). A closer examination of the SE-gain scores of those children who had low math SE before the intervention revealed a value close to the alpha level of 0.05 ($p = 0.067$) but that was deemed not significant by that standard. A pairwise comparison using the Mann-Whitney U test between the children with low math-SE in the two groups revealed a higher increase (intermediate effect size) in math SE among the SE group than in the skill-group participants ($U = 162.00$, $Z = 2.16$, $p = 0.031$, $r = 0.39$). The difference in the increase was close to the pre-set alpha level (but not achieving it) when the SE group was compared with the control group ($U = 45.50$, $Z = -1.83$, $p = 0.068$, $r = 0.36$); however, the effect size was intermediate. The skill and control groups did not differ from each other, and effect sizes indicated no effect ($U = 104.50$, $Z = 0.11$, $p = 0.913$, $r = 0.02$).

RQ2: Effects of Interventions on Source Experiences and the Relation Between Changes in Source Experiences and in Math SE

The changes in the sources of math SE (total score, mastery experiences, social persuasions, vicarious experiences, and emotional and physiological states) were analyzed by using repeated-measures ANOVA with time (pre-test1 vs. pre-test2 vs. post-test vs. follow-up) as a within-subject factor and *intervention* group as a between-subjects factor. A significant main effect of time was found, indicating that children's source experiences increased during the intervention when analyzing an overall total score [$F_{(1,58)} = 5.44$, $p = 0.023$, $\eta_p^2 = 0.09$] and in specific types of sources of mastery experiences [$F_{(1,58)} = 4.56$, $p = 0.037$, $\eta_p^2 = 0.07$] and emotional and psychological states [$F_{(1,58)} = 4.59$, $p = 0.036$, $\eta_p^2 = 0.09$] across the sample. Moreover, there was a significant interaction between time and group in social persuasions [$F_{(1,58)} = 5.43$, $p = 0.023$, $\eta_p^2 = 0.09$], indicating that social persuasion experiences strengthened in the SE group and decreased in the skill group. Due to non-normal distribution findings related to sources of vicarious experiences and emotional and psychological states, the results were confirmed by using a non-parametric Friedman test. The findings of non-significant changes in vicarious experiences during the intervention were fully supported by the non-parametric analyses ($\chi^2 = 0.78$, df = 1, $p = 0.736$), and the results related to emotional and psychological states were in line with the parametric analyses, although they did not reach a significance level of 0.05 ($\chi^2 = 2.81$, df = 1, $p = 0.093$). The comparisons in source gain scores during the intervention were conducted by using an independent sample t-test and confirmed by the Mann-Whitney U test for sources of emotional and psychological states and vicarious experiences. The only difference was found in the gain scores of social persuasions favoring the SE group [$t(58) = -2.53$, $p = 0.014$].

The association between the gain scores in the source and math SE (during the intervention) were analyzed by using Spearman's rank-order correlation coefficient (**Table 5**). Changes in math SE among the SE-group participants were correlated with changes in mastery experiences ($r_S = 0.48$, $p = 0.010$) and social persuasions ($r_S = 0.43$, $p = 0.024$). The correlation between the other two sources and math SE varied from small (vicarious experiences) to intermediate (emotional and psychological states); the correlation did not reach the pre-set level of significance with the emotional and psychological states ($p = 0.077$). Changes in the source experiences and math SE were not related among the skill-group participants, as the correlations were generally very low, varying mainly from 0.09 to 0.18. The only exception was the association between changes in mastery experiences and math-SE, which was at the intermediate level and close to the pre-set level of significance ($r_S = 0.32$, $p = 0.085$).

RQ3: Differences in Math SE and Changes in Calculation Fluency During the Intervention

In order to analyze the influence of the level and changes in math SE on skill development, first the within-group changes in math SE among children with different SE profiles (high SE, low-to-high SE, low-increasing SE, and low SE) were analyzed over the four assessment points (**Figure 1**). A non-parametric Friedman test of differences among the repeated measures was conducted separately for each group, both with raw scores (absolute change) and standardized scores (adjusted with the average grade level and variation) (**Table 6**). Changes in the calculation fluency during the assessed time period were found for all groups when analyzing raw scores, and for the high SE and low-to-high SE profiles when analyzing z-score changes. Moreover, a *post-hoc* analysis with the Wilcoxon signed-rank test showed that when using raw scores, there was a significant change in calculation

TABLE 5 | Spearman's rank-order correlation coefficient between gain scores in source experiences and in self-efficacy among SKILL-group and SE-group (RQ2).

	1.	2.	3.	4.	5.	6.
Self-efficacy (gain score)	-	0.48*	0.43*	0.24	0.34	0.29
Mastery experiences (gain score)	0.32	-	0.31	0.35	0.11	0.62***
Social persuasions (gain score)	0.09	0.22	-	0.20	0.23	0.43*
Vicarious experiences (gain score)	0.18	0.32	0.32	-	0.00	0.66***
Emotional and physiological states (gain score)	0.10	0.06	−0.08	0.19	-	−0.37
Source experiences (gain of sum score)	0.18	0.60***	0.49**	0.56**	−0.31	-

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. Correlations for SKILL-group are below the diagonal; correlations for SE-group are above the diagonal.*

TABLE 6 | Changes in calculation fluency among children with different self-efficacy profile (RQ3).

Group	N	Score		Calculation fluency				Friedman test	Paired comparison		
				Pre1	Pre2	Post	Follow-up		Pre1 vs. Pre2	Pre2 vs. Post	Post vs. Follow-up
High SE	15	Raw	*Md*	14	19	26	27	33.53*** (3, 15)	−1.49	−3.47** (adj. $P = 0.003$)	0.64
		Z-score	*Md*	−1.1	−0.87	−0.6	−0.96	18.04** (3, 15)	−0.85	−3.11** (adj. $P = 0.011$)	1.70
Low-to-high SE	16	Raw	*Md*	14	19.5	27	28	30.75*** (3, 16)	−1.85	−2.47* (adj. $P = 0.082$)	−0.48
		Z-score	*Md*	−1.12	−1.03	−0.6	−0.84	16.64** (3, 16)	−1.37	−2.05* (adj. $p = 0.240$)	0.55
Increasing low SE	9	Raw		14	16	21	19	20.30*** (3, 9)	−1.34	−1.83	0.09
		Z-score	*Md*	−1.27	−1.2	−0.91	−1.1	2.47 (3, 9)	NA	NA	NA
Low SE	18	Raw		19	22	26	25	20.30*** (3, 18)	−1.87	−1.94* (adj. $p = 0.317$)	0.19
		Z-score	*Md*	−1.17	−1.04	−0.95	−1.02	4.47 (3, 18)	NA		NA

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.*

fluency during the intervention in the high SE, low-to-high SE, and low-SE profile groups and a close but not significant change ($p = 0.068$) in the low-increasing SE group. The effect sizes (r) for changes during the intervention were large for the high SE group and intermediate for the other three SE groups (**Table 7**). None of the groups showed significant development during the baseline or follow-up ($p < 0.05$). When analyzing the z-scores, the high SE-group and low-to-high SE-group approached their average grade level in calculation fluency during the intervention but not during the baseline or follow-up. The size of the improvement was large for the high SE group and intermediate for the low-to-high SE group.

When comparing the gain scores in calculation fluency during the intervention using the Kruskal-Wallis test, statistically significant differences were found [$\chi^2(59, 3) = 8.00$, $p = 0.047$]. The paired comparison revealed that the high SE group improved more in calculation fluency during the intervention than the low SE group ($z = 2.68$, $p = 0.007$), and this finding remained when taking into account the Bonferroni correction for multiple tests ($p = 0.043$). No other statistically significant differences were found between the SE-profile groups.

DISCUSSION

This study extended previous research by comparing whether children's math self-efficacy (math SE) can be supported by a pure calculation strategy training or whether explicit SE support targeting the four sources of self-efficacy introduced by social-cognitive theory (Bandura, 1997) integrated with strategy training has added benefits for children's math SE, sources of math SE, and their calculation fluency. Special education teachers implemented these interventions at schools for children with poor calculation skills. First, this study examined how math SE changed among children who participated in calculation strategy training either with (SE group) or without explicit SE intervention (skill group). Second, changes in the four source experiences (mastery experiences, social persuasions, vicarious experiences, and emotional and physiological states) were examined by comparing the two intervention groups (SE and skill groups). Also, the relationship between the changes in the SE-source experiences and changes in SE beliefs was analyzed. Third, we examined how children with different SE levels (i.e., SE profiles formed based on the pre-intervention SE level and changes during the interventions) improved in calculation fluency.

The results showed, first, that low-performing children's math SE, that is, their beliefs about their capability to do and learn math, improved in both intervention groups (the SE and skill groups). However, only the intervention that combined strategy training and math-SE support enhanced math SE for children with low SE. Second, both interventions strengthened mastery experiences and lowered experiences related to negative emotional and psychological states. However, experiences of social persuasions increased only among children in the SE group. Moreover, changes in mastery experiences and social persuasions were positively associated with changes in math

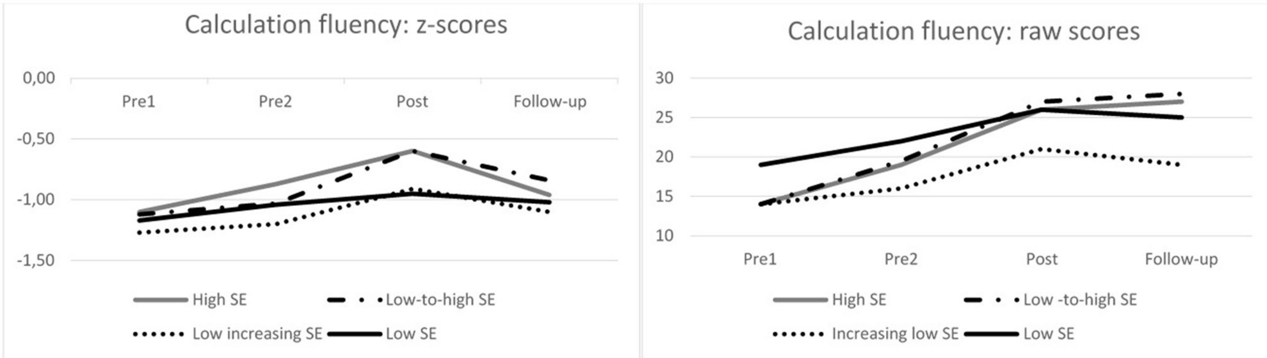

FIGURE 1 | Development of calculation fluency among children with different SE-profile.

TABLE 7 | Effect sizes for changes in calculation fluency (RQ3).

Group	N		Effect sizes (r)		
			Pre1 vs. Pre2	Pre2 vs. Post	Post vs. Follow-up
High SE	15	Raw	0.27	**0.63**	0.12
		Z-score	0.16	**0.57**	0.31
Low-to-high SE	16	Raw	0.33	0.44	0.08
		Z-score	0.24	0.36	0.10
Increasing low SE	9	Raw	0.32	0.43	0.02
		Z-score	NA	NA	NA
Low SE	18	Raw	0.31	0.32	0.03
		Z-score	NA	NA	NA

Large effect sizes are written in bold. Following intervals for r were used according to Cohen (1988): no effect <0.1; small effect 0.1–0.3; intermediate effect 0.3–0.5; >0.5 large effect.

SE only among children who received explicit SE intervention (SE group). Third, a high level of math SE was related to positive development in calculation fluency during strategy training; children with high SE and children whose SE changed during the intervention from low to high SE showed more skill development, approaching their average grade level. In contrast, children with low SE did not reach their age peers in calculation fluency.

Changes in Math-SE During Interventions

The findings showed a significant increase in math SE in both intervention groups (SE and skill) but not among the control group, suggesting that the changes in math SE were due to the provided interventions. This interpretation was further supported by the fact that changes in math SE took place during the intervention period and no change in math SE was found during the baseline or follow-up. Thus, it seems that providing individually challenging but accessible tasks and targeted strategy training can increase math SE in addition to improving calculation fluency itself (Koponen et al., 2018). There are several possible reasons for these positive effects. First, both interventions provided opportunities to practice and to perform successfully in math tasks despite difficulties, which is not the situation in business-as-usual instruction where educational plans are often followed and tasks are not tailored to the child's skill level. Moreover, it is possible that implementing the training in small groups with peers having similar skill levels might have lowered the excitement and nervousness related to expectations for performance and worry about failing in math.

Although improvement in math SE was found among both intervention groups, the level of math SE for children with initially low math SE changed during the interventions only in the SE group, in which a large effect size was found. It seems that the students most in need of support—for both poor mathematical skills and low math SE—need explicit SE support to be able to see their progress and change their beliefs about their own math skills. Skill training itself was not found to be sufficient to change math SE among these children, although changes in skills were found. Thus, our findings provide empirical support for the theory-derived assumption that by enabling positive source experiences through explicit SE intervention, it is possible to enhance children's SE. This finding of the malleability of math SE aligns with previous results of self-efficacy research in other academic domains, that is, in reading (Aro et al., 2018) and in writing (García and de Caso, 2006). These findings further support the effectiveness of source-based SE interventions, especially for children with low SE, and highlight the importance of integrating explicit self-efficacy feedback and practices into instruction provided at schools.

Changes in Source Experiences and Their Relation to Changes in SE During Interventions

In general, children in both intervention groups experienced more positive source experiences (i.e., total score of the four sources) after the interventions. A more detailed analysis of each of the source experiences revealed that children reported more mastery experiences and fewer negative arousals (i.e., emotional and psychological states) after the interventions across both intervention groups. The findings suggest that calculation strategy training administered in small groups of students with similar difficulties and using tasks with an appropriate difficulty level provides students with opportunities both to experience mastery in tasks and to decrease the negative emotional reactions related to math. These results are in line with suggestions that mastery experiences can be provided by using individually challenging but accessible tasks (Bandura, 1994). In everyday school life, many children who have problems with basic calculation skills have the same educational aims and curricula as their peers who do not have problems learning math. Following the same instructions and facing daily challenges at school are not likely to provide mastery experiences but, instead, lead to experiences of failure which can influence on emotional and psychological states as well. However, if students experience only easy successes, it could lead them to expect quick results and become easily discouraged by failure (Bandura, 1994), and thus, individual learning plans with individually adjusted challenge levels are important in educational support. The element of an appropriate difficulty level of tasks was present in both intervention groups. A smooth decrease found in emotional and psychological states in both intervention groups could be explained by a sense of mastery created from appropriately difficult math tasks, which could have reduced the negative emotions toward math, such as math anxiety, that has been shown to be dependent on task difficulty (Pantoja et al., 2020). In support of this interpretation, psychological state and mastery experiences were found to correlate strongly in a study that examined the sources of SE in math among middle school students (Usher and Pajares, 2009).

Changes in mastery experiences were positively associated with changes in math SE among the SE group. Mastery experience has previously been found to relate to math SE among third grade elementary school students (Joët et al., 2011), and our results extended these previous cross-sectional findings by providing stronger evidence of associations and confirming theoretical assumptions that mastery experiences are central sources of math SE. Both intervention groups exhibited positive growth in mastery experiences during the interventions; however, changes in mastery experiences were related more strongly to changes in math SE among the SE group. One explanation for this finding might be that children in the SE group received feedback and were involved in practices that explicitly guided them in making interpretations and linking experiences of success and mastery to their capability to do and learn math. This is in line with the claim that the effect of successful performance on SE varies according to how various personal and situational contributions are interpreted and weighted (Bandura, 1997). This notion implies that a teacher can promote and support a child's individual interpretation of their successful performances and help the child to see these experiences as signs of their capability to successfully learn or perform math in the future. Performance accomplishments may not automatically lead to mastery interpretation or add confidence to one's capability in math. Rather, this is something that the teacher can and should explicitly support, for instance, by making the child's progress visible to the child and highlighting the interpretation that improvement is a result of the child's practice, which demonstrates his or her capability to learn math.

Only children in the explicit SE intervention (SE group) experienced increasing social persuasions over time. In addition, change in social persuasions was positively associated with change in math SE only in the SE group. It was somewhat surprising to find an increase only in the SE group, because, at first glance, social persuasions could be considered a rather self-evident element of teaching and general instruction. Our findings support the positive effects of explicit positive feedback given for effort on training and skill development as well as encouragement of the group members to provide positive feedback for each other. It seems that although children likely receive verbal persuasions of their skills in normal teaching practices, students experience teacher support as more persuasive when teachers are instructed and guided to give more explicit and positive feedback on students' progress and efforts. The teachers were instructed to provide feedback on progress, success, and effort systematically during each training session, which might strengthen the experiences of being praised. In addition to the teacher's verbal persuasions, children were also encouraged to pay attention and praise others' learning and improvement; children in the SE group received persuasions from other children more frequently than those in the skill group (see below). This might not be a typical part of the business-as-usual support, where social persuasion is mainly received from teachers. Thus, this could be a significant factor to consider when developing learning environments supporting SE. It may also be that when children learn to see the progress and effort of their peers and to encourage them, they may learn to recognize their own progress and efforts and praise themselves (Pajares, 2006).

The finding that change in social persuasions is positively associated with changes in math SE among the SE group is in line with the proposal that particularly younger students use the persuasions received from others when forming beliefs of their own capabilities (Bandura, 1997) and in line with recent findings in reading showing that these experiences shape SE development (Peura et al., 2021). The social persuasion provided in the SE intervention was more explicit and systematically provided than the spontaneous positive feedback children likely have received at school. The teachers were instructed to give self-referenced feedback and focus on self-improvement rather than on triumph over others (Bandura, 1997). Moreover, the feedback was targeted to help the child to see their progress and focus on improvement, no matter how small that improvement might have been. In prior studies, students who received self-referenced feedback were shown to have higher SE than those who received other-referenced feedback or norm-referenced feedback (Shih and Alexander, 2000; Chan and Lam, 2008). This is an important and encouraging finding that clarified important features of feedback for enhancing SE. As Bandura (1997) has emphasized, social persuasion does not obviously enhance SE, and it may actually be even easier to undermine rather than enhance an individual's SE through social persuasions. Social persuasions should focus on self-improvement rather than on triumph over others (Bandura, 1997). This understanding may be especially needed for encouraging low-performing students who may experience disappointing results despite their efforts and constant struggle with learning. Moreover, social persuasions should be realistic because unrealistic boosts in efficacy are quickly disconfirmed by disappointing results from one's efforts (Bandura, 1997; Pajares, 2006). These issues were emphasized in the present SE interventions.

To ensure that interventions were implemented as planned, the children completed fidelity ratings for questions on how often they experienced practices and feedback that were planned to provide experiences in the four sources of SE. The children in the SE group reported more actions related to all four source experiences, but no differences were found in general features concerning the intervention atmosphere and content. This finding suggests that the SE intervention was implemented as planned to cover all four sources of SE. This was encouraging, since it emphasized the ecological validity of the present study by providing research evidence for SE intervention programs that can be implemented rather easily in schools.

The heterogeneity found in the changes of the four source experiences as well as in their association with SE were not likely due to fidelity issues, because expected differences between two intervention groups were systematically found in practices and feedback targeted at providing positive experiences in all four sources. Thus, this study provided new knowledge regarding the malleability of sources of SE by showing that, at least among elementary school children, source experiences differed according to how easily they could be changed (i.e., malleability). Moreover, the source experiences seemed to be differently weighted in relation to SE, as has been suggested to occur among older children (Chen and Usher, 2013). Among elementary school children, mastery experiences and social persuasions seemed to be the most relevant efficacy-building experiences in math.

Differences in the Level and Changes in SE and Calculation Fluency Improvement During Interventions

Finally, we focused on whether the differences in the level and changes of math-SE were visible in calculation fluency improvement during intervention. Children from both intervention groups were classified into four different source SE profiles: high SE, low-to-high SE, low-increasing SE, and low SE. The results indicated that children with high SE before and after the intervention developed the most in calculation fluency during the intervention, and they also approached their average grade level as indicated by the analyses using standard scores. These findings align with those of previous longitudinal studies (Pajares and Graham, 1999; Phan, 2012b), in which the level of SE was found to predict later math performance. Similar findings were also made in reading that showed that children with high SE benefit more from skill training than those with low SE (Ronimus et al., 2020). As children with high SE are suggested to put forth more effort and persistence in learning situations and to choose more learning activities (Bandura, 1986, 1997), it is not surprising that they also improved more, as was shown in our study. Children who changed from low to high SE also improved in calculation fluency and approached their average grade level during the interventions. This finding does not allow a causal conclusion of the unidirectional relations (i.e., that increasing self-efficacy boosted skill development). Rather, alternative interpretations that improvement in math achievement boosted math SE or there were reciprocal influences are possible. Reciprocal interactions between self-efficacy and achievement are supported in social-cognitive theory.

Children with low SE before and after the interventions showed significant development in calculation fluency during the interventions but did not approach the average grade level. The differences in the findings using raw scores and z-scores during the interventions can be explained by the fact that the low SE group mainly included older children (although not solely), and although there was improvement in calculation fluency during the intervention, it was not large enough to change their position within the distribution in the grade. Thus, by exploring both raw scores and z-scores, we obtained a more comprehensive picture of how calculation skills improved when grade-level expectations were taken into account.

Finally, children with a higher but still low math SE before and after the intervention (low-increasing SE) showed improvement in calculation fluency during the interventions but did not approach their average grade level during the interventions. It would have been interesting to see whether a longer intervention would have led to a stronger increase in both skills and SE because there was a smooth but positive trend for both self-efficacy and calculation fluency development.

Altogether, these findings support the view that high SE is related to stronger improvement in learning, and because math SE was shown to be malleable with the interventions provided, it is relevant to take it into account as a specific area of support at school and home. Our findings challenge the results from a recent meta-analytic study (Talsma et al., 2018) that suggests unilateral relations from achievement to SE among children, and instead, emphasize that high SE forms a stronger basis for learning among elementary school children, and thus, children's positive self-efficacy beliefs should be included as an important pedagogical aim in teaching along with objectives related to academic achievement and learning. However, the finding indicating that high SE did not boost the calculation fluency development during the baseline or follow-up highlights the importance of systematic, intensive, and continuous support for SE and of targeted strategy training for poor-performing children. Thus, low-performing children need ongoing support. An integrated approach that combines strategy training and SE intervention seems beneficial, especially among children with low calculation fluency and low math SE.

Limitations and Directions for Future Research

Some limitations of this study should be considered when interpreting the findings. The main limitations were related to the quasi-experimental nature of the design. To emphasize the high societal value, this study was implemented in ecologically valid conditions by teachers as part of the everyday school routine;

thus, a blinded and fully random matching of the participants was not possible. Moreover, the children were carefully selected for interventions, and because of the randomization at the school level, the SE and skill groups did not differ in calculation fluency in pre-assessments. However, the level of SE was not controlled for when matching, and there was a large variation from low to high SE in both intervention groups. A larger sample would have made it possible to analyze the individual variation in more detail. Moreover, because of the moderate sample sizes, it was not possible to analyze the findings for boys and girls separately, although gender might moderate the effects of the interventions on both source experiences and math SE (see Chen and Usher, 2013). Because of the limited available resources, procedures that would allow closer monitoring of the reliability and validity of the interventions (e.g., video recordings) could not be conducted. The measures taken to guarantee the fidelity of the results (teacher training, a session-by-session manual, diary completion, meetings, and phone calls during the intervention) support the assertion that the programs were implemented following the program manual and intervention design.

Moreover, in the present study we used Bandura's socio-cognitive theory as a theoretical frame. For the sake of clarity we did not introduce related and partially overlapping concepts, such as math anxiety (compare to physiological and emotional state). However, math anxiety is important factor and related both to self-efficacy as well as skill development (e.g., Sorvo et al., 2019). In future, intervention studies should include, the broader set of items representing the different dimensions of math anxiety, such as cognitive and affective (e.g., Ho et al., 2000; Sorvo et al., 2019) in order to exam the interaction with math-SE and math anxiety more deeply. Furthermore, by using person oriented approaches it's possible to clarify the predictive relation of these intertwined factors by examining individual profiles formed across these emotional and motivational factors and their relation with skill development or response to support. Moreover, SE beliefs are linked to child's behavior and self-regulation in learning situation (Bandura, 1986, 2001) as well as to metacognitive skills (Cera et al., 2013) which were not examined in the present study. In addition to self-regulation, also external regulation stemming from the context is relevant especially in group-based interventions as the context may or may not promote positive proactivity and foster regulation. Thus, they are relevant factors to consider in future research when trying to understand the link between SE and skill development. Finally, intervention were implemented in small groups, but as a limitation, information of interactions among children or with teacher were not collected, and thus, the effect of these factors were not explored.

Practical Implications

There are several practical implications. The explicit intervention that targeted the four sources of self-efficacy, integrated with intensified strategy training and implemented by teachers in small groups, was effective in building positive self-beliefs and positive efficacy experiences as well as increasing math skills. This suggests that feedback that highlights the self-monitoring of progress and personal accomplishments is well-suited for building a sense of efficacy, which in turn promotes math achievement. The present study showed that children with low calculation fluency and low math SE did not benefit from pure strategy training to the same extent as children with low calculation fluency but high math SE. More importantly, the most vulnerable children, those with low math SE and low skills, seemed to benefit from explicit SE support. Thus, in addition to identifying children who have a low skill level and are therefore in need of intensified training, it is important to identify a child's level of SE and understand how it influences the child's behavior, such as persistence and effort in learning situations. Providing mastery experiences and social persuasions seem to be promising approaches to enhance math SE among elementary school children. Most importantly, the SE intervention program was integrated with skill training and implemented by special education teachers as part of their normal work to support low-performing children; thus, it can be directly applied at schools.

DATA AVAILABILITY STATEMENT

The datasets presented in this article are not readily available because written consent from parents allow only research group members to analyze and publish data. Requests to access the datasets should be directed to tuire.k.koponen@jyu.fi.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by University of Jyväskylä Ethical Committee. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

All co-authors have made contributions appropriate for assumption of authorship and were in agreement with the content of the manuscript and byline order.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2021.714379/full#supplementary-material

REFERENCES

Ahn, H. S., Bong, M., and Kim, S. I. (2017). Social models in the cognitive appraisal of self-efficacy information. *Contemp. Educ. Psychol.* 48, 149–166. doi: 10.1016/j.cedpsych.2016.08.002

Arens, A., Katrin, A., Frenzel, C., and Thomas, G. (2020). Self-concept and self-efficacy in math: longitudinal interrelations and reciprocal linkages with achievement. *J. Exp. Educ.* 1–19. doi: 10.1080/00220973.2020.1786347

Aro, T., Viholainen, H., Koponen, T., Peura, P., Räikkönen, E., Salmi, P., et al. (2018). Can reading fluency and self-efficacy of reading fluency be enhanced with an intervention targeting the sources of self-efficacy? *Learn. Individ. Differ.* 67, 53–66. doi: 10.1016/j.lindif.2018.06.009

Arslan, A. (2013). Investigation of relationship between sources of self-efficacy beliefs of secondary school students and some variables. *Educational Sciences: Theory & Practice*, 13, 1983–1993. doi: 10.12738/estp.2013.4.1753

Ayotola, A., and Adedeji, T. (2009). The relationship between mathematics self-efficacy and achievement in mathematics. *Proc. Soc. Behav. Sci.* 1, 953–957. doi: 10.1016/j.sbspro.2009.01.169

Bandura, A. (1986). *Social Foundations of Thought and Action: A Social Cognitive Theory*. Hoboken, NJ: Prentice-Hall.

Bandura, A. (1994). "Self-efficacy," in *Encyclopedia of Human Behavior (Reprinted in H. Friedman [Ed.], Encyclopedia of mental health. Academic Press, 1998)*, ed V. S. Ramachaudran (https://www.google.com/search?sxsrf=ALeKk01n-ThGNNx4ajiWAUGjcDYU5HwZvA:1626259386317&q=Cambridge,+Massachusetts&stick=H4sIAAAAAAAAAOPgE-LUz9U3MM8rzi5X4gAxDQszzLW0spOt9POL0hPzMqsSSzLz81A4VhmpiSmFpYlFJalFxYtYJZwTc5OKMlPSU3UUfBOLixOTM0qLU0tKinewMgIAvcQbN2EAAAA&sa=X&ved=2ahUKEwiPtKKosOLxAhV6wjgGHaaeC6MQmxMoATAgegQIHhAD Cambridge, MA: Academic Press), 71–81.

Bandura, A. (1997). *Self-Efficacy: The Exercise of Control*. New York, NY: W. H. Freeman and Company.

Bandura, A. (2001). Social cognitive theory: an agentic perspective. *Annual Review of Psychology*, 52, 1–26. doi: 10.1146/annurev.psych.52.1.1

Bandura, A. (2006). "Guide for constructing self-efficacy scales," in *Self-Efficacy Beliefs of Adolescents*, eds F. Pajares and T.C. Urdan (Charlotte, NC: Information Age Publishing), 307–337.

Britner, S. L., and Pajares, F. (2006). Sources of science self-efficacy beliefs of middle school students. *J. Res. Sci. Teach.* 43, 485?-499.

Canobi, K. H. (2004). Individual differences in children's addition and subtraction knowledge. *Cogn. Dev.* 19, 81–93. doi: 10.1016/j.cogdev.2003.10.001

Cera, R., Mancini, M., and Antonietti, A. (2013). Relationships between metacognition, self-efficacy and self-regulation in learning. *J. Educ. Cult. Psychol. Stud.* 4, 115–141. doi: 10.7358/ecps-2013-007-cera

Chan, J. C. Y., and Lam, S. F. (2008). Effects of different evaluative feedback on students' self-efficacy in Learning. *Instruct. Sci.* 38, 37–58. doi: 10.1007/s11251-008-9077-2

Chen, J. A., and Usher, E. L. (2013). Profiles of the sources of science self-efficacy. *Learn. Individ. Differ.* 24, 11–21. doi: 10.1016/j.lindif.2012.11.002

Chen, P., and Zimmerman, B. (2007). A Cross-national comparison study on the accuracy of self-efficacy beliefs of middle-school mathematics students. *J. Exper. Educ.* 75, 221–244. doi: 10.3200/JEXE.75.3.221-244

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences*. Mahwah, NJ: Erlbaum.

Field, A. (2013). *Discovering Statistics Using IBM SPSS Statistics*. Thousand Oaks, CA: Sage.

Galla, B. M., Wood, J. J., Tsukayama, E., Har, K., Chiu, A. W., and Langer, D. A. (2014). A longitudinal multilevel model analysis of the within-person and between-person effect of effortful engagement and academic self-efficacy on academic performance. *J. Sch. Psychol.* 52, 295–308. doi: 10.1016/j.jsp.2014.04.001

García, J. N., and de Caso, A. M. (2006). Changes in writing self-efficacy and writing products and processes through specific training in the self-efficacy beliefs of students with learning disabilities. *Learn. Disabil. Contemp. J.* 4, 1–27.

Geary, D. C. (1993). Mathematical disabilities: cognitive, neuropsychological, and genetic components. *Psychol. Bull.* 114, 345–362. doi: 10.1037/0033-2909.114.2.345

Geary, D. C. (2004). Mathematics and learning disabilities. *J. Learn. Disabil.* 37, 4–15. doi: 10.1177/00222194040370010201 Available online at: http://www.ldw-ldcj.org/

Grigg, S., Perera, H. N., McIlveen, P., and Svetleff, Z. (2018). Relations among math self-efficacy, interest, intentions, and achievement: a social cognitive perspective. *Contemp. Educ. Psychol.* 53, 73–86. doi: 10.1016/j.cedpsych.2018.01.007

Hampton, N. Z., and Mason, E. (2003). Learning disabilities, gender, sources of self- efficacy, self-efficacy beliefs, and academic achievement in high school students. *J. Sch. Psychol.* 41, 101–111. doi: 10.1016/S0022-4405(03)00028-1

Hannula, M. S., Bofah, E., Tuohilampi, L., and Metsämuuronen, J. (2014). "A longitudinal analysis of the relationship between mathematics-related affect and achievement in Finland," in *Proceedings of the 38th Conference of the IGPME and the 36th conference of the PME-NA*, eds S. Oesterle, P. Liljedahl, C. Nicol, and D. Allan (Vancouver, BC: PME), 249–256.

Ho, H. Z., Senturk, D., Lam, A. G., Zimmer, J. M., Hong, S., and Okamoto, Y. (2000). The affective and cognitive dimensions of math anxiety: a cross-national study. *J. Res. Math. Educ.* 31, 362?-379. doi: 10.2307/749811

Hoffman, B., and Spatariu, A. (2008). The influence of self-efficacy and metacognitive prompting on math problem-solving efficiency. *Contemp. Educ. Psychol.* 33, 875–893. doi: 10.1016/j.cedpsych.2007.07.002

Honicke, T., and Broadbent, J. (2016). The influence of academic self-efficacy on academic performance: a systematic review. *Educ. Res. Rev.* 17, 63–84. doi: 10.1016/j.edurev.2015.11.002

Hornstra, L., van der Veen, I., and Peetsma, T. (2016). Domain-specificity of motivation: a longitudinal study in upper primary school. *Learn. Individ. Differ.* 51, 167–178. doi: 10.1016/j.lindif.2016.08.012

Hornstra, L., van der Veen, I., Peetsma, T., and Volman, M. (2013). Developments in motivation and achievement during primary school: a longitudinal study on group-specific differences. *Learn. Individ. Differ.* 23, 195–204. doi: 10.1016/j.lindif.2012.09.004

Joët, G., Usher, E. L., and Bressoux, P. (2011). Sources of self-efficacy: an investigation of elementary school students in France. *J. Educ. Psychol.* 103:649. doi: 10.1037/a0024048

Kaskens, J., Segers, E., Goei, S. L., van Luit, J. E. H., and Verhoeven, L. (2020). Impact of children's math self- concept, math self-efficacy, math anxiety, and teacher competencies on math development. *Teach. Teach. Educ.* 94:103096. doi: 10.1016/j.tate.2020.103096

Kaufmann, L., Pixner. S., and Goebel, S. (2011). Finger usage and arithmetic in adults with math difficulties: evidence from a case report. *Front. Psychol.* 2. doi: 10.3389/fpsyg.2011.00254

Kearns, D. M., and Fuchs, D. (2013). Does cognitively focused instruction improve the academic performance of low-achieving students? *Except. Child.* 79:263. doi: 10.1177/001440291307900200

Kitsantas, A., Cheema, J., and Ware, H. W. (2011). Mathematics achievement: the role of homework and self-efficacy beliefs. *J. Adv. Acad.* 22, 310–339. doi: 10.1177/1932202X1102200206

Klassen, R. (2002). A question of calibration: a review of the self-efficacy beliefs of students with learning disabilities. *Learn. Disabil. Q.* 25, 88–102. doi: 10.2307/1511276

Klassen, R. (2004). A cross-cultural investigation of the efficacy beliefs of South Asian immigrant and Anglo non-immigrant early adolescents. *J. Educ. Psychol.* 96, 731–742. doi: 10.1037/0022-0663.96.4.731

Koponen, T., and Mononen, R. (2010). The 2-minute addition fluency test (Unpublished).

Koponen, T., Mononen, R., Kumpulainen, T., and Puura, P. (2011). SELKIS-Yhteenlaskua Ymmärtämään. Yhteenlaskutaidon Harjoitusohjelma. [Improving Addition Skills: SELKIS Intervention Program]. Jyväskylä: Niilo Mäki Institute and Haukkarannan koulu.

Koponen, T., Sorvo, R., Dowker, A., Raäikkönen, E., Viholainen, H., Aro, M., et al. (2018). Does multi-component strategy training improve calculation fluency among poor performing elementary school children? *Front. Psychol.* 9:1187. doi: 10.3389/fpsyg.2018.01187

Lau, C., Kitsantas, A., Miller, A. D., and Rodgers, E. B. D. (2018). Perceived responsivity for learning, self-efficacy, and sources of self-efficacy in mathematics: a study international baccalaureate primary years programs students. *Soc. Psychol. Educ.* 21, 603–620. doi: 10.1007/s11218-018-9431-4

Multon, K. D., Brown, S. D., and Lent, R. W. (1991). Relation of self-efficacy beliefs to academic outcomes: a meta-analytic investigation. *J. Couns. Psychol.* 38, 30–38. doi: 10.1037/0022-0167.38.1.30

Pajares, F. (2006). "Self-efficacy during childhood and adolescence: implications for teachers and parents," in *Adolescence and Education: Self-Efficacy Beliefs of Adolescents*, eds F. Pajares and T. Urdan (https://www.google.com/search?sxsrf=ALeKk03m2_dE3QpXQfDFbWVIAUycnPFK9w:1626260085523&q=Charlotte,+North+Carolina&stick=H4sIAAAAAAAAAOPgE-LSz9U3MDHONSo2UOIAsdOKkyy0tLKTrfTzi9IT8zKrEksy8_NQOFYZqYkphaWJRSWpRcWLWCWdMxKLcvJLSlJ1FPzyi0oyFJwTi_JzMvMSd7AyAgDg1hIfYwAAAA&sa=X&ved=2ahUKEwjUu9b1suLxAhVFzTgGHSPCC-gQmxMoATAfegQIIxAD Charlotte, NC: Information Age Publishing), 339–367.

Pajares, F., and Graham, L. (1999). Self-efficacy, motivation constructs, and mathematics performance of entering middle school students. *Contemp. Educ. Psychol.* 24, 124–139. doi: 10.1006/ceps.1998.0991

Pajares, F., Johnson, M. J., and Usher, E. L. (2007). Sources of writing self-efficacy beliefs of elementary, middle, and high school students. *Res. Teach. Engl.* 42, 104–120. Available online at: http://www.jstor.org/stable/40171749

Pantoja, N., Schaeffer, M., Rozek, C., Beilock, S., and Levine, S. (2020). Children's math anxiety predicts their math achievement over and above a key foundational math skill. *J. Cogn. Dev.* 21, 709–728. doi: 10.1080/15248372.2020.1832098

Peura, P., Aro, T., Räikkönen, E., Viholainen, H., Koponen, T., Usher, E. L., et al. (2021). Trajectories of change in reading self-efficacy: a longitudinal analysis of self-efficacy and its sources. *Contemp. Educ. Psychol.* 64:101947. doi: 10.1016/j.cedpsych.2021.101947

Phan, H. P. (2012a). The development of English and mathematics self-efficacy: a latent growth curve analysis. *J. Educ. Res.* 105, 196–209. doi: 10.1080/00220671.2011.552132

Phan, H. P. (2012b). Relations between informational sources, self-efficacy, and academic achievement: a developmental approach. *Educ. Psychol.* 32, 81–105. doi: 10.1080/01443410.2011.625612

Richardson, M., Abraham, C., and Bond, R. (2012). Psychological correlates of university students' academic performance: a systematic review and meta-analysis. *Psychol. Bull.* 138, 353–387. doi: 10.1037/a0026838

Ronimus, M., Eklund, K., Westerholm, J., Ketonen, R., and Lyytinen, H. (2020). A mobile game as a support tool for children with severe difficulties in reading and spelling. *J. Comput. Assist. Learn.* 36, 1011–1025. doi: 10.1111/jcal.12456

Schunk, D. H. (1983). Developing children's self-efficacy and skills: the roles of social comparative information and goal setting. *Contemp. Educ. Psychol.* 8, 76–86. doi: 10.1016/0361-476X(83)90036-X

Schunk, D. H. (1985). Participation in goal setting: effects on self-efficacy and skills of learning-disabled children. *J. Spec. Educ.* 19, 307–317. doi: 10.1177/002246698501900307

Schunk, D. H. (1989). "Self-efficacy and cognitive skill learning," in *Research on Motivation in Education, Vol. 3: Goals and Cognitions*, eds C. Ames and R. Ames (Cambridge, MA: Academic Press), 13–44.

Schunk, D. H., and Hanson, A. R. (1985). Peer models: Influence on children's self-efficacy and achievement. *J. Educ. Psychol.* 77, 313–322. doi: 10.1037/0022-0663.77.3.313

Shih, S.-S., and Alexander, J. M. (2000). Interacting effects of goal setting and self- or other-referenced feedback on children's development of self-efficacy and cognitive skill within the Taiwanese classroom. *J. Educ. Psychol.* 92, 536–543. doi: 10.1037/0022-0663.92.3.536

Soland, J. (2019). Modeling academic achievement and self-efficacy as joint developmental processes: evidence for education, counseling, and policy. *J. Appl. Dev. Psychol.* 65:101076. doi: 10.1016/j.appdev.2019.101076

Sorvo, R., Koponen, T., Viholainen, H., Aro, T., Räikkönen, E., Peura, P., et al. (2019). Development of math anxiety and its longitudinal relationships with arithmetic achievement among primary school children. *Learn. Individ. Differ.* 69, 173–181. doi: 10.1016/j.lindif.2018.12.005

Talsma, K., Schüz, B., Schwarzer, R., and Norris, K. (2018). I believe, therefore I achieve (and vice versa): a meta-analytic cross-lagged panel analysis of self-efficacy and academic performance. *Learn. Individ. Differ.* 61, 136–150. doi: 10.1016/j.lindif.2017.11.015

Unrau, N. J., Rueda, R., Son, E., Polanin, J. R., Lundeen, R. J., and Muraszewski, A. K. (2017). Can reading self-efficacy be modified? a meta-analysis of the impact of interventions on reading self-efficacy. *Rev. Educ. Res.* 88, 167–204. doi: 10.3102/0034654317743199

Usher, E. L., and Pajares, F. (2006). Sources of academic and self-regulatory efficacy beliefs of entering middle school students. *Contemp. Educ. Psychol.* 31, 125–141. doi: 10.1016/j.cedpsych.2005.03.002

Usher, E. L., and Pajares, F. (2008). Sources of self-efficacy in school: critical review of the literature and future directions. *Rev. Educ. Res.* 78, 751–796. doi: 10.3102/0034654308321456

Usher, E. L., and Pajares, F. (2009). Sources of self-efficacy in mathematics: a validation study. *Contemp. Educ. Psychol.* 34, 89–101. doi: 10.1016/j.cedpsych.2008.09.002

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Understanding the Impact of the Psychological Cognitive Process on Student Learning Satisfaction: Combination of the Social Cognitive Career Theory and SOR Model

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In higher education, student learning satisfaction is a significant predictor of learning that indicates the commitment students have to their learning and future academic achievement. The study combines the social cognitive career theory (SCCT) and the stimulus-organism-response (SOR) model to explore the psychological cognition and attitudes derived from students during their learning, discusses the pattern of student learning satisfaction enhancement from the aspect of process, and further understands the relationships among social support systems, interaction relationships, self-efficacy, generic skills, and learning satisfaction. In this study, 800 valid copies of questionnaires were collected from 12 universities through purposive sampling, and the structural model was analyzed by partial least squares structural equation modeling (PLS-SEM). The results showed that the relationships among all the constructs were positive and showed a significant effect; furthermore, the research results showed that self-efficacy and student generic skills had a significantly indirect effect in the model—specifically, a mediating effect. Finally, corresponding theoretical and practical implications were put forward based on the research results.

Keywords: generic skills, interaction relationship, learning satisfaction, PLS-SEM, social support, self-efficacy

INTRODUCTION

Student learning has always been valued by scholars, especially in discussing how to enhance student learning effectiveness and learning engagement (Pike et al., 2011, 2012; Peng and Chen, 2019; Li et al., 2020; Peng et al., 2021). Past studies have stated that better learning effectiveness represents students with strong learning motivation and commitment, which are reflected in their learning achievements because of their learning preferences (Pike et al., 2011; Li et al., 2020). Self-determination theory mentions that students can decide their own roles in learning and have a high degree of intrinsic motivation and autonomy to understand the importance of learning and improve learning effectiveness (Vallerand et al., 1997; Shogren et al., 2014; Sergis et al., 2018). However, although Western theories emphasizing intrinsic motivational factors have proven their importance in Eastern society, the cultural differences in Asia make students more likely to face the social expectations of their families and other interpersonal relationships, thus forcing themselves to learn in conformity with the expectations of family members (Chang et al., 2011; Marambe et al., 2012; Li et al., 2020). Although most students pursue differences in grades and performance, it is more important for them to find their own preferences and interests in learning and cultivate their professional capabilities and knowledge base; therefore, learning satisfaction is another psychological dimension of learning effectiveness. Furthermore, learning satisfaction also reflects the effects of the learning students engage in. Liu et al. (2020) used social cognitive career theory to discuss the employability of students and replace the discussion of learning effectiveness in these students with actual skill growth (Peng, 2019). Different from past research, learning satisfaction can be used to determine the psychological state of the learning that students have (Kong and Yan, 2014; Pan, 2014) and construct a vital source of future learning motivation (Oyarzun et al., 2018; Alqurashi, 2019); in other words, the higher the learning satisfaction, the higher the intrinsic motivation and actual learning effectiveness (Yilmaz, 2017). Therefore, this research will explore the pre-variables of learning satisfaction and understand how to promote student learning satisfaction.

In regard to the study of learning satisfaction, since Lent and Brown proposed the Social Cognitive Career Theory (SCCT) in 2006, many scholars began to build a research framework based on the SCCT model for exclusive research situations (Lent et al., 2017; Lent and Brown, 2019; Liu et al., 2020; Lee et al., 2021; Pandita et al., 2021). Peng et al. (2021) used the SCCT model to conduct a cross-cultural comparative analysis, using teacher knowledge transfer as a pre-variable to explore the relationship among model variables. Although the SCCT model is widely used by scholars to explore the cognitive influence path of individuals facing external environmental stimuli, it rarely mentions the evolution process of the mental state (Lent and Brown, 2013; Park et al., 2018; Zhai et al., 2020). Mehrabian and Russel (1974) proposed the SOR model, which pointed out that all individuals' behavioral responses or psychological changes are stimulated by the external environment, and the individual will inductively process the stimulus and adjust the psychological interaction to produce an appropriate response (Zhai et al., 2020; Pandita et al., 2021). The SOR model describes the connection between stimuli (such as external factors) that will affect organisms (cognition and emotion of people) and the response people have to the stimulus (such as behavior). Stimulus (S) refers to input, which is an external factor related to the environment. Organisms are things that will respond to stimuli (Eroglu et al., 2003), which include emotions, feelings, and emotions to these stimuli. Reaction (R) refers to actions and reactions students have to organisms (Buxbaum, 2016). Human beings are organisms that produce emotional and psychological elements and the mood, emotions, or attitudes that respond to stimuli; thus, the stimulus-organism-response (SOR) model has been extended (Zhai et al., 2020). In the context of this research, social support systems and interaction relationships are conceptualized as stimuli, self-efficacy and generic skills are the dominant organisms, and student satisfaction is the response. The process of student participation stems from the stimulation of the learning environment (Hazeltine and Schumacher, 2016). Therefore, this study will build an SOR model based on the variables of the SCCT model and explore student satisfaction by combining the characteristics of the two models. Scholars believe that the setting of pre-variables will affect the subsequent psychological response of the individuals (Zhai et al., 2020), while most of the stimulus variables studied in the past emphasize the external and internal influences that affect the learning of students in the classroom; thus, the research context focused on classroom level (Yang et al., 2021). However, whether or not the psychological cognitive results will remain the same or similar after students leave the classroom, there is an unsolved black box (Wong, in press). In order to avoid the impact of endogenous variation that may be brought about by the pre-variables designed at the classroom level, this research will propose important external pre-factors from the school level (Ghosh and Fouad, 2017; Zhang et al., 2018) to further enhance the generalization of the research, including the campus social support system and student interaction.

The school is a small social system, and student life, the process of learning, and peer communication in the school continuously affect the quality of student learning and engagement degree (Mattanah et al., 2012). Scholars believe that the higher the input in learning support, the greater the motivation and intention of students to engage and the improve how they adapt to campus life (Matsuda et al., 2014; Ghosh and Fouad, 2017). Similarly, scholars pointed out that most of the situations in which students feel powerless or helpless in learning may come from their inability to feel the care they have for learning, and the inability to obtain effective support for difficult-to-understand courses (Hen and Goroshit, 2014; Yssel et al., 2016). Thus, if the peer learning interaction is low, it may cause a vicious circle of the Matthew effect (Otto and Kistner, 2017). Therefore, the social support system in school and interaction relationships can be used to explore the important external pre-factors affecting student learning satisfaction and the stimulating variable roles of the two in the SOR model.

External support systems and interaction relationships may have a significant impact on learning satisfaction, but whether in the SOR or the SCCT model, these systems still need to undergo transformations in their internal mechanisms or psychological cognitive factors (Isik, 2013; Chan, 2020) to form a clear relationship. In the SCCT model, self-efficacy is a key cognitive factor that acts as an intermediary bridge between environmental factors and satisfaction (Hen and Goroshit, 2014; Chan, 2020); as a satisfaction model constructed through self-efficacy, it can also strengthen the overall effect of the preceding factors on the dependent variables. In other words, individuals with a high degree of self-efficacy can effectively identify the resources of the external environment and leverage them to solve or perform real-world problems and tasks (Liu et al., 2020; Lee et al., 2021). In addition to self-efficacy, students also need to recognize the knowledge, skills, and basic literacy they have learned (Coates and Richardson, 2012; Tremblay et al., 2012), which reflects the substantial effects of the pre-factors; especially in the SCCT model, cognitive learning output is an important intermediary variable that highlights the influence of pre-variables and self-efficacy on learning satisfaction. Therefore, this study will further

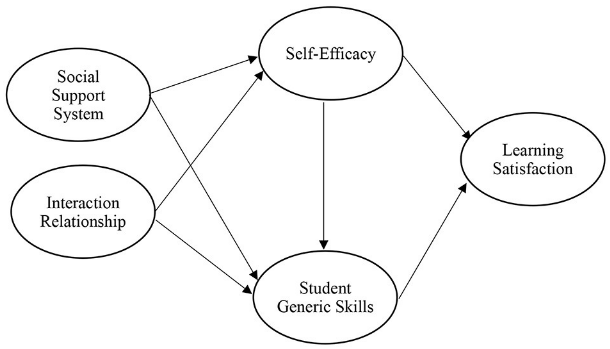

FIGURE 1 | Research framework.

explore the mediating effects of the self-efficacy and generic skills of students in the model. Based on above arguments, this study provides a conceptual framework as **Figure 1**.

LITERATURE REVIEW

SCCT and SOR Model

The social cognitive career theory model is based on the social cognitive theory (SCT) of A. Bandura by Lent et al. (1994). It is divided into three models, and they are the "interest model" that is fond of a certain career field, the "selection" model that converts interest into specific career intentions, and the "career achievement model" that chooses to enter a certain career field to show professional performance (Lent and Brown, 2013, 2019). Therefore, the SCCT considers the interaction between the individual, environment, and behavior to explain the formation of professional interests, planning of personal educational choices and career directions, and choice of a certain professional field of achievement performance, etc. (Lent et al., 2008; Liu et al., 2020; Lee et al., 2021). Since the subject of this research is college students, it focuses on the interest model and the selection model. However, the SCCT model seldom mentions the changes in the psychological cognition of students during the learning process, especially the external factors that affect psychological cognition. The SCCT model emphasizes the interaction of context on preferences and choices. When the SCCT was introduced 25 years ago, the theory initially included (a) career and academic interest development, (b) choice, and (c) performance. It was later expanded to include two additional models, with one focusing on education and career satisfaction or happiness and the other focusing on the process of self-management throughout the career life cycle (Brown and Lent, 2019). The SCCT explained that the intention to pursue a specific goal in a career comes from the judgment a person has on what they think is feasible (self-efficacy) and the possible impact of their expected actions (outcome expectations) (Bandura, 1989). In addition, the concept of outcome expectations can be further subdivided into internal and external aspects (Lanero et al., 2016). Internal result expectations refer to factors related to personal accomplishment, work, independence, and learning opportunities. On the other hand, external result expectations refer to economic remuneration, job security, and social recognition.

The SOR model consists of three structures—namely, stimulus, organism, and response—, which determine the behavioral outcome of an event. The concept of stimulus and response is described as "a part of behavior and environment." Sudden changes in the environment will affect the psychological and emotional stability of an individual, thereby further promoting changes in their behavior. Stimulus is defined as "influencing the individual," and is the external force that affects the mental state of an individual (Fu et al., 2021). An organism can be referred to as the internal process and structure between the external stimulus of a person and their final action, reaction, or response. The intervention process and structure include perceptual, physiological, sensory, and thinking activities (Pandita et al., 2021). In the field of environmental psychology, the SOR model explains that various external factors can be used as stimuli (S), which in turn affect the internal state of the individual (O), and thus the behavioral response exhibited by the individual® (Zhai et al., 2020; Fu et al., 2021). On the basis of the SCCT model, adding the concept of the SOR model will help this study explain the changes in the mental cognition of students during the learning process and their subsequent learning intentions and behavioral responses. The SOR model helps explain the internal psychological changes caused by the individual being stimulated by the environment (Lin et al., 2020).

In the context of this research, the social support system and interaction are conceptualized as stimuli, self-efficacy and basic literacy are the dominant organisms, and student satisfaction is the response. The process of student participation stems from the stimulation of the learning environment (Hazeltine and Schumacher, 2016). Since the subject of this research is college students, it focuses on the interest model and the selection model. However, the SCCT model seldom mentions the changes in the psychological cognition of students during the learning process, especially the external factors that affect psychological cognition. The SCCT model emphasizes the interaction of context on preferences and choices.

Learning Satisfaction

Satisfaction is the perception of the difference between previous expectations and perceived achievement (Nagy, 2018). Keller (1983) defines learning satisfaction as the overall positive evaluation of a student of his or her learning experience (Bunce et al., 2017; Li et al., 2017; Hew et al., 2020). Satisfaction can only be measured after learning activities (Li, 2018; Nagy, 2018). Li (2018) pointed out that learning satisfaction is the feeling and attitude toward the learning process; this feeling and attitude are formed by the joy that students feel when their learning activities or learning process meet their physical and psychological needs. Nelson (2016) regards learning satisfaction as a combination of good perception and positive attitude. This is because learning activities can meet personal needs; that is, learners can perceive the satisfaction of personal learning needs during the learning process. Emtinan (2018) pointed out that student satisfaction reflects how learners perceive their learning experience (Keller, 1983; Li et al., 2017; Weidlich and Bastiaens, 2017). The importance of the learning satisfaction of students is highly correlated with the dropout rate, determination, motivation, and determination of these students to complete a degree and succeed.

The self-efficacy of college students is significantly related to student satisfaction. Learner satisfaction reflects the perceptions students have of their learning experience (Emtinan, 2018). Satisfaction is the basic result of learners because it can affect their motivation level, which, in turn, is an important psychological factor that affects the learning of students. Learner satisfaction is an important dependent variable because it has a strong positive correlation with the perceived teaching quality of learners, especially in the traditional university learning environment (Hew et al., 2020). The suggestion of learning satisfaction as an important outcome is also consistent with recent marketization forces, which treat students as consumers of educational products or services (Bunce et al., 2017).

Self-Efficacy

The SCCT has accumulated numerous empirical studies, showing that the self-efficacy of individual variables, the expectation of results, and the interest in learning can strengthen the investment a person has in a certain field, with self-efficacy being the most critical variable (Lent et al., 1994, 2010; Liu et al., 2020; Lee et al., 2021). The individual effectiveness not only affects how they think, feel, motivate, and then act, but it is the process that also affects how individuals choose behaviors, how much effort they are willing to put into execution, and how much emotion and pressure they can bear (Pan, 2014; Chan, 2020). Self-efficacy refers to the ability of an individual to judge how to complete a specific task or action, and it is also one of the most important self-regulatory mechanisms that affect individual behavior. In other words, self-efficacy means a subjective judgment of the ability of an individual to organize a plan before actual action in order to achieve a certain goal (Hen and Goroshit, 2014; Pan, 2014). When individuals have high self-efficacy, they are willing to set higher goals when faced with tasks, are less afraid of failure, and will persist to overcome obstacles when encountering difficulties; on the contrary, when the self-efficacy of these individuals are low, they will be reluctant to really take action, and when faced with difficulties, they will easily give up and not want to continue to persevere (Erdem and Demirel, 2007).

Previous studies have provided strong evidence that self-efficacy is a positive predictor of performance outcomes for different subjects. Self-efficacy "can predict students' academic performance in various fields and levels (Lent et al., 2008; Liu et al., 2020; Lee et al., 2021)." There is a large body of evidence to support the direct impact of self-efficacy beliefs on academic performance (Doménech-Betoret et al., 2017). Lee and Mendlinger (2011) indicated that perceived self-efficacy serves as an antecedent to learning satisfaction and has a positive effect. Good academic performance improves the self-confidence of students in learning, and, in turn, their self-efficacy. Therefore, self-efficacy is a powerful predictor of learner satisfaction. Based on the above discussion, the following hypothesis can be obtained:

H1: The self-efficacy of students is positively correlated to their learning satisfaction.

Student Generic Skills

Generic skills can be regarded as generic attributes, key skills, and core competencies. They are widely mentioned in the community, education, and work-life. In addition to discussing from the perspective of students, they also include human resources. Generic skills have also been included in national and international qualification frameworks such as the European Qualifications Framework (EQF), clearly indicating any knowledge, skills, and competencies recognized by the learner (European Parliament and European Council, 2008). Many scholars also emphasize that generic skills can be used to compare the education situation between countries and provide directions for improving the quality of teaching and learning (Coates and Richardson, 2012; Tremblay et al., 2012). Studies have even pointed out that generic skills can be used as key skills that students need to have in the labor market in the future. Even in different majors and disciplines, they must have such general skills, such as organizing skills, knowledge acquisition, and problem-solving skills (Tynjälä et al., 2006; Virtanen et al., 2009; Arevalo et al., 2010). Although generic skills are not as important as employability and other abilities for task execution in the workplace, this ability reflects the intuitive response the learner has to daily life, as well as their views and insights on problems. Therefore, in this study, the concept of generic skills will be used as an important skill for students to improve upon through external stimuli during the learning process. Virtanen and Tynjälä (2018) pointed out that the essence of studying generic skills is that it can improve the existing curriculum design and learning environment and enable students to have a deeper understanding of their self-concept and self-role. Students with higher self-efficacy tend to be more engaged, work harder, spend a substantial amount of time trying their best to complete duties (Chan, 2020), pursue challenging goals, and become hardworking. Researchers believe that self-efficacy may affect learning motivation and increase academic achievement (Hsieh et al., 2007). The more sense of self-efficacy students have, the more willing they will be to spend their energy on learning; thus, they can master more generic skills. Satoshi et al. (2009) shed light on the self-efficacy of generic skills students have as a new measure for learning outcomes. The study also provided empirical evidence of possible correlations between the self-efficacy of generic skills students have and their choice of a major. In addition to developing abilities and acquiring the skills to perform course tasks, students need to establish a strong belief that they can successfully complete these tasks (Chan, 2020). Therefore, it seems that the self-efficacy component of motivation reflects positive academic performance (Komarraju et al., 2010). Based on the above discussion, the following hypothesis can be obtained:

H2: The self-efficacy of students is positively correlated to their generic skills.

Generic skills have hidden characteristics, which are different from subject-specific knowledge or hard skills. These skills emphasize the cognitive and emotional growth of students (Zepke and Leach, 2010; Freudenberg et al., 2011). In the dynamic teaching process, teachers guide students into interactive social processes (Jones, 2009; Virtanen and Tynjälä, 2018), by creating social contexts to support the learning process of students and maintain relationships with them (Barrie et al., 2009). Students continuously convert and extend conceptual skills and knowledge in the classroom tasks set by the teacher, and thus obtain substantive generic skills through close collaboration and social interaction with their classmates (Precision Consultancy, 2007). When students recognize that generic skills have been substantially improved, it means that there is a pleasant learning atmosphere in the classroom, which not only improves the knowledge of the exclusive subject but also improves the positive view a student has of their self-concept (Freudenberg et al., 2011). This is further reflected in learning satisfaction. Teo et al. (2012) noted that students who have received training in group work, such as generic skills, are more likely to report a high level of satisfaction with the peer evaluation process in the group work assessment task. Therefore, the hypothesis of this research is as follows:

H3: The generic skills of students are positively correlated to their learning satisfaction.

Social Support System

Since the mid-1970s, there has been an increasing interest in social support as a coping factor related to physical health (Bruwer et al., 2008; Ermis-Demirtas et al., 2018). Social support has been regarded as a multidimensional construct and defined in various ways (Cobb, 1976; Kang and Nancy, 1996; Williams et al., 2004; Bruwer et al., 2008; Ellonen et al., 2008; Vollmann et al., 2010). Social support is defined as the perception a person has of specific or general supports from people in their context, which contribute and/or act as a buffer for their wellbeing (Demaray and Malecki, 2002; Malecki and Demaray, 2003; Vedder et al., 2005; Marambe et al., 2012; Ermis-Demirtas et al., 2018; Wilson et al., 2020). Especially in adolescents research, social support is regarded as a manifestation of the community (Ellonen et al., 2008; Lippman et al., 2014). Perceived social support can also be related to wellbeing (Rosenfeld et al., 2000; Vedder et al., 2005; Haber et al., 2007; Camara et al., 2017; Fogaca, 2021). Furthermore, poor social support could predict low levels of outcomes in the psychology and academics of students (Rosenfeld et al., 2000; Malecki and Demaray, 2003; Haber et al., 2007). Social support is considered a social resource, social asset, or social network that people can use when they need help, assistance, advice, approval, protection, comfort, or support. It covers information that a person cares about, respects, and values, is part of a network of communication, and is a two-way responsibility (Cobb, 1976).

Vollmann et al. (2010) found social support to be the most beneficial in reinforcing student self-esteem (Camara et al., 2017). According to Kang and Nancy (1996), students, as customers of the universities, have a need for social support. Social support is an important dimension in improving self-efficacy (Maleki-Saghooni et al., 2020). The self-efficacy of a person is positively correlated with the social support they receive. In other words, the more social support a person receives, the higher their sense of self-efficacy (Wang et al., 2015). Social support plays an important role in the vigorous development of the entire life cycle, especially during periods of change, such as the dramatic changes that represent adolescence (Ellonen et al., 2008; Lippman et al., 2014). Past research on adolescents has shown that perceived social support is significantly correlated with positive emotions and high activeness. On the contrary, perceived social support is negatively related to the internalization and externalization of negative emotions and adolescent symptoms, including aggressiveness. Social support can increase the self-esteem and self-confidence of adolescents (Orkibi et al., 2018). Liu et al. (2020) and Xu et al. (2021) also showed that social support from teachers and peers has significantly positive correlations with self-efficacy. Based on the above reasons, the following hypothesis is made:

H4: The social support systems of students are positively correlated to their self-efficacy.

Researchers have discovered the relationship between perceived social support and various academic achievements. There is an association between social support and academic indicators (for example, grades, standardized achievement tests, and teacher ratings). The relationship between social support and academic performance of adolescents (such as attendance, avoidance of problem behaviors, grade level, prosocial behaviors, school satisfaction, and school continuity) positively facilitates learning engagement. In academic research, a relationship was found between various specific supports (for example, listening and emotional support) and positive learning outcomes (Malecki and Demaray, 2003). A large body of research shows that there is a positive correlation between social support and results that educators are particularly interested in, such as student motivation, school adaptation, school belonging, dropout rate, ability to deal with daily school troubles, especially learning and academic behavior. The more social support a student receives, the higher level of generic skills of the student. In addition, social support directly or indirectly improves the academic performance and abilities of students, including test scores and usual results (Rosenfeld et al., 2000). As a result, the following hypothesis is formed:

H5: The social support systems of students are positively correlated to their generic skills.

Interaction Relationship

The interaction relationship is intended to establish a good tacit understanding and consensus among learners in the process of contact, exchange, and communication with others in the learning environment (Pike et al., 2012; Kim and Lundberg, 2016; Peng, 2019). In social capital, interpersonal interactions play an important role of contact (Carton and Goodboy, 2015; Brouwer et al., 2016; Peng, 2019). Through interaction relationships, individuals can strengthen their sources of information and knowledge in social networks, consolidate the links between existing relationships, and make information transmission in social networks smoother (Komarraju et al., 2010). Any individual contact and communication encountered by students were playing an important role in the learning process, such as teachers, classmates, administrative staff, etc. (Komarraju et al., 2010; Kuo et al., 2014; Kim and Lundberg, 2016). Komarraju et al. (2010) pointed out that students with good interaction relationships can more easily adapt to campus life and acquire more information and knowledge needed for learning (Han et al., 2020), which can strengthen positive mental cognition and substantive skills acquisition of these students (Martin and Rimm-Kaufman, 2015). Kim and Lundberg (2016) pointed out that the interaction relationship between students and teachers will encourage students to derive higher academic engagement; thus, having the motivation to challenge themselves and then produce and acquire good learning results and skills (Bowman and Park, 2015).

Scholars pointed out that the establishment and maintenance of social relationships help individuals (students) to integrate into various groups and obtain valuable information and knowledge in each of their social networks (Martin and Rimm-Kaufman, 2015; Brouwer et al., 2016; Han et al., 2020). All relationships must be established through interaction. If students have strong interaction relationships, they can perceive any available resources to complete their course tasks and face learning challenges more confidently in the learning process (Kuo et al., 2014; Martin and Rimm-Kaufman, 2015). Related research has pointed out that the stronger the social and interaction relationship of students, the stronger their self-efficacy in learning skills and knowledge acquisition (Wang et al., 2015; Brouwer et al., 2016). Xu et al. (2021) indicated that students with more social capital from peers/teachers are likely to be more involved in their learning environment and actively participate in learning activities, thus improving self-efficacy. Based on the above description, the inference assumption is as follows:

H6: The interaction relationships of students are positively correlated to their self-efficacy.

In many studies, it has been pointed out that the interaction relationship between students and teachers has a significant positive correlation with learning effectiveness in students. Tynjälä et al. (2016) studied the social competence of students in a Finnish university. Based on the socio-cultural approach, they used Interaction Skills in a Group and in Networks (ISGN) and Social and Emotional Skills in Teaching (SEST) to establish students with good social relations. In the learning community, students shared knowledge with each other and developed collaboration to complete tasks (Han et al., 2020). With the intervention of social cognitive psychology and philosophical diagnosis, students were guided to strengthen their interaction with each other, so as to enhance their initiative to participate and gain more substantial experience and intuitive responses to problems (Zepke and Leach, 2010). Therefore, students with stronger interaction relationships can change their personality traits according to the social environment of different tasks. Under the change of adjustment ability, the generic skills of students will also improve (Pike et al., 2011). Therefore, based on the above content, the inference assumption is as follows,

H7: The interaction relationships of students are positively correlated to their generic skills.

Based on hypotheses 1–7, we developed the research question as follows: What is the relationship between learning satisfaction and self-efficacy, generic skills of students, social support systems, and interaction relationships based on the SCCT model and SOR model?

METHODOLOGY

Sampling

The purposes of this research are to explore the learning satisfaction of students in the learning process and analyze the impact of the social support provided by the school and the interaction relationship on students. The research sample in this study comprised undergraduates. Purposive sampling was adopted. However, this sampling suffers from several disadvantages. Vulnerability to errors in judgment by researchers, low level of reliability and high level of bias, and inability to generalize research findings are the three main disadvantages of purposive sampling. To avoid these disadvantages, some conditions were set during sampling in this study to make the samples obtained better conform to sample reliability and, therefore, improve the generalization of the study. Since the sampling objects were college students and the number of maternal populations was huge, in order to make the research results closer to the issues that this research study intended to explore, some sampling conditions were set during the sampling process. First of all, as subject differences may have an impact on student learning, in order to reduce the impact of the subject on this research model, the subjects were divided into two categories: social sciences and natural sciences. The samples of the two subjects were collected on average. Second, since the cognition of the interaction relationship and the social support system takes time to be felt, the sample did not include freshmen; only sophomores, juniors, and seniors were collected. This study selected 12 Taiwanese universities and then sent 2,000 questionnaires to them. After sampling, a total of 800 questionnaires were returned for an effective response rate of 40%. Since freshmen were not familiar with the learning environment, all participants in this study were sophomore, junior, and senior students. **Table 1** shows the descriptive statistics of the samples.

Due to the different genders and types of disciplines, a systematic error might have arisen, bringing the external validity of the study into question. Thus, several independent-samples *t*-tests were used to verify whether the groups of male vs. female and social sciences vs. natural sciences differed significantly in terms of research dimensions. The results indicated that the groups did not significantly differ, so it was deemed appropriate to merge the samples from different genders and disciplines.

Measures

Most of the scales in the questionnaire were adopted from previous studies and modified to suit the research context. In studying the social support system, four items were developed on the basis of a prior scale and item analyses with Asian applications

TABLE 1 | Descriptive statistics.

Characteristic	Scale	n	Percentage
Gender	Male	453	56.6
	Female	347	43.4
Part-time job	Yes	488	61.0
	No	312	39.0
Scholarship	Yes	322	40.2
	No	478	59.8
First-generation college student	Yes	433	54.1
	No	367	45.9
Majors	Social science	423	52.9
	Natural science	377	41.1.
Dedication to class preparation	Yes	336	42.0
	No	464	58.0

(Ryan, 2004). To divide interaction relationships into student-faculty interaction (four items) and interpersonal environment (three items), we adopted the scale proposed by Pike et al. (2012). The scale is based on the characteristics of undergraduates in Western countries, such as the US, and its credibility and validity have been verified; therefore, we found the scale suitable for expansion to the Asian context. Self-efficacy can be referred to as the degree of the perceptual ability of an individual to achieve a goal. The scale was revised to integrate six items of higher reliability and validity by Rigotti et al. (2008). For generic skills, students were asked to evaluate themselves with an instrument proposed by Freudenberg et al. (2011). The instrument adopted 10 broad skills, nine of which describe commonly identified areas of generic skills, such as interpersonal skills, self-management skills, learning and adaptability skills, problem-solving skills, concept and analysis skills, oral communication, team skills, information literacy skills, and written communication skills.

Learning satisfaction measurement items were adopted based on a previous scale (Hong et al., 2016) and focused on the satisfaction degree of undergraduate students with their learning process and environment, including 5 items. All items were measured with a five-point Likert scale (1 = totally disagree; 5 = totally agree) and are shown in **Table 2**.

RESULTS

Assessment of Measurement Model

All scales used in this study were found to be reliable, with Cronbach's α ranging from 0.83 to 0.96. **Table 3** shows the reliability of each scale and the factor loadings for each item therein. In order to gauge validity, this study employed confirmatory factor analysis (CFA) using AMOS 23.0 to verify the construct validity (both convergent and discriminant) of the scales. According to Hair's et al. (2010) recommended validity criteria, CFA results show standardized factor loading of higher than 0.7; average variance extracted (AVE) ranges between 0.539 and 0.729; composite reliability (CR) ranges between 0.8 and 0.918. All three criteria for convergent validity were met, and correlation coefficients were all less than the square root of the AVE within one dimension, suggesting that each dimension in this study had good discriminant validity.

Testing Structural Model Fit

Before proceeding to examine the structural model, we first tested the model fit. Henseler et al. (2015) proposed three model fitting parameters: the standardized root mean square residual (SRMR), the normed fit index (NFI), and the exact model fit. According to Henseler et al. (2015), the evaluation standards for convergent validity are (1) the NFI should be larger than 0.9, (2) the SRMR should be <0.08, and (3) the exact model fit, which tests the statistical (bootstrap-based) inference of the discrepancy between the empirical covariance matrix and the covariance matrix implied by the composite factor model. Dijkstra and Henseler (2015) suggested the *d_LS* (squared Euclidean distance) and *d_G* (geodesic distance) as two different ways to compute this discrepancy. Henseler et al. (2015) indicated that d_{ULS} and $d_G <$ than the 95% bootstrapped quantile (HI 95% of d_{ULS} and HI 95% of d_G).

In this study, the SRMR value was 0.063 (<0.08), the NFI was 0.912 (>0.90), and the $d_{ULS} <$ bootstrapped HI 95% of d_{ULS} and $d_G <$ bootstrapped HI 95% of d_G, indicating the data fits the model well.

Inner Model Analysis

Partial least squares structural equation modeling (PLS-SEM) was adopted to construct the structural model; specifically, the verification of the structural model was performed using SmartPLS 3.0 (path analysis). To assess the structural model, Hair et al. (2017) suggested looking at the R^2, beta (β), and the corresponding *t*-values *via* a bootstrapping procedure with a resample of 5,000. They also suggested that, in addition to these basic measures, researchers should also report the predictive relevance (Q^2) as well as the effect sizes (f^2). Prior to hypotheses testing, the values of the variance inflation factor (VIF) were determined. The VIF values were <5, ranging from 1.377 to 2.274. Thus, there were no multicollinearity problems among the predictor latent variables (Hair et al., 2017).

Figure 2, **Table 4** show the results of the hypothesized relationships and standardized coefficients in the inner model. The results showed that a social support system was positively and significantly related to student self-efficacy ($\beta = 0.370$, $p < 0.001$) and student generic skills ($\beta = 0.170$, $p < 0.001$), supporting H1 and H2. Similarly, interaction relationships were positively and significantly related to student self-efficacy ($\beta = 0.212$, $p < 0.001$) and student generic skills ($\beta = 0.266$, $p < 0.001$), supporting H3 and H4. In addition, our results found that student self-efficacy was positively and significantly related to student generic skills and learning satisfaction, supporting H5 and H6. Finally, student generic skills were positively and significantly related to student learning satisfaction, supporting H7. The Stone-Geisser Q2 values obtained through the blindfolding procedures for student self-efficacy ($Q^2 = 0.184$), student generic skills ($Q^2 = 0.266$), and student learning satisfaction ($Q^2 = 0.222$) were larger than zero, supporting the predictive relevance of the model (Hair et al., 2017).

TABLE 2 | Instruments description.

Construct	Variables	Items
Social support	Social support	I can feel the instructional resources input by the school
		I can feel the resources of academic support input by the school
		I can feel that the school has an explicit input of resources in serving students (the efficiency of the administrative department)
		I can feel the school's dedication to enhancing students' well-being
Interaction relationship	Student-faculty interaction	Discussed grades or assignments with an instructor
		Talked about career plans with a faculty member or advisor
		Discussed ideas from your readings or classes with faculty members outside of class
		Worked with faculty members on activities other than coursework
	Interpersonal environment	Developed a good relationship with other classmates
		Developed a good relationship with teachers
		Developed a good relationship with administrative staff and offices
Self-efficacy	Self-efficacy	I can remain calm when facing difficulties in my job because I can rely on my abilities
		When I am confronted with a problem in my learning tasks, I can usually find several solutions
		Whatever comes my way in my learning tasks, I can usually handle it
		My past experiences in my learning tasks have prepared well for my occupational future
		I meet the goals that I set for myself in my learning tasks
		I feel prepared for most of the demands in my learning tasks
Generic skills	Generic skills	Teacher makes me proud to being associated with him/her
		Teacher has a "sense of mission" which he/she transmits to me
		Teacher displays conviction in his/her ideas, beliefs, and values
		Teacher specifies the importance of having a strong sense of purpose
Learning satisfaction	Learning satisfaction	Course contents inspired me to learn more professional skills
		Course contents solved past problems I had when learning my major
		The interactive style of course contents improved my professional skills
		Course contents make me want to continue learning from it
		I enjoy course contents with peers while we improve our professional skills together

TABLE 3 | Measurement properties.

	1	2	3	4	5	6	7	8
1 Social support								
2 Faculty	0.541							
3 Peer	0.596	0.625						
4 Self-efficacy	0.556	0.409	0.485					
5 Creativity	0.383	0.355	0.378	0.472				
6 Critical think	0.462	0.408	0.407	0.504	0.771			
7 Meta cognition	0.425	0.480	0.359	0.427	0.619	0.749		
8 Learning sati	0.503	0.520	0.481	0.528	0.414	0.458	0.431	
Mean	3.695	3.237	3.608	3.746	3.439	3.429	3.252	3.448
SD	0.635	0.816	0.708	0.625	0.764	0.730	0.794	0.774
α	0.926	0.925	0.815	0.898	0.869	0.869	0.818	0.900
AVE	0.604	0.816	0.730	0.662	0.884	0.719	0.846	0.716
CR	0.938	0.947	0.890	0.922	0.938	0.911	0.917	0.926

Examination of Mediating Effects

To establish a structural model, self-efficacy and student generic skills in the SCCT and SOR models can be regarded as intermediary variables. In order to understand whether the two have intermediary effects, a bootstrapping procedure was further carried out on the structural model. Results displayed in **Table 5** indicate that the indirect effects of self-efficacy and student generic skills were supported. It shows that the setting

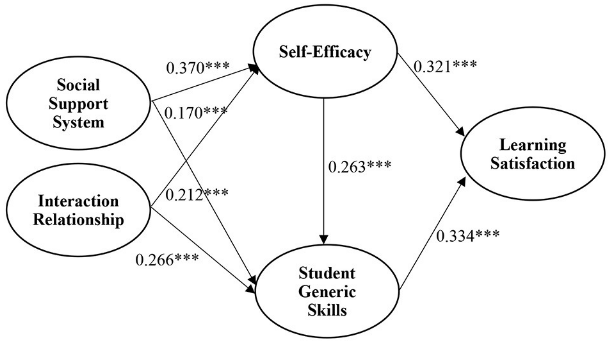

FIGURE 2 | Structural model. ***$p < 0.001$.

of important intermediary variables plays an important role in either the SCCT model or the SOR model. In particular, self-efficacy, similar to the results of previous studies, can highlight the effects of pre-variables in the model, forming strong intrinsic motivation and cognition, which are then reflected in the outcome variables.

DISCUSSION AND CONCLUSIONS

Discussion

This research combines the SCCT and SOR models to construct a conceptual model that includes psychosocial cognition and the mental operation process and explores how to enhance the learning satisfaction of students from a process point of view. In the SCCT model, although the interactions among the individuals, their environments, and their behaviors are emphasized, there is a foreseeable gap in the formation of the internal psychological cognition of the individual and its reflection in the subsequent behavior and attitude under the influence of external stimuli. The addition of the SOR model can help us more rigorously explain the development process of the inner psychological cognition of students in a learning environment that receives external stimuli and its enhancement effect on learning satisfaction. The research results point out that the model has a good fit and a positive and significant effect on all paths, which further strengthens the rationality of the model in this research.

The research results point out that the institutional-level antecedent of a social support system has a positive and significant effect on self-efficacy and student generic skills. The findings of this research show that, if the university provides a more diverse or rich social support system, students will feel that they are valued by the school and obtain corresponding information and resources in the process of completing the course tasks and have the confidence and ability to do so. It has been found that the positive effect of social support on self-efficacy conforms to the research results from Liu et al. (2020) and Xu et al. (2021), which provides a second verification that, under the research background of the Asian area, social support can effectively improve the self-efficacy of students and enhance the generalization of the SCCT research and theory. Students are available to deal with various challenges faced with confidence and abilities, as well as obtaining a lot of learning experience from them. This is similar to the results of Malecki and Demaray (2003), Wang et al. (2015), and Orkibi et al. (2018), who stated that students who do not have self-directed learning skills in the process of achieving course tasks will not know how to do the same in the learning process, thus having more feelings of disability and helplessness (Yilmaz, 2017). The results of this study, similar to the results of the studies in the literature, indicate that a social support system is an important predictor of self-efficacy and student generic skills in the SCCT model.

Similarly, the research results point out that the individual-level antecedent of an interaction relationship has a positive and significant effect on self-efficacy and student generic skills as stated in hypothetical inference. Research findings provide clear information expressing that students, who continue to maintain and establish interaction relationships, can strengthen learning collaboration between peers through close social relationships, and acquire rich experience and skills in the learning process. The research results echo the research of Pike et al. (2012) and Peng (2019), emphasizing that the interpersonal and interaction relationships of students play an important role in campus life and enrich the generality of the application of social capital in the SCCT and SOR models. Despite the study from Pike et al. (2012) stating that only the influence of an interaction relationship on student learning outcomes was verified and no theoretical framework was added for discussion, the operational definition from Pike et al. (2012) was used as the antecedent in the theoretical framework in this study; the interaction relationship was confirmed to be available for not only improving student learning outcomes but also having substantial positive effects on psychological factors.

As some cross-cultural research results show, different from Western students, the learning environment of students in Eastern societies or Asian regions emphasizes the importance of relationships. Thus, the positive learning thoughts, feelings, and behaviors of students will be affected by the mutual links in their social relations (Chang et al., 2011). The hypothesis points out that self-efficacy will positively affect student generic skills. The research results are similar to those from Satoshi et al. (2009), that is, high self-efficacy can make the acquisition of generic skills and professional competence more accessible to students in a more effective way. The research results support this argument, and the role of self-efficacy as a mediator in the SCCT model has also been verified. These results are similar to previous studies (Doménech-Betoret et al., 2017; Liu et al., 2020; Xu et al., 2021). They all believe that they have higher self-efficacy. Students can increase their learning input in the learning situation set by the teacher. When students detect the improvement of their own generic skills, the satisfaction students have with their psychological needs will be affected (Pan, 2014). Similarly, many researchers have designed a sound research framework from the SCCT model (Liu et al., 2020), deducing that various internal and external learning process variables will affect students in their formation of a high degree of self-efficacy. Through a social support system and interaction relationships, in addition to enhancing the self-efficacy of internal

TABLE 4 | Results of the hypotheses testing.

Paths	Std. β	Std. error	*t*-value	Decision	Significance CI (2.50–97.5%)	VIF	f^2
H1: SSS→SE	0.370	0.042	8.757	Support	CI (0.291–0.453)	2.274	0.114
H2: SSS→SGS	0.170	0.044	3.860	Support	CI (0.081–0.256)	2.452	0.023
H3: IR→SE	0.212	0.043	4.888	Support	CI (0.125–0.292)	2.274	0.037
H4: IR→SGS	0.266	0.042	6.389	Support	CI (0.182–0.347)	2.393	0.061
H5: SE→SGS	0.263	0.040	6.537	Support	CI (0.180–0.340)	1.512	0.074
H6: SE→LS	0.321	0.036	9.009	Support	CI (0.254–0.392)	1.377	0.117
H7: SGS→LS	0.334	0.035	9.563	Support	CI (0.265–0.401)	1.377	0.127

CI, Confidence intervals (Lower bound—Upper bound).

TABLE 5 | Indirect effect of the structural model.

Paths	Std. β	Std. error	*t*-value	Decision
SSS→SE→LS	0.119	0.020	5.984	Support
SSS→SGS→LS	0.057	0.017	3.363	Support
IR→SE→LS	0.068	0.017	4.021	Support
IR→SGS→LS	0.089	0.019	4.703	Support
SSS→SE→SGS	0.097	0.019	5.080	Support
IR→SE→SGS	0.056	0.014	4.085	Support

learning motivation, students can also indirectly strengthen their professional competence and soft skills.

Finally, the research results show that self-efficacy and generic skills have a positive impact on learning satisfaction. This result is consistent with the final attitude cognition and behavioral response in the SCCT and SOR models proposed by scholars. The research findings are also similar to Kong and Yan (2014)'s research results, pointing out that learning satisfaction is related to the academic development achievements of students. Under the premise of learning self-efficacy and enhancement of generic skills, students can feel a high degree of academic achievement on their own, thereby enhancing their learning satisfaction (Nandi et al., 2015). This discovery provides significant support for both the SCCT model and the SOR model. These results correspond with those of Wu et al. (2019), Cupani et al. (2010), Zhai et al. (2020), and Fu et al. (2021); on the basis of the SCCT and SOR models, they believe that learning environment differences between stimulus and learning influence the learning status and learning activities of students, causing knowledge and skills-gaining to differ. Our findings are largely consistent with those from these prior studies, supporting the availability of the SCCT model across a range of theoretical frameworks. It shows the importance of cognitive psychology in the processing of external stimuli, and also proposes a more complete theoretical model and contribution to the SCCT model.

Educational Practices

Practically, the results of this study may provide useful guidance for higher education institutions, faculties, administrators, and teachers on student learning satisfaction development. First, the social support system of a school has a significant effect on the enhancement of the self-efficacy and generic skills of students. It means that students pay attention to the changes in the learning environment if the school attaches great importance to them during the learning process. The social support system can play an effective role when students feel learning powerlessness, learning frustration, and helplessness. For example, the school provides more meta-media learning equipment, after-school tutoring mechanism, teacher's learning care, etc. With these tangible equipment and software and intangible psychological support, students can reduce their learning difficulties, improve their input in learning, and enhance their motivation to complete learning tasks.

Second, the study found that the interactions and social capital of students also have a clear positive impact on self-efficacy and generic skills. Interaction relationships and social capital are external connections maintained and established by students themselves. When the relationship between external connections becomes closer and more numerous, more resources, information, and knowledge can be effectively obtained, which is conducive for the cultivation of psychological functions and abilities. However, not all students can take the initiative to establish and cultivate their interaction relationships, especially their relationships with teachers; in other words, teachers or schools must provide more opportunities for interaction between teachers and students, with teachers moving beyond a passive role. This research suggests that schools or teachers can provide after-school consultation activities. With these consultations, teachers can fully understand the problems or learning difficulties faced by students and provide effective help. Furthermore, teachers can also provide more teamwork in the course, as these activities provide opportunities for students to communicate with each other and collaborate to solve classroom tasks, thereby strengthening the interaction between the three parties.

Third, the study found that student self-efficacy and generic skills not only have a significant effect on learning satisfaction but also play an important intermediary role in the model. Most previous studies emphasized practical knowledge or hard skills. However, students can clearly express the acquired explicit skills, but seldom mention them with higher implicit skills or emotional cognition. Thus, this study presented actual evidence pointing out that implicit skills or cognition are more helpful to improve the learning satisfaction of students. Therefore, this research suggests that schools should offer more general education courses related to majors and encourage teachers to carry out more functional teaching activities, which will help students develop more generic skills and enhance their satisfaction with learning.

Limitations

The research results contribute to the literature on the SCCT and SOR models and student learning satisfaction; nevertheless, some limitations still exist and represent further research directions. First, the SSCT and SOR models have obtained considerable status in the psychological field, but only a few studies have considered the relationship between the building mechanism and learning satisfaction of undergraduate students in higher education. Although the building mechanism (social support system and interaction relationship) was constructed with reference to the SCCT and SOR models in this study and important learning theories can be derived from the research results, other motivation theories, such as attribution theory, self-efficacy theory, and hierarchy needs theory must still be applied to explain how to trigger learning in undergraduate students. Thus, it is suggested that future research can utilize different theoretical models in order to identify relevant psychological dimensions influencing the learning satisfaction of students. Second, this study required students to self-report details on their psychological building mechanism as the indicator, mainly because actual data is confidential and not easily obtained. However, errors may exist in the self-statements students made of their psychological status. The link between the building mechanism and learning satisfaction may be better understood if the actual psychological status of students could be assessed, with due consideration for research ethics. Besides, this study suggests that future researchers should include interview contents and observations by students on the learning status in their studies to support the research results and make a comprehensive judgment. Third, due to restrictions of time and space, only 14 universities were sampled in this study, with 800 valid questionnaires in total. Future research could explore and compare other groups, in addition to expanding the quantity of samples and improving the research representativeness, so as to provide additional insights relevant to higher education policy. Finally, Wong (2020) put forward that there may be differences in after-school and in-class psychological cognitive results produced by students, and there is an unsolved black box between them. However, this classification was not analyzed in this study. Thus, in this study, the researchers also suggest that future studies compare the after-class and in-class differences and offer more valuable insights into the unsolved black box.

DATA AVAILABILITY STATEMENT

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

ETHICS STATEMENT

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

AUTHOR CONTRIBUTIONS

This study is a joint work of the four authors. MP and GZ contributed to the ideas of educational research, collection of data, and empirical analysis. MP, GZ, and XY contributed to the data analysis, design of research methods, and tables. XY and YY participated in developing a research design, writing, and interpreting the analysis. All four authors contributed to the literature review and conclusions.

REFERENCES

Alqurashi, E. (2019). Predicting student satisfaction and perceived learning within online learning environments. *Dist. Educ.* 40, 133–148. doi: 10.1080/01587919.2018.1553562

Arevalo, J., Pitknen, S., Gritten, D., and Tahvanainen, L. (2010). Market-relevant competencies for professional foresters in European graduate education. *Int. For. Rev.* 12, 200–208. doi: 10.1505/ifor.12.3.200

Bandura, A. (1989). Regulation of cognitive processes through perceived self-efficacy. *Dev. Psychol.* 25, 729–735. doi: 10.1037/0012-1649.25.5.729

Barrie, S., Hughes, C., and Smith, C. (2009). *The National Graduate Attributes Project: Key Issues to Consider in the Renewal of Learning and Teaching Experiences to Foster Graduate Attributes*. Sydney, NSW: Australian Learning and Teaching Council.

Bowman, N. A., and Park, J. J. (2015). Not all diversity interactions are created equal: Cross-racial interaction, close interracial friendship, and college student outcomes. *Res. High. Educ.* 56, 601–621. doi: 10.1007/s11162-015-9365-z

Brouwer, J., Jansen, E., Flache, A., and Hofman, A. (2016). The impact of social capital on self-efficacy and study success among first-year university students. *Learn. Individ. Differ.* 52, 109–118. doi: 10.1016/j.lindif.2016.09.016

Brown, S. D., and Lent, R. W. (2019). Social cognitive career theory at 25: progress in studying the domain satisfaction and career self-management models. *J. Career Assess.* 27, 563–578. doi: 10.1177/1069072719852736

Bruwer, B., Emsley, R., Kidd, M., Lochner, C., and Seedat, S. (2008). Psychometric properties of the Multidimensional Scale of Perceived Social Support in youth. *Compr. Psychiatry* 49, 195–201. doi: 10.1016/j.comppsych.2007.09.002

Bunce, L., Baird, A., and Jones, S. E. (2017). The student-as-consumer approach in higher education and its effects on academic performance. *Stud. High. Educ.* 42, 1958–1978. doi: 10.1080/03075079.2015.1127908

Buxbaum, O. (2016). *Key Insights Into Basic Mechanisms of Mental Activity*. Berlin: Springer.

Camara, M., Bacigalupe, G., and Padilla, P. (2017). The role of social support in adolescents: are you helping me or stressing me out? *Int. J. Adolesc. Youth* 22, 123–136. doi: 10.1080/02673843.2013.875480

Carton, S. T., and Goodboy, A. K. (2015). College students' psychological well-being and interaction involvement in class. *Commun. Res. Rep.* 32, 180–184. doi: 10.1080/08824096.2015.1016145

Chan, C. C. (2020). Social support, career beliefs, and career self-efficacy in determination of Taiwanese college athletes' career development. *J. Hosp. Leis. Sport Tour. Educ.* 26:100232. doi: 10.1016/j.jhlste.2019.100232

Chang, L., Mak, M. C., Li, T., Wu, B. P., Chen, B. B., and Lu, H. J. (2011). Cultural adaptations to environmental variability: an evolutionary account of East–West differences. *Educ. Psychol. Rev.* 23, 99–129. doi: 10.1007/s10648-010-9149-0

Coates, H., and Richardson, S. (2012). An international assessment of bachelor degree graduates' learning outcomes. *High. Educ. Manage. Policy* 23, 1–19. doi: 10.1787/hemp-23-5k9h5xkx575c

Cobb, S. (1976). Social support as a moderator of life stress. *Psychosom. Med*. 38, 300–314. doi: 10.1097/00006842-197609000-00003

Cupani, M., de Minzi, M. C. R., Pérez, E. R., and Pautassi, R. M. (2010). An assessment of a social-cognitive model of academic performance in mathematics in Argentinean middle school students. *Learn. Individ. Diff.* 20, 659–663. doi: 10.1016/j.lindif.2010.03.006

Demaray, M. K., and Malecki, C. K. (2002). The relationship between perceived social support and maladjustment for students at risk. *Psychol. Sch.* 39, 305–316. doi: 10.1002/pits.10018

Dijkstra, T. K., and Henseler, J. (2015). Consistent partial least squares path modeling. *MIS Q.* 39, 297–316. doi: 10.25300/MISQ/2015/39.2.02

Doménech-Betoret, F., Abellán-Roselló, L., and Gómez-Artiga, A. (2017). Self-efficacy, satisfaction, and academic achievement: the mediator role of Students' expectancy-value beliefs. *Front. Psychol.* 8:1193. doi: 10.3389/fpsyg.2017.01193

Ellonen, N., Kaariainen, J., and Autio, V. (2008). Adolescent depression and school social support: a multilevel analysis of a Finnish sample. *J. Commun. Psychol.* 36, 552–567. doi: 10.1002/jcop.20254

Emtinan, A. (2018). Predicting student satisfaction and perceived learning within online learning environments. *Dist. Educ.* 40, 1–16.

Erdem, E., and Demirel, Ö. (2007). Teacher self-efficacy belief. *Soc. Behav. Pers.* 35, 573–586. doi: 10.2224/sbp.2007.35.5.573

Ermis-Demirtas, H., Watson, J. C., Karaman, M. A., Freeman, P., Kumaran, A., Haktanir, A., et al. (2018). Psychometric properties of the multidimensional scale of perceived social support within Hispanic college students. *Hisp. J. Behav. Sci.* 40, 472–485. doi: 10.1177/0739986318790733

Eroglu, S. A., Machleit, K. A., and Davis, L. M. (2003). Empirical testing of a model of online store atmospherics and shopper responses. *Psychol. Mark.* 20, 139–50. doi: 10.1002/mar.10064

European Parliament and European Council (2008). *Recommendation of the European Parliament and of the Council of 23 April 2008 on the Establishment of the European Qualifications Framework for Lifelong Learning, Official Journal of the European Union, 6 May, C 111/1-7*.

Fogaca, J. L. (2021). Combining mental health and performance interventions: coping and social support for student-athletes. *J. Appl. Sport Psychol.* 33, 4–19. doi: 10.1080/10413200.2019.1648326

Freudenberg, B., Brimble, M., and Cameron, C. (2011). WIL and generic skill development: the development of business students' generic skills through work-integrated learning. *Asia Pac. J. Coop. Educ.* 12, 79–93.

Fu, S., Chen, X., and Zheng, H. (2021). Exploring an adverse impact of smartphone overuse on academic performance via health issues: a stimulus-organism-response perspective. *Behav. Inform. Technol.* 40, 663–675. doi: 10.1080/0144929X.2020.1716848

Ghosh, A., and Fouad, N. A. (2017). Career adaptability and social support among graduating college seniors. *Career Dev. Q.* 65, 278–283. doi: 10.1002/cdq.12098

Haber, M. G., Cohen, J. L., Lucas, T., and Baltes, B. B. (2007). The relationship between self-reported received and perceived social support: a meta-analytic review. *Am. J. Community Psychol.* 39, 133–144. doi: 10.1007/s10464-007-9100-9

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., and Tatham, R. L. (2010). *Multivariate Data Analysis*. Pearson Education.

Hair, J. F. Jr., Sarstedt, M., Ringle, C. M., and Gudergan, S. P. (2017). *Advanced Issues in Partial Least Squares Structural Equation Modeling*. SAGE Publications. doi: 10.1007/978-3-319-05542-8_15-1

Han, S. H., Yoon, S. W., and Chae, C. (2020). Building social capital and learning relationships through knowledge sharing: a social network approach of management students' cases. *J. Knowl. Manag.* 24, 921–939. doi: 10.1108/JKM-11-2019-0641

Hazeltine, E., and Schumacher, E. H. (2016). Understanding central processes: the case against simple stimulus-response associations and for complex task representation. *Psychol. Learn. Motiv.* 64, 195–245. doi: 10.1016/bs.plm.2015.09.006

Hen, M., and Goroshit, M. (2014). Academic procrastination, emotional intelligence, academic self-efficacy, and GPA: a comparison between students with and without learning disabilities. *J. Learn. Disabil.* 47, 116–124. doi: 10.1177/0022219412439325

Henseler, J., Ringle, C. M., and Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J. Acad. Market. Sci.* 43, 115–135. doi: 10.1007/s11747-014-0403-8

Hew, K. F., Hu, X., Qiao, C., and Tang, Y. (2020). What predicts student satisfaction with MOOCs: a gradient boosting trees supervised machine learning and sentiment analysis approach. *Comput. Educ.* 145:103724. doi: 10.1016/j.compedu.2019.103724

Hong, J. C., Hwang, M. Y., Szeto, E., Tsai, C. R., Kuo, Y. C., and Hsu, W. Y. (2016). Internet cognitive failure relevant to self-efficacy, learning interest, and satisfaction with social media learning. *Comput. Hum. Behav.* 55, 214–222. doi: 10.1016/j.chb.2015.09.010

Hsieh, P., Sullivan, J. R., and Guerra, N. S. (2007). A closer look at college students: self-efficacy and goal orientation. *J. Adv. Acad.* 18, 454–476. doi: 10.4219/jaa-2007-500

Isik, E. (2013). Perceived social support and locus of control as the predictors of vocational outcome expectations. *Educ. Sci. Theory Pract.* 13, 1426–1430.

Jones, A. (2009). Generic attributes as espoused theory: the importance of context. *High. Educ.* 58, 175–191. doi: 10.1007/s10734-008-9189-2

Kang, Y. S., and Nancy, M. R. (1996). The importance of consumer market interactions as a form of social support for elderly consumers. *J. Public Policy Mark.* 15, 108–117. doi: 10.1177/074391569601500110

Keller, J. (1983). "Motivational design of instruction," in *Instructional Design Theories and Models: An Overview of Their Current Status*, ed C. Reigeluth (Hillsdale, NJ: Erlbaum), 386–434.

Kim, Y. K., and Lundberg, C. A. (2016). A structural model of the relationship between student–faculty interaction and cognitive skills development among college students. *Res. High. Educ.* 57, 288–309. doi: 10.1007/s11162-015-9387-6

Komarraju, M., Musulkin, S., and Bhattacharya, G. (2010). Role of student–faculty interactions in developing college students' academic self-concept, motivation, and achievement. *J. Coll. Stud. Dev.* 51, 332–342. doi: 10.1353/csd.0.0137

Kong, H., and Yan, Q. (2014). The relationship between learning satisfaction and career competencies. *Int. J. Hosp. Manag.* 41, 133–139. doi: 10.1016/j.ijhm.2014.05.013

Kuo, Y. C., Walker, A. E., Schroder, K. E., and Belland, B. R. (2014). Interaction, internet self-efficacy, and self-regulated learning as predictors of student satisfaction in online education courses. *Internet High. Educ.* 20, 35–50. doi: 10.1016/j.iheduc.2013.10.001

Lanero, A., V zquez, J. L., and Aza, C. L. (2016). Social cognitive determinants of entrepreneurial career choice in university students. *Int. Small Bus. J.* 34, 1053–1075. doi: 10.1177/0266242615612882

Lee, J. W., and Mendlinger, S. (2011). Perceived self-efficacy and its effect on online learning acceptance and student satisfaction. *J. Serv. Sci. Manag.* 4:243. doi: 10.4236/jssm.2011.43029

Lee, T. C., Yao-Ping Peng, M., Wang, L., Hung, H. K., and Jong, D. (2021). Factors influencing employees' subjective wellbeing and job performance during the COVID-19 global pandemic: the perspective of social cognitive career theory. Front. Psychol. 12:577028. doi: 10.3389/fpsyg.2021.577028

Lent, R. W., and Brown, S. D. (2013). Social cognitive model of career self-management: toward a unifying view of adaptive career behavior across the life span. *J. Couns. Psychol.* 60, 557–568 doi: 10.1037/a0033446

Lent, R. W., and Brown, S. D. (2019). Social cognitive career theory at 25: empirical status of the interest, choice, and performance models. *J. Vocat. Behav.* 115:103316. doi: 10.1016/j.jvb.2019.06.004

Lent, R. W., Brown, S. D., and Hackett, G. (1994). Toward a unifying social cognitive theory of career and academic interest, choice, and performance. *J. Vocat. Behav.* 45, 79–122. doi: 10.1006/jvbe.1994.1027

Lent, R. W., Ireland, G. W., Penn, L. T., Morris, T. R., and Sappington, R. (2017). Sources of self-efficacy and outcome expectations for career exploration and decision-making: a test of the social cognitive model of career self-management. *J. Vocat. Behav.* 99, 107–117. doi: 10.1016/j.jvb.2017.01.002

Lent, R. W., Lopez, A. M. Jr., Lopez, F. G., and Sheu, H. B. (2008). Social cognitive career theory and the prediction of interests and choice goals in the computing disciplines. *J. Vocat. Behav.* 73, 52–62. doi: 10.1016/j.jvb.2008.01.002

Lent, R. W., Paixao, M. P., Da Silva, J. T., and Leitão, L. M. (2010). Predicting occupational interests and choice aspirations in Portuguese high school students: a test of social cognitive career theory. *J. Vocat. Behav.* 76, 244–251. doi: 10.1016/j.jvb.2009.10.001

Li, K., Peng, M. Y. P., Du, Z., Li, J., Yen, K. T., and Yu, T. (2020). Do specific pedagogies and problem-based teaching improve student employability? A cross-sectional survey of college students. Front. Psychol. 11:1872. doi: 10.3389/fpsyg.2020.01872

Li, N., Marsh, V., Rienties, B., and Whitelock, D. (2017). Online learning experiences of new versus continuing learners: a large-scale replication study. *Assess. Eval. High. Educ.* 42, 657–672. doi: 10.1080/02602938.2016.1176989

Li, Y. (2018). Effects of the application of mobile learning to criminal law education on learning attitude and learning satisfaction. *EURASIA J. Math. Sci. Technol. Educ.* 14, 3355–3362. doi: 10.29333/ejmste/91730

Lin, J., Lin, S., Turel, O., and Xu, F. (2020). The buffering effect of flow experience on the relationship between overload and social media users' discontinuance intentions. *Telemat. Informat.* 49:101374. doi: 10.1016/j.tele.2020.101374

Lippman, L., Moore, K., Guzman, L., Ryberg, R., McIntosh, H., Ramos, M., et al. (2014). "Studying aspects of flourishing among adolescents," in *Flourishing Children* (New York, NY: Springer), 1–23.

Liu, X., Peng, M. Y. P., Anser, M. K., Chong, W. L., and Lin, B. (2020). Key teacher attitudes for sustainable development of student employability by social cognitive career theory: the mediating roles of self-efficacy and problem-based learning. *Front. Psychol.* 11:1945. doi: 10.3389/fpsyg.2020.01945

Malecki, C. K., and Demaray, M. K. (2003). What type of support do they need? investigating student adjustment as related to emotional, informational, appraisal, and instrumental support. *Sch. Psychol. Q.* 18, 231–252. doi: 10.1521/scpq.18.3.231.22576

Maleki-Saghooni, N., Amel Barez, M., and Karimi, F. Z. (2020). Investigation of the relationship between social support and breastfeeding self-efficacy in primiparous breastfeeding mothers. *J. Matern. Fetal Neonatal Med.* 33, 3097–3102. doi: 10.1080/14767058.2019.1568986

Marambe, K. N., Vermunt, J. D., and Boshuizen, H. P. (2012). A cross-cultural comparison of student learning patterns in higher education. *High. Educ.* 64, 299–316. doi: 10.1007/s10734-011-9494-z

Martin, D. P., and Rimm-Kaufman, S. E. (2015). Do student self-efficacy and teacher-student interaction quality contribute to emotional and social engagement in fifth grade math? *J. Sch. Psychol.* 53, 359–373. doi: 10.1016/j.jsp.2015.07.001

Matsuda, T., Tsuda, A., Kim, E., and Deng, K. (2014). Association between perceived social support and subjective well-being among Japanese, Chinese, and Korean college students. *Psychology* 5, 491–499. doi: 10.4236/psych.2014.56059

Mattanah, J. F., Brooks, L. J., Brand, B. L., Quimby, J. L., and Ayers, J. F. (2012). A social support intervention and academic achievement in college: does perceived loneliness mediate the relationship? *J. Coll. Couns.* 15, 22–36. doi: 10.1002/j.2161-1882.2012.00003.x

Mehrabian, A., and Russel, J. (1974). *An Approach to Environmental Psychology*. Cambridge, MA: Witt press.

Nagy, J. T. (2018). Evaluation of online video usage and learning satisfaction: an extension of the technology acceptance model. *Int. Rev. Res. Open Distrib. Learn.* 19, 160–185. doi: 10.19173/irrodl.v19i1.2886

Nandi, D., Ashour, A. S., Samanta, S., Chakraborty, S., Salem, M. A., and Dey, N. (2015). Principal component analysis in medical image processing: a study. *Int. J. Image Mining* 1, 65–86. doi: 10.1504/IJIM.2015.070024

Nelson, C. (2016). *Continued Growth in Accessibility of AACSB-Accredited Online Degrees*. Available online at: http://aacsbblogs.typepad.com/dataandresearch/2016/10/index.html

Orkibi, H., Hamama, L., Gavriel-Fried, B., and Ronen, T. (2018). Pathways to adolescents' flourishing: linking self-control skills and positivity ratio through social support. *Youth Soc.* 50, 3–25. doi: 10.1177/0044118X15581171

Otto, B., and Kistner, S. (2017). Is there a Matthew effect in self-regulated learning and mathematical strategy application?-assessing the effects of a training program with standardized learning diaries. *Learn. Individ. Differ.* 55, 75–86. doi: 10.1016/j.lindif.2017.03.005

Oyarzun, B., Stefaniak, J., Bol, L., and Morrison, G. R. (2018). Effects of learner-to-learner interactions on social presence, achievement and satisfaction. *J. Comput. High. Educ.* 30, 154–175. doi: 10.1007/s12528-017-9157-x

Pan, Y. H. (2014). Relationships among teachers' self-efficacy and students' motivation, atmosphere, and satisfaction in physical education. *J. Teach. Phys. Educ.* 33, 68–92. doi: 10.1123/jtpe.2013-0069

Pandita, S., Mishra, H. G., and Chib, S. (2021). Psychological impact of covid-19 crises on students through the lens of Stimulus-Organism-Response (SOR) model. *Child. Youth Serv. Rev.* 120:105783. doi: 10.1016/j.childyouth.2020.105783

Park, I. J., Kim, M., Kwon, S., and Lee, H. G. (2018). The relationships of self-esteem, future time perspective, positive affect, social support, and career decision: a longitudinal multilevel study. *Front. Psychol.* 9:514. doi: 10.3389/fpsyg.2018.00514

Peng, M. Y. P. (2019). Testing the mediating role of student learning outcomes in the relationship among students' social capital, international mindsets, and employability. *Asia Pac. Educ. Res.* 28, 229–237. doi: 10.1007/s40299-018-00431-3

Peng, M. Y. P., and Chen, C. C. (2019). The effect of instructor's learning modes on deep approach to student learning and learning outcomes. *Educ. Sci. Theor. Pract.* 19, 65–85.

Peng, M. Y. P., Wang, L., Yue, X., Xu, Y., and Feng, Y. (2021). A study on the influence of multi-teaching strategy intervention program on college students' absorptive capacity and employability. *Front. Psychol.* 12:631958. doi: 10.3389/fpsyg.2021.631958

Pike, G. R., Kuh, G. D., McCormick, A. C., Ethington, C. A., and Smart, J. C. (2011). If and when money matters: the relationships among educational expenditures, student engagement and students' learning outcomes. *Res. High. Educ.* 52, 81–106. doi: 10.1007/s11162-010-9183-2

Pike, G. R., Smart, J. C., and Ethington, C. A. (2012). The mediating effects of student engagement on the relationships between academic disciplines and learning outcomes: an extension of Holland's theory. *Res. High. Educ.* 53, 550–575 doi: 10.1007/s11162-011-9239-y

Precision Consultancy (2007). *Graduate Employability Skills, Prepared for Business, Industry, and Higher Education Collaboration Council*. Brandon, SD: Barton.

Rigotti, T., Schyns, B., and Mohr, G. (2008). A short version of the occupational self-efficacy scale: structural and construct validity across five countries. *J. Career Assess.* 16, 238–255. doi: 10.1177/1069072707305763

Rosenfeld, L. B., Richman, J. M., and Bowen, G. L. (2000). Social support networks and school outcomes: the centrality of the teacher. *Child Adolesc. Soc. Work J.* 17, 205–225. doi: 10.1023/A:1007535930286

Ryan, J. F. (2004). The relationship between institutional expenditures and degree attainment at baccalaureate colleges. *Res. High. Educ.* 45, 97–114. doi: 10.1023/B:RIHE.0000015691.02545.61

Satoshi, S., Suzuki, K., and Gregory, B. (2009). Students' major choice in accounting and its effect on their self-efficacy towards generic skills: an australian study. *Asian Rev. Account.* 18, 131–147 doi: 10.1108/13217341011059390

Sergis, S., Sampson, D. G., and Pelliccione, L. (2018). Investigating the impact of Flipped Classroom on students' learning experiences: a self-determination theory approach. *Comput. Hum. Behav.* 78, 368–378. doi: 10.1016/j.chb.2017.08.011

Shogren, K. A., Kennedy, W., Dowsett, C., Villarreal, M., and Little, T. D. (2014). Exploring essential characteristics of selfdetermination for diverse students using data from NLTS2. *Career Dev. Trans. Except. Individ.* 37, 168–176. doi: 10.1177/2165143413486927

Teo, S. T., Segal, N., Morgan, A. C., Kandlbinder, P., Wang, K. Y., and Hingorani, A. (2012). Generic skills development and satisfaction with groupwork among business students: effect of country of permanent residency. *Educ. Train.* 54, 472–487. doi: 10.1108/00400911211254262

Tremblay, K., Lalancette, D., and Roseveare, D. (2012). *Assessment of Higher Education Learning Outcomes: Feasibility Study Report, Volume 1-Design and Implementation*. Paris: Organisation for Economic Co-operation and Development.

Tynjälä, P., Slotte, V., Nieminen, J., Lonka, K., and Olkinuora, E. (2006). "From university to working life: graduates' workplace skills in practice," in *Higher Education and Working Life: Collaborations, Confrontations and Challenges*, 73–88.

Tynjälä, P., Virtanen, A., Klemola, U., Kostiainen, E., and Rasku-Puttonen, H. (2016). Developing social competence and other generic skills in teacher education: applying the model of integrative pedagogy. *Eur. J. Teach. Educ.* 39, 368–387. doi: 10.1080/02619768.2016.1171314

Vallerand, R. J., Fortier, M. S., and Guay, F. (1997). Self-determination and persistence in a real-life setting: toward a motivational model of high school dropout. *J. Pers. Soc. Psychol.* 72:1161. doi: 10.1037/0022-3514.72.5.1161

Vedder, P., Boekaerts, M., and Seegers, G. (2005). Perceived social support and well being in school: the role of students' ethnicity. *J. Youth Adolesc.* 34, 269–278. doi: 10.1007/s10964-005-4313-4

Virtanen, A., and Tynjälä, P. (2018). Factors explaining the learning of generic skills: a study of university students' experiences. *Teach. High. Educ.* 24, 880–894. doi: 10.1080/13562517.2018.1515195

Virtanen, K. A., Lidell, M. E., Orava, J., Heglind, M., Westergren, R., Niemi, T., et al. (2009). Functional brown adipose tissue in healthy adults. *N. Engl. J. Med.* 360, 1518–1525. doi: 10.1056/NEJMoa0808949

Vollmann, M., Scharloo, M., Salewski, C., Dienst, A., Schonauer, K., and Renner, B. (2010). Illness representations of depression and perceptions of the helpfulness of social support: comparing depressed and never-depressed persons. *J. Affect. Disord.* 125, 213–220. doi: 10.1016/j.jad.2010.01.075

Wang, C. M., Qu, H. Y., and Xu, H. M. (2015). Relationship between social support and self-efficacy in women psychiatrists. *Chin. Nurs. Res.* 2, 103–106. doi: 10.1016/j.cnre.2015.10.002

Weidlich, J., and Bastiaens, T. (2017). Explaining social presence and the quality of online learning with the SIPS model. *Comput. Hum. Behav.* 72, 479–487. doi: 10.1016/j.chb.2017.03.016

Williams, P., Barclay, L., and Schmied, V. (2004). Defining social support in context: a necessary step in improving research, intervention, and practice. *Qual. Health Res.* 14, 942–960. doi: 10.1177/1049732304266997

Wilson, J. M., Weiss, A., and Shook, N. (2020). Mindfulness, self-compassion, and savoring: factors that explain the relation between perceived social support and well- being. *Pers. Individ. Diff.* 152:109568. doi: 10.1016/j.paid.2019.109568

Wong, R. (2020). When no one can go to school: does online learning meet students' basic learning needs? *Interact. Learn. Environ.* 1–17. doi: 10.1080/10494820.2020.1789672

Wong, Y. L. (in press). 'Entitlement' and 'Legitimacy' as emotional capital: living out class through a critical educational failure by community-college students in Hong Kong. *Stud. High. Educ.* 1–14. doi: 10.1080/03075079.2020.1776244

Wu, W., Wang, H., Zheng, C., and Wu, Y. J. (2019). Effect of narcissism, psychopathy, and machiavellianism on entrepreneurial intention-the mediating of entrepreneurial self-efficacy. *Front. Psychol.* 10:360. doi: 10.3389/fpsyg.2019.00360

Xu, P., Peng, M. Y. P., and Anser, M. K. (2021). Effective learning support towards sustainable student learning and well-being influenced by global pandemic of COVID-19: a comparison between mainland china and taiwanese students. *Front. Psychol.* 12:561289. doi: 10.3389/fpsyg.2021.561289

Yang, J., Peng, M. Y. P., Wong, S., and Chong, W. (2021). How e-learning environmental stimuli influence determinates of learning engagement in the context of COVID-19? SOR model perspective. *Front. Psychol.* 12:584976. doi: 10.3389/fpsyg.2021.584976

Yilmaz, R. (2017). Exploring the role of e-learning readiness on student satisfaction and motivation in flipped classroom. *Comput. Hum. Behav.* 70, 251–260. doi: 10.1016/j.chb.2016.12.085

Yssel, N., Pak, N., and Beilke, J. (2016). A door must be opened: perceptions of students with disabilities in higher education. *Int. J. Disabil. Dev. Educ.* 63, 384–394. doi: 10.1080/1034912X.2015.1123232

Zepke, N., and Leach, L. (2010). Beyond hard outcomes:'Soft'outcomes and engagement as student success. *Teach. High. Educ.* 15, 661–673. doi: 10.1080/13562517.2010.522084

Zhai, X., Wang, M., and Ghani, U. (2020). The SOR (stimulus-organism-response) paradigm in online learning: an empirical study of students' knowledge hiding perceptions. *Interact. Learn. Environ.* 28, 586–601. doi: 10.1080/10494820.2019.1696841

Zhang, M., Zhang, J., Zhang, F., Zhang, L., and Feng, D. (2018). Prevalence of psychological distress and the effects of resilience and perceived social support among Chinese college students: does gender make a difference? *Psychiatry Res.* 267, 409–413. doi: 10.1016/j.psychres.2018.06.038

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An Online Experiment During COVID-19: Testing the Influences of Autonomy Support Toward Emotions and Academic Persistence

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Wang Y, Zhang J and Lee H (2021) An Online Experiment During COVID-19: Testing the Influences of Autonomy Support Toward Emotions and Academic Persistence. Front. Psychol. 12:747209. doi: 10.3389/fpsyg.2021.747209

Students' academic persistence is a critical component of effective online learning. Promoting students' academic persistence could potentially alleviate learning loss or drop-out, especially during challenging time like the COVID-19 pandemic. Previous research indicated that different emotions and autonomy support could all influence students' academic persistence. However, few studies examined the multidimensionality of persistence using an experimental design with students' real-time emotions. Using an experimental design and the Contain Intelligent Facial Expression Recognition System (CIFERS), this research explored the dynamic associations among real-time emotions (joy and anxiety), autonomy support (having choice and no choice), self-perceived persistence, self-reliance persistence, and help-seeking persistence. 177 college students participated in this study online via Zoom during COVID-19 university closure. The results revealed that having choice and high intensity of joy could promote students' self-reliance persistence, but not help-seeking persistence. Interestingly, students who perceived themselves as more persistent experienced more joy during experiment. The theoretical and practical implications on facilitating students' academic persistence were discussed.

Keywords: academic persistence, emotion, autonomy support, online learning, joy, anxiety

INTRODUCTION

A question educators and researchers frequently ask is how to encourage students to learn persistently, especially in online settings (e.g., Vansteenkiste et al., 2004; Jung and Lee, 2018). Under the COVID-19 pandemic, cultivating students' learning persistence is more critical than ever in order to prevent learning loss and drop-out induced by school closures (Bao, 2020, 115; Dorn et al., 2020, 2-3). Despite learning loss, COVID-19 also raised mental health challenges, such as stress and anxiety, for college students (Odriozola-González et al., 2020; Charles et al., 2021). It is crucial to understand how to facilitate learning persistence while students are under stress and anxiety when going through challenging life incidences like the COVID-19 pandemic. Would autonomy support still effectively promote students' learning persistence and positive emotions in terms of online learning experience during COVID, as suggested by self-determination theory (Deci and Ryan, 2000)? How do different kinds of emotions constrain or elicit academic persistence? The purposes of this study are (a) provide a better understanding of academic persistence; (b) explore the associations among emotions, choice (as the indicator of autonomy support), and academic persistence. Specifically, this study used an experimental design to answer the questions: How do different emotions (joy and anxiety) and with/without choice influence students' academic persistence?

THEORETICAL BACKGROUND

Previous literature suggested the potential association among academic persistence, emotions, and autonomy support (e.g., Bonneville-Roussy et al., 2013; O'Neill and Thomson, 2013). The conceptualization of academic persistence and how emotion and autonomy influence academic persistence will be reviewed in this section.

Academic Persistence

It is still hard to define academic persistence, as consensus has not been made concerning the definition of persistence. There are two major controversies: (1) trait vs. state; (2) help-seeking behavior. Early research defined academic persistence as the consistent investment in learning despite obstacles, difficulties, failures, and situations (Zimmerman and Risemberg, 1997). However, recent research argued that persistence is more complex (Roland et al., 2018). It can vary from person to person, depending on the situation and one's personal preference. The early definition took the trait-dependent view and suggested that persistence is a stable trait, which means that a persistent person will struggle through hardship to achieve their goals across various domains and settings (Sellman et al., 1997; Sommer and Baumeister, 2002). However, the later definition took the state-dependent view that persistence is no more than a state, so people who persist in one context might not persist in a different situation (Baker et al., 2008; Hershkovitz and Nachmias, 2009).

The second controversy is around help-seeking behavior. Even though help-seeking behaviors could help students continue on a challenge or difficult task (Jackson et al., 2003; Terrell et al., 2015), most of the time, persistence was seen as a self-reliance physical and mental process. Some researchers viewed help-seeking behavior as a sign of weakness (Tyssen et al., 2004).

This research would like to propose a new definition for academic persistence to address the conceptual issues stated above. As discussed, previous research had debates around trait vs. state and whether help-seeking is a form of persistence. This research would like to move away from trait vs. state debate and trade help-seeking as a form of persistence because student overthrows their psychological barrier of being seen weak and tries to achieve their academic goals by asking for help. The current study defined academic persistence as an individual's self-perceived and actual willpower and behaviors (may vary in different situations) to overcome obstacles, difficulties, and failures by oneself or by seeking help from others to achieve learning goals. This definition contains three types of persistence: self-perceived (trait), self-reliance (state), and help-seeking persistence (state). Self-perceived persistence is how a person thinks he or she will behave when facing difficulties and obstacles. The latter two types of persistence are individual's actual reactions when facing difficulties or challenges in learning. Self-reliance persistence means a person continues to work hard on the problem by oneself. Help-seeking persistence is defined as a person seeks help from others to overcome obstacles and complete an arduous task.

Persistence is not only hard to define, it is also extremely hard to measure and quantify because of its multidimensionality and dynamic nature. Scholars used self-report scales (Renaud-Dubé et al., 2015) and the amount of time invested (Pelletier et al., 2001; Jõesaar et al., 2011) measure persistence. However, experimental studies of persistence are limited and often do not reflect real-world problem-solving scenarios. More importantly, few experimental studies have captured the multidimensionality of persistence. In this study, a self-reported scale and experimental design are implemented in order to capture the three aspects of persistence. The measurement of academic persistence will be specified in the "Materials and Methods" section.

Besides the calling for a better understanding of academic persistence, it is also essential to understand what supports students' academic persistence. Whether persistence could depend on (a) students' emotions (Tulis and Ainley, 2011); (b) autonomy support (Pelletier et al., 2001). The following section will review the literature on emotion and autonomy to explain how these two factors would influence academic persistence.

Emotion

Emotions in this study were defined as the various emotions directly induced by learning activities and learning outcomes. Traditionally, researchers study cognition and emotion separately, and emotions have not been studied intensively in education before the 1990s (Pekrun, 2019). The recent 20 years sees a rise in studies of emotion in education, as emotions were discovered to activate and deactivate cognition and metacognition processes (e.g., persistence) related to learning (Artino and Jones, 2012; King and Areepattamannil, 2014; Ramirez-Arellano et al., 2019).

Emerging literature addresses the importance of emotions in the online learning context (e.g., Feidakis et al., 2014; D'Errico et al., 2016). O'Regan (2013) concluded that emotions played a central role in students' lived online learning experience through interviews with eleven students. Both anxiety and excitement were stood out in students' discussion of the online learning experience. D'Errico et al. (2018) also detected and classified 11 cognitive emotions students showed in video-lecture and chat with teachers. Parlangeli et al. (2012) argued that, within online learning, cognitive emotions were crucial, but social emotions also needed attention. Most of the studies concerning emotions in an online context aimed to address the importance of emotions or identify the types of emotions students demonstrated, but not much research explored the association of these emotions and students' academic persistence.

However, in the traditional face-to-face learning context, there was burgeoning consciousness of the significant role of emotions in students' academic performance (Tulis and Fulmer, 2013). Anxiety, especially test and math anxiety, was studied massively as a predictor for academic performance (Cassady and Johnson, 2002; Zeidner, 2014; Putwain et al., 2016). Anxiety is the outcome of negative (unpleasant) emotions like anger and frustration, and most of the time associated with academic performance negatively (Chapell et al., 2005; Karatas et al., 2013). There is also joy, which is seen as the outcome of enjoyment. Such joy of learning deepens the learning process and promotes academic achievement (Goetz et al., 2008; Villavicencio and Bernardo, 2013; Putwain et al., 2016).

Not only associated with academic performance, joy and anxiety also potentially related to academic persistence. Students who experience positive emotion (joy) would perceive themselves have enough ability or resources to achieve their goal. On the other hand, students with unpleasant emotions (anxiety) would be frustrated by the current situation and avoiding continuing their goals (Linnenbrink and Pintrich, 2002; Ainley et al., 2005; Tulis and Ainley, 2011). Aforementioned research suggested a potential association between these two emotions and students' persistence, so the joy of solving specific problems or the anxiety activated by failures or challenging tasks would be this study's focused emotions.

Most previous studies used questionnaires to measure emotions, for instance, the Achievement Emotions Questionnaire (AEQ; Pekrun et al., 2011) and the Epistemically-Related Emotion Scale (EES; Pekrun et al., 2017). However, the research mentioned above, and the self-reported questionnaires have several limitations. Firstly, they did not provide the real-time emotional status during students' problem-solving process. Secondly, self-reported data has widely acknowledged drawbacks: for instance, participants would conceal their real opinion, and discrepancies might exist between how people behave and how people think they would behave (Sallis and Saelens, 2000; Subar et al., 2015). Thirdly, self-reported data does not provide observed valence and activation of synchronous emotions during task completion, but these characteristic of synchronous emotions are essential for learning (Pekrun, 2006).

To address these limitations, this study incorporated the Contain Intelligent Facial Expression Recognition System (CIFERS) to measure two dimensions of emotions: valence (positive or negative) and activation (activating or deactivating) (Pekrun, 2000, 2006). CIFERS could track students' macro- and micro-facial expressions as indicators for different emotions (both positive and negative). It could also provide information on real-time emotion change, emotion intensity (activating and deactivating), as well as the specific time an emotion occurs. Before elucidating more on CIFERS in the "Materials and Methods" section, certain suspicion must be squelched: why use a facial expression as an emotion indicator and whether this approach is accurate? The implication of facial expression in emotion studies was presented below to answer these two questions.

Facial Expression and Emotion

Facial expressions have long been used to indicate emotions and stayed central in emotion studies (Tomkins and McCarter, 1964; Russell, 1994; Ruba and Repacholi, 2020). The accuracy of using facial expressions to identify emotions has been justified through many ways, for instance, self-report instruments (Matsumoto, 1987; Matsumoto et al., 2000) and facial coding systems (Ekman et al., 1980; Clark et al., 2020; Rosenberg and Ekman, 2020). There is debate around the universality of facial expression. Early research discovered that even people in an isolated tribe in New Guinea shared the same emotional interpretation of facial expression (Izard, 1992). This finding was later replicated by Matsumoto (1992) and Ekman (1994). Other researchers questioned such findings. For instance, Jack et al. (2009, 2012) argued that facial expressions are not universal. However, they can only prove that the intensity of emotions and degree of the movement of people's faces are different. More importantly, the differences they identified did not exist in facial expression but in how people use their own cultural understandings to interpret facial expressions. In this paper, we believed that facial expressions, both macro and micro facial expressions, are shared by different cultures; only the intensity and interpretation might be different from culture to culture (Ekman and Friesen, 2003; Cowen and Keltner, 2020).

The CIFERS equipment adopted in this research was established based on Ekman and Rosenberg (1997) and Rosenberg and Ekman (2020) facial expression theory and facial coding systems, which divided the face into 47 units. With CIFERS, the facial movement could be obtained within 50 ms. CIFERS's basic mechanism is out of the scope of this research, but more information could be found in **Supplementary Appendix A** and previous studies (Scherer and Scherer, 2011; Krumhuber et al., 2012). The CIFERS has one more advantage: its artificial intelligent feature allows it to improve its own accuracy through data collection. It has already been trained and improved by more than 100,000 people's emotional data before this study (see **Supplementary Appendix A** for more information). The CIFERS collects macro-facial expressions and micro-facial expressions, which means even when students try to conceal their emotions, the machine could still identify that emotion.

Autonomy

Besides emotions, another factor that would affect academic persistence is autonomy support. According to self-determination theory, autonomy is the basic psychological need to make choices without pressure, external control, or compulsions (Deci and Ryan, 2000). It has been primarily acknowledged that having autonomy would support learning persistence (Pelletier et al., 2001; Vansteenkiste et al., 2004; Bonneville-Roussy et al., 2013). Specifically, in Pelletier et al. (2001) study, student-athletes who perceived more autonomy support were persistent longer in the sports that they play. Bonneville-Roussy et al. (2013) also found in a longitudinal study that college students are more persistent in learning within an autonomy-supportive environment.

Autonomy support not only associates with academic persistence but also impacts an individual's emotional function. In Wang et al. (2007) longitudinal investigation, if under an autonomy support parenting style, children had functioned better emotionally, while a constraining parenting style would dampen children's emotional functioning for both the United States and Chinese seventh-grade students. Another research also supported such findings. If parents and teachers showed more support for children's autonomous behavior, children's emotions would be more positive, and they were better at emotion regulation (Liew et al., 2011). Most of the time, autonomy support was manifested as providing choices to students (Benita et al., 2014; Lewthwaite et al., 2015). In this study, we adopted the same approach of conveying choice as a way of autonomy support.

THE CURRENT RESEARCH

Above all, the proposed theoretical framework of this study was presented in **Figure 1**. As discussed, autonomy support would induce both higher persistence and positive emotion (joy). Moreover, positive emotion could promote persistence. Many previous studies justified the association between autonomy support, emotion, and academic persistence partially. However, to our knowledge, few research studied the relationships among these three factors together, especially in an online experimental setting during a challenging time like the COVID-19 pandemic. More specifically, not many research manipulated the with/without autonomy support (choice/no choice conditions) and track students' real-time emotions by considering different kinds of persistence (self-perceived persistence, self-reliance persistence, and help-seeking persistence).

In this study, college students were recruited online during the COVID-19 school closure. An experiment (with the control group: no choice; experiment group: choice) and online tasks were designed to record participants' task performance, time spent on each item, and testing behaviors as academic persistence indicators. The task procedure will be specified in the "Materials and Methods" section. To address the research question stated above, four hypotheses were proposed basing on previous research.

Hypothesis 1: If a student's autonomy is supported (with choice), he/she will be more persistent (both self-reliance and help-seeking persistence) comparing to students with no autonomy support (no choice).

Hypothesis 2: If a student's autonomy is supported (with choice), he/she will have more positive emotion (joy) and less negative emotion (anxiety) comparing to students with no autonomy support (no choice).

Hypothesis 3: If a student has more intensive positive emotion (joy), then he or she will be more persistent during the task compared to the student who has less intensive positive emotion. If a student has more intensive negative emotion (anxiety), then he or she will be less persistent during the task compared to the student with less intensive negative emotion.

Hypothesis 4: Students who had a choice and with more intensive positive emotion (joy) should reflect a high persistence level (self-perceived, self-reliance, and help-seeking persistence). More specifically, positive emotion (joy) is expected to promote learning persistence, whereas negative emotions (anxiety) should diminish persistence. Students in the autonomy-supported (with choice) group would be more persistent and more joyful.

MATERIALS AND METHODS

Sample and Procedures

To determine the required sample size, we conducted the Power Analysis based on the root mean squared error of approximation (RMSEA) in Structural Equation Modeling. The results showed that to achieve the power for acceptable RMSEA, the lower bound of sample sizes is 66 in each group. There were 177 college students randomly sampled from a university to ensure sufficient power for statistical inference. An experiment related to persistence was performed with participants being randomly assigned to either an experiment group (n = 88) or a control group (n = 89). In the control group, participants were allowed to choose which type of task (either math or literacy) they prefer to complete. Participants will be given no choice in the experimental group. The demographic information was presented in **Table 1**.

Instruments

Before starting the experiment, participants were asked to answer an online survey. The survey includes demographic information, a persistence scale, and an anxiety scale.

Persistence

The self-perceived persistence was measured by a scale developed by Howard and Crayne (2019). The scale had five items (e.g., "I keep on going when the going gets tough"), and the reliability was 0.79.

Controlling Factors

This study also introduced several controlling factors when predicting persistence: trait anxiety (10 items; State-Trait Anxiety Inventory; Spielberger et al., 1999), gender, performance (measured by the sum scores of the task), and response time to eliminate potential confounding effects (see **Figure 2**).

Experiment Procedure

The experiment aims to determine whether students exhibit different persistence levels under the choice or non-choice scenarios and different emotions. Participants had the chance to solve either math or literacy problems. Each participant was asked to answer 25 questions in both the experiment and control group. The questions were taken from the Cultural Fair Intelligence Test (CFIT) from the Genius Tests.[1] The CFIT provides types of tasks suited to the various task conditions in this experiment.

Participants would sign up for the study through a university's data collection system, and then the online system assigned a four-digit research ID to the student. A Zoom meeting link would be provided to the participant. The instruction would notify the participant to temporarily change their Zoom ID to their four-digit research ID temporarily before the experiment Zoom meeting. When a participant joined the research Zoom Meeting, the investigator would send him/her a consent form via the Zoom chat function. The participant would E-sign a consent form (concealed the emotion tracking information for the test's accuracy), which indicated all the experiment information and

[1] https://geniustests.com/iq-tests/culture-fair-intelligence-scale

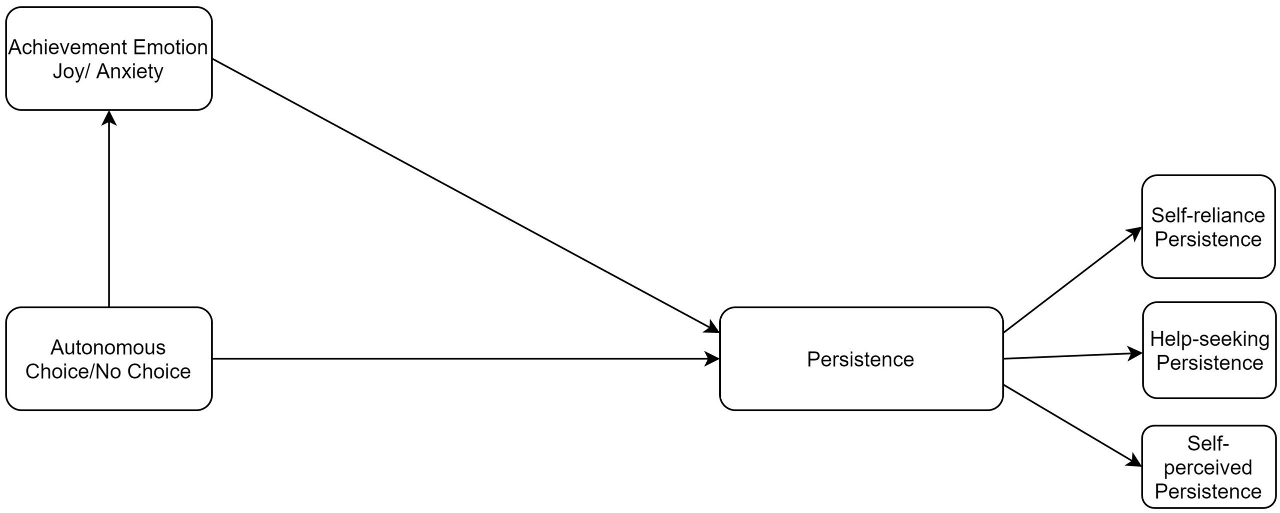

FIGURE 1 | Theoretical framework.

TABLE 1 | Demographic information.

Category	Number of participants	Percentage
Age		
18–20	97	54.8%
21–22	44	24.8%
23–35	26	14.7%
36–57	10	5.6%
Gender		
Male	18	10.2%
Female	159	89.8%
Race		
White	145	81.9%
Black	28	15.8%
Asian	2	1.1%
Others	2	1%

clarified that participants could drop out of the study anytime if they feel uncomfortable. After signing the consent form, the investigator would send out an online survey (specified above) link via the Zoom chat function. When the participant finished the survey, he/she would be randomly assigned to a treatment condition (choice vs. no choice).

Participants in the experiment group could choose freely from the two groups of tasks (i.e., math and literacy tasks). Participants in the control group were presented with the math and literacy tasks, but the investigator will assign only one task type randomly to participants without providing any option for choice. Participants were informed that the task has 25 questions, and there was no time limit. Whenever they answer a question wrong, they can work on the questions by themselves more, or click the hint button, or skip the question. After assigning the group, if the participants did not have questions about the task, the investigator would be on mute and turn off the video to give the participant time to solve the 25 questions. The emotion tracking machine (specified in the next section) would be started at this point to capture participants' facial expressions. Participants were asked to show their faces and try to face their camera the whole time.

The instructions in the assigned task stated that participants could answer as many items as possible correctly with no time limit. When participants answered a question incorrectly, they were given three options. (1) They can skip the question, in which case their answer will be considered wrong. (2) They can request a hint and then continue solving the question; if they come to the correct answer after receiving the hint, their answer will be considered correct. (3) They can continue to try to solve the question by themselves without a hint until they get the right answer. For example, if the question is, *Bruce likes 324 but not 325. He likes 2,500 but not 2,400. He likes 121, but not 122. Which does he like? (a) 900; (b) 800; (c) 700; (d) 600*. If the participant's answer is (a), then he/she gets it correct and will automatically move to the next question. If the student's answer is not (a), then he/she can choose to skip the question by clicking the skip button and move to the next question. The participant can also choose the hint option by clicking the hint button, and then the system will show the hint: James likes square numbers, then the student can continue to solve the problem. Persistence would be calculated according to students' actual behaviors, and the specific method will be discussed in the "Plan of Analysis" section.

After the participant finished the task, he/she would be asked to sign a post-experiment consent form which indicated that their facial expression data were captured. If they allowed the research team to use the data, they would sign the form. After E-sign the post consent form, the participant could leave the Zoom session.

Equipment to Measure Emotion

A facial tracking system was running through the duration of the experiment as participants complete their assigned

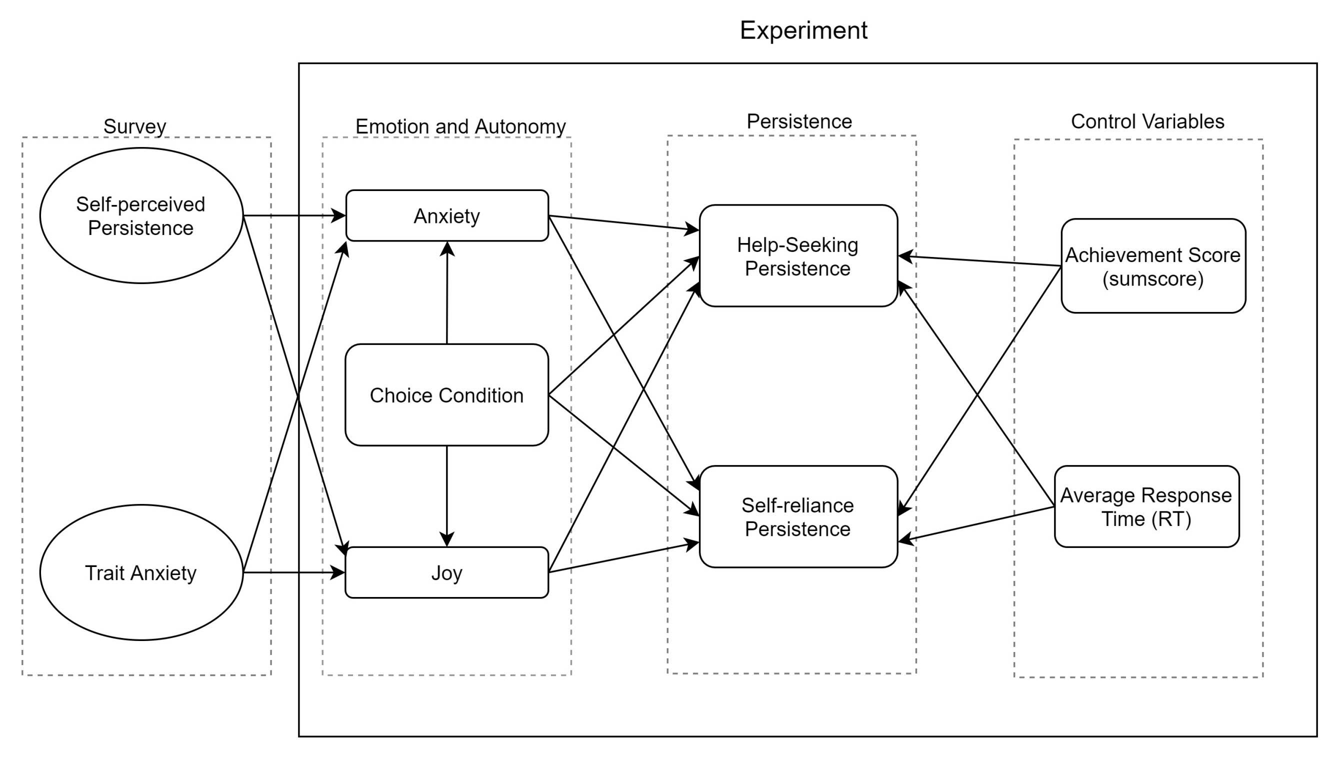

FIGURE 2 | Proposed structural equation modeling analysis model.

tasks to track their emotional state. The Contain Intelligent Facial Expression Recognition System (CIFERS) camera would capture participants' real-time facial expressions from the Zoom window. CIFERS is a software program that uses macro- and micro-expression data modeling to track individuals' facial movements and determine participants' cognitive and psychological states. The software recorded participants' 11 basic emotions and emotional changes over time (more information about the equipment appears in **Supplementary Appendix A**). This study used joy and anxiety as the targeted emotions.

Plan of Analysis

Data analysis was conducted following two steps. In the first step, we categorized each item responses for each participant into three types of persistence behaviors (self-reliance behavior, help-seeking behavior, and low persistence) according to three criteria: (1) the number of times participants click the "submit" button (participants have to try at least one); (2) whether they clicked "hint" button, and (3) whether they skipped an item. Moreover, the total response time for each group of items was recorded (T_{sr}, T_{hs}, T_l) which represented the time length they showed self-reliance behavior, help-seeking behavior, and low persistence accordingly during the experiment. In the second step, we analyzed five regression models in which the three types of persistence were considered as outcomes.

TABLE 2 | Scoring rules for persistence.

Persistence	HINT	SKIP	TRY
Self-reliance	N	N	>1
Help-seeking	Y	Y/N	>1
No persistence	Y	N	1
No persistence	N	Y	1
No persistence	Y	Y	1

As shown in **Table 2**, each participant's persistence was defined using participants' behaviors. Specifically, the criteria for item-level persistence were as follows: items with self-reliance behavior – the individual responded to an item more than once, did not ask for hints, and did not skip the item; items with help-seeking behavior – similar to self-reliance persistence except the individual asked for hints; items without persistent behavior – the individual answer incorrectly and skipped the items, so they did not demonstrate high or moderate persistence. The persistence index Yp in this study was defined as the total time spent on the items which show specific persistence behavior for participant p. We set J as the total number of items, p as the person index, and i as the item index. For example, each participant's time interval showing self-reliance behavior can be computed as follow:

$$\boldsymbol{Y_p} = \sum_{j=1}^{J} \boldsymbol{T_{pj} I_j} \quad (1)$$

where Y_p is a $P \times 3$ test-level persistence score vector representing three types of persistence scores for total participants. I_j is an indicator matrix for item j suggesting whether this item shows specific persistence behavior, whose values were either 0 or 1 and I is $J \times 3$ matrix; for example, $I_{1p} = [1, 0, 0]$ indicated that Item 1 shows self-reliance behavior for person p. T_{pj} represents the time response vector for item j answered by person p and then T is a $P \times J \times 3$ matrix.

We use the regression model below to examine Hypothesis 1:

$$\mathbf{Y_{persis} = SS + RT + choice} \quad (2)$$

where Y_{persis} is one of two types of persistence indices of interest (help-seeking persistence or self-reliance persistence), SS (sum scores) represents the achievement scores which were computed with the number of items each participant answer correctly, RT (response time) represents the total time each participant used, choice indicates whether the participant was allowed to select the type of task.

To examine Hypothesis 2, we estimated the following regression models:

$$\mathbf{Anxiety = choice + gender + trait\_of\_anxiety} \quad (3)$$

$$\mathbf{Joy = choice + gender + trait\_of\_anxiety} \quad (4)$$

where *Anxiety* and *Joy* are the maximum level of that emotion of participants during the experiment; *gender* indicates whether the participants are females or males; *trait_of_anxiety* indicates the state of anxiety level measured by State-Trait Anxiety Inventory. There were two major reasons for using the maximum level of anxiety and joy. Firstly, according to previous literature, only a higher level of emotional arousal would induce behavior and influence the decision-making process (Kaufman, 1999; Hu et al., 2015). Secondly, using other indices, for instance, mean (total emotion show/time), would be inaccurate since students were not showing joy or anxiety all the time during the experiment.

To examine Hypothesis 3, we used the regression model as follow:

$$\mathbf{Y_{persis} = SS + RT + Anxiety} \quad (5)$$

$$\mathbf{Y_{persis} = SS + RT + Joy} \quad (6)$$

Finally, to examine Hypothesis 4, a structural equation model containing all variables was fitted to test the effects of emotion and choice condition (see **Figure 2**). In SEM, the dependent variable was either the emotion index (*Anxiety* or *Joy*) or persistence index (Y_{persis}); independent variables were the choice condition, anxiety, and joy. Other controlling variables included anxiety traits, achievement scores (SS), and average response time (RT). To examine the goodness-of-fit of SEM, root mean square error of approximation (RMSEA), and maximum likelihood (ML)-based standardized root mean squared residual (SRMR) were reported to evaluate the adequacy of the model. RMSEA and SRMR values close to or lower than 0.08 are acceptable, although values approaching 0.05 are preferable (Hu and Bentler, 1999).

RESULTS

Table 2 showed participants' demographic information, including age, gender, ethnicity, and sexual orientation. **Table 3** showed the descriptive statistics of dependent and independent variables, including the persistence scores, the proportion of choice condition, maximum joy, and anxiety level. The ranges for persistence scores, joy, and anxiety are all 0–100. The emotion data were extracted from the CIFERS background data.

For *Hypothesis 1*, controlling the effects of response time and sum scores (task performance), we found that whether having a choice (autonomy support) has significant positive effect on self-reliance persistence ($\beta = 0.290$, $p < 0.05$) but no significant effect on either help-seeking persistence ($\beta = -0.064$, $p = 0.587$) or self-perceived persistence ($\beta = 0.010$, $p = 0.912$). The results partially support Hypothesis 1 that if a student's autonomy is supported, he/she may have higher self-reliance persistence.

For *Hypothesis 2*, the results showed that after controlling the effects of the anxiety trait and gender, there is no significant relationship between participants' maximum joy level with whether they have choice or not ($\beta = 8.765$, $p = 0.205$). There is also no significant association between participants' maximum anxiety level with whether they have a choice ($\beta = -0.806$, $p = 0.400$). Thus, the results did not support Hypothesis 2.

For *Hypothesis 3*, the regression results showed that participants' maximum level of joy had an approximately significant association with self-perceived persistence at the level 0.05 ($\beta = 0.002$, $p = 0.066$), but we did not confirm that it related to the help-seeking ($\beta = -0.002$, $p = 0.210$) and self-reliance persistence ($\beta = -0.002$, $p = 0.347$). On the other hand, participants' maximum anxiety level seemed to have a significant negative association with self-reliance persistence ($\beta = -0.025$, $p < 0.05$) but no significant relationship with the other help-seeking persistence ($\beta = 0.009$, $p = 0.306$). Thus, the results partially support Hypothesis 3.

For *Hypothesis 4*, as shown in **Figure 3**, the SEM has acceptable model fit [SRMR = 0.072, RMSEA = 0.049, CFI = 0.918, TLI = 0.9, χ^2 (203) = 284.57, $p < 0.01$]. The results of SEM with maximum likelihood (ML) estimation showed that controlling for the effects of sum scores (task performance), response time, gender, and anxiety trait, whether having a choice (autonomy support) was significantly associated with self-reliance persistence ($\beta = 0.157$, $p = 0.022$) but not significantly related to the help-seeking persistence ($\beta = -0.027$, $p = 0.62$), which partially supports our Hypothesis 4. As for the effects of emotion on persistence, the results showed that the maximum anxiety level has an approximately

TABLE 3 | Descriptive statistics.

Variables	Mean or %	SD
Help-seeking persistence	264.96	248.53
Self-reliance persistence	180.53	161.82
Participant in choice condition	49.7%	0.50
Maximum joy level	61.99	45.39
Maximum anxiety level	97.69	6.15

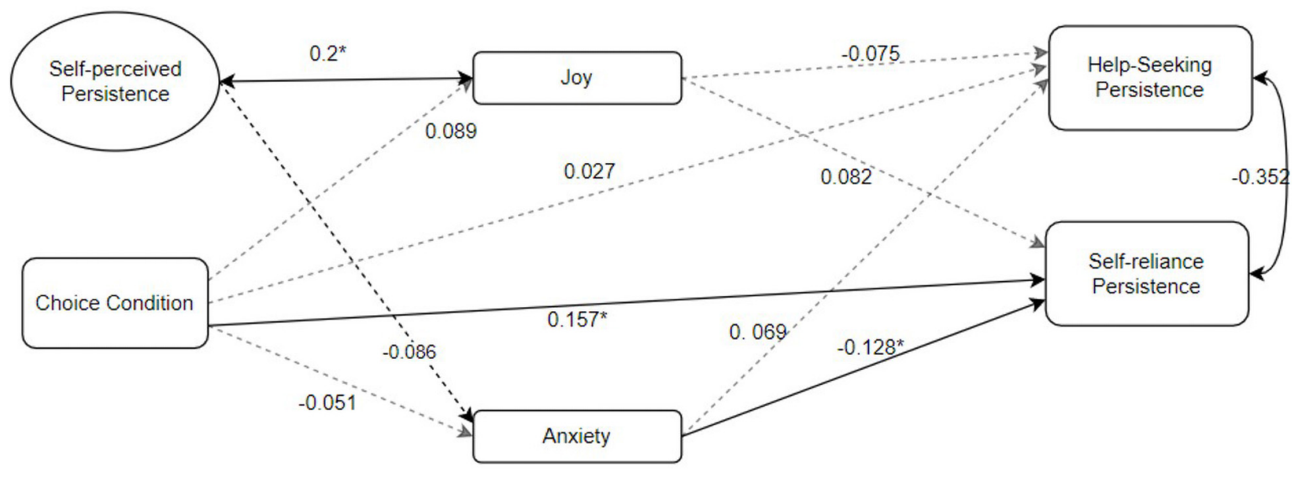

FIGURE 3 | Structural equational modeling results. *$p < 0.05$. Omitted controlling factors include: gender (help-seeking persistence*: β = 0.107, p = 0.049; self-reliance persistence: β = –0.103, p = 0.055; anxiety: β = 0.003, p = 0.968; joy: β = –0.071, p = 0.339); trait of anxiety (help-seeking persistence: β = –0.026, p = 0.668; self-reliance persistence: β = –0.073, p = 0.356; anxiety: β = 0.079, p = 0.353; joy: β = –0.030, p = 0.722); sum scores (help-seeking persistence*: β = –0.122, p = 0.025; self-reliance persistence*: β = 0.349, $p < 0.001$); Response Time (help-seeking persistence*: β = 0.693, $p < 0.001$; self-reliance persistence: β = 0.069, p = 0.307).

significant effect on self-reliance persistence at the alpha level 0.05 (β = −0.128, p = 0.060) but not on help-seeking persistence (β = 0.069, p = 0.2). Additionally, self-perceived persistence significantly affects the maximum joy level (β = 0.2, $p < 0.001$).

DISCUSSION

This study explored the association among academic persistence, autonomy support, and emotions within the online environment during the COVID-19 pandemic. Results of regression and structural equation models supported some of the hypotheses.

Partially consistent with Hypothesis 1, having choice did promote students' self-reliance persistence but did not show relation with help-seeking persistence. Hypothesis 2 was not supported by our study, as different choice conditions did not influence students' joy or anxiety. Hypothesis 3 was partially supported, as being joyful during the task will promote students' self-reliance persistence, and being anxious during the task would diminish self-reliance persistence. Moreover, emotions did not relate to other kinds of persistence. After controlling for participants' trait anxiety, gender, response time, and sum scores (task performance), the Hypothesis 4 testing results showed that having choice was positively associated with self-reliance persistence. In contrast, no choice and having high anxiety were related to lower self-reliance persistence. Moreover, if the self-perceived persistence is high, then the participants were more likely to have high intensity of joy during the task.

Additionally, the relationships among different kinds of persistence were justified in this study. Self-reliance persistence and help-seeking persistence were associated with each other negatively, while self-perceived persistence did not show any significant association with either self-reliance persistence or help-seeking persistence. Such results indicated that how much a student believed he/she is persistent does not represent how he/she would actually behave during the problem-solving process. Moreover, students who adopted self-reliance persistent would be less likely to adopt help-seeking persistence. Specifically, if an individual usually solves problems by himself/herself would be less likely to seek help from others, and vice versa, but eventually, people would achieve their goals.

Findings of the association between choice and academic persistence were consistent with previous research and justified the direct relationships of choice with different types of persistence (Bonneville-Roussy et al., 2013; Yurdakul, 2017). After controlling for task performance, trait anxiety, performance, and response time, college students in the choice group would show more self-reliance persistence in the problem-solving tasks. This finding means no matter he/she good at math or not, by having choice, students were more likely to solve challenging tasks by themselves. However, whether students would like to seek help to continue solving the questions did not show a significant relationship with having or not having a choice. Such finding showed that given a choice or not did not affect a students' likelihood to seek help to continue solving a challenging task.

Findings of the association between emotions and academic persistence were partially aligned with previous studies and also added new perspectives to current literature. Positive emotion (joy) promoted self-reliance persistence, while negative emotion (anxiety) undermines self-reliance persistence (Tulis and Ainley, 2011; Yu et al., 2020). Specifically, indicated by the real-time emotional tracking system, students who experienced joy would be more likely to solve the problem by themselves, but if students experience high intensity of anxiety, they would not continue working on the problem. Interestingly, when participants' self-perceived persistence was high, they would show more joy during the problem-solving process. However, help-seeking persistence did not show any association with both joy and anxiety.

There are several theoretical contributions of this research by using an experimental approach and tracking real-time emotions. Firstly, this study offered a new approach to define academic persistence. To the best of our knowledge, this study is the first one that considered academic persistence from both trait and state perspectives. It conceptualized academic persistence from three aspects: self-perceived persistence (trait), self-reliance persistence (state), and help-seeking persistence (state). As suggestions by our research, individuals have their perceived persistence, but they could behave differently in different situations, so self-perceived (self-reported) persistence might not be reliable in certain circumstances. Whether an individual good at a learning activity or not, his or her perceived persistence does not lead to more persistent behaviors in that activity.

Secondly, this study provided new ways to measure academic persistence. Going beyond previous studies which used the time or frequency to measure persistence, this study used individuals' actual persistent behaviors as the indicators. This behavioral tracking approach could provide a new perspective to study multidimensional and dynamic cognitive and metacognitive processes similar to persistence, such as self-regulation, critical thinking, or creativity.

Thirdly, adding on previous research which addressed emotions (Linnenbrink and Pintrich, 2002; Tulis and Ainley, 2011) and autonomy support (Pelletier et al., 2001; Vansteenkiste et al., 2004) could promote academic persistence, the current study specified that only self-reliance persistence would be influenced by emotions and autonomy support. If students decided to ask for help to overcome a difficulty, their persistence would not be influenced by emotions and autonomy support. Contradicting previous research (Wang et al., 2007; Liew et al., 2011), as a way of autonomy support, having choice or not seemed uninfluential toward college students' emotions in an online setting. However, more research is needed to examine such finding. Fourthly, instead of using self-report data, this study is one of the first studies that considered real-time emotions and the intensity of emotions during students' problem-solving process.

Besides theoretical contributions, the present findings have several practical implications. Firstly, if students are going through a difficult time (e.g., life tragedies, the COVID-19 pandemic), a teacher should provide more choices for students to help cultivate students' self-reliance learning persistence in an online learning environment. Secondly, if self-reliance persistence is not always achievable, teachers should be more assessable in ways like instant feedback or prompt email reply to promote students' help-seeking persistence. Thirdly, providing emotional support would help with students' self-reliance persistence. The proper way of emotional support would significantly improve students' self-reliance persistence. Recent research indicated that teachers' emotions and teacher-student relationship could impact students' emotions (Goetz et al., 2021), so teachers being positive and cheerful would promote students' positive emotion, and eventually promote self-reliance persistence. Fourthly, this research would be helpful for establishing a more supportive and sustainable online learning environment by incorporating more autonomy supports and instant feedback system in the course structure or teacher-student communications. Such environment would promote students' self-reliance and help-seeking persistence, which could potentially alleviate learning loss, drop-out, and learning anxiety during difficult life period (e.g., COVID-19, grief, mental health problems, or other life tragedies).

LIMITATION AND FUTURE DIRECTIONS

This study provided both new theoretical and practical contributions, but some findings should be interpreted with caution due to the following limitations. Firstly, the majority of our participants were female college students, so the generalizability to male students might be wakened. Another limitation of this study is that only one summative score of emotions (maximum level) was used in the analysis. Action unites (i.e., the response process data), a novice approach to explore assessment data, were not employed in this study. Thus, the dynamic process of participants' emotions was not considered in this study. The association between fluctuated emotions and persistence behavior has not been examined in the study because SEM cannot analyze time-series data. Moreover, other academic emotions, such as frustration or boredom, should be considered essential for learning persistence (D'Errico et al., 2018; Narayan and Sharma, 2021). Future studies should address these emotions.

In future studies, dynamic structure equation models (DSEM) could address the causal relationship between emotion and persistence. Future studies could also include more diverse student samples, which could improve the findings' generalizability (e.g., including samples from other countries). A more racially and ethnically diverse population will have more practical implications, which can apply to different learning environments with different cultural backgrounds. Additionally, longitudinal analysis of the association between emotion and persistence is needed to infer the potential causal relationship between emotion and persistence. Further consideration of other emotions and see students' facial signals as convey evaluative (students' criticism or disagreement) meanings that can contribute to understanding on the other side students' autonomy (Poggi et al., 2013).

Regardless of the limitation stated above, this study provided meaningful results on how real-time emotions and autonomy support influence different kinds of academic persistence with an experimental design and a new method of assessing emotions.

DATA AVAILABILITY STATEMENT

Raw data were generated at the Micro-Facial Expression Tracking Lab, University of Alabama. Derived data supporting the findings of this study are available from the corresponding author YW on request.

ETHICS STATEMENT

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

AUTHOR CONTRIBUTIONS

YW designed the research and drafted the manuscript. JZ was in charge of the data analysis. HL contributed to the literature review and data collection. All authors contributed to the article and approved the submitted version.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2021.747209/full#supplementary-material

REFERENCES

Ainley, M., Corrigan, M., and Richardson, N. (2005). Students, tasks and emotions: identifying the contribution of emotions to students' reading of popular culture and popular science texts. *Learn. Instruc. Feelings Emot. Learn. Proc.* 15, 433–447. doi: 10.1016/j.learninstruc.2005.07.011

Narayan, A. K., and Sharma, U. (2021). Adapting to COVID-19 disruptions: student engagement in online learning of accounting. *Accoun. Res. J.* 34, 261–269. doi: 10.1108/ARJ-09-2020-0293

Artino, A. R., and Jones, K. D. (2012). Exploring the complex relations between achievement emotions and self-regulated learning behaviors in online learning. *The Int. Higher Educ. Emot. Online Learn. Environ.* 15, 170–175. doi: 10.1016/j.iheduc.2012.01.006

Baker, R., Walonoski, J., Heffernan, N., Roll, I., Corbett, A., and Koedinger, K. (2008). Why students engage in 'gaming the system' behavior in interactive learning environments. *J. Interact. Learn. Res.* 19, 185–224.

Bao, W. (2020). COVID-19 and online teaching in higher education: a case study of peking university. *Hum. Behav. Emerg. Technol.* 2, 113–115. doi: 10.1002/hbe2.191

Benita, M., Roth, G., and Deci, E. L. (2014). When are mastery goals more adaptive? It depends on experiences of autonomy support and autonomy. *J. Educ. Psychol.* 106, 258–267. doi: 10.1037/a0034007

Bonneville-Roussy, A., Vallerand, R. J., and Bouffard, T. (2013). The roles of autonomy support and harmonious and obsessive passions in educational persistence. *Learn. Indiv. Diff.* 24, 22–31. doi: 10.1016/j.lindif.2012.12.015

Cassady, J. C., and Johnson, R. E. (2002). Cognitive test anxiety and academic performance. *Contemporary Educ. Psychol.* 27, 270–295. doi: 10.1006/ceps.2001.1094

Chapell, M. S., Blanding, Z. B., Silverstein, M. E., Takahashi, M., Newman, B., Gubi, A., et al. (2005). Test anxiety and academic performance in undergraduate and graduate students. *J. Educ. Psychol.* 97, 268–274. doi: 10.1037/0022-0663.97.2.268

Charles, N. E., Strong, S. J., Burns, L. C., Bullerjahn, M. R., and Serafine, K. M. (2021). Increased mood disorder symptoms, perceived stress, and alcohol use among college students during the COVID-19 pandemic. *Psychiatry Res.* 296:113706. doi: 10.1016/j.psychres.2021.113706

Clark, E. A., Kessinger, J., Duncan, S. E., Bell, M. A., Lahne, J., Gallagher, D. L., et al. (2020). The facial action coding system for characterization of human affective response to consumer product-based stimuli: a systematic review. *Front. Psychol.* 11:920. doi: 10.3389/fpsyg.2020.00920

Cowen, A. S., and Keltner, D. (2020). Universal facial expressions uncovered in art of the ancient americas: a computational approach. *Sci. Adv.* 6:eabb1005. doi: 10.1126/sciadv.abb1005

Deci, E. L., and Ryan, R. M. (2000). The 'what' and 'why' of goal pursuits: human needs and the self-determination of behavior. *Psychol. Inquiry* 11, 227–268. doi: 10.1207/S15327965PLI1104_01

D'Errico, F., Paciello, M., and Cerniglia, L. (2016). When emotions enhance students' engagement in e-learning processes. *J. e-Learn. Know. Soc.* 12:10.

D'Errico, F., Paciello, M., De Carolis, B., Vattanid, Al, Palestra, G., and Anzivino, G. (2018). Cognitive emotions in e-learning processes and their potential relationship with students' academic adjustment. *Int. J. Emot. Educ.* 10, 89–111.

Dorn, E., Hancock, B., Sarakatsannis, J., and Viruleg, E. (2020). *COVID-19 and Student Learning in the United States*. London: The Hurt Could Last a Lifetime.

Ekman, P. (1994). Strong evidence for universals in facial expressions: a reply to Russell's mistaken critique. *Psychol. Bull.* 115, 268–287.

Ekman, P., Freisen, W. V., and Ancoli, S. (1980). Facial Signs of emotional experience. *J. Personal. Soc. Psychol.* 39, 1125–1134. doi: 10.1037/h0077722

Ekman, P., and Friesen, W. V. (2003). *Unmasking the Face: A Guide to Recognizing Emotions from Facial Clues*. Los Altos, CA: ISHK.

Ekman, P., and Rosenberg, E. L. (1997). *What the Face Reveals: Basic and Applied Studies of Spontaneous Expression Using the Facial Action Coding System (FACS)*. Oxford: Oxford University Press.

Feidakis, M., Daradoumis, T., CaballÃ, S., and Conesa, J. (2014). Embedding emotion awareness into e-learning environments. *Int. J. Emerg. Technol. Learn.* 9, 39–46.

Goetz, T., Bieleke, M., Gogol, K., van Tartwijk, J., Mainhard, T., Lipnevich, A. A., et al. (2021). Getting along and feeling good: reciprocal associations between student-teacher relationship quality and students' emotions. *Learn. Instruct.* 71:101349. doi: 10.1016/j.learninstruc.2020.101349

Goetz, T., Frenzel, A. C., Hall, N. C., and Pekrun, R. (2008). Antecedents of academic emotions: testing the internal/external frame of reference model for academic enjoyment. *Contemporary Educ. Psychol.* 33, 9–33. doi: 10.1016/j.cedpsych.2006.12.002

Hershkovitz, A., and Nachmias, R. (2009). Learning about online learning processes and students' motivation through web usage mining. *Int. J. E-Learn. Learn. Objects* 5, 197–214.

Howard, M. C., and Crayne, M. P. (2019). Persistence: defining the multidimensional construct and creating a measure. *Personal. Indiv. Diff.* 139, 77–89. doi: 10.1016/j.paid.2018.11.005

Hu, L. T., and Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. *Struct. Equat. Model. Multidisc. J.* 6, 1–55.

Hu, Y., Wang, D., Pang, K., Xu, G., and Guo, J. (2015). The effect of emotion and time pressure on risk decision-making. *J. Risk Res.* 18, 637–650.

Izard, C. E. (1992). Basic emotions, relations among emotions, and emotion-cognition relations. *Psychol. Rev.* 99, 561–565.

Jack, R. E., Blais, C., Scheepers, C., Schyns, P. G., and Caldara, R. (2009). Cultural confusions show that facial expressions are not universal. *Curr. Biol.* 19, 1543–1548. doi: 10.1016/j.cub.2009.07.051

Jack, R. E., Garrod, O. G. B., Yu, H., Caldara, R., and Schyns, P. G. (2012). Facial expressions of emotion are not culturally universal. *Proc. Natl. Acad. Sci. U.S.A.* 109, 7241–7244. doi: 10.1073/pnas.1200155109

Jackson, A. P., Smith, S. A., and Hill, C. L. (2003). Academic persistence among native american college students. *J. College Stud. Dev.* 44, 548–565. doi: 10.1353/csd.2003.0039

Jõesaar, H., Hein, V., and Hagger, M. S. (2011). Peer influence on young athletes' need satisfaction, intrinsic motivation and persistence in sport: A 12-month prospective study. *Psychol. Sport Exer.* 12, 500–508. doi: 10.1016/j.psychsport.2011.04.005

Jung, Y., and Lee, J. (2018). Learning engagement and persistence in massive open online courses (MOOCS). *Comput. Educ.* 122, 9–22. doi: 10.1016/j.compedu.2018.02.013

Karatas, H., Alci, B., and Aydin, H. (2013). Correlation among high school senior students test anxiety, academic performance and points of university entrance exam. *Educ. Res. Rev.* 13, 919–926.

Kaufman, B. E. (1999). Emotional arousal as a source of bounded rationality. *J. Econ. Behav. Organ.* 38, 135–144.

King, R. B., and Areepattamannil, S. (2014). What students feel in school influences the strategies they use for learning: academic emotions and cognitive/meta-cognitive strategies. *J. Pacific Rim Psychol.* 8, 18–27. doi: 10.1017/prp.2014.3

Krumhuber, E. G., Tamarit, L., Roesch, E. B., and Scherer, K. R. (2012). FACSGen 2.0 animation software: generating three-dimensional FACS-valid facial expressions for emotion research. *Emotion* 12, 351–363. doi: 10.1037/a0026632

Lewthwaite, R., Chiviacowsky, S., Drews, R., and Wulf, G. (2015). Choose to move: the motivational impact of autonomy support on motor learning. *Psychon. Bull. Rev.* 22, 1383–1388. doi: 10.3758/s13423-015-0814-7

Liew, J., Johnson, A. Y., Smith, T. R., and Thoemmes, F. (2011). Parental expressivity, child physiological and behavioral regulation, and child adjustment: testing a three-path mediation model. *Early Educ. Dev.* 22, 549–573. doi: 10.1080/10409289.2010.481551

Linnenbrink, E. A., and Pintrich, P. R. (2002). Achievement goal theory and affect: an asymmetrical bidirectional model. *Educ. Psychol.* 37, 69–78. doi: 10.1207/S15326985EP3702_2

Matsumoto, D. (1987). The role of facial response in the experience of emotion: more methodological problems and a meta-analysis. *J. Personal. Soc. Psychol.* 52, 769–774. doi: 10.1037/0022-3514.52.4.769

Matsumoto, D. (1992). American-japanese cultural differences in the recognition of universal facial expressions. *J. Cross Cultural Psychol.* 23, 72–84. doi: 10.1177/0022022192231005

Matsumoto, D., LeRoux, J., Wilson-Cohn, C., Raroque, J., Kooken, K., Ekman, P., et al. (2000). A new test to measure emotion recognition ability: matsumoto and ekman's japanese and caucasian brief affect recognition test (JACBART). *J. Nonverbal Behav.* 24, 179–209. doi: 10.1023/A:1006668120583

Odriozola-González, P., Planchuelo-Gómez, Á., Irurtia, M. J., and de Luis-García, R. (2020). Psychological symptoms of the outbreak of the covid-19 confinement in spain. *J. Health Psychol.* 30:1359105320967086. doi: 10.1177/1359105320967086

O'Neill, S., and Thomson, M. M. (2013). Supporting academic persistence in low-skilled adult learners. *Support Learn.* 28, 162–172. doi: 10.1111/1467-9604.12038

O'Regan, K. (2003). Emotion and e-learning. *J. Asynch. Learn. Netw.* 7, 78–92.

Parlangeli, O., Marchigiani, E., Guidi, S., and Mesh, L. (2012). Disentangled emotions in blended learning. *Int. J. Hum. Factors Ergon.* 1, 41–57.

Pekrun, R. (2000). "A social-cognitive, control-value theory of achievement emotions," in *Motivational Psychology of Human Development: Developing Motivation and Motivating Development*, ed. J. Heckhausen (New York, NY: Elsevier Science), 143–163. doi: 10.1016/S0166-4115(00)80010-2

Pekrun, R. (2006). The control-value theory of achievement emotions: assumptions, corollaries, and implications for educational research and practice. *Educ. Psychol. Rev.* 18, 315–341. doi: 10.1007/s10648-006-9029-9

Pekrun, R. (2019). Inquiry on emotions in higher education: progress and open problems. *Stud. Higher Educ.* 10, 1806–1811.

Pekrun, R., Goetz, T., Frenzel, A. C., Barchfeld, P., and Perry, R. P. (2011). Measuring emotions in students' learning and performance: the achievement emotions questionnaire (AEQ). *Contemporary Educ. Psychol. Stud. Emot. Acad. Engag.* 36, 36–48. doi: 10.1016/j.cedpsych.2010.10.002

Pekrun, R., Vogl, E., Muis, K. R., and Sinatra, G. M. (2017). Measuring emotions during epistemic activities: the epistemically-related emotion scales. *Cogn. Emot.* 31, 1268–1276. doi: 10.1080/02699931.2016.1204989

Pelletier, L. G., Fortier, M. S., Vallerand, R. J., and Brière, N. M. (2001). Associations among perceived autonomy support, forms of self-regulation, and persistence: a prospective study. *Motiv. Emot.* 25, 279–306. doi: 10.1023/A:1014805132406

Poggi, I., D'Errico, F., and Vincze, L. (2013). Comments by words, face and body. *J. Mult. User Interf.* 7, 67–78.

Putwain, D. W., Daly, A. L., Chamberlain, S., and Sadreddini, S. (2016). "'Sink or Swim": buoyancy and coping in the cognitive test anxietyacademic performance relationship.'. *Educ. Psychol.* 36, 1807–1825. doi: 10.1080/01443410.2015.1066493

Ramirez-Arellano, A., Bory-Reyes, J., and Hernández-Simón, L. M. (2019). Emotions, motivation, cognitive–metacognitive strategies, and behavior as predictors of learning performance in blended learning. *J. Educ. Comput. Res.* 57, 491–512. doi: 10.1177/0735633117753935

Renaud-Dubé, A., Guay, F., Talbot, D., Taylor, G., and Koestner, R. (2015). The relations between implicit intelligence beliefs, autonomous academic motivation, and school persistence intentions: a mediation model. *Soc. Psychol. Educ.* 18, 255–272. doi: 10.1007/s11218-014-9288-0

Roland, N., Frenay, M., and Boudrenghien, G. (2018). Understanding academic persistence through the theory of planned behavior: normative factors under investigation. *J. College Stud. Retention Res. Theory Practice* 20, 215–235. doi: 10.1177/1521025116656632

Rosenberg, E. L., and Ekman, P. (2020). *What the Face Reveals: Basic and Applied Studies of Spontaneous Expression Using the Facial Action Coding System (FACS).* Oxford: Oxford University Press.

Ruba, A. L., and Repacholi, B. M. (2020). Do preverbal infants understand discrete facial expressions of emotion? *Emotion Rev.* 12, 235–250. doi: 10.1177/1754073919871098

Russell, J. A. (1994). Is there universal recognition of emotion from facial expression? A review of the cross-cultural studies. *Psychol. Bull.* 115, 102–141. doi: 10.1037/0033-2909.115.1.102

Sallis, J. F., and Saelens, B. E. (2000). Assessment of physical activity by self-report: status, limitations, and future directions. *Res. Quart. Exerc. Sport* 71, 1–14. doi: 10.1080/02701367.2000.11082780

Scherer, K. R., and Scherer, U. (2011). Assessing the ability to recognize facial and vocal expressions of emotion: construction and validation of the emotion recognition index. *J. Nonverbal Behav.* 35:305. doi: 10.1007/s10919-011-0115-4

Sellman, J. D., Mulder, R. T., Sullivan, P. F., and Joyce, P. R. (1997). Low Persistence predicts relapse in alcohol dependence following treatment. *J. Stud. Alcohol.* 58, 257–263. doi: 10.15288/jsa.1997.58.257

Tomkins, S. S., and McCarter, R. (1964). "What and where are the primary affects? some evidence for a theory". *Accessed* 25:2021.

Sommer, K. L., and Baumeister, R. F. (2002). Self-evaluation, persistence, and performance following implicit rejection: the role of trait self-esteem. *Personal. Soc. Psychol. Bull.* 28, 926–938. doi: 10.1177/014616720202800706

Spielberger, C. D., Sydeman, S. J., Owen, A. E., and Marsh, B. J. (1999). "Measuring anxiety and anger with the state-trait anxiety inventory (STAI) and the state-trait anger expression inventory (STAXI)," in *In The Use of Psychological Testing for Treatment Planning and Outcomes Assessment*, 2nd Edn, ed. M. E. Maruish (Mahwah, NJ: Lawrence Erlbaum Associates Publishers), 993–1021.

Subar, A. F., Freedman, L. S., Tooze, J. A., Kirkpatrick, S. I., Boushey, C., Neuhouser, M. L., et al. (2015). Addressing current criticism regarding the value of self-report dietary data. *J. Nut.* 145, 2639–2645. doi: 10.3945/jn.115.219634

Terrell, S., Snyder, M., Dringus, L., and Maddrey, E. (2015). A grounded theory of connectivity and persistence in a limited residency doctoral program. *Qualit. Rep.* 17:62. doi: 10.46743/2160-3715/2012.1747

Tulis, M., and Ainley, M. (2011). Interest, enjoyment and pride after failure experiences? Predictors of students' state-emotions after success and failure during learning in mathematics. *Educ. Psychol.* 31, 779–807. doi: 10.1080/01443410.2011.608524

Tulis, M., and Fulmer, S. M. (2013). Students' motivational and emotional experiences and their relationship to persistence during academic challenge in mathematics and reading. *Learn. Indiv. Diff.* 27, 35–46. doi: 10.1016/j.lindif.2013.06.003

Tyssen, R., Røvik, J. O., Vaglum, P., Grønvold, N. T., and Ekeberg, O. (2004). Help-seeking for mental health problems among young physicians: is it the most ill that seeks help? A longitudinal and nationwide study. *Soc. Psychiatry Psychiatric Epidemiol.* 39, 989–993. doi: 10.1007/s00127-004-0831-8

Vansteenkiste, M., Simons, J., Lens, W., Sheldon, K. M., and Deci, E. L. (2004). Motivating learning, performance, and persistence: the synergistic effects of intrinsic goal contents and autonomy-supportive contexts. *J. Personal. Soc. Psychol.* 87, 246–260. doi: 10.1037/0022-3514.87.2.246

Villavicencio, F. T., and Bernardo, A. B. I. (2013). Positive academic emotions moderate the relationship between self-regulation and academic achievement. *Br. J. Educ. Psychol.* 83, 329–340. doi: 10.1111/j.2044-8279.2012.02064.x

Wang, Q., Pomerantz, E. M., and Chen, H. (2007). The role of parents' control in early adolescents' psychological functioning: a longitudinal investigation in the united states and china. *Child Dev.* 78, 1592–1610. doi: 10.1111/j.1467-8624.2007.01085.x

Yu, J., Huang, C., Han, Z., He, T., and Li, M. (2020). Investigating the influence of interaction on learning persistence in online settings: moderation or mediation of academic emotions? *Int. J. Environ. Res. Public Health* 17:2320. doi: 10.3390/ijerph17072320

Yurdakul, C. (2017). An investigation of the relationship between autonomous learning and lifelong learning. *Int. J. Educ. Res. Rev.* 2, 15–20. doi: 10.24331/ijere.309968

Zeidner, M. (2014). "Anxiety in education," in *International Handbook of Emotions in Education*, eds R. Pekrun and L. Linnenbrink-Garcia (Routledge).

Zimmerman, B. J., and Risemberg, R. (1997). Becoming a self-regulated writer: a social cognitive perspective. *Contemporary Educ. Psychol.* 22, 73–101. doi: 10.1006/ceps.1997.0919

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The Role of the Home Learning Environment on Early Cognitive and Non-Cognitive Outcomes in Math and Reading

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The home learning environment (HLE) has been considered to contribute to children's early math and reading development. Previous studies examined the HLE by examining the influence of parent-child math and reading activities on math and reading outcomes, however also parents' own perceptions of math and reading and their math anxiety (MA) and reading anxiety (RA) contribute to the HLE but the latter factors have been scarcely explored. The aim of this study was to provide a more holistic view of the HLE and its relations with children's cognitive and non-cognitive outcomes in math and reading at the start of primary school. This paper examined the relations within the HLE, and the relations between the HLE and children's early math and reading outcomes. Participants were 301 first-grade children and their parents. The HLE was measured by the parent questionnaire. Children's digit comparison, number line estimation, letter knowledge and phonological awareness skills were measured as well as their math and reading anxiety levels. The results demonstrated a significant association between parents' perceptions and their anxiety towards math and reading. No significant associations were found between parents' perceptions towards math and the frequency of home numeracy activities, whereas significant relations were found in the domain of reading. Socioeconomic status was found to provide a unique contribution in children's digit comparison and math anxiety, while no significant relations were observed between other HLE factors and children's outcomes. The current study suggests the importance of including parents' perceptions and feelings to explore the dynamics of the HLE and its impact on children's math and reading outcomes.

Keywords: home learning environment, home numeracy environment, home literacy environment, early numeracy, early literacy

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INTRODUCTION

Math and reading abilities are essential in people's life. They are not only the foundation of basic education and later academic performance, but also contribute to future economic and social life such as employability and political participation (Hulme & Snowling, 2013; Schneider et al., 2017; OECD, 2019). Previous studies observed that math and reading abilities begin to develop long before entering primary school, and individual differences in their development already exist at the start of formal instruction (Aunola, Leskinen, Lerkkanen, & Nurmi, 2004; Duncan et al., 2007). Moreover, such differences at the start of formal instruction seem to persist in later learning, even after interventions (Aunola et al., 2004; Hulme & Snowling, 2013). Therefore, it is important to explore what contributes to these individual differences in initial math and reading outcomes before formal instruction.

Children's math and reading developments are multi-dimensional processes influenced by not only their individual factors, such as cognitive and non-cognitive factors (Ramirez et al., 2018, 2019), but also environmental factors such as the home learning environment (HLE) (Anders et al., 2012; Skwarchuk, Sowinski, & LeFevre, 2014; Susperreguy, Douglas, Xu, Molina-Rojas, & LeFevre, 2018). The HLE has been generally understood as the way in which families engage and provide children interactive activities and resources (e.g., puzzles and books) related to math and reading (Manolitsis et al., 2013; Niklas & Schneider, 2017a). However, previous studies often operationalised the HLE only by measuring the frequency of home learning activities (e.g. Manolitsis et al., 2013) whereas also parents' own perceptions and feelings towards math and reading may be an important part of the HLE as well (Kluczniok et al., 2013). In addition, little is known about the HLE's impact on children's non-cognitive outcomes in math and reading, such as math anxiety (MA) and reading anxiety (RA).

This study aims to provide a comprehensive view of the HLE by examining multiple measures. In addition to measuring the activities parents do with their children, this study includes also measures of parents' own perceptions of math and reading as well as parents' own MA and RA. Furthermore, we explore the role of the HLE on children's early cognitive and non-cognitive outcomes in math and reading. First, cognitive and non-cognitive factors in the domain of math and reading are described which are predictive for later academic performance. Second, several components of the HLE, the relationships between these components and how these might influence children's cognitive and non-cognitive outcomes are discussed.

Individual Factors in Children's Math and Reading Development

Domain-Specific Cognitive Factors of Math

Previous research has established that early math abilities, basic intuitive skills such as symbolic and non-symbolic number knowledge, are crucial in children's math development (Sasanguie et al., 2012; Schneider et al., 2017). Symbolic number knowledge refers to an understanding and ability to use numerosity representation by digits, and non-symbolic number knowledge refers to that by non-digits (Sasanguie et al., 2012; Schneider et al., 2017). Some studies demonstrated that symbolic number knowledge is more crucial to math development than non-symbolic number knowledge (Schneider et al., 2017).

To examine early math abilities, digit comparison and number line estimation tasks are frequently adopted in multiple studies, using digits for symbolic and dots for non-symbolic number knowledge assessments (Schneider et al., 2017, 2018). Cross-sectional and longitudinal associations have been shown between early math precursors with broader mathematical competence such as counting, arithmetic, and algebra (Aunola et al., 2004; De Smedt et al., 2013; Sasanguie et al., 2013). Furthermore, early numerical skills are foundational to acquire higher-level mathematical competence. In sum, to enhance math development, stimulation of these early math abilities is crucial.

Domain-Specific Cognitive Factors of Reading

The literature on reading development states the importance of early reading precursors for future reading achievement (Schatschneider, Fletcher, Francis, Carlson, & Foorman, 2004). Gunn et al. (1995) use the term "emergent literacy" to refer to such early reading precursors, which begins to develop before formal reading instruction by acquiring through home environment, preschool or other informal environments. Emergent literacy consists of literacy knowledge (e.g., letter knowledge, phonological awareness, text structure comprehension) and literacy experiences such as story reading (Gunn et al., 1995).

Among these early reading precursors, letter knowledge and phonological awareness have been proved to be the best predictors for reading achievement across several studies (Sénéchal & LeFevre, 2002; Niklas & Schneider, 2017b). Letter knowledge encompasses of awareness of print, knowledge of letter sounds and letter names, which lead to acquisition of new vocabulary (Schatschneider et al., 2004). Phonological awareness is broadly defined as an ability to understand the sound structure of oral language (Niklas & Schneider, 2017b). Many developmental studies have shown that individual differences in phonological awareness and letter knowledge influenced beginning word-reading skills as well as later reading skills at least through fourth grade (Wagner et al., 1997; Lyytinen et al., 2006). A meta-analysis by Melby-Lervåg et al., 2012 revealed that phonemic awareness was the strongest correlate of individual differences in word reading ability.

Domain-Specific Non-Cognitive Factors of Math

Recently, researchers have shown an increased interest in domain-specific non-cognitive factors in children's math development, namely MA. MA is broadly understood as a feeling of anxiety and tension in math-related situations (Dowker et al., 2016; Ramirez et al., 2018). Various studies observed a negative correlation between MA and math performance, which could be partially explained by MA's influence on working memory (see review by Dowker et al., 2016). For example, Cargnelutti et al. (2017) conducted a study on Grade 4 students to explore the relation between cognitive factors (working memory and magnitude processing speed) and non-cognitive factors (general anxiety and MA). In this study, they observed that students with higher MA were likely to perform weaker in math than their peers with lower MA.

Interestingly, MA seems to have a different impact on children with different gender. A study by Van Mier, Schleepen, and Van den Berg (2019) showed that girls were more likely to have higher MA than boys, and a correlation between MA and performance was significant only for girls. Additionally, it is known that MA increases as children grow, maybe due to the increase in general anxiety in adolescence, or as a result of facing parents' and teachers' negative attitudes toward math (Dowker et al., 2016). However, with a limited number of studies, the parents' role on children's MA remains unclear (Dowker et al., 2016).

Domain-Specific Non-Cognitive Factors of Reading

Regarding reading development, domain-specific non-cognitive factors such as reading motivation, self-concept, and anxiety have been examined by multiple studies (Katzir et al., 2018; Ramirez et al., 2019). Recently, there has been a renewed interest especially in the role of RA in children's reading development. RA, a negative reaction or fear against acts and situations of reading (Ramirez et al., 2019), is suggested as a factor which undermines reading performance. Ramirez et al. (2019) demonstrated that RA of the first and second grade students were negatively associated to their reading performance, and this relation was stronger than the association between their positive reading affect (interest and positive attitude) and reading performance. In the study by Katzir et al. (2018), the relation between early reading skills and non-cognitive factors such as RA and reading self-concept of second graders were explored, and it was found that there was a moderate but negative correlation between RA and reading self-concept. Taken together, RA may be a critical component which impacts not only concurrent reading performance, but also later reading achievement.

The Relation Between Early Numeracy and Literacy

Research has emphasized the importance of cross-domain relations between early numeracy and literacy. A recent review on the similarities and differences between the development of reading, writing and number acquisition by Moura et al., 2021 emphasized how precursors of math are related to reading development and vice versa. For example, Krajewski and Schneider (2009) showed that individual differences in phonological awareness assessed at an early stage in kindergarten influence math performance in school assessed a few months later. Also, studies investigating children and adults with reading difficulties showed that people with a reading disorder show poorer performance on particular mathematical tasks like fact retrieval (De Smedt et al., 2010; Göbel, 2015).

Home Learning Environment

The impact of the HLE on math and reading has been examined separately by most of the studies; the home environment concerning math is called the *home numeracy environment*, and that of reading is named the *home literacy environment* (LeFevre et al., 2009; Niklas & Schneider, 2017b).

Home Numeracy Environment

Frequency of Home Numeracy Activities

Extensive research has examined *home numeracy activities*, math activities parents do with their children (del Río et al., 2017; LeFevre et al., 2009; Susperreguy et al., 2018). Typically, researchers examined the home numeracy environment by requesting parents to report frequency of home numeracy activities. These practices include not only parents' teaching of math, but also math-related activities in various contexts at home (LeFevre et al., 2009; Skwarchuk et al., 2014).

To illustrate the complexity of home numeracy activities and its effects on children's math development, Skwarchuk et al. (2014) developed a home numeracy model, which categorises two types of home numeracy activities: *formal numeracy activities* which aims to teach math concepts (e.g., counting, arithmetic), and *informal numeracy activities* without such aim but related to math (e.g., playing number related games at home, assisting while parents cook). Drawing from this model, multiple studies found the link between home numeracy activities and children's math performance. Positive relations were shown between formal numeracy activities and children's math performance (Sasanguie et al., 2012; Skwarchuk et al., 2014; Huntsinger et al., 2016; Mutaf Yıldız et al., 2018). Skwarchuk et al. (2014) demonstrated that formal numeracy activities predicted symbolic number knowledge. Mutaf Yıldız et al., 2018 found a significant association between children's enumeration and the home numeracy activities. Moreover, advanced formal numeracy activities have been presented as a strong predictor of children's math performance (Skwarchuk et al., 2014; Huntsinger et al., 2016). In contrast, the relation between informal numeracy activities and children's math performance has been debated. Some studies found a link between informal numeracy activities and non-symbolic arithmetic knowledge of children (Skwarchuk et al., 2014; Susperreguy et al., 2018), whereas Huntsinger et al. (2016) found a negative correlation between informal home numeracy activities and children's math performance.

Parents' Perceptions of Math

Multiple studies examined the relationship between parents' perceptions of math and the frequency of math activities they provide to their children at home. Perceptions of math are generally understood as their beliefs, interests, and attitude toward math (Skwarchuk, 2009; Skwarchuk et al., 2014). Susperreguy et al. (2018) found that parents with more positive math attitudes and higher academic expectations toward their children reported a higher frequency of advanced math activities provided to their children at home. Additionally, parents' own positive math experiences were found as a predictor of children's math performance (Skwarchuk, 2009). Together, these studies indicate that parents' perceptions of math may be a critical component of the home numeracy environment which fosters children's math development.

Parents' MA

With limited number of studies, the role of parents' MA on children's math development remains unclear. del Río et al. (2017) showed that parents with lower MA were more likely to frequently do advanced math-related activities with their kindergartener children than parents with higher MA. Maloney et al. (2015) examined the intergenerational impact of MA from parents to their first and second grade children, and found a negative significant relation between parents' MA and children's math achievement when parents reported to give frequent help in their children's math homework. Moreover, this negative correlation was statistically significant even after controlling for parents' math knowledge and children's school factors such as teachers' factors (MA and math knowledge) and their schools' SES levels (Maloney et al., 2015). These findings may imply that parents' support in children's math development do not always result in a positive impact on children's math performance, considering the role of parents' MA. Overall, previous studies underscore the importance of more examinations on the role of parents' MA in children's math development.

Home Literacy Environment

Frequency of Home Literacy Activities

Multiple studies examined the link between home literacy activities and children's early reading performance. Similar to home numeracy activities, home literacy activities are broadly separated into *formal literacy activities*, which involves formal literacy instruction and *informal literacy* activities, which do not aim but touch literacy concepts (Sénéchal and LeFevre, 2002). Sénéchal and LeFevre (2002) observed that formal literacy activities were related to the children's emergent literacy skills such as decoding skills and letter knowledge, whereas informal literacy activities (e.g., storybook reading) accounted for vocabulary and listening comprehension skills. Moreover, they found that vocabulary and listening comprehension were not significant reading predictors in Grade 1, while emergent literacy skills and phonological awareness were significant predictors.

The findings of Sénéchal and LeFevre (2002) were replicated by some studies (Niklas & Schneider, 2013; Skwarchuk et al. (2014). In contrast, some scholars confirmed only a part of those findings (Liu et al., 2018), indicating that mixed findings exist in the relation between home literacy activities and children's reading performance (cf. Sénéchal & LeFevre, 2002; Skwarchuk et al., 2014). Generally, home literacy activities are found to be an important predictor for not only early literacy skills but also for reading achievement (Huntsinger et al., 2016; Manolitsis et al., 2013; Niklas & Schneider, 2013, 2017a). Yeo et al. (2014) found that parents who provide frequent reading activities generally had children who performed higher in reading than their peers. Huntsinger et al. (2016) found that reading activities provided by parents significantly predicted children's concurrent reading scores. Thus, home literacy activities, especially formal literacy activities, seem to be a key aspect of the home literacy environment. Furthermore, the recent studies suggest the need of more examinations of the home literacy model across different cultural contexts.

Parents' Perceptions of Reading

While many studies focused on parents' perceptions of their children's reading performance (e.g., Martini & Sénéchal, 2012), few studies focused on parents' own perceptions of reading in the field of HLE. Baker and Scher (2002) observed that parents' own pleasure in reading was a strong predictor of children's motivation in reading for enjoyment, accounting for 16% of variance. Moreover, children whose parents enjoy reading as a pleasure are found to have more positive attitudes than their peers whose parents perceive reading as a skilled activity (Baker & Scher, 2002). Since motivated readers are likely to engage in more reading activities and have higher reading achievement (Tunmer & Greaney, 2008), the impact of parents' perceptions of reading should not be underestimated.

Parents' RA

In comparison to MA, research on parents' RA is scarce. A study by Dobbs-Oates, Pentimonti, Justice, and Kaderavek (2015) demonstrated that parents' negative beliefs in shared reading was a robust predictor of children's letter knowledge; the fewer negative beliefs the parents had towards shared reading, the higher the children tended to perform on the letter knowledge task. Although Dobbs-Oates et al. (2015) did not focus on parents' RA, their study indicates that parents' own negative attitudes towards reading may impact their children's reading performance. Furthermore, as argued above, parents' positive attitude towards reading (e.g., reading motivation) has been known to have positive impacts on children's reading attitude. This suggests that children's non-cognitive outcomes in reading may be also influenced by parents' negative attitude towards reading (i.e., RA). Therefore, like MA, intergenerational effects of RA would be interesting to explore.

Cross-Domain Relations Between the HLE and Children's Development

Recent studies examined the cross-domain relations between the HLE and children's math and reading development (Anders et al., 2012; Segers, Kleemans, & Verhoeven, 2015; Napoli & Purpura, 2018). Findings about relations between children's math outcomes and the HLE seem to be incompatible. Anders et al. (2012) and Manolitsis et al. (2013) demonstrated that both home numeracy environment and home literacy environment were significant predictors of children's early math skills. On the contrary, Segers et al. (2015) and Susperreguy et al. (2018) showed that parents' reports of literacy activities did not predict children's early numeracy skills.

A few studies examined the impact of the HLE on children's math and reading outcomes simultaneously. A longitudinal study by Huntsinger et al. (2016) showed that home numeracy activities predicted concurrent math and reading outcomes of children, however such math activities did not continue predicting children's reading outcomes a year later. Napoli and Purpura (2018) examined the cross-domain relations between the home numeracy environment and the home literacy environment. The home numeracy environment was found to be a predictor of children's numeracy and vocabulary, while the home literacy environment did not predict children's numeracy (Napoli & Purpura, 2018). Overall, the cross-domain relations between the HLE and children's outcomes are still unclear.

Impact of SES

SES, indicated by parents' educational levels and income, is frequently examined as a factor that impacts the HLE (Chung, 2015; del Río et al., 2017; Niklas & Schneider, 2013). SES is known as a predictor of children's early math and reading skills (Hartas, 2011; Anders et al., 2012), and the HLE is considered to play a mediating role between SES and children's cognitive skills in math and reading (del Río et al., 2017; Niklas & Schneider, 2013; Mutaf Yıldız et al., 2018). A recent review of 37 articles on the relationship between home numeracy and mathematical skills concluded that there are positive associations between home numeracy activities and SES (Mutaf Yıldız et al., 2018). However, the moderating effects of SES on the relation between home numeracy and children's mathematical skills still has to be disentangled.

Elliott and Bachman (2018) suggest a relation between parents' math cognitions and SES; they claim that communication between parents and children or cultural capitals may be different across parents' educational levels, as their beliefs of education could be influenced by their educational backgrounds. For the association between SES and frequency of home learning activities, mixed findings exist. Susperreguy et al. (2018) observed that parents with higher education level were likely to provide advanced numeracy activities to their children more frequently than parents with lower education level. On the other hand, del Río et al. (2017) found that low-SES mothers engaged in advanced numeracy activities more than high-SES mothers. All in all, more examination is needed to explore the relations between SES and other HLE factors.

Gaps in Research

Although extensive research has been conducted on the HLE, multiple gaps remain. Firstly, few studies examined the impact of parents' own perceptions toward math/reading and parents MA/RA (i.e., indirect factors of the HLE), and how they relate to the frequency of home learning activities (e.g., Skwarchuk et al., 2014; Susperreguy et al., 2018). Particularly, parents' MA/RA seem to be neglected in numerous studies.

Secondly, only a few studies examined the impact of these indirect measures (e.g. parents' perceptions towards math/reading) of the HLE on cognitive outcomes of children (e.g., del Río et al., 2017). From the Vygotskian view which highlights importance of social interactions with more knowledgeable people such as parents in children's learning (Niklas & Schneider, 2017a; Elliott & Bachman, 2018), the indirect measures of the HLE on children's cognitive outcomes is understudied, although they may impact interactions between parents and children.

Thirdly, the relations between the HLE and children's non-cognitive outcomes such as MA and RA are not sufficiently explored (Cargnelutti et al., 2017). Notably, far too little attention has been paid to the impact of the indirect factors of the HLE on children's non-cognitive outcomes. Since the importance of non-cognitive factors in children's math and reading development has been acknowledged, more studies should address how the HLE is related to these aspects in addition to cognitive factors.

Present Study

This study aims to provide a more holistic view of the HLE and its relations with children's cognitive and non-cognitive performance in math and reading. To fill the research gap, this paper addresses three research questions. Firstly, this paper explored how the HLE factors are related. Specifically, it examined how parents' indirect factors (i.e. parents' perceptions of math/reading and MA/RA), direct factors (frequency of the home learning activities in math and reading), and SES were related. Additionally, the cross-domain relationships between the home numeracy environment and the home literacy environment were examined. A positive relation between parents' perceptions of math and frequency of the home numeracy activities, and a positive relation between parents' perceptions of reading and frequency of the home learning activities were expected.

Secondly, this study investigated the relations between the HLE factors and the children's cognitive outcomes in math and reading. Positive relations between the frequency of home learning activities and children's cognitive outcomes in each domain were hypothesized. Also, positive associations between parents' perceptions of math and children's cognitive outcomes in math, and the same associations in the reading domain were predicted. Moreover, positive relations between SES and children's cognitive outcomes were expected.

Thirdly, the relations between the HLE factors and the children's non-cognitive outcomes in math and reading were explored. This research question which explores the impact of the HLE's on children's non-cognitive outcomes is exploratory.

The relations to be examined in this study are summarised in **Figure 1**. For children's cognitive factors, digit comparison and number line estimation tasks were examined for math ability, while letter knowledge and phonological awareness were chosen as predictors for their reading ability. Participants were at the start of primary school at the time of the data collection, so it was too early to assess arithmetic skills or reading fluency. The predictors were selected for their robustness as precursors for early development in math and reading. At the start of first grade, most children were able to perform early math and reading tasks due to formal (e.g. preschool) and informal (e.g. home) learning experiences. For children's non-cognitive factors, MA and RA were examined. This choice was motivated by the relative scarcity of research on MA and RA of young children, especially in relation to the HLE.

To the best of our knowledge, this is the first study to include parents' own perceptions of math and reading together with their MA and RA. This study aimed to provide a more comprehensive view of the HLE in comparison to previous studies. Moreover, this study included both math and reading domains of the HLE as well as children's outcomes, which enabled us to give a broader view of the HLE and its relations with children's performance.

METHODS

Participants

Participants were 336 children in Grade 1 and their parents from 10 primary schools in Flanders, Belgium. This sample was chosen because at the start of grade 1, children have received little formal math and reading instruction yet and therefore instruction has limited impact on children's performance. Moreover, children of this age are able to perform tests and questionnaires measuring their cognitive and noncognitive factors in a reliable way (which is more difficult to achieve with kindergartners due to difficulties with understanding and expressing feelings). Parental consent forms were obtained from the participating children. The return

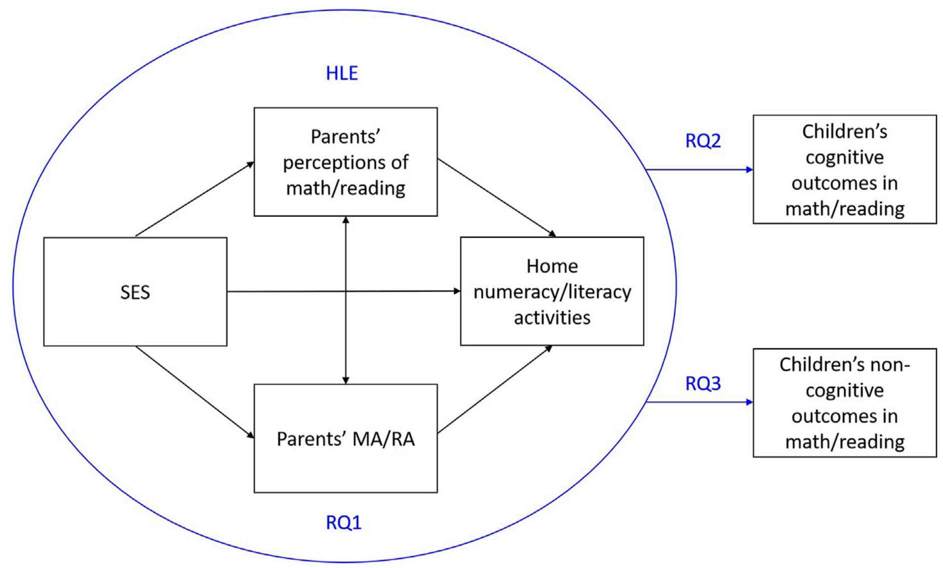

FIGURE 1 | A conceptual model summarising the relations within the HLE and the relations between the HLE and children's outcomes which to be examined in this study.

rate of the parents' questionnaire was 89.6%. Children whose parents did not submit the questionnaire were excluded (n = 35). The final participants consisted of 301 first graders (137 boys, M_{age} = 6.35 years) and their parents. The majority (88%) of the participants' home language was Dutch; 30 families (10%) spoke other languages than Dutch as their home language, and this data was missing for six families (2%).

The independent sample t-test revealed significant differences between the children included in the analyses and those excluded. On average, the excluded children were older by 0.22 years ($t(331) = -2.92$; $p = 0.00$), and 28.6% of the excluded children spoke other languages than Dutch at home ($t(326) = 3.4$, $p = 0.00$).

Data Collection

The data was collected from the participants in the context of the larger-scaled LEAPS research project (https://www.imec-int.com/nl/imec-icon/research-portfolio/leaps) to develop a self-learning system based on adaptive learning (see also Vanbecelaere et al., 2019, 2020). For children's data, the pretest results of the study by Vanbecelaere et al. (2020) were used in this analysis. The data was collected at their schools in the beginning of the academic year during the school hours. Although various measures were taken in this study, several efforts were made to avoid over-testing children (for details, see Vanbecelaere et al., 2020).

For parents, a paper questionnaire was distributed in the parents' meetings in October 2017 where explanation about the research project was provided. During these meetings, the researchers provided translation of the questionnaire for parents who needed assistance in Dutch. The parents who did not attend these meetings received the paper questionnaire from their children's teachers. Parents were requested to submit the completed questionnaire to the schools via their children by the specified date, and they received a reminder 1 week before the deadline if they had not submitted yet. The researchers collected the paper questionnaires from the schools.

Materials

Children's Measurement

Cognitive Outcomes

To assess cognitive outcomes in math, digit comparison and number line estimation tasks were used. For reading, letter knowledge and phonological awareness were measured.

For digit comparison, a paper-and-pencil one-digit subtest of the Symbolic Magnitude Processing Test (SYMP Test; Brankaer, Ghesquière, & De Smedt, 2017) was used. The subtest consists of 60 pairs of single digits (1–9) shown in four columns with 15 pairs. The distance between two digits of the pair was one for the half of the pairs, and three or four for the other half. The task included all the possible combinations of these distances, and the digit pairs were presented randomly. Children were asked to indicate the larger digit of each pair and solve as many items as possible in 30 s. The SYMP Test was selected for its reported satisfactory reliability (r = 0.70 for Grade 1) and satisfying construct and criterion-related validities, indicated by significant and stable correlations with math achievement (Brankaer et al., 2017). Considering the possible influence by children's general motor speed, a paper-and-pencil test for motor speed was also given (Brankaer et al., 2017). The number of correctly answered items was used for the outcome index.

For the number line estimation task, children were asked to mark a target number on an empty number line. The number line was 25 cm length with 0 on the left and 10 on the right endpoints, and the to-be-positioned number was presented at the centre, 6 cm above this line. Children performed nine trials in total, for all the digits (1–9) at random. Percent absolute error (*PAE*) for each trial was calculated with the formula by Siegler and Booth, 2004, (p. 432):

$$PAE = \frac{Estimate - Target\ Number}{Scale\ of\ Estimates} \times 100$$

The mean of all the nine trials' PAE was used as the outcome index.

The letter knowledge task (Aarnoutse, Beernink, & Verhagen., 2016) measured the extent of children's ability to match letter sounds to graphemes. The task included 21 items, where each item had a picture of a caterpillar with 22 graphemes placed respectively in its segments. Children were asked to listen to the letter uttered by the instructor, and then shade the matching grapheme of the caterpillar. The Cronbach's alpha of the test was 0.90 (Verhagen, Aarnoutse, & Van Leeuwe, 2009).

For the phonological awareness task (Aarnoutse et al., 2016), children listened to isolated letter sounds of a word (e.g., b-u-s), and indicated the corresponding image out of four different images. 24 items were given to the children in this task, including four practice items. This test has satisfactory reliability (Cronbach's alpha = 0.89; Verhagen et al., 2009) and consistent validity (Aarnoutse, et al., 2016; Verhagen et al., 2009).

Non-Cognitive Outcomes

Children's MA was measured by the adapted version of Child Math Anxiety Questionnaire by Ramirez, Chang, Maloney, Levine, and Beilock (2016). Specifically, the questionnaire was translated into Dutch, the number of items were reduced from 16 to 8, and some of the math problems were adapted into Flemish contexts (cf. Vanbecelaere et al., 2020). In parallel, the RA scale composed of 8 items was developed by Vanbecelaere et al. (2020) based on the Flemish reading curriculum. The adapted MA and RA scales (see supplementary materials) had a Cronbach's alpha of 0.77 respectively (Vanbecelaere et al., 2020). The levels of MA and RA was measured by a 4-point Likert scale from *very scared* (1) to *not scared at all* (4). To encourage children's interpretation, a picture of a face was paired with each anxiety level. The corresponding mean scores were used for the outcome indices of MA and RA.

Measurement of HLE

The HLE was measured by the questionnaire about the following three variables each for math and reading: parents' perceptions, parents' domain-specific anxiety, and the frequency of home learning activities. If 75% of the items were answered for each variable, the means were calculated. If not, they were eliminated from the analyses. The questionnaire was conducted in Dutch (English translations are included in supplementary materials).

Parents' Perceptions of Math and Reading

We developed four items each to measure parents' perceptions of math and reading. Parents answered their preference and opinions of math and reading on a 5-point Likert scale respectively, ranging from *strongly disagree* (1) to *strongly agree* (5). The coding for item B was reversed as it inquires negative attitude towards math or reading. The questionnaire had satisfactory reliability; both parents' perceptions of math and reading had the Cronbach's alpha of 0.84. The mean scores of each scale were used as indices.

Parents' MA and RA

Parents' MA was assessed with *The Abbreviated Math Anxiety Scale (AMAS)* by Hopko et al. (2003). The scale consisted of nine items, and parents were asked to answer their degree of anxiety in math-related situations with a 5-point Likert scale, ranging from *not nervous at all* (0) to *very nervous* (4). The internal consistency of the AMAS was satisfactory (Cronbach's alpha = 0.90). In parallel with the AMAS, we developed a parents' RA scale with nine items (Cronbach's alpha = 0.89). Each mean score was used as indices of MA and RA.

Frequency of Home Numeracy Activities and Home Literacy Activities

For frequency of the home learning activities, the questionnaire developed by Skwarchuk et al. (2014) was used. Parents reported the frequency of 13 numeracy activities and 11 literacy activities they do with their children based on the following 5-point Likert scale: *never* (0), *monthly* (1), *weekly* (2), *several times per week* (3), and *daily* (4). The sums of the items were used as indices of home numeracy and literacy activities. The Cronbach alpha's of the home numeracy and literacy activities scale can be found in the results section.

SES

The maternal degree was asked in the parents' questionnaire as a proxy of children's SES. Our sample was slightly oriented to higher SES, however considered as representative of the Flemish population (Statbel, 2019); 19.6% reported to have a degree from lower secondary education or below, labelled as *low* SES; 36.5% had a degree from higher secondary education, labelled as *middle* SES; and 42.2% had a tertiary education degree, labelled as *high* SES. This information was missing for 1.7% of the participants.

Data Analysis

The data analysis was conducted with IBM SPSS Statistics for Windows, Version 26.0. Supplementary materials and data are freely available at: https://osf.io/39xrv/?view_only=d51baa573daa4eaf978e9ad7dd79bdba. Firstly, following Skwarchuk et al. (2014), principal component analyses (PCA) were conducted for home numeracy and literacy activities for data reduction. For the first research question, correlation analysis was conducted to examine the relations among the HLE factors, namely parents' perceptions of math/reading, MA/RA, frequency of home numeracy/literacy activities, and SES. To address the second and the third research questions, the relations between the HLE factors and children's cognitive and non-cognitive outcomes were examined by correlational analyses and one-way ANOVA. In this analysis, children's gender and age were treated as control variables. If meaningful correlations were observed, regression analyses were conducted to examine the unique contributions of the variables. All the statistical tests were conducted at $\alpha = 0.05$ level. More detailed

TABLE 1 | Bivariate correlations among the HLE factors.

	1	2	3	4	5	6
1. Parents' perceptions of math						
2. Parents' MA	−0.451**					
3. Frequency of home numeracy activities	0.055	0.05				
4. Parents' perception of reading	0.057	−0.07	0.153**			
5. Parents' RA	0.007	0.379**	−0.09	−0.492**		
6. Frequency of home literacy activities	−0.015	0.016	0.716**	0.206**	−0.130*	

Note. N = *289.* *p < *0.05,* **p < *0.0.*

explanation about the conducted analyses can be found in the results section.

RESULTS

Data Reduction of Home Learning Activities

Following Skwarchuk et al. (2014), the home learning activities whose frequencies close to the theoretical minimum (0) and maximum (4) with less than one standard deviation were eliminated (see supplementary data). Specifically, item A and K of the home literacy activities were excluded (see **Supplementary Table S5** in **Supplementary Material**). Next, PCAs were conducted for the frequencies of the home numeracy activities and the home literacy activities respectively to explore the components, and consequently group the related activities. Since missing data in each activity was less than 10, they were replaced with mean (Field, 2018, p. 804–805). The results of PCAs were non-satisfactory, as more than 50% of non-redundant residuals had absolute values greater than 0.05 in both numeracy and literacy activities. Concerning this unsatisfactory fit (Cf. Field, 2018, p. 812), the results of PCA were not used for further analyses. Instead, mean scores were calculated for home numeracy activities (Cronbach's alpha = 0.87) and literacy activities (Cronbach's alpha = 0.83) for further analyses.

Relations Among HLE Factors

To examine the relationship within the HLE factors, bivariate correlations were computed (**Table 1**, descriptive statistics are in **Supplementary Material**). In the math domain, a significant negative correlation between parents' math perceptions and parents' MA was observed, indicating that parents with more positive perceptions towards math were more likely to have less MA. No statistically significant correlations were found between frequency of home numeracy activities and parents' perceptions of math or MA. Hence, the hypothesised positive correlation between parents' perceptions of math and frequency of home numeracy activities was not confirmed. In the reading domain, all three factors were observed to be significantly correlated with each other. Parents' perceptions of reading were negatively correlated with parents' RA. As hypothesised, a positive correlation between parents' perceptions of reading and frequency of home literacy activities were observed. Thus, parents with more positive perceptions towards reading were likely to have less RA and do reading-related activities with their children more frequently. Parents' RA was.

Negatively correlated with frequency of home literacy activities, meaning that parents with higher RA were likely to do reading-related activities with their children less frequently.

For cross-domain relations, a significant correlation between parents' MA and RA was found, meaning that parents who experience higher MA were more likely to also have RA. Moreover, frequency of home numeracy activities was highly correlated with frequency of home literacy activities. Therefore, parents who do math-related activities with their children more frequently were likely to do reading-related activities more frequently. Lastly, a small but positive correlation was observed between frequency of home numeracy activities and parents' perceptions of reading.

One-way ANOVA was conducted to compare means of the HLE factors on SES levels. Welch F tests and Games-Howell's post-hoc tests were used for parents' perceptions of math, MA and RA, as heterogeneity of variance was identified. For the other variables, Gabriel post-hoc tests were adopted, as sample size differed across SES levels (Field, 2018).

In the math domain, a significant mean difference among SES on parents' perceptions of math was found, F (2, 166.45) = 12.883, $p < 0.001$, $\eta^2 = 0.08$. A Games-Howell's post-hoc test demonstrated that high SES parents had a significantly higher mean score of the perceptions of math than low SES (p < 0.001) and middle SES parents (p = 0.001). No significant mean difference was found between low SES and middle SES parents (p = 0.27). Concerning MA, a significant mean difference in parents' MA on SES levels was found, F (2, 141.94) = 4.80, p =0.01, $\eta^2 = 0.03$. A Games-Howell's post-hoc test showed that the mean score of high SES parents was significantly lower than that of low SES parents (p = 0.03). No significant mean difference was found between high and middle SES parents (p = 0.06) and low and middle SES parents (p = 0.69). There was no significant mean difference of frequency of home numeracy activities on SES levels, F (2, 289) = 0.41, p = 0.67, $\eta^2 = 0.003$. Overall, high SES parents were likely to have more positive perceptions of math and less MA compared to low and middle SES parents. Frequency of home numeracy activities did not significantly differ across parents' SES levels.

In the reading domain, a significant mean difference of parents' perceptions of reading on SES levels was found, F (2, 293) = 7.57, p = 0.001, $\eta^2 = 0.05$. A Gabriel post-hoc test indicated that the mean score of high SES parents was significantly higher than middle SES (p = 0.01) and low SES parents (p = 0.001). However, no significant mean difference was observed between

TABLE 2 | Correlations among control variables, HLE factors and children's cognitive outcomes.

	1	2	3	4	5	6	7	8	9	10	11	12
1. Age												
2. Gender	−0.113											
3. Motor speed	0.178**	0.074										
4. Digit comparison	0.177**	−0.059	0.527**									
5. NLE (PAE)	−0.002	0.044	−0.08	−0.160**								
6. Letter knowledge	0.231**	0.107	0.230**	0.385**	−0.08							
7. Parents' perceptions of math	−0.118	0.053	0.066	0.105	−0.088	0.069						
8. Parents' MA	0.08	−0.017	−0.07	−0.116	0.069	−0.105	−0.462**					
9. Home numeracy activities	0.006	0.07	0.101	0.106	−0.062	0.047	0.05	0.079				
10. Parents' perceptions of reading	−0.104	−0.057	.162**	.177**	0.01	0.109	0.053	−0.083	0.113			
11. Parents' RA	0.06	0.03	−0.104	−0.093	−0.042	−0.017	0.014	0.366**	−0.049	−0.493**		
12. Home literacy activities	−0.023	0.117	0.112	0.107	−0.004	0.066	−0.014	0.052	0.713**	0.201**	−0.091	

Note. NLE (PAE) = number line estimation (percentage absolute error). N *= 270. **p < 0.01.*

low and middle SES parents (p = 0.61). No significant mean difference was found for parents' RA and frequency of home literacy activities across SES levels, F (2, 153.60) = 0.60, p = 0.55, η^2 = 0.004 for RA and F (2, 288) = 0.64, p =0.53, η^2 = 0.004 for frequency of home literacy activities. Taken together, the high SES parents had a significantly more positive perceptions of reading than the low and middle SES parents. However, parents' RA and the frequency of the home literacy activities were not significantly different among SES levels on average.

Relations Between HLE Factors and Children's Cognitive Outcomes

The ceiling effect was observed in phonological awareness, as 42.2% of children had all the trials correct. Hence, phonological awareness was omitted for further analyses. No outliers, a score below or above three standard deviations, were detected in children's cognitive outcomes (see **Supplementary Material** for descriptive statistics).

Bivariate correlations were computed to examine the relation between children's cognitive outcomes and the HLE factors with control variables (**Table 2**). For control variables, no significant correlations between gender and children's cognitive outcomes were found, whereas age had significant correlations with digit comparison and letter knowledge. The motor speed was a control variable for digit comparison. The analysis revealed no significant correlation between children's early math skills and the home numeracy environment, or between children's early reading skills and the home literacy environment. A significant correlation was found between children's digit comparison and parents' perceptions of reading.

One-way ANOVA was conducted to examine the associations between SES and children's cognitive outcomes. A significant mean difference among SES in children's digit comparison was observed, $F(2, 288) = 14.515$, $p < 0.001$, $\eta^2 = 0.1$. A Gabriel post-hoc test showed that the mean score of high SES children was significantly higher than middle SES (p = 0.002) and low SES children (p < 0.001). The mean difference between middle SES and low SES children was not significant (p = 0.06). No significant mean difference in number line estimation was found on levels of SES, $F(2, 279) = 0.810$, p = 0.45, η^2 = 0.01. For letter knowledge, no significant mean difference was observed on levels of SES, F(2, 287) = 1.157, p =0 .32, η^2 = 0.01. In sum, high SES children performed in digit comparison significantly higher than low and middle SES peers, however no significant difference was observed in other cognitive outcomes across SES levels. A hierarchical regression analysis was conducted to examine the unique contribution of SES on digit comparison, after controlling age, gender and motor speed in the first model (see **Supplementary Material**). SES accounted for 4.8% of the variance in digit comparison, F_{change} (2,282) = 10.396, p < 0.001.

Relations Between HLE Factors and Children's Non-Cognitive Outcomes

Three outliers (a score above or below three standard deviations from the mean) were found in children's MA and children's RA. However, skewness was smaller than |1|, and the boxplots did not detect any outliers. Hence, no child was removed from this analysis.

Bivariate correlations were calculated to examine the relations among children's non-cognitive outcomes, the HLE factors and control variables (**Table 3**). We observed significant correlations between gender and children's MA as well as RA. It should be reminded that children's MA and RA were ranged from *very scared* (1) to *not scared at all* (4). Hence, this indicates that girls were more likely to have higher MA and RA. Age was not significantly correlated with neither children's MA or RA. Regarding the HLE, no statistically significant correlation was observed between children's non-cognitive outcomes and the HLE factors.

One-way ANOVA was conducted to compare means of children's non-cognitive outcomes based on SES. A significant mean difference among SES on children's MA was found, F(2, 287) = 4.046, p = 0.02, η^2 = 0.03. The Gabriel post hoc test showed that the mean score of high SES children was significantly higher than that of middle SES children (p = 0.014), however the difference was not significant from low SES children's mean score (p = 0.57). No significant mean difference in MA was observed between middle and low SES children (p = 0.56). For children's RA, no significant mean difference was found across SES levels, F(2, 287) = 0.838, p =.43, η^2 = 0.001.

TABLE 3 | Correlations among control variables, HLE factors and children's non-cognitive outcomes.

	1	2	3	4	5	6	7	8	9	10
1. Age										
2. Gender	−0.097									
3. Children's MA	0.007	−0.230**								
4. Children's RA	−0.055	−0.118*	0.639**							
5. Perceptions of math	−.120*	0.03	0.061	0.017						
6. Parents' MA	0.082	0.008	−0.021	−0.03	−0.463**					
7. Home numeracy activities	0.005	0.063	0.09	0.071	0.05	0.062				
8. Perceptions of reading	−0.085	−0.057	0.089	−0.011	0.056	−0.071	0.152*			
9. Parents' RA	0.051	0.035	−0.021	0.037	0.003	0.368**	−0.083	−0.498**		
10. Home literacy activities	−0.033	0.092	0.068	0.07	−0.005	0.03	0.726**	0.213**	−0.116	

Note. N = 283. *p < 0.05, **p < 0.01.

To examine the unique contribution of SES on children's MA, a hierarchical regression analysis was conducted. This was examined in the second model, after entering the control variables in the first model (see **Supplementary Material**). SES accounted for 2.2% of the variance in children's MA, F_{change} (2,283) = 3.306, $p = 0.04$.

DISCUSSION

This study proposed a more holistic conceptualisation of the HLE compared to previous literature. We scrutinised the HLE by investigating parents' perceptions of math/reading and MA/RA, frequency of home numeracy and literacy activities and SES. Particularly, we explored (1) the relations among the HLE factors, (2) the relations between the HLE factors and children's cognitive outcomes in math and reading, and (3) the relations between the HLE factors and children's non-cognitive outcomes in math and reading. With a multifaceted view of the HLE, this study disentangled the complexity in relations between the HLE and children's early math and reading abilities.

Relations Within the HLE Factors

Regarding the relations within the HLE factors, the hypotheses pointed to a positive relation between parents' perceptions of math and the frequency of home numeracy activities, and likewise for the reading domain. The correlational analysis demonstrated that this hypothesis was confirmed only in reading; a statistically significant correlation was found between parents' perceptions of reading and frequency of home literacy activities, however not for math. A similar result was observed in Skwarchuk et al. (2014), who also found a significant relation between parents' attitude and home activities only in reading. On the contrary, Susperreguy et al. (2018) observed that parents with more positive math attitudes and higher academic expectations reported a higher frequency of home numeracy (mapping and operational) activities. These incompatible results may be due to the differences in age of children. Thompson, Napoli, and Purpura (2017) showed that frequency and levels of home numeracy activities depend on children's ages. Our participants were approximately 2 years older than the participants in Susperreguy et al. (2018), and 1 year older than those in Skwarchuk et al. (2014). The set of home numeracy activities by Skwarchuk et al. (2014) may not have been the best measure to reflect the actual learning activities of older children as in our study. All in all, future work is needed to examine these relations.

In both math and reading domains, moderate negative correlations were observed between parents' perceptions and anxiety in math and reading, indicating that how they perceive math or reading both concurrently and retrospectively were associated with domain-specific anxiety. This finding underscores the importance of examining MA and RA in learning, in consideration of the association between them and learning experiences. For the relations between indirect and direct measures of the HLE, no significant correlation was found between parents' MA and frequency of home numeracy activities. This outcome is contrary to that of del Río et al. (2017) who found a significant negative relation. On the other hand, RA had a small but significant negative correlation with frequency of home literacy activities. These results suggest that indirect measures of the HLE partially explain the differences in quality of the young children's HLE.

SES was found to be associated with parents' perceptions of math and reading, and parents' MA, whereas no significant relation was found with home learning activities. In line with Hartas (2011) our participating parents provide a wide range of learning activities for their children at home regardless of their SES. However, parents' capability of supporting children may be different across SES or parents' educational levels. Hence, it is critical to take into account indirect measures of the HLE as well as SES when planning interventions on parents to support their children's learning.

For the cross-domain relationships, a moderate significant relation between MA and RA, and a strong positive relation between the frequency of home numeracy activities and that of home literacy activities were identified. This means that parents who provide more home numeracy activities were likely to provide home literacy activities. Although no significant correlation between parents' perceptions of math and that of reading was found, our findings imply that parents tended to value both math and reading activities equally for their children. In sum, our study suggests that parents' perceptions and domain-specific anxiety plays a part in building HLE to stimulate children's early math and reading abilities.

The Relations Between the HLE and Children's Cognitive Outcomes

The second research question investigated the relations between the HLE factors and children's cognitive outcomes in math and reading. It was hypothesised that there would be a positive relation between the frequency of home learning activities and children's cognitive outcomes in math and reading domains respectively. The correlation analysis demonstrated no significant relations between the home learning environment and children's early math and reading skills. One-way ANOVA showed a significant relation between children's SES levels, indicated by their maternal education levels, and the digit comparison. Hence, the findings of the current study do not support the previous research (e.g., Skwarchuk et al., 2014). For example, Skwarchuk et al. (2014) found a positive relation between children's symbolic number knowledge (number identification, magnitude, counting and ordinal numbers) and advanced formal home numeracy activities. Mutaf Yıldız et al., 2018 observed a significant relation between symbolic number line estimation and the home numeracy, however the relation between digit comparison and the home numeracy was insignificant. This discrepancy could be attributed to the differences in kinds of home learning activities adopted in each study, which may have tapped into different early math abilities of children. For reading, another possible explanation for this inconsistency is test materials. For instance, Skwarchuk et al. (2014) and Huntsinger et al. (2016), who found a significant relation between the reading-related activities and children's reading skills, conducted a test including both letter knowledge and word knowledge. Hence, the HLE might provide significant impact on early reading ability which involves words and their meaning rather than letter knowledge.

The Relations Between the HLE and Children's Non-Cognitive Outcomes

Regarding the third research question, there was no statistically significant relation between the HLE factors and children's non-cognitive outcomes in this study. There are two possible explanations for this finding. Firstly, the contents children learn through the home numeracy activities in their early stage of learning math (e.g., basic number knowledge) may be different from the math concepts which parents are fond of or anxious with. Secondly, children and their parents have a different amount of experiences in math, which may contribute in different levels of MA (Ramirez et al., 2018). In this study, no significant impact by the HLE on children's MA and RA was observed. However, previous studies demonstrated that such domain-specific anxiety increases over ages (Dowker et al., 2016). Also, the level of MA and RA might change as they learn more advanced math and reading. Therefore, it might be possible that the relation between the HLE and children's non-cognitive outcomes in math and reading might change over time. Thus, future studies should conduct a longitudinal study to explore the impact of HLE on children's non-cognitive development in math and reading.

For associations between SES and children's non-cognitive outcomes, a significant mean difference on SES levels was found in MA. Moreover, this association was significant even after age and gender were controlled. In this study, children from middle SES demonstrated the highest MA and the high SES peers scored the lowest on average, and only the mean difference between middle SES and the high SES was statistically significant. This is a different pattern from parents' MA, in which low SES parents had the highest score on MA and high SES parents scored the lowest. However, both parents and children of high SES were likely to have lower MA than their peers. One possibility which may explain such similar pattern is the parents' talk. Gunderson et al. (2012) showed that parents' own feelings about math are likely to impact on what they say about math. Considering the finding of this study which showed the relations between parents' perceptions of math and SES, indexed by their educational levels, it may be that what parents convey about math and reading might have been influenced by their own learning experiences through education, which eventually impact children's MA and RA. For RA, like parents' RA, no significant mean difference on SES levels was found. However, it cannot be denied that this relation becomes significant as children gain more experiences in reading, since RA is also influenced by children's reading achievement (Ramirez et al., 2019).

Limitations

Several limitations in this study should be discussed. Firstly, although the PCAs on the frequency of home numeracy and literacy activities conducted by Skwarchuk et al. (2014) were successfully replicated by some of the previous studies (e.g., Susperreguy et al., 2018), the PCAs in this study were not a satisfactory fit. It may be that the questionnaire on the frequency of home learning activities by Skwarchuk et al. (2014) was not the most suitable in terms of our participants' age. Second, the children whose parents did not respond the questionnaire were omitted from the data analyses. Significant differences in age and home languages were observed between the excluded and included children. Hence, the result might have not completely reflected the Flemish educational context characterised by children's multi-cultural backgrounds and grade retention system. The difficulty in reaching these parents is a lesson for future studies to consider alternative way of communication, such as giving personal reminder. Third, the present study is correlational thus causal relationships cannot be inferred. However, manipulation of indirect measures of the HLE and children's non-cognitive factors is neither practical nor ethical. Fourth, limitations in the measurements should be discussed. The activities parents do with their children are usually not a direct training of the specific skills that were assessed in this study. Previous studies have shown that transfer from what children know and can do during daily activities being reflected in test performance is difficult to achieve (Reynvoet et al., 2021). Also, this study did not include children's general cognitive abilities such as working memory or IQ which are known to influence children's math and reading outcomes (Niklas & Schneider, 2013; Dowker et al., 2016; Ramirez et al., 2019). Additionally, children's reading ability was resultingly measured only by letter knowledge. As in previous studies, measurements of word knowledge may supplement further understanding of the relations between the HLE and children's reading ability (Skwarchuk et al., 2014; Huntsinger et al., 2016).

Furthermore, children's non-cognitive outcomes were also measured solely by the questionnaire. Although the scales adopted in this study were developed for young children, some might argue that children as young as our participants might have difficulty in self-reporting their anxiety levels (e.g., Ramirez et al., 2018). Finally, although this study aimed to grasp a holistic view of the impact of HLE, the HLE was examined only by questionnaire. Hence, it cannot rule out the possibility of social desirability effect in the questionnaire. However, considering the variety of parents' responses, our choice of questionnaire can be considered as adequate to measure the HLE.

Future Directions

Future studies should have a longitudinal design to examine the HLE's impact on children's cognitive and non-cognitive development in math and reading over time. Moreover, adding qualitative measures of the HLE such as observations and interviews could provide more comprehensive understanding of the relations between the HLE and children's math and reading development. Including physiological measurements to existing scales could also supplement the assessment of children's MA and RA (Ramirez et al., 2018). In order to extend our findings from correlational studies, intervention studies on parents' factors can be conducted for exploring causal relationships between the indirect measures of the HLE and children's outcomes (e.g., Schaeffer et al., 2018).

To develop a full picture of children's early math and reading development, it may be important to examine the impact of preschool environment together with HLE; preschool is another influential environment for children to encounter math and reading concepts, and teachers also play a significant role in their learning (Gunderson et al., 2012). Future research could also look into how different early education systems influence the relation between the HLE and children's outcomes. As in Flanders participation rate to formal caring environments and preschool is high, the HLE might play a less significant role here compared to countries where children spend more time at home during early childhood. Additionally, future studies should include the wider view of literacy and numeracy brought by digital technology development when examining the HLE's impact on children's leaning, since many young children learn math and reading with digital texts and apps both at home and school recently (Griffith, Hagan, Heymann, Heflin, & Bagner, 2020), and their familiarity and learning with digital technology seems to be influenced by parents' factors, i.e., the HLE (Neumann, 2014).

CONCLUSION

The present study provided a more holistic view of the HLE by examining the multiple variables of the HLE and disentangled its relations with children's cognitive and non-cognitive performance in math and reading. The significant relation between indirect measures and direct measures were observed in the home numeracy environment, whereas a significant relation was absent in the home literacy environment. SES was found to be related with parents' perceptions of math and reading, and parents' MA, however not with home learning activities. Among the relations between the HLE factors and children's outcomes in math and reading, only SES was found to be related to children's digit comparison and MA. During the COVID-19 pandemic, the HLE obtained increased significance due to lockdowns and closed schools. Against this background, the results obtained in this study become even more significant as parents' perceptions and anxiety towards reading are associated with the frequency of learning activities parents do with their children. Furthermore, although in this study we could not find a relation between children's SES background and the home learning activities, it is possible that inequalities widened during the pandemic due to financial constraints, stress, social isolation, and so forth. Overall, the current study demonstrated the importance of including indirect measures of the HLE to explore the dynamics of the HLE. Further work is required to investigate the associations between the HLE and children's cognitive and non-cognitive outcomes in math and reading, taking into account how these factors develop over time.

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: **Supplementary Material** and data are freely available at: https://osf.io/39xrv/?view_only = d51baa573daa4eaf978e9ad7dd79bdba.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by SMEC (Social and Societal Ethics Committee), G-2017 09907. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

SV, BR, and FD contributed to conception and design of the study. SV was responsible for the data collection. KM and SV organised the datafile. KM performed the statistical analysis and wrote the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2021.746296/full#supplementary-material

REFERENCES

Aarnoutse, C., Beernink, J., and Verhagen, W. (2016). *Toetspakket Beginnende Geletterdheid [Early Literacy]*. Amersfoort, Netherlands: CPS.

Anders, Y., Rossbach, H.-G., Weinert, S., Ebert, S., Kuger, S., Lehrl, S., et al. (2012). Home and Preschool Learning Environments and Their Relations to the Development of Early Numeracy Skills. *Early Child. Res. Q.* 27 (2), 231–244. doi:10.1016/j.ecresq.2011.08.003

Aunola, K., Leskinen, E., Lerkkanen, M.-K., and Nurmi, J.-E. (2004). Developmental Dynamics of Math Performance from Preschool to Grade 2. *J. Educ. Psychol.* 96 (4), 699–713. doi:10.1037/0022-0663.96.4.699

Baker, L., and Scher, D. (2002). Beginning Readers' Motivation for Reading in Relation to Parental Beliefs and Home Reading Experiences. *Reading Psychol.* 23 (4), 239–269. doi:10.1080/713775283

Brankaer, C., Ghesquière, P., and De Smedt, B. (2017). Symbolic Magnitude Processing in Elementary School Children: A Group Administered Paper-And-Pencil Measure (SYMP Test). *Behav. Res. Methods* 49 (4), 1361–1373. doi:10.3758/s13428-016-0792-3

Cargnelutti, E., Tomasetto, C., and Passolunghi, M. C. (2017). The Interplay between Affective and Cognitive Factors in Shaping Early Proficiency in Mathematics. *Trends Neurosci. Edu.* 8-9, 28–36. doi:10.1016/j.tine.2017.10.002

De Smedt, B., Taylor, J., Archibald, L., and Ansari, D. (2010). How Is Phonological Processing Related to Individual Differences in Children's Arithmetic Skills. *Dev. Sci.* 13 (3), 508–520. doi:10.1111/j.1467-7687.2009.00897.x

De Smedt, B., Noël, M.-P., Gilmore, C., and Ansari, D. (2013). How Do Symbolic and Non-symbolic Numerical Magnitude Processing Skills Relate to Individual Differences in Children's Mathematical Skills? A Review of Evidence from Brain and Behavior. *Trends Neurosci. Edu.* 2 (2), 48–55. doi:10.1016/j.tine.2013.06.001

del Río, M. F., Susperreguy, M. I., Strasser, K., and Salinas, V. (2017). Distinct Influences of Mothers and Fathers on Kindergartners' Numeracy Performance: The Role of Math Anxiety, Home Numeracy Practices, and Numeracy Expectations. *Early Edu. Dev.* 28 (8), 939–955. doi:10.1080/10409289.2017.1331662

Dobbs-Oates, J., Pentimonti, J. M., Justice, L. M., and Kaderavek, J. N. (2015). Parent and Child Attitudinal Factors in a Model of Children's Print-Concept Knowledge. *J. Res. Reading* 38 (1), 91–108. doi:10.1111/j.1467-9817.2012.01545.x

Dowker, A, Sarkar, A, and Looi, CY (2016). Mathematics Anxiety: What Have We Learned in 60 Years. *Front Psychol* 7, 508. doi:10.3389/fpsyg.2016.00508

Duncan, G. J., Dowsett, C. J., Claessens, A., Magnuson, K., Huston, A. C., Klebanov, P., et al. (2007). School Readiness and Later Achievement. *Dev. Psychol.* 43 (6), 1428–1446. doi:10.1037/0012-1649.43.6.1428

Elliott, L., and Bachman, H. J. (2018). SES Disparities in Early Math Abilities: The Contributions of Parents' Math Cognitions, Practices to Support Math, and Math Talk. *Dev. Rev.* 49, 1–15. doi:10.1016/j.dr.2018.08.001

Field, A. (2018). *Discovering Statistics Using IBM SPSS Statistics*. 5th ed. London: Sage.

Göbel, S. M. (2015). *Number Processing and Arithmetic in Children and Adults with reading Difficulties*.

Griffith, S. F., Hagan, M. B., Heymann, P., Heflin, B. H., and Bagner, D. M. (2020). Apps as Learning Tools: A Systematic Review. *Pediatrics* 145 (1), e20191579. doi:10.1542/peds.2019-1579

Gunderson, E. A., Ramirez, G., Levine, S. C., and Beilock, S. L. (2012). The Role of Parents and Teachers in the Development of Gender-Related Math Attitudes. *Sex Roles* 66 (3–4), 153–166. doi:10.1007/s11199-011-9996-2

Gunn, B. K., Simmons, D. C., and Kameenui, E. J. (1995). Emergent Literacy: A Synthesis of the Research. Eugene, OR: The National Center to Improve the Tools of Educators. Retrieved from Available at: https://www.researchconnections.org/childcare/resources/2776/pdf

Hartas, D. (2011). Families' social backgrounds matter: socio-economic factors, home learning and young children's language, literacy and social outcomes. *British Educational Research Journal* 37 (6), 893–914. doi:10.1080/01411926.2010.506945

Hopko, DR, Mahadevan, R, Bare, RL, and Hunt, MK (2003). The Abbreviated Math Anxiety Scale (AMAS): construction, validity, and reliability. *Assessment* 10 (2), 178–82. doi:10.1177/1073191103010002008

Hulme, C, and Snowling, MJ (2013). Learning to Read: What We Know and What We Need to Understand Better. *Child. Dev Perspect* 7 (1), 1–5. doi:10.1111/cdep.12005

Huntsinger, C. S., Jose, P. E., and Luo, Z. (2016). Parental Facilitation of Early Mathematics and reading Skills and Knowledge through Encouragement of home-based Activities. *Early Child. Res. Q.* 37, 1–15. doi:10.1016/j.ecresq.2016.02.005

Katzir, T., Kim, Y. G., and Dotan, S. (2018). Reading Self-Concept and Reading Anxiety in Second Grade Children: The Roles of Word Reading, Emergent Literacy Skills, Working Memory and Gender. *Front. Psychol.* 9, 1180. doi:10.3389/fpsyg.2018.01180

Kluczniok, K., Lehrl, S., Kuger, S., and Rossbach, H.-G. (2013). Quality of the home Learning Environment during Preschool Age - Domains and Contextual Conditions. *Eur. Early Child. Edu. Res. J.* 21 (3), 420–438. doi:10.1080/1350293x.2013.814356

Krajewski, K., and Schneider, W. (2009). Exploring the Impact of Phonological Awareness, Visual-Spatial Working Memory, and Preschool Quantity-Number Competencies on Mathematics Achievement in Elementary School: Findings from a 3-year Longitudinal Study. *J. Exp. Child. Psychol.* 103 (4), 516–531. doi:10.1016/j.jecp.2009.03.009

LeFevre, J.-A., Skwarchuk, S.-L., Smith-Chant, B. L., Fast, L., Kamawar, D., and Bisanz, J. (2009). Home Numeracy Experiences and Children's Math Performance in the Early School Years. *Can. J. Behav. Science/Revue Canadienne Des Sci. Du Comportement* 41 (2), 55–66. doi:10.1037/a0014532

Liu, C., Georgiou, G. K., and Manolitsis, G. (2018). Modeling the Relationships of Parents' Expectations, Family's SES, and home Literacy Environment with Emergent Literacy Skills and Word reading in Chinese. *Early Child. Res. Q.* 43, 1–10. doi:10.1016/j.ecresq.2017.11.001

Lyytinen, H., Erskine, J., Tolvanen, A., Torppa, M., Poikkeus, A.-M., and Lyytinen, P. (2006). Trajectories of reading Development: A Follow-Up from Birth to School Age of Children with and without Risk for Dyslexia. *Merrill-Palmer Q.* 52, , 2006 1982, 514–546. doi:10.1353/mpq.2006.0031

Maloney, E. A., Ramirez, G., Gunderson, E. A., Levine, S. C., and Beilock, S. L. (2015). Intergenerational Effects of Parents' Math Anxiety on Children's Math Achievement and Anxiety. *Psychol. Sci.* 26 (9), 1480–1488. doi:10.1177/0956797615592630

Manolitsis, G., Georgiou, G. K., and Tziraki, N. (2013). Examining the Effects of home Literacy and Numeracy Environment on Early reading and Math Acquisition. *Early Child. Res. Q.* 28 (4), 692–703. doi:10.1016/j.ecresq.2013.05.004

Martini, F., and Sénéchal, M. (2012). Learning Literacy Skills at home: Parent Teaching, Expectations, and Child Interest. *Can. J. Behav. Sci. / Revue Canadienne Des Sci. Du Comportement* 44 (3), 210–221. doi:10.1037/a0026758

Melby-Lervåg, M., Lyster, S. A., and Hulme, C. (2012). Phonological Skills and Their Role in Learning to Read: a Meta-Analytic Review. *Psychol. Bull.* 138 (2), 322–352. doi:10.1037/a0026744

Moura, R., Haase, V. G., Lopes-Silva, J. B., Batista, L. T., Rocha de Freitas, F., Bahnmueller, J., et al. (2021). "Reading and Writing Words and Numbers: Similarities, Differences, and Implications," in *Diversity Dimensions in Mathematics and Language Learning* (Berlin, Boston: De Gruyter), 291–312. doi:10.1515/9783110661941-015

Mutaf Yıldız, B., Sasanguie, D., De Smedt, B., and Reynvoet, B. (2018). Frequency of Home Numeracy Activities Is Differentially Related to Basic Number Processing and Calculation Skills in Kindergartners. *Front. Psychol.* 9, 340. doi:10.3389/fpsyg.2018.00340

Napoli, A. R., and Purpura, D. J. (2018). The home Literacy and Numeracy Environment in Preschool: Cross-Domain Relations of Parent-Child Practices and Child Outcomes. *J. Exp. Child. Psychol.* 166, 581–603. doi:10.1016/j.jecp.2017.10.002

Neumann, M. M. (2014). An Examination of Touch Screen Tablets and Emergent Literacy in Australian Pre-school Children. *Aust. J. Edu.* 58 (2), 109–122. doi:10.1177/0004944114523368

Niklas, F., and Schneider, W. (2017a). Home Learning Environment and Development of Child Competencies from Kindergarten until the End of Elementary School. *Contemp. Educ. Psychol.* 49, 263–274. doi:10.1016/j.cedpsych.2017.03.006

Niklas, F., and Schneider, W. (2013). Home Literacy Environment and the Beginning of reading and Spelling. *Contemp. Educ. Psychol.* 38 (1), 40–50. doi:10.1016/j.cedpsych.2012.10.001

Niklas, F., and Schneider, W. (2017b). Intervention in the home Literacy Environment and Kindergarten Children's Vocabulary and Phonological Awareness. *First Lang.* 37 (5), 433–452. doi:10.1177/0142723717698838

OECD (2019). *Skills Matter: Additional Results from the Survey of Adult SkillsOECD Skills Studies*. Paris: OECD Publishing. doi:10.1787/1f029d8f-en

Ramirez, G., Chang, H., Maloney, E. A., Levine, S. C., and Beilock, S. L. (2016). On the Relationship between Math Anxiety and Math Achievement in Early Elementary School: The Role of Problem Solving Strategies. *J. Exp. Child. Psychol.* 141, 83–100. doi:10.1016/j.jecp.2015.07.014

Ramirez, G., Fries, L., Gunderson, E., Schaeffer, M. W., Maloney, E. A., Beilock, S. L., et al. (2019). Reading Anxiety: An Early Affective Impediment to Children's Success in Reading. *J. Cogn. Dev.* 20 (1), 15–34. doi:10.1080/15248372.2018.1526175

Ramirez, G., Shaw, S. T., and Maloney, E. A. (2018). Math Anxiety: Past Research, Promising Interventions, and a New Interpretation Framework. *Educ. Psychol.* 53 (3), 145–164. doi:10.1080/00461520.2018.1447384

Reynvoet, B., Vanbecelaere, S., Depaepe, F., and Sasanguie, D. (2021). "Intervention Studies in Math: A Metareview," in *Heterogeneous Contributions to Numerical Cognition* (Academic Press), 283–308. doi:10.1016/b978-0-12-817414-2.00012-9

Sasanguie, D., Göbel, S. M., Moll, K., Smets, K., and Reynvoet, B. (2013). Approximate Number Sense, Symbolic Number Processing, or Number-Space Mappings: what Underlies Mathematics Achievement. *J. Exp. Child. Psychol.* 114 (3), 418–431. doi:10.1016/j.jecp.2012.10.012

Sasanguie, D., Van den Bussche, E., and Reynvoet, B. (2012). Predictors for Mathematics Achievement? Evidence from a Longitudinal Study. *Mind, Brain Edu.* 6 (3), 119–128. doi:10.1111/j.1751-228X.2012.01147.x

Schaeffer, M. W., Rozek, C. S., Berkowitz, T., Levine, S. C., and Beilock, S. L. (2018). Disassociating the Relation between Parents' Math Anxiety and Children's Math Achievement: Long-Term Effects of a Math App Intervention. *J. Exp. Psychol. Gen.* 147 (12), 1782–1790. doi:10.1037/xge0000490

Schatschneider, C., Fletcher, J. M., Francis, D. J., Carlson, C. D., and Foorman, B. R. (2004). Kindergarten Prediction of Reading Skills: A Longitudinal Comparative Analysis. *J. Educ. Psychol.* 96 (2), 265–282. doi:10.1037/0022-0663.96.2.265

Schneider, M., Beeres, K., Coban, L., Merz, S., Susan Schmidt, S., Stricker, J., et al. (2017). Associations of Non-symbolic and Symbolic Numerical Magnitude Processing with Mathematical Competence: A Meta-Analysis. *Dev. Sci.* 20 (3), e12372. doi:10.1111/desc.12372

Schneider, M., Merz, S., Stricker, J., De Smedt, B., Torbeyns, J., Verschaffel, L., et al. (2018). Associations of Number Line Estimation with Mathematical Competence: A Meta-Analysis. *Child. Dev.* 89 (5), 1467–1484. doi:10.1111/cdev.13068

Segers, E., Kleemans, T., and Verhoeven, L. (2015). Role of Parent Literacy and Numeracy Expectations and Activities in Predicting Early Numeracy Skills. *Math. Thinking Learn.* 17 (2–3), 219–236. doi:10.1080/10986065.2015.1016819

Sénéchal, M., and LeFevre, J.-A. (2002). Parental Involvement in the Development of Children's Reading Skill: A Five-Year Longitudinal Study. *Child. Dev.* 73 (2), 445–460. doi:10.1111/1467-8624.00417

Siegler, R. S., and Booth, J. L. (2004). Development of Numerical Estimation in Young Children. *Child. Dev.* 75 (2), 428–444. doi:10.1111/j.1467-8624.2004.00684.x

Skwarchuk, S.-L. (2009). How Do Parents Support Preschoolers' Numeracy Learning Experiences at Home. *Early Child. Educ J* 37 (3), 189–197. doi:10.1007/s10643-009-0340-1

Skwarchuk, S. L., Sowinski, C., and LeFevre, J. A. (2014). Formal and Informal home Learning Activities in Relation to Children's Early Numeracy and Literacy Skills: the Development of a home Numeracy Model. *J. Exp. Child. Psychol.* 121, 63–84. doi:10.1016/j.jecp.2013.11.006

Statbel. (2019). Onderwijsniveau van de Belgische bevolking van 15-64 jaar [Education level of the Belgian population aged 15-64]. Available at: https://statbel.fgov.be/nl/themas/werk-opleiding/opleidingen-en-onderwijs/onderwijsniveau#figures(Accessed April 15 2020)

Susperreguy, M. I., Douglas, H., Xu, C., Molina-Rojas, N., and LeFevre, J.-A. (2020). Expanding the Home Numeracy Model to Chilean Children: Relations Among Parental Expectations, Attitudes, Activities, and Children's Mathematical Outcomes. *Early Child. Res. Q.* 50, 16–28. S0885200618300814. doi:10.1016/j.ecresq.2018.06.010

Thompson, R. J., Napoli, A. R., and Purpura, D. J. (2017). Age-related Differences in the Relation between the home Numeracy Environment and Numeracy Skills. *Inf. Child. Dev.* 26 (5), e2019. doi:10.1002/icd.2019

Tunmer, W. E., and Greaney, K. T. (20082008). "Reading Intervention Research: An Integrative Framework," in *The SAGE Handbook of Dyslexia*. Editors A. Fawcett, F Manis, and G. Reid (Los Angeles: Sage).

Van Mier, H. I., Schleepen, T. M. J., and Van den Berg, F. C. G. (2019). Gender Differences Regarding the Impact of Math Anxiety on Arithmetic Performance in Second and Fourth Graders. *Front. Psychol.* 9, 2690. doi:10.3389/fpsyg.2018.02690

Vanbecelaere, S., Van den Berghe, K., Cornillie, F., Sasanguie, D., Reynvoet, B., and Depaepe, F. (2019). The Effectiveness of Adaptive versus Non-adaptive Learning with Digital Educational Games. *J. Comput. Assist. Learn.* 36, 502–513. doi:10.1111/jcal.12416

Vanbecelaere, S., Van den Berghe, K., Cornillie, F., Sasanguie, D., Reynvoet, B., and Depaepe, F. (2020). The Effects of Two Digital Educational Games on Cognitive and Non-cognitive Math and reading Outcomes. *Comput. Edu.* 143, 103680. doi:10.1016/j.compedu.2019.103680

Verhagen, W. G. M., Aarnoutse, C. A. J., and van Leeuwe, J. F. J. (2009). The Predictive Power of Phonemic Awareness and Naming Speed for Early Dutch Word Recognition. *Educ. Res. Eval.* 15 (1), 93–116. doi:10.1080/13803610802663912

Wagner, RK, Torgesen, JK, Rashotte, CA, Hecht, SA, Barker, TA, Burgess, SR, Donahue, J, and Garon, T (1997). Changing relations between phonological processing abilities and word-level reading as Children Develop from Beginning to Skilled Readers: a 5-year Longitudinal Study. *Dev. Psychol.* 33 (3), 468–479. doi:10.1037//0012-1649.33.3.468

Yeo, L. S., Ong, W. W., and Ng, C. M. (2014). The Home Literacy Environment and Preschool Children's Reading Skills and Interest. *Early Edu. Dev.* 25 (6), 791–814. doi:10.1080/10409289.2014.862147

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Cognition and Academic Performance: Mediating Role of Personality Characteristics and Psychology Health

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This study uses personality and psychology health characteristics of high school students as intermediary variables to study how cognitive ability affects academic performance, and analyzes memory, information processing, presentation, logical reasoning, and thinking transformation ability in high school students. In this study, the structural equation model (SEM) was used to analyze the mediating effect, and the bootstrap method was used to test the significance of the mediating effect. The participants were 572 high school students from Beijing, China. They completed a survey that included questions on cognitive ability, personality characteristics, and psychology health. This study uses structural equation modeling for mediation analysis. Through the analysis of four models of comprehensive academic performance, Chinese academic performance, mathematics academic performance, and English academic performance, the results of the study showed that cognitive ability has a significant effect on academic performance, and personality characteristics and psychology health play a partially mediating role between cognitive ability and English academic performance. The mediation effect is about 40%.

Keywords: cognitive ability, personality characteristics, psychology health, academic performance, mediation

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INTRODUCTION

Research has emphasized the important role of cognitive ability in the learning process. In educational practice, subsequently, attention has been paid to the cultivation of strong cognitive abilities in students. However, a series of studies have shown that cognitive ability is not the only factor that determines the level of academic performance in students (Shao, 1983). An individual's academic performance might not only be determined by their cognitive abilities, but also by their overall positive mental state. However, there are only a few previous studies on the mechanism of cognitive ability affecting academic performance. This study uses the personality characteristics and psychology health of high school students as mediating variables to study the influence mechanism of cognitive ability on academic performance. This study aims to identify the mediating effect of personality and psychology health characteristics on cognitive ability and academic performance, to further clarify the influencing mechanisms of cognitive ability on the academic performance of high school students.

The Impact of Cognitive Ability on Academic Performance

Cognitive ability refers to the ability of the human brain to process, store and extract information, including processes such as attention, memory, and reasoning ability. It is the key psychological element for people to successfully complete an activity (Sternberg and Sternberg, 2009) and is currently one of the most studied and most stable predictors of academic performance (Matthias et al., 2016; Vilia et al., 2017). Previous studies have focused on the direct impact of individual-level cognitive ability on academic performance (Kuncel et al., 2004; Miriam et al., 2011). A study by Xu and Li (2015) on 4,743 junior high school students found that selective attention, short-term memory, and reasoning ability are significant predictors of linguistic and mathematics performance. Rohde and Thompson (2007) found that cognitive ability directly predicts academic performance, and the correlation between the two is as high as 0.38. Ian (2006) conducted a 5-year follow-up study of more than 70,000 British students and found that the correlation between general cognitive ability at 11 years old and academic performance at 16 years old was 0.81. Paulo used multiple regression stepwise analysis and standardized regression coefficients (β) to evaluate the relationship between the inference dimensions and physical and chemical achievements in each semester of the three semesters and found that reasoning ability was significantly positively correlated with students' physical and chemical performance (Grass et al., 2017). Liu measured 499 Chinese children's cognitive abilities such as visual space, arithmetic, and reading, and collected their mathematics and Chinese learning scores for two consecutive academic years in the same year of the cognitive test and the year after the cognitive test. Correlation analysis shows that visual space, arithmetic, and reading ability are significantly related to academic performance (Liu et al., 2021).

Although the relationship between general cognitive ability and academic performance seems clear, it is difficult to fully understand the mechanism of their complex relationship. In a learning context, the importance of cognitive abilities in human learning activities can only be more deeply reflected by including specific cognitive abilities in the scope of investigation (David, 2005) because learning activities not only involve different specific abilities, but these abilities also work together in unpredictable ways. As such, there is still no consensus on how model cognitive ability influences academic performance (Formazin et al., 2011). Zhang (2008) found that the correlation coefficients between logical reasoning ability (LRA) and Chinese and mathematics scores are all around 0.3, while the level of attention is not significantly correlated with the scores of the two subjects. However, Xu and Li (2015) found that selective attention has a significant correlation with the performance of the two subjects, and the correlation coefficient between reasoning ability and the performance of Chinese and mathematics is between 0.4 and 0.5. These results indirectly confirmed that cognitive ability only influences academic performance as a whole, and that conclusions cannot be drawn yet regarding the complex interaction of individual factors on academic performance.

The Mediating Role of Personality Characteristics

Many studies have shown a certain correlation between students' academic performance and their personality factors. Gerhard (1996) has confirmed through experimental studies that personality factors have a certain impact on academic performance while Leino (1989) and others believed that non-intellectual factors, including personality characteristics, were the main cause of academic performance. American scholar Gough (1964) used the "California Psychological Inventory" (CPI) to investigate 18 personality factors of middle school students and make a correlation analysis with their academic performances, and found that there were at least eight personality factors (such as the desire to dominate, sense of responsibility, socialization, tolerance, independence, etc.) that correlated significantly with academic performance. Richardson et al. (2009) measured five major personality characteristics as well as achievement motivation. They found that both, rigor and achievement motivation, could explain the changes in grade point average (GPA) for students. The impact is regulated by their achievement motivation. Adrian and Tomas (2005) also examined the internal relationship between individual personality characteristics and knowledge level and found that rigor and openness had a significant positive correlation with knowledge level. Through research, Ruffing found that general cognitive ability is positively correlated with academic performance, and there are obvious personality differences. Differences in personality characteristics can explain the incremental variance that exceeds general cognitive ability (Ruffing et al., 2015).

Although there has been prior research on the relationship between cognitive ability and personality characteristics, they were mainly based on qualitative research or correlation analyses, which led to only a few effective identifications of a causal relationship between them. Cognitive ability and personality characteristics, as the two major components of individual psychology, are both independent and related (Li and Zhang, 2015), but there are different opinions on their relevance given that cognitive ability and personality characteristics are indicators to measure different dimensions of ability (James et al., 2006). Most factors of personality characteristics and cognitive ability are very weakly correlated, so the two can be independently used as explanatory variables of individual behavior (Ackerman and Heggestad, 1997); even though some scholars believe that cognitive ability and personality characteristics will affect each other (Borghans et al., 2008). Tania's research on personality traits has a significant impact on information processing ability (IPA) and found that different personality traits, especially conscientiousness, will reduce the impact on performance according to the increase in education level, indicating that personal personality has a greater impact on the promotion of academic achievement (Cerni et al., 2021). In recent years, the causal relationship between the two has been paid more attention. There is literature reporting the use of long-term tracking survey data to verify the causal relationship between personality characteristics and cognitive ability from theoretical and empirical aspects and found that cognitive ability can significantly affect the development of personality characteristics (Heckman et al., 2018).

The Mediating Role of Psychology Health

Psychology health is a person's subjective experience. It includes not only positive emotions, but also all aspects of personal life. It refers to the ability to show a positive and healthy mental state in all aspects of learning, life, interpersonal communication, and self-awareness (Hu and Xiao, 2021).

There is a general correlation between psychology health and personality characteristics, but the correlation between psychology health and personality trait factors is not completely consistent and the coefficients are different (Wang, 2021). In psychology health, personality characteristics play an important role. The theory of personality characteristics believes that personality characteristics can determine a person's behavior. Indeed, some studies have shown that there is a high correlation between the personality characteristics of students and their psychology health. For example, the more extroverted the students are, the less likely they are to have psychology symptoms (Chu et al., 2019). The personality characteristics that affect psychology health mainly include optimism, easygoingness, trust, and enthusiasm. For example, solitary and highly sensitive students tend to be neurotic and incompatible, which is not conducive to their own development. Many studies have shown that the level of a student's psychology health is closely related to their level of learning efficiency (Wu, 2021).

Secondly, existing studies mostly focus on the relationship between psychology health and psychological characteristics (Wang and Zhang, 2012; Wu et al., 2018), and not on the impact of psychology health on academic performance. However, academic performance is one of the important indicators of student development and educational outcomes (Wang and Jessica, 2016), as well as an important part of the psychology health mechanism (Zhang et al., 2017). Limited empirical research suggests that the psychology health of Chinese adolescents is closely related to their academic performance (Zhang and Liu, 2001).

According to the S-C-R theoretical model established by cognitive psychological theorists, it is not the stimulus itself that affects individual behavior, but our perception of the event. In this model, S (stimulus) refers to the components that can cause stimulus in the entire external world, including external events, situations, interpersonal relationships, and their own behavior; C (consciousness) refers to consciousness and experience; R (response) refers to response (Wang, 2008), therefore, students with stronger cognitive abilities will obtain more stimulus information from the outside world, and their understanding of this information will be deeper, and their judgments and responses to the outside world will be more autonomous. This judgment and response to external stimulus information can reflect the psychology health of students. So the strength of cognitive ability can significantly affect the psychology health of students.

Research Hypothesis

This study combines the classification of cognitive ability by Wo and Lin (2000), Xu and Li (2015) and Liang et al. (2020) and divides cognitive ability into working memory ability (MA), IPA, representational ability (RA), LRA, and thinking conversion ability (TCA). It explores the specific influence of different cognitive abilities on academic performance and puts forward the following hypotheses:

Hypothesis 1a: MA is positively correlated with academic performance.
Hypothesis 1b: IPA is positively correlated with academic performance.
Hypothesis 1c: RA is positively correlated with academic performance.
Hypothesis 1d: LRA is positively correlated with academic performance.
Hypothesis 1e: TCA is positively correlated with academic performance.

At the same time, existing studies have focused more on the impact of individual factors of cognitive ability and personality characteristics on academic performance; thus, the correlation between cognitive ability and personality characteristics remains unclear. For the causal relationship between cognitive ability and personality characteristics, only a few empirical studies have been conducted with personality characteristics as an intermediary for the influence of cognitive ability. Therefore, this study uses personality characteristics as an intermediary variable to analyze the influence of cognitive ability on academic performance, and analyze how cognitive ability influences academic performance. We propose the following hypothesis:

Hypothesis 2: Personality characteristics play a mediating role between cognitive ability and academic performance.

In addition, this study uses psychology health as an intermediary variable to analyze the impact of cognitive ability on academic performance, and how cognitive ability affects academic performance. We propose the following hypothesis:

Hypothesis 3: Psychology health mediates between cognitive ability and academic performance.

MATERIALS AND METHODS

Participants

This research was approved by the Research Ethics Committee of the School of Humanities and Social Sciences, University of Science and Technology Beijing, and the data used in the study was provided by the Affiliated Middle School of the University. This study was conducted following the regulations that have been established for human subject protection. This study selected 572 students from a high school in Beijing as the sample, with 291 boys (50.87%) and 281 girls (49.23%). Among the students, there were 225 in the first year (115 boys and 110 girls), 178 in the second year (83 boys and 95 girls) and 169 in the third year (93 boys and 76 girls). As shown in **Table 1**.

Procedure

All the tests in this study were conducted on the campus of the Affiliated Middle School of the University of Science and Technology, Beijing. The school teachers uniformly organized all students to enter the computer lab for testing. The test content included questions on middle school level cognitive ability, personality characteristics, and psychology health. The overall duration of the test was 2 h and 30 min.

Measures

Cognitive Ability

The test was conducted using the stimulus information cognitive ability value test system designed by Wo (2010). The test method uses techniques such as subtraction reaction time and addition reaction time (accurate to nanoseconds). Students are provided with visual stimuli, including text, images, and animations. Following this, the total number of fixation points and fixation durations of multiple cognitive areas that emerged from the test students' feedback are recorded, and the cognitive accuracy of the students is analyzed and tested according to the feedback records. The students are tested for cognitive index value, and cognitive accuracy is obtained through statistical methods to obtain the quantified value of cognitive ability, which is converted into a T-score for the final cognitive ability value. The cognitive abilities tested include five types: MA, IPA, RA, LRA, and TCA. The cognitive ability values obtained by this test method are centered at 100 and have a normal distribution trend in the range of ±50, which has high discrimination validity. Cronbach's alpha in this study ranged from 0.80 to 0.90.

Personality Characteristics

The personality test scale for middle school students was designed by Zhang et al. (2005). The scale has a total of 48 test questions, including four dimensions: planning, self-control, persistence, daring. We set up 12 questions for each one dimensions, and the items were evaluated on a 5-point Likert scale: 1 (very inconsistent), 2 (relatively inconsistent), 3 (uncertain), 4 (relatively consistent), and 5 (very consistent). After accumulation, this is converted into a T-score as the student's ability value. Though this test, students' overall academic status can be obtained. The Cronbach α coefficient of each dimension of the scale is between 0.60 and 0.93, and the test–retest reliability is 0.85. The validity is 0.91.

TABLE 1 | Distribution of participating students.

Grade	Number of students			
	Boys	Proportion (%)	Girls	Proportion (%)
First grade	115	51.11	110	48.89
Second grade	83	46.63	95	53.37
Third grade	93	55.03	76	44.97
Total	291	50.87	281	49.23

Psychology Health

The psychology health test scale for middle school students was designed by Pan et al. (2005). The scale has a total of 24 test items, including four dimensions, namely optimism, trust, gregariousness, and enthusiasm. Each dimension is set with six test items. The items were evaluated on a 5-point Likert scale: 1 (very inconsistent), 2 (relatively inconsistent), 3 (uncertain), 4 (relatively consistent), and 5 (very consistent). After accumulation, this is transformed into a T-score as the student's psychology health value. The Cronbach α coefficient of each dimension of the scale is between 0.79 and 0.91, and the test–retest reliability is 0.81. The validity is 0.87.

Academic Performance

This research uses the average of the three most recent test scores of students from the test as their academic performance. Because students choose different subjects, this research only selects the compulsory subjects of Chinese, Mathematics, and English for all students. The results were graded according to the rankings (the lowest score was 0), and the total scores of the three subjects were accumulated.

Data Analysis

This study first uses Pearson's correlation analysis to explore the relationship between variables, before using the structural equation model (SEM) to analyze the relationship between cognitive ability, personality characteristics, and psychology health, based on the intermediary analysis process proposed by Wen and Ye (2014). The Bootstrap method is used to test the significance of the mediating role of personality characteristics and psychology health in cognitive ability and academic performance, to obtain the robust standard error and confidence interval of the parameter estimation. If the confidence interval does not include zero, the statistical result is significant (Erceg and Mirosevich, 2008).

RESULTS

Common Method Deviation Test

In order to reduce the common method deviations caused by self-reported questionnaires, this study emphasized the authenticity of the answers during the data collection process; the scale and the order of the questions were randomly set for program control. We used Harman's single factor test to test the effect of program control (Podsakoff et al., 2003), while exploratory factor analysis was conducted on three variables (cognitive ability, personality characteristics, and psychology health) at the same time. It was found that after the rotation, the characteristic roots of eight factors were greater than 1, and the explanatory rate of the first factor was 14.38% (far less than the critical value of 40%), which indicates that the degree of variation in the common method used in this study was within the acceptable range (Wang et al., 2016).

Descriptive and Bivariate Analyses

The mean values, standard deviations, and intercorrelations of the variables are presented in **Table 2**. As can be seen from the table, cognitive ability, personality characteristics, psychology health, and academic performance (TS) are all significantly positively correlated, while there are also significant correlations between the sub-items in personality characteristics and psychology health.

Measurement Model Check

Before the mediation effect test, confirmatory factor analysis was needed to test the measurement model. Three latent variables are used in this study, namely cognitive ability (including five indicators of MA, IPA, LRA, RA, and TCA), personality characteristics (including four indicators of planning, self-control, persistence, and daring), and psychology health (including four indicators of optimism, gregariousness, trust, and enthusiasm). The test results show that the model fits well, $\chi^2(62) = 334.72$, CFI = 0.925, TLI = 0.943, SRMR = 0.067, RMESA = 0.086, and the 90% confidence interval of RMSEA is [0.077, 0.096], indicating that the fitting indicators are all within a good range. **Table 3** also shows that the standardized load of each index on the corresponding factor is significant ($p < 0.001$).

Intermediary Model Checking

In this study, the SEM was used to investigate the influence of cognitive ability, personality characteristics, and psychology health on academic performance, and the maximum likelihood estimation method was used to test the hypothesis model in **Figure 1**.

According to the intermediary analysis process proposed by Wen and Ye (2014), after controlling the influence of gender and age, the SEM is used to analyze the direct effect model of cognitive ability on academic performance. The results show that cognitive ability significantly positively predicts academic performance ($\beta = 0.873$, $p < 0.001$). After that, personality characteristics and psychology health were used as intermediary variables along with cognitive ability and academic performance.

Model 1: Comprehensive Academic Performance

The fitting index indicators of the SEM were: $\chi^2(73) = 412.35$, CFI = 0.897, TLI = 0.902, SRMR = 0.072, RMESA = 0.090, the 90% confidence interval of RMSEA is [0.082, 0.099], and the results show that the model fits well.

From the path diagram of the relationship between cognitive ability, personality characteristics, psychology health and Comprehensive academic performance (**Figure 1**), it can be seen

TABLE 2 | Means, standard deviations, and intercorrelations for variables.

	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. MA	105.112	15.829	1																
2. IPA	102.197	13.246	0.151**	1															
3. RA	106.144	7.305	−0.034	0.209**	1														
4. LRA	103.138	9.887	0.036	0.076	0.083*	1													
5. TCA	94.158	17.286	0.168**	0.396**	0.340**	0.075	1												
6. Planning	101.621	15.934	0.085*	0.176**	0.117**	0.102*	0.200**	1											
7. Self-control	106.256	15.586	0.310**	0.455**	0.271**	0.222**	0.529**	0.402**	1										
8. Persistence	103.419	15.624	0.219**	0.305**	0.126**	0.145**	0.336**	0.549**	0.592**	1									
9. Daring	99.187	16.53	0.131**	0.227**	0	0.086*	0.160**	0.339**	0.389**	0.484**	1								
10. Optimism	101.401	15.963	0.066	0.115**	0.054	0.079	0.079	0.225**	0.281**	0.302**	0.391**	1							
11. Gregariousness	103.025	15.446	0.006	0.163**	0.029	0.018	0.105*	0.207**	0.184**	0.221**	0.325**	0.471**	1						
12. Trust	94.55	15.761	0.065	0.177**	0.092*	−0.002	0.119**	0.153**	0.251**	0.218**	0.206**	0.441**	0.392**	1					
13. Enthusiasm	101.233	16.427	0.016	0.141**	0.023	0.039	0.126**	0.216**	0.222**	0.232**	0.333**	0.564**	0.745**	0.420**	1				
14. Chinese	57.818	25.728	0.217**	0.509**	0.214**	0.127*	0.586**	0.636**	0.562**	0.662**	0.414**	0.36**	0.42**	0.295**	0.498**	1			
15. Mathematics	50.48	28.912	0.206**	0.543**	0.238**	0.135*	0.614**	0.661**	0.616**	0.704**	0.451**	0.38**	0.438**	0.315**	0.517**	0.975**	1		
16. English	50.262	28.892	0.199**	0.566**	0.253**	0.136*	0.632**	0.665**	0.645**	0.723**	0.469**	0.391**	0.45**	0.332**	0.532**	0.944**	0.989**	1	
17. TS	159.56	82.698	0.209**	0.546**	0.238**	0.134*	0.618**	0.661**	0.616**	0.705**	0.450**	0.381**	0.441**	0.318**	0.521**	0.982**	0.999**	0.989**	1

*N = 572; *p < 0.05; **p < 0.001.*

TABLE 3 | Factor loading coefficient table.

Variable	Non-std (Coef.)	SD	z (CR)	Std
Cognitive ability				
TCA	1.000	–	–	0.632***
IPA	0.704	0.072	9.725	0.581***
MA	0.419	0.075	5.588	0.288***
RA	0.239	0.035	6.743	0.356***
LRA	0.175	0.045	3.868	0.194***
Personality characteristics				
Planning	1.000	–	–	0.574***
Self-control	1.345	0.104	12.952	0.788***
Daring	0.996	0.096	10.404	0.550***
Persistence	1.326	0.103	12.874	0.776***
Psychology health				
Optimism	1.000	–	–	0.639***
Gregariousness	1.215	0.077	15.793	0.810***
Enthusiasm	1.436	0.089	16.131	0.901***
Trust	0.763	0.071	10.724	0.500***

***$p < 0.001$.

that cognitive ability positively predicts personality characteristics ($\gamma = 0.677$, $p < 0.001$) and psychology health ($\gamma = 0.319$, $p < 0.001$), while personality characteristics ($\gamma = 0.976$, $p < 0.001$) and psychology health ($\gamma = 0.505$, $p < 0.001$) both positively predict Comprehensive academic performance. The direct effect of cognitive ability and Comprehensive academic performance is also significant ($\gamma = 0.565$, $p < 0.001$).

Based on the mediation model in **Figure 1**, the non-parametric percentile Bootstrap method is used to further test the significance of the mediating effect of personality characteristics and psychology health. The sampling number is 1,000, and the confidence interval is 95%. The results show that personality characteristics plays Partial mediation effect between cognitive ability and Comprehensive academic performance [mediating effect = 0.289, SE = 0.054, $p < 0.001$, 95% CI = (0.578, 0.775)], while psychology health also plays a role in the relationship between cognitive ability and Comprehensive academic performance, there is Partial mediation between cognitive ability and Comprehensive academic performance [mediation effect = 0.077, SE = 0.011, $p < 0.001$, 95% CI = (0.215, 0.423)]. It can be concluded that personality characteristics and psychology health play a partially mediating role between cognitive ability and Comprehensive academic performance. The mediating effect is $(0.289 + 0.077)/(0.289 + 0.077 + 0.565) = 0.393$ (39.3%).

The Sobel test can also be used to test the significance of the mediation effect. The calculation results are shown in **Table 4**.

It can be seen from **Table 4** that the mediating effect of personality characteristics between cognitive ability and Comprehensive academic performance is significant ($z = 4.24$, $p < 0.05$). The mediating effect of psychology health between cognitive ability and Comprehensive academic performance is significant ($z = 4.21$, $p < 0.05$).

Model 2: Chinese Academic Performance

The fitting index indicators of the SEM were: $\chi^2(73) = 391.111$, CFI = 0.893, TLI = 0.907, SRMR = 0.070, RMESA = 0.087, the 90% confidence interval of RMSEA is [0.079, 0.960], and the results show that the model fits well.

From the path diagram of the relationship between cognitive ability, personality characteristics, psychology health and Chinese academic performance (**Figure 2**), it can be seen that cognitive ability positively predicts personality characteristics ($\gamma = 0.723$, $p < 0.001$) and psychology health ($\gamma = 0.339$, $p < 0.001$), while personality characteristics ($\gamma = 0.332$, $p < 0.05$) and psychology health ($\gamma = 0.235$, $p < 0.001$) both positively predict Chinese academic performance. The direct effect of cognitive ability and Chinese academic performance is also significant ($\gamma = 0.568$, $p < 0.001$).

Based on the mediation model in **Figure 2**, the non-parametric percentile Bootstrap method is used to further test the significance of the mediating effect of personality characteristics and psychology health. The sampling number is 1,000, and the confidence interval is 95%. The results show that personality characteristics plays Partial mediation effect between cognitive ability and Chinese academic performance [mediating effect = 0.240, SE = 0.098, $p < 0.05$, 95% CI = (0.616, 0.817)], while psychology health also plays a role in the relationship between cognitive ability and Chinese academic performance, there is Partial mediation between cognitive ability and Chinese academic performance (mediation effect = 0.079, SE = 0.012, $p < 0.001$, 95% CI = [0.236, 0.444]). It can be concluded that personality characteristics and psychology health play a partially mediating role between cognitive ability and Chinese academic performance. The mediating effect is $(0.240 + 0.079)/(0.240 + 0.079 + 0.568) = 0.360$ (36.0%).

The Sobel test can also be used to test the significance of the mediation effect. The calculation results are shown in **Table 5**.

It can be seen from **Table 5** that the mediating effect of personality characteristics between cognitive ability and Chinese academic performance is significant ($z = 2.41$, $p < 0.05$). The mediating effect of psychology health between cognitive ability and Chinese academic performance is significant ($z = 4.09$, $p < 0.05$).

Model 3: Mathematics Academic Performance

The fitting index indicators of the SEM were: $\chi^2(73) = 408.55$, CFI = 0.897, TLI = 0.902, SRMR = 0.071, RMESA = 0.090, the 90% confidence interval of RMSEA is [0.081, 0.098], and the results show that the model fits well.

From the path diagram of the relationship between cognitive ability, personality characteristics, psychology health and Mathematics academic performance (**Figure 3**), it can be seen that cognitive ability positively predicts personality characteristics ($\gamma = 0.683$, $p < 0.001$) and psychology health ($\gamma = 0.322$, $p < 0.001$), while personality characteristics ($\gamma = 0.430$, $p < 0.001$) and psychology health ($\gamma = 0.237$, $p < 0.001$) both positively predict Mathematics academic performance. The direct effect of cognitive ability and Mathematics academic performance is also significant ($\gamma = 0.556$, $p < 0.001$).

Based on the mediation model in **Figure 3**, the non-parametric percentile Bootstrap method is used to further test the significance of the mediating effect of personality characteristics and psychology health. The sampling number is 1,000, and the confidence interval is 95%. The results show that personality characteristics plays Partial mediation effect between cognitive ability and Mathematics academic performance [mediating effect = 0.294, SE = 0.057, $p < 0.001$, 95% CI = (0.582, 0.780)], while psychology health also

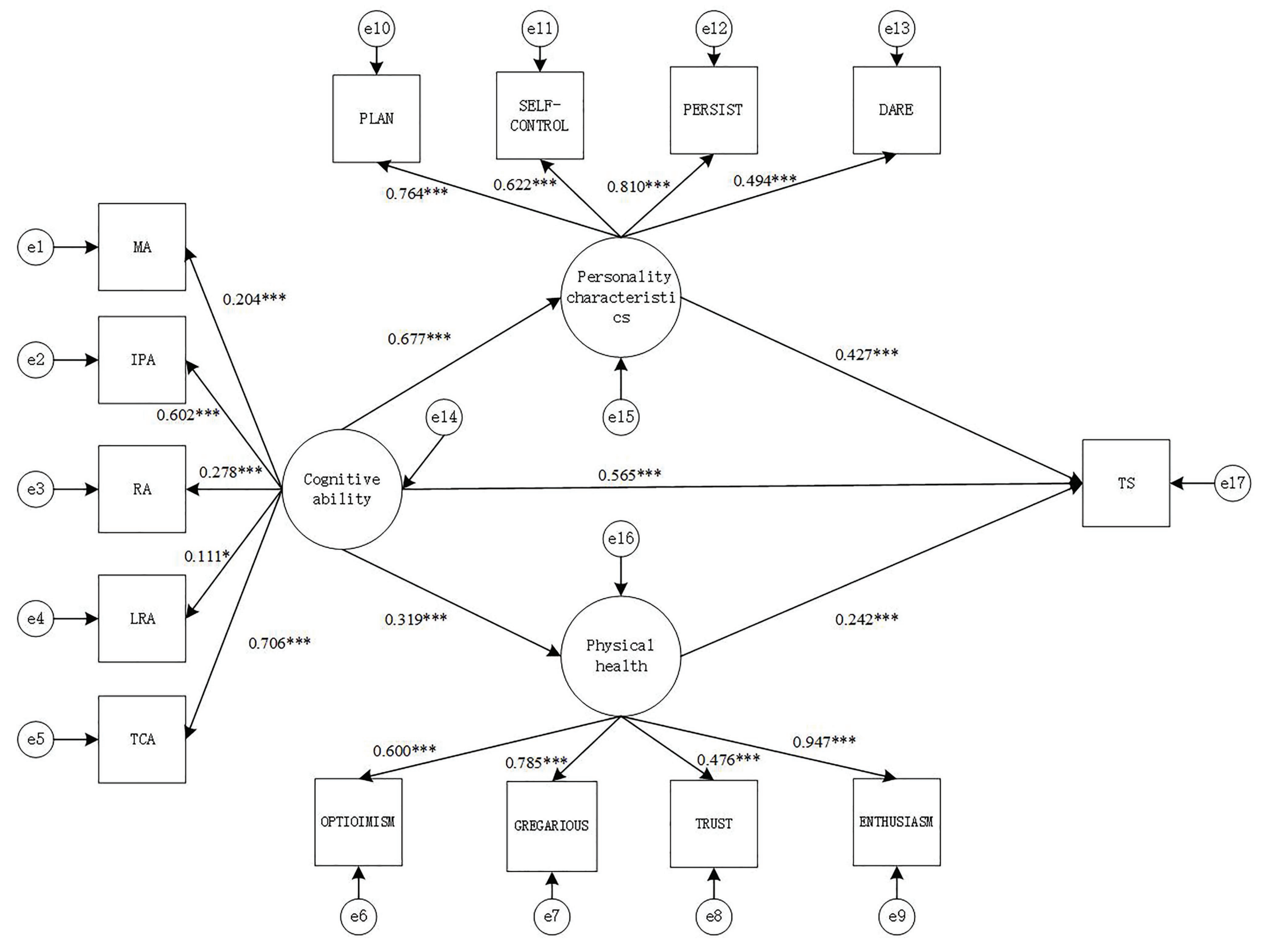

FIGURE 1 | Structural equation intermediary relationship model diagram (model 1). MA, memory ability; IPA, information processing ability; RA, representation ability; LRA, logical reasoning ability; TCA, thinking conversion ability; TS, academic performance. *$p < 0.05$, and ***$p < 0.001$.

TABLE 4 | Sobel test results (model 1).

		z	SE	*p*
a_1	0.677	4.24266762	0.06813614	0
S_{a1}	0.061			
b_1	0.427			
S_{b1}	0.093			
a_2	0.319	4.21188639	0.0183286	0
S_{a2}	0.062			
b_2	0.242			
S_{b2}	0.033			

a_1, regression coefficient of cognitive ability and personality characteristics; s_{a1}, corresponding SE; b_1, regression coefficient of personality characteristics and comprehensive academic performance; s_{b1}, corresponding SE; a_2, regression coefficient of cognitive ability and psychology health; s_{a2}, corresponding SE; b_2, regression coefficient of mental psychology and Comprehensive academic performance; and s_{b2}, corresponding SE.

plays a role in the relationship between cognitive ability and Mathematics academic performance, there is Partial mediation between cognitive ability and Mathematics academic performance [mediation effect = 0.076, SE = 0.011, $p < 0.001$, 95% CI = (0.218, 0.427)]. It can be concluded that personality characteristics and psychology health play a partially mediating role between cognitive ability and Mathematics academic performance. The mediating effect is $(0.294 + 0.076)/(0.294 + 0.076 + 0.556) = 0.400$ (40.0%).

The Sobel test can also be used to test the significance of the mediation effect. The calculation results are shown in **Table 6**.

It can be seen from **Table 6** that the mediating effect of personality characteristics between cognitive ability and Mathematics academic performance is significant ($z = 4.20$, $p < 0.05$). The mediating effect of psychology health between cognitive ability and Mathematics academic performance is significant ($z = 4.21$, $p < 0.05$).

Model 4: English Academic Performance

The fitting index indicators of the SEM were: $\chi^2(73) = 440.55$, CFI = 0.897, TLI = 0.952, SRMR = 0.075, RMESA = 0.094, the 90% confidence interval of RMSEA is [0.085, 0.102], and the results show that the model fits well.

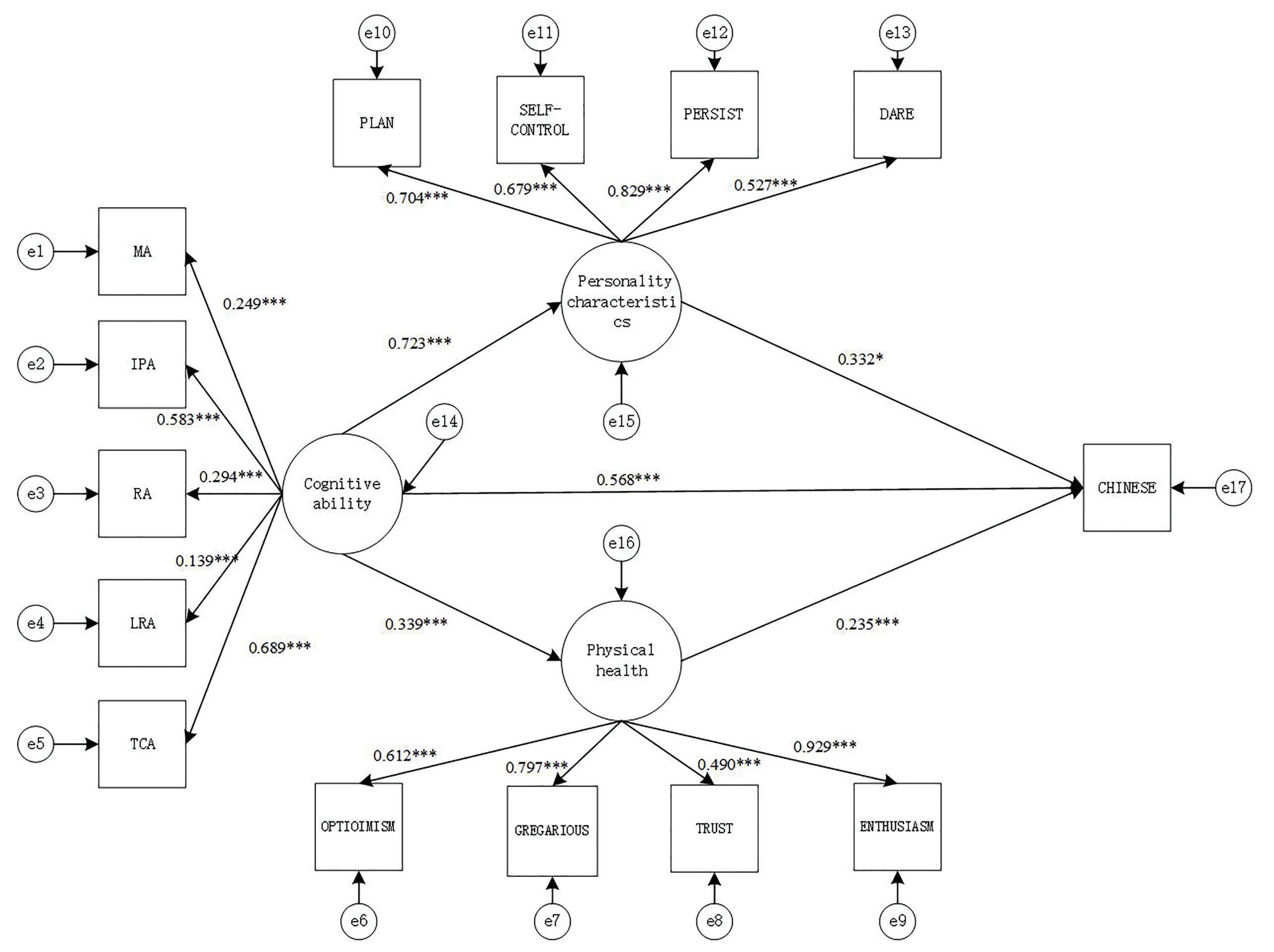

FIGURE 2 | Structural equation intermediary relationship model diagram (model 2). MA, memory ability; IPA, information processing ability; RA, representation ability; LRA, logical reasoning ability; TCA, thinking conversion ability; TS, academic performance. *$p<0.05$, and ***$p<0.001$.

TABLE 5 | Sobel test results (model 2).

		z	SE	*p*
a_1	0.723	2.40633065	0.09975188	0.01611367
S_{a1}	0.062			
b_1	0.332			
S_{b1}	0.135			
a_2	0.339	4.09627496	0.01944816	0
S_{a2}	0.062			
b_2	0.235			
S_{b2}	0.038			

a_1, regression coefficient of cognitive ability and personality characteristics; s_{a1}, corresponding SE; b_1, regression coefficient of personality characteristics and Chinese academic performance; s_{b1}, corresponding SE; a_2, regression coefficient of cognitive ability and psychology health, s_{a2}, corresponding SE; b_2, regression coefficient of mental psychology and Chinese academic performance; and s_{b2}, corresponding SE.

From the path diagram of the relationship between cognitive ability, personality characteristics, psychology health and English academic performance (**Figure 4**), it can be seen that cognitive ability positively predicts personality characteristics ($\gamma=0.647$, $p<0.001$) and psychology health ($\gamma=0.305$, $p<0.001$), while personality characteristics ($\gamma=0.455$, $p<0.001$) and psychology health ($\gamma=0.244$, $p<0.001$) both positively predict English academic performance. The direct effect of cognitive ability and English academic performance is also significant ($\gamma=0.584$, $p<0.001$).

Based on the mediation model in **Figure 4**, the non-parametric percentile Bootstrap method is used to further test the significance of the mediating effect of personality characteristics and psychology health. The sampling number is 1,000, and the confidence interval is 95%. The results show that personality characteristics plays Partial mediation effect between cognitive ability and English academic performance [mediating effect = 0.294, SE = 0.042, $p<0.001$, 95% CI = (0.545, 0.747)], while psychology health also plays a role in the relationship between cognitive ability and English academic performance, there is Partial mediation between cognitive ability and English academic performance (mediation effect = 0.075, SE = 0.010, $p<0.001$, 95% CI = [0.205, 0.410]). It can be concluded that personality characteristics and psychology health play a partially mediating role between cognitive ability

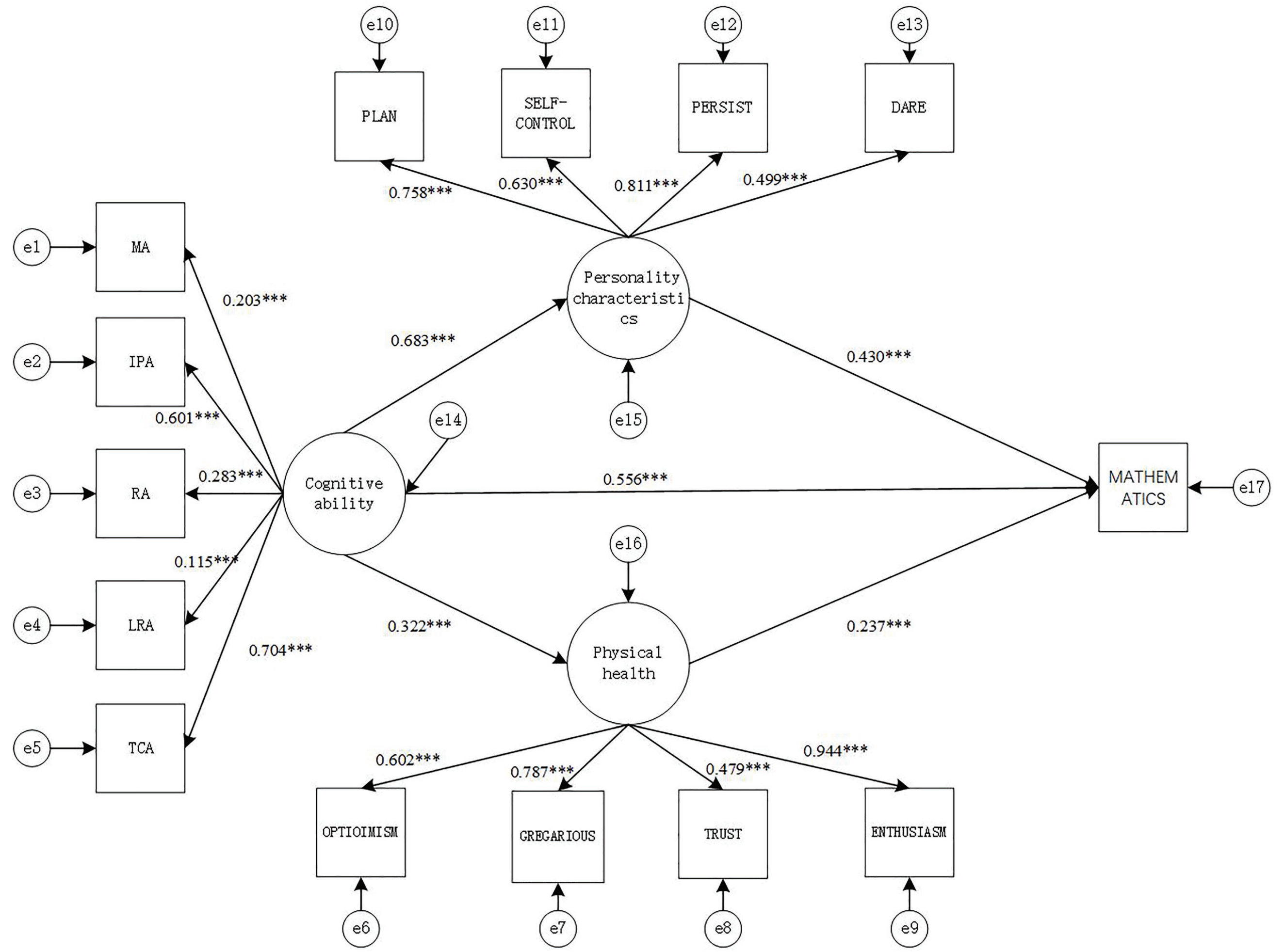

FIGURE 3 | Structural equation intermediary relationship model diagram (model 3). MA, memory ability; IPA, information processing ability; RA, representation ability; LRA, logical reasoning ability; TCA, thinking conversion ability; TS, academic performance. ***$p < 0.001$.

TABLE 6 | Sobel test results (model 3).

		z	SE	p
a_1	0.683	4.19639532	0.06998626	0
S_{a1}	0.061			
b_1	0.430			
S_{b1}	0.095			
a_2	0.322	4.20844315	0.01813355	0
S_{a2}	0.062			
b_2	0.237			
S_{b2}	0.033			

a_1, regression coefficient of cognitive ability and personality characteristics; s_{a1}, corresponding SE; b_1, regression coefficient of personality characteristics and Mathematics academic performance; s_{b1}, corresponding SE; a_2, regression coefficient of cognitive ability and psychology health; s_{a2}, corresponding SE; b_2, regression coefficient of mental psychology and Mathematics academic performance; and s_{b2}, corresponding SE.

and English academic performance. The mediating effect is $(0.294+0.075)/(0.2940+0.075+0.584)=0.387$ (38.7%).

The Sobel test can also be used to test the significance of the mediation effect. The calculation results are shown in **Table 7**.

It can be seen from **Table 7** that the mediating effect of personality characteristics between cognitive ability and English academic performance is significant ($z=5.06$, $p<0.05$). The mediating effect of psychology health between cognitive ability and English academic performance is significant ($z=4.22$, $p<0.05$).

According to the above model, we can find that cognitive ability has a significant effect on academic performance, and personality characteristics and psychology health play a partially mediating role between cognitive ability and English academic performance. The mediation effect is about 40%. Therefore, Hypothesis 2 and Hypothesis 3 are supported (**Table 7**).

DISCUSSION

Impact of Cognitive Ability on Academic Performance

Previous studies have recognized cognitive ability as a psychological feature and a condition for the smooth realization

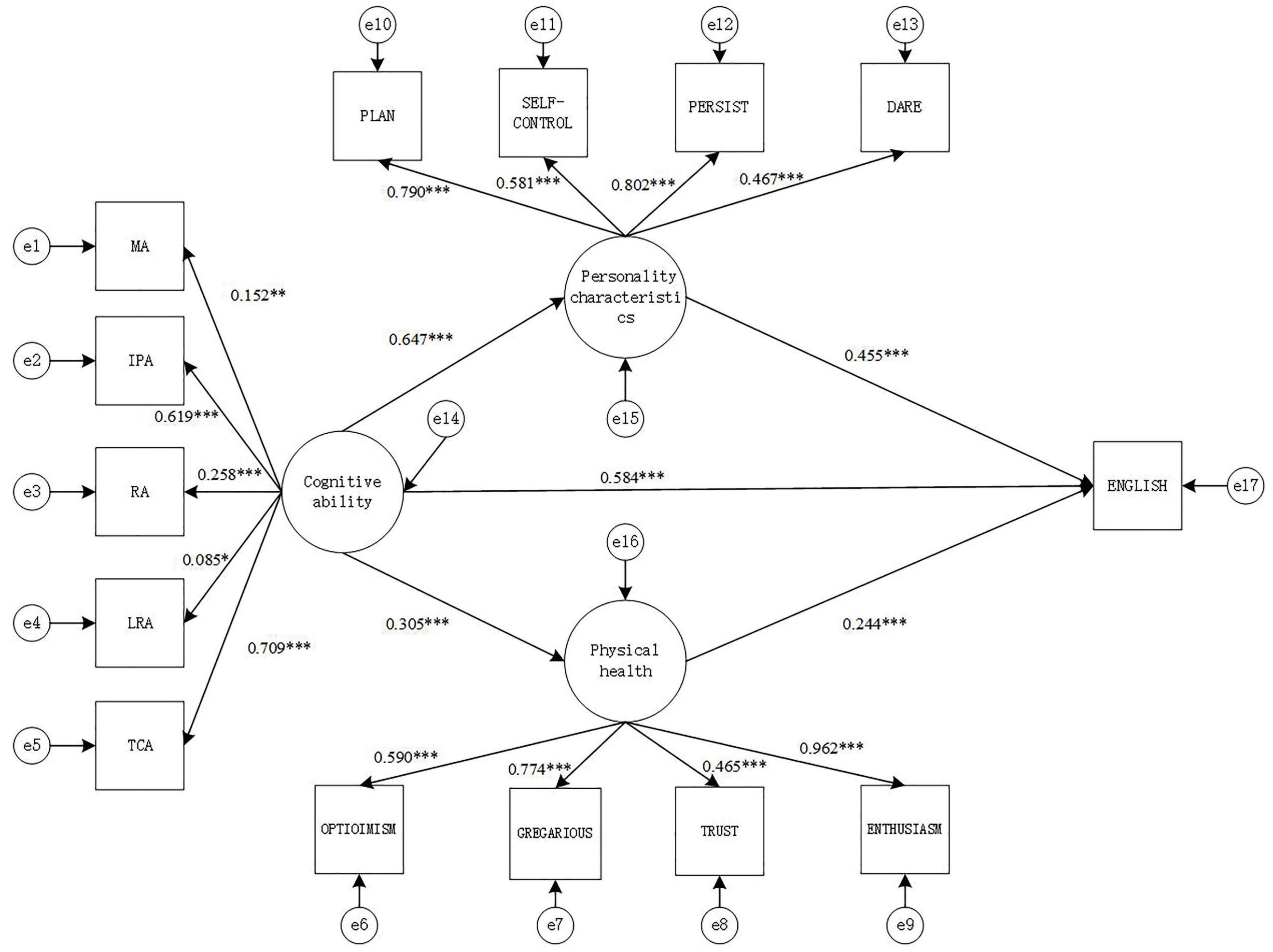

FIGURE 4 | Structural equation intermediary relationship model diagram (model 4). MA, memory ability; IPA, information processing ability; RA, representation ability; LRA, logical reasoning ability; TCA, thinking conversion ability; TS, academic performance. *$p < 0.05$, **$p < 0.01$, and ***$p < 0.001$.

TABLE 7 | Sobel test results (model 4).

		z	SE	*p*
a_1	0.647	5.06142095	0.05816252	0
S_{a1}	0.061			
b_1	0.455			
S_{b1}	0.079			
a_2	0.305	4.22044278	0.01763322	0
S_{a2}	0.061			
b_2	0.244			
S_{b2}	0.031			

a_1, regression coefficient of cognitive ability and personality characteristics; s_{a1}, corresponding SE; b_1, regression coefficient of personality characteristics and English academic performance; s_{b1}. corresponding SE; a_2, regression coefficient of cognitive ability and psychology health; s_{a2}, corresponding SE; b_2, regression coefficient of mental psychology and English academic performance; and s_{b2}, corresponding SE.

of learning activities (Matthias et al., 2016). High school is a good place for students to effectively improve their learning ability because different subjects have different ability requirements from students. MA can effectively help students improve memory, recitation, and other supporting content. At the same time, it interacts with IPA to improve students' reading comprehension ability. This is particularly evident in Chinese and English reading. Therefore, in students with good MA, academic performance is also better (Yu et al., 2014).

Representational ability plays an important role in the learning of spatial knowledge in subjects such as mathematics. At the same time, RA can also stimulate associative memory to recite Chinese and English related knowledge, which makes students perform better academically (Lin et al., 2003). TCA is reflected in the speed and accuracy of thought transformation, so any subject learning is inseparable from this ability. Especially in high school mathematics, students with strong TCA can easily summarize and master ideas and methods of completing new math problems, and proficiently apply them to similar problems (Liu, 1988). LRA is divided into two types: inductive reasoning and deductive reasoning. The influence of LRA on academic performance is mostly concentrated in mathematics (Zhu et al., 2020). In recent years, the examination of students in Chinese and English has also been emphasized with the changes in the content of Chinese examinations. Given the logic and rigor of Chinese and English exams (Hu, 2017), LRA has also been shown to affect the scores in the reading part of the Chinese and English exams. IPA is mainly represented by reading comprehension ability and is also related to the efficiency of listening to lectures. Higher IPA fosters in students a greater ability to understand and master reading in the classroom, the formation of knowledge systems, and better academic performance in examinations (Yuan and Wen, 2003).

The Mediating Role of Personality Characteristics on Cognitive Ability and Academic Performance

Personality characteristics play a complete mediating role in the relationship between cognitive ability and academic performance. Personality internally restricts and determines the unique tendencies and characteristics of individual behaviors (Allport, 1937). Individual learning behavior may be influenced by changes in the environment, but learning activities are inherently guided by stable personality characteristics (Nie et al., 2011). The typical response of personality to situational stimuli is immediate, automatic, emotional, and almost reflexive. But sometimes individuals will use volition control strategies to prevent personality characteristics from triggering stimuli, thereby making an impulsive response. It influences and temporarily changes the individual's personality characteristics through strategies such as planning, persistence, self-control, and courage to respond to the situation by avoiding some impulsive behaviors, producing other positive behaviors (Mischel, 1983; Mischel and Shoda, 1998). In the analysis of the mediating effect of each sub-item of cognitive ability and personality characteristics, it was also found that self-control in personality characteristics played a complete mediating role between the five cognitive abilities and TS, while planning, persistence, and daring played a full intermediary role. This is because students with high cognitive ability tend to spend less time and get academic satisfaction when completing the same learning task. Therefore, students with high cognitive ability are usually more likely to have higher self-confidence in learning, and are more willing to planning, self-control, and persevere in learning (Liang et al., 2020); similarly, when students with high cognitive abilities come across problems in their studies, they are usually more motivated to solve these problems in order to boost their learning confidence and their sense of accomplishment, and subsequently their own personality characteristics.

Generally speaking, students with higher levels of self-regulation, self-planning, and self-monitoring in their personality characteristics maintain a better and more stable mood when faced with stressful situation. According to the self-determination theory, if students who have the internal and external conditions that satisfy psychological stability (such as self-planning and self-control) can produce behavioral results that promote learning (such as academic performance; Ryan and Deci, 2000). So that students can construct a learning cycle system of planning-execute-persistence-adjustment, so as to carry out learning activities efficiently and achieve better academic performances (Lin, 2020).

The Mediating Role of Psychology Health Between Cognitive Ability and Academic Performance

Psychology health plays a complete mediating role in the relationship between cognitive ability and academic performance, which also supports the claim that the impact of psychology health on academic performance might be greater compared to cognitive ability (Zeng, 2020). The results of this study are consistent with the formation mechanism of Psychology Health Theory (Zhang et al., 2017). Psychology health is internalized by external stimulation (for example, learning achievement and satisfaction), and the psychological quality closely related to people's adaptation-development-creation behavior (for example, academic performance), which acts as a "bridge" between cognitive ability and academic performance (Nie et al., 2018). It can be observed that students with high levels of cognitive ability generally have stronger self-management and self-monitoring abilities, and their emotional responses are more moderate than those with average to poor cognitive ability. When students are in an active learning state, it is possible to get a greater sense of achievement from the learning process (Jia et al., 2009). In this way, when students perceive positive academic performance from the outside world, it can not only directly promote students' academic development, but also enhance students' psychology health, thus, indirectly improving their academic performances. In addition, easy-going and enthusiastic students generally have good social skills, which helps them maintain a positive learning attitude, and exhibit confidence in the face of academic setbacks and failures (Jia et al., 2009; Fu et al., 2016), which is conducive to improving their academic performance.

Limitations and Future Directions

One limitation of this study was the small sample size. The next step, for further research, should be to select more schools in other provinces in China for research and comparison. In addition, when considering the factors that affect students' cognitive abilities, this study only considered the parallel mediating effects between personality characteristics and psychology health, but not the chain mediating effects of personality characteristics and psychology health. We were thus unable to consider the impact of cross-terms on cognitive ability and academic performance. Future studies can focus on this area, for more valuable research results.

CONCLUSION

In this study, personality characteristics and psychology health are used as mediating variables between cognitive ability and academic performance. The SEM and the Bootstrap method are used to test the mediating effect. The results of the study showed that cognitive ability has a significant effect on academic performance, and personality characteristics and psychology health play a partially mediating role between cognitive ability and English academic performance. The mediation effect is about 40%.

DATA AVAILABILITY STATEMENT

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

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by The Research Ethics Committee of the School of Humanities and Social Sciences, University of Science and Technology Beijing. 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

YS and SQ contributed to conception and design of the study. YS contributed to data collection, performed the statistical analysis, and wrote the first draft of the manuscript. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2021.774548/full#supplementary-material

REFERENCES

Ackerman, P. L., and Heggestad, E. D. (1997). Intelligence, personality, and interests: evidence for overlapping traits. *Psychol. Bull.* 121, 219–245. doi: 10.1037/0033-2909.121.2.219

Adrian, F., and Tomas, C. P. (2005). Personality, intelligence and general knowledge. *Learn. Individ. Differ.* 16, 79–90. doi: 10.1016/j.lindif.2005.07.002

Allport, G. W. (1937). Personality: a psychological interpretation. *Am. J. Sociol.* 7, 127–131. doi: 10.1037/h0053611

Borghans, L., Angela, L. D., James, J. H., and Bas, T. W. (2008). The economics and psychology of personality traits. *J. Hum. Resour.* 43, 972–1059. doi: 10.1111/j.0042-7092.2007.00700.x

Cerni, T., Di Benedetto, A., and Rumiati, R. I. (2021). The contribution of personality and intelligence toward cognitive competences in higher education. *Front. Psychol.* 12:621990. doi: 10.3389/fpsyg.2021.621990

Chu, T. K., Yao, H. X., and Guo, M. L. (2019). The clinical value of levofloxacin-containing chemotherapy regimen in the treatment of retreatment of sputum smear-positive pulmonary tuberculosis. *Lab. Med. Clin.* 10, 1425–1427. doi: 10.3969/j.issn.1672-9455.2019.10.032

David, F. L. (2005). The role of nonverbal ability tests in identifying academically gifted students: an aptitude perspective. *Gift. Child Q.* 49, 111–138. doi: 10.1177/001698620504900203

Erceg, D. M., and Mirosevich, V. M. (2008). Modern robust statistical methods: an easy way to maximize the accuracy and power of your research. *Am. Psychol.* 63, 591–601. doi: 10.1037/0003-066X.63.7.591

Formazin, M., Schroeders, U., Kller, O., Wilhelm, O., and Westmeyer, H. (2011). Studierendenauswahl im fach psychologie. *Psychol. Rundsch.* 62, 221–236. doi: 10.1026/0033-3042/a000093

Fu, F. R., Chen, X. Y., Wang, L., and Yang, F. (2016). Developmental trajectories of academic achievement in Chinese children: contributions of early social-behavioral functioning. *J. Educ. Psychol.* 108, 1001–1012. doi: 10.1037/edu0000100

Gerhard, B. (1996). Personality traits, learning stratigies, and performance. *Eur. J. Personal.* 10, 337–352. doi: 10.1002/(SICI)1099-0984(199612)10:53.0.CO;2-7

Gough, H. G. (1964). Academic performance in high school as predicted from the California Psychological Inventory. *J. Educ. Psychol.* 55, 174–180. doi: 10.1037/h0046186

Grass, J., Strobel, A., and Strobel, A. (2017). Cognitive investments in academic success: the role of need for cognition at university. *Front. Psychol.* 8:790. doi: 10.3389/fpsyg.2017.00790

Heckman, J. J., Humphries, J. E., and Veramendi, G. (2018). Returns to education: the causal effects of education on earnings, health, and smoking. *J. Polit. Econ.* 126, S197–S246. doi: 10.1086/698760

Hu, X. D. (2017). The principles and paths of the core competence of Chinese in the college entrance examination. *J. China Exam.* 7, 58–65. doi: 10.19360/j.cnki.11-3303/g4.2017.07.012

Hu, W. K., and Xiao, H. (2021). Personality characteristics of junior college students in a certain university and its influence on mental health. *Psychol. Monthly* 8, 5–6. doi:10.19738/j.cnki.psy.2021.08.003

Ian, J. D., Steve, S., Pauline, S., and Cres, F. (2006). Intelligence and educational achievement. *Intelligence* 35, 13–21. doi: 10.1016/j.intell.2006.02.001

James, J. H., Jora, S., and Sergio, U. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *J. Labor Econ.* 24, 411–482. doi: 10.1086/504455

Jia, Y. M., Ling, G. M., Chen, X. Y., and Lu, Z. H. (2009). The influence of student perceptions of school climate on socioemotional and academic adjustment: a comparison of Chinese and American adolescents. *Child Dev.* 80, 1514–1530. doi: 10.1111/j.1467-8624.2009.01348.x

Kuncel, N. R., Hezlett, S. A., and Ones, D. S. (2004). Academic performance, career potential, creativity, and job performance: can one construct predict them all? *J. Pers. Soc. Psychol.* 86, 148–161. doi: 10.1037/0022-3514.86.1.148

Leino, A. L. (1989). A study of learning styles. *Res. Bull.*

Li, T., and Zhang, W. T. (2015). International trends in the study of personality economics. *Econ. Perspect.* 8, 128–143.

Liang, X. L., He, J., and Liu, P. P. (2020). The influence of cognitive ability on academic performance of junior middle school students: a mediated moderation model. *Psychol. Dev. Educ.* 4, 449–461. doi: 10.16187/j.cnki.issn1001-4918.2020.04.08

Lin, S. H. (2020). The relationship between initiative personality, study initiative and academic performance of high school students. *Mental Heal. Edu. Prim. Second.* 18, 15–21.

Lin, C. D., Wo, J. Z., and Liu, H. J. (2003). An EEG study on the intelligence development of primary and middle school students. *Stud. Psychol. Behav.* 1, 5–10.

Liu, Y. (1988). On the cultivation of thinking conversion ability in middle school mathematics teaching. *J. Yangzhou Univ., Nat. Sci. Ed.* 3, 110–114. doi: 10.19411/j.1007-824x.1988.03.021

Liu, S., Wei, W., Chen, Y., Hugo, P., and Zhao, J. (2021). Visual–spatial ability predicts academic achievement through arithmetic and reading abilities. *Front. Psychol.* 11:591308. doi: 10.3389/fpsyg.2020.591308

Matthias, S., Miriam, A., Nicolas, B., and Samuel, G. (2016). Choosing between what you want now and what you want most: self-control explains academic performance beyond cognitive ability. *Personal. Individ. Differ.* 94, 168–172. doi: 10.1016/j.paid.2016.01.029

Miriam, V., Franzis, P., and Heinz, H. (2011). Mental abilities and school achievement: a test of a mediation hypothesis. *Intelligence* 39, 357–369. doi: 10.1016/j.intell.2011.06.006

Mischel, M. W. (1983). The development of children's knowledge of self-control strategies. *Child Dev.* 54, 603–619. doi: 10.2307/1130047

Mischel, W., and Shoda, Y. (1998). Reconciling processing dynamics and personality dispositions. *Annu. Rev. Psychol.* 49, 229–258. doi: 10.1146/annurev.psych.49.1.229

Nie, Y. G., Yang, A., and Zeng, M. X. (2011). Adolescents' metacognition, big five personality and the relationship between learning adaptation behavior. *Psychol. Dev. Educ.* 2, 151–157. doi: 10.16187/j.cnki.issn1001-4918.2011.02.011

Nie, Q., Zhang, D. J., Teng, S. J., Lu, X. Y., and Guo, C. (2018). School atmosphere perceived by students and subjective and objective academic achievement: the mediating role of psychological quality and its dimensions. *Psychol. Dev. Educ.* 6, 715–723. doi: 10.16187/j.cnki.issn1001-4918.2018.06.10

Pan, J., Wo, J. Z., and Dong, J. M. (2005). "Formulation of norm of mental health scale for senior high school students." in *Collection of Abstracts of Papers of the Tenth National Conference of Psychology*. eds. Chinese Psychological Society; October 22, 2005. 335.

Podsakoff, P. M., Mac Kenzie, S. B., Lee, J. Y., and Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *J. Appl. Psychol.* 88, 879–903. doi: 10.1037/0021-9010.88.5.879

Richardson, M., Abraham, C., Anderson, J. C., Gerbing, D. W., Bandalos, D. L., Finney, S. J., et al. (2009). Conscientiousness and achievement motivation predict performance. *Eur. J. Personal.* 23, 589–605. doi: 10.1002/per.732

Rohde, T. E., and Thompson, L. A. (2007). Predicting academic achievement with cognitive ability. *Intelligence* 35, 83–92. doi: 10.1016/j.intell.2006.05.004

Ruffing, S., Wach, F.-S., Spinath, F. M., Brünken, R., and Karbach, J. (2015). Learning strategies and general cognitive ability as predictors of gender- specific academic achievement. *Front. Psychol.* 6:1238. doi: 10.3389/fpsyg.2015.01238

Ryan, R. M., and Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *Am. Psychol.* 55, 68–78. doi: 10.1037//0003-066x.55.1.68

Shao, R. Z. (1983). *Educational Psychology: Principles of Learning and Teaching.* Shanghai: Shanghai Education Press.

Sternberg, R. J., and Sternberg, K. (2009). *Cognitive Psychology*. *6th Edn*. Belmont, CA: Wadsworth, Cengage Learning.

Vilia, P. N., Candeias, A. A., Neto, A. S., Franco, M. S., and Melo, M. (2017). Academic achievement in physics-chemistry: the predictive effect of attitudes and reasoning abilities. *Front. Psychol.* 8:1064. doi: 10.3389/fpsyg.2017.01064

Wang, Q. (2008). On the relationship between metacognition and mental health of college students. *Soc. Sci. Rev.* 3, 257–258.

Wang, Y. B. (2021). Research on the relationship between personality traits and mental health of students from single-parent families in higher vocational colleges. *J. Zhejiang Inst. Commun.* 2, 76–81.

Wang, M. T., and Jessica, L. D. (2016). School climate: a review of the construct, measurement, and impact on student outcomes. *Educ. Psychol. Rev.* 28, 315–352. doi: 10.1007/s10648-015-9319-1

Wang, Y. L., Qin, Y. L., Xiao, C., and Lin, X. Y. (2016). The relationship between parental conflict and adolescent self-harm: a moderated mediation model. *Psychol. Dev. Educ.* 3, 377–384. doi: 10.16187/j.cnki.issn1001-4918.2016.03.15

Wang, X. Q., and Zhang, D. J. (2012). The criticism and amendment for the dual-factor model of mental health: from Chinese psychological Suzhi research perspectives. *Int. J. Clin. Med.* 3, 319–327. doi: 10.4236/ijcm.2012.35063

Wen, Z. L., and Ye, B. J. (2014). Analysis of mediation effect: method and model development. *Adv. Psychol. Sci.* 22, 731–745. doi: 10.3724/SP.J.1042.2014.00731

Wo, J. Z. (2010). Stimulating information cognitive ability value test system and method. CN101779960A.

Wo, J. Z., and Lin, C. D. (2000). Research on the development of adolescents' self-monitoring ability. *J. Psychol. Sci.* 1, 10–15. doi: 10.16719/j.cnki.1671-6981.2000.01.003

Wu, L. G. (2021). The correlation between college students' mental health and academic achievement-based on a survey of 1399 college students in an agricultural university. *J. Shanxi Univ. Soci. Sci.* 8, 39–43. doi: 10.16396/j.cnki.sxgxskxb.2021.08.008

Wu, L. L., Zhang, D. J., Cheng, G., and Hu, T. Q. (2018). Bullying and social anxiety in Chinese children: moderating roles of trait resilience and psychological Suzhi. *Child Abuse Negl.* 76, 204–215. doi: 10.1016/j.chiabu.2017.10.021

Xu, F., and Li, C. H. (2015). The influence of junior middle school students' cognitive ability on academic achievement. *J. Psychol. Sci.* 1, 11–18. doi: 10.16719/j.cnki.1671-6981.2015.01.033

Yu, B., Le, G. A., and Liu, H. J. (2014). Working memory and self-regulation. *Adv. Psychol. Sci.* 22, 772–781. doi: 10.3724/SP.J.1042.2014.00772

Yuan, L. X., and Wen, J. Y. (2003). Research on the relationship between middle school students' learning strategies and academic achievement. *J. Guangdong Univ. Educ.* 1, 7–12.

Zeng, J. X. (2020). Research on the relationship between mental health and academic performance of high school students. *J. Teach. Manag.* 27, 22–25.

Zhang, J. L. (2008). Comparison of logical reasoning ability, metacognition, attention level and academic performance of primary and middle school students. *J. Psychol. Sci.* 3, 707–710. doi: 10.16719/j.cnki.1671-6981.2008.03.035

Zhang, D. J., and Liu, Y. L. (2001). Research on the correlation between mental quality and academic achievement of senior high school students. *J. Psychol. Sci.* 1, 110–111. doi: 10.16719/j.cnki.1671-6981.2001.01.034

Zhang, D. J., Su, Z. Q., and Wang, X. Q. (2017). Thirty years of research on the psychological quality of children and adolescents: retrospect and prospect. *Stud. Psychol. Behav.* 1, 3–11.

Zhang, H., Wo, J. Z., and Liu, C. M. (2005). "The formulation of the norm of personality scale for senior high school students." in *Collection of Abstracts of Papers of the Tenth National Conference of Psychology*. eds. Chinese Psychological Society; October 22, 2005. 782.

Zhu, L. M., Ke, S., and Wu, L. S. (2020). Investigation and research on the development level of high school students' mathematical and logical reasoning ability. *J. Tianjin Norm Univ. Ele. Edu. Ed.* 4, 18–23. doi: 10.16826/j.cnki.1009-7228.2020.04.004

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Creative Mathematical Reasoning: Does Need for Cognition Matter?

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A large portion of mathematics education centers heavily around imitative reasoning and rote learning, raising concerns about students' lack of deeper and conceptual understanding of mathematics. To address these concerns, there has been a growing focus on students learning and teachers teaching methods that aim to enhance conceptual understanding and problem-solving skills. One suggestion is allowing students to construct their own solution methods using creative mathematical reasoning (CMR), a method that in previous studies has been contrasted against algorithmic reasoning (AR) with positive effects on test tasks. Although previous studies have evaluated the effects of CMR, they have ignored if and to what extent intrinsic cognitive motivation play a role. This study investigated the effects of intrinsic cognitive motivation to engage in cognitive strenuous mathematical tasks, operationalized through Need for Cognition (NFC), and working memory capacity (WMC). Two independent groups, consisting of upper secondary students ($N = 137$, mean age 17.13, $SD = 0.62$, 63 boys and 74 girls), practiced non-routine mathematical problem solving with CMR and AR tasks and were tested 1 week later. An initial *t*-test confirmed that the CMR group outperformed the AR group. Structural equation modeling revealed that NFC was a significant predictor of math performance for the CMR group but not for the AR group. The results also showed that WMC was a strong predictor of math performance independent of group. These results are discussed in terms of allowing for time and opportunities for struggle with constructing own solution methods using CMR, thereby enhancing students conceptual understanding.

Keywords: algorithmic reasoning, working memory capacity, Need for Cognition (NFC), mathematical struggle, creative mathematical reasoning

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INTRODUCTION

A solid grasp of mathematics is a valuable life skill and a foundational goal of the Swedish national curriculum (Skolverket, 2019; The Swedish National Agency for Education). However, how to best teach and learn mathematics is a long-debated subject, both in Sweden and internationally (Loveless, 2004). A recurring concern in this debate is a lack of conceptual understanding among students for the mathematics they learn and utilize (Battista, 2001; Lithner, 2008). It is, therefore, hardly a surprise that learning and teaching methods that place a strong emphasis on conceptual understanding have been gaining more attention in the last decades (Gollub, 2002; Stylianides and Stylianides, 2007; Lithner, 2008, 2017; Shield and Dole, 2013). However, much of the mathematical education still centers around memorization and repetition, denoted as rote learning, rather than conceptual understanding (Bergqvist, 2007; Bergqvist and Lithner, 2012; Boesen et al., 2014). Indeed, in a study by Jäder et al. (2019) examining mathematic textbooks from 12 countries, it was discovered that most tasks (79%) could be solved using predefined solutions or algorithms, and an additional 13% of tasks required only minor tweaking of a previously provided template. This reliance on rote learning and imitation-based reasoning implies that when facing a task, students often problem-solve by recalling and applying algorithms they have previously memorized, based on perceived similarities to older tasks, but with little conceptual understanding of those algorithms (Lithner, 2008; Boesen et al., 2010). As a result, students reuse memorized potentially inadequate methods and thus struggle to understand why they failed or why their mathematical models did not fit (Battista, 2001).

An alternative is helping students achieve a deeper conceptual understanding by letting them create their own solution methods. Lithner (2008) presented a research framework that characterizes different types of mathematical reasoning. In this framework rote learning and imitation-based mathematical reasoning are connected to *algorithmic reasoning* (AR). Learners recall and apply previously memorized solution methods or algorithms, but with no conceptual insight or reflection on why that method should be applied. AR is contrasted with *creative mathematical reasoning* (CMR), where students create solutions when encountering new problems. CMR is defined by three criteria: (1) Novelty: the learner creates a new solution method or re-creates a forgotten one; (2) Plausibility: The learner can make arguments supporting this choice of strategy and why conclusions reached through applying the method are true or plausible; and (3) Anchoring: these arguments must be anchored in the intrinsic mathematical properties of the components used in the reasoning sequence. This process of creating a new solution implies that the learners have less support or instructions provided to them. It is argued that allowing for struggle with mathematical problems facilitates learning and develops conceptual understanding (Hiebert and Grouws, 2007; Fyfe and Rittle-Johnson, 2017). Such mathematical struggle is a key aspect of CMR (Jonsson et al., 2016).

To date, several studies have consistently found that practicing non-routine mathematical problem solving with CMR tasks is superior to practicing with AR tasks for performance on post-test assessments (Jonsson et al., 2014, 2016, 2020a; Karlsson et al., 2015; Norqvist et al., 2019b). Moreover, using transfer tasks (untrained tasks), Jonsson et al. (2020a) found empirical evidence that practicing with CMR tasks enhanced conceptual understanding of mathematics better than practicing by AR tasks. The theoretical justification is that in order to solve a task without an available solution method, it is necessary to understand the underlying mathematics, while an AR task may be solved without activating such understanding by simply following a recipe.

A critical feature of these studies has been to include measures of individual differences in cognitive abilities, such as working memory and fluid intelligence. These constructs are well-established predictors for mathematical achievement (Carroll, 1993; Floyd et al., 2003; Andersson and Lyxell, 2007; Ashcraft and Krause, 2007; Campos et al., 2013; Peng et al., 2019). The overall finding is that cognitive ability is a strong predictor of performance but is independent of practice conditions (i.e., AR or CMR; Jonsson et al., 2020a).

Another factor of importance, but which has not previously been in focus, is the role that individual differences in intrinsic cognitive motivation play in learning, here operationalized through the construct Need for Cognition (NFC; Weissgerber et al., 2018). NFC is considered a stable personality trait defined as "differences among individuals in their tendency to engage in and enjoy thinking" (Cacioppo and Petty, 1982, p. 116). NFC is not a measure of intelligence or cognitive abilities *per se* but rather a reflection of individual preference to exert more cognitive effort (Hill et al., 2016; Sandra and Otto, 2018; Weissgerber et al., 2018). NFC has been shown to predict academic achievement (Elias and Loomis, 2002) and positive associations between NFC and numerical ability have been observed (Bruine, de Bruin et al., 2015). However, the relationship between NFC and the CMR/AR distinction is unexplored. NFC is positively related to personality traits such as Openness to Experience and Conscientiousness and has repeatedly been found to have a weak to modest positive correlation to fluid intelligence, averaging around $r = 0.20$ to $r = 0.30$ (Fleischhauer et al., 2010; Furnham and Thorne, 2013; Hill et al., 2013) as well as being predictive of school success in terms of grade point average (Strobel et al., 2019). Although Hill et al. (2013) found no relationship between NFC and working memory, a follow-up study showed that working memory mediated the relationship between NFC and intelligence (Hill et al., 2016). Hill et al. (2016) argued that average working memory abilities are necessary for NFC to have a positive effect on intelligence tests. Furthermore, a study by Gonthier and Roulin (2020) found that working memory capacity (WMC) and Need for Cognition (NFC) predicted the type of strategy used on intelligence tests (Raven's Advanced Progressive Matrices). High NFC and WMC were linked to the selection of more complex and accurate problem-solving strategies, and working memory moderated the shift toward simpler, less accurate strategies as the tasks grew more demanding. Individuals with both high NFC and WMC continued to use more complex and effective strategies throughout the tasks (Gonthier and Roulin, 2020). Albeit solving Ravens matrices is different from solving mathematical tasks it has been argued that there are many similarities between mathematical tasks typically used in schools and tasks on tests that aim to measure fluid intelligence (Blair et al., 2005).

The positive correlations between NFC, WMC and math achievements (e.g., Ashcraft and Krause, 2007; Hill et al., 2016) indicate that NFC and WMC influence math performance. Hence, as CMR tasks invoke struggle in students as a key part of the strategy's effectiveness (Jonsson et al., 2016), how engaged and motivated a student is to struggle with CMR tasks could be an important factor in their degree of success.

Based on previous finding that cognitive ability is a strong predictor of performance but is independent of practice conditions (CMR/AR) and the assumption that practicing with CMR tasks include struggle and that high NFC is associated with more complex task solving strategies, we posed three hypotheses: (1) practicing with CMR tasks is hypothesized to be superior to practicing with AR tasks on subsequent test performance (2) WMC is hypothesized to significantly predict test performance, independent of group. (3) NFC is hypothesized to significantly predict test performance for the CMR group but not the AR group.

MATERIALS AND METHODS

In the present study, we extend a previously published experiment Jonsson et al. (2020a, experiment 1), which in turn was part of a larger data collection, including a battery of nine cognitive tests (see Jonsson et al., 2020b for a detailed description of all cognitive tasks). In Jonsson et al. (2020a, experiment 1), two independent groups of upper secondary students engaged in practicing either CMR tasks ($N = 65$) or AR tasks ($N = 72$). They solved 14 CMR and AR task sets, respectively, and were tested 1 week later on two types of practiced tasks and two types of transfer test tasks (see below for a description of both post-test practiced and transfer tasks). Moreover, measures of fluid intelligence using Raven's Advanced Progressive Matrices (Raven et al., 2003) and a measure of complex working memory, denoted as operation span (Unsworth and Engle, 2005), were used to form a composite score of cognitive proficiency. A proficiency score that was entered together with group (AR/CMR) and math track (level of math education) as factors in a multivariate ANOVA. The multivariate ANOVA and four follow-up ANOVAs revealed significant CMR effects for all four different types of post-test tasks. The analyses also revealed a main effect of cognitive proficiency, but no multivariate group × cognitive proficiency interaction and no effect of math tracks. Hence the effect of group on the test tasks was independent of cognitive proficiency and math tracks.

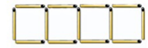
From the same data set, we here extracted measures of working memory assessing WMC and NFC in conjunction with a composite score of the four test tasks as the outcome variable. Working memory is important, for example, in the selection of non-verbal problem-solving strategies. Beilock et al. (2007) found that working memory influences students' mathematical problem-solving strategies. Working memory capacity is a key for controlling attention and inhibiting irrelevant information (Engle et al., 1999; Unsworth and Engle, 2005) and for retrieval from secondary memory (Shelton et al., 2010). Deficiencies in working memory have been connected to increased mathematical difficulties in children (Andersson and Lyxell, 2007).

Participants

One hundred and fifty students were enrolled in the study. Six participants dropped out, and an additional seven had to be discarded due to administrative errors, so the experiment included 137 Swedish upper secondary students from the north of Sweden (63 boys and 74 girls, mean age of 17.13, $SD = 0.62$). Participants were recruited in class, from both natural science and social science programs and randomly assigned to either the AR or the CMR group. All participants were fluent in Swedish. Written informed consent was obtained from the students in accordance with the Helsinki declaration. The Regional Ethics Committee at Umeå University, Sweden, approved the study (see Jonsson et al., 2020a, experiment 1 for details). Of those 137 participants, three did not answer all items in the NFC survey and one did not respond to all tasks in the post-test. For these participants, data were replaced using regression imputation in AMOS 27.

A *Practice AR-task, method provided.*

When squares are put in a row, it looks like the figure on the right, 13 matches are needed for four squares.



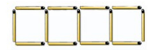
If x is the number of squares, then the number of matches y could be calculated by the function $y = 3x + 1$.

Example: If 4 squares are put in a row, then $y = 3x + 1 = 3 \times 4 + 1 = 13$ matches are needed.

How many matches are needed to get 100 squares in a row?

B *Practice CMR-task, constructing method.*

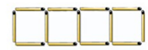
When squares are put in a row, it looks like the figure on the right, 13 matches are needed for four squares.



How many matches are needed to get 100 squares in a row?

C *Practice CMR-task, constructing formula*

When squares are put in a row, it looks like the figure on the right, 13 matches are needed for four squares.



If x is the number of squares put in a row and y is the number of matches needed to build the squares.

How could you describe y as a function of *x*?

FIGURE 1 | Examples of AR and CMR practice tasks and how they were presented to the students on their laptop screen. **(A)** AR practice task; **(B)** CMR tasks practice task; **(C)** CMR task asking for the formula.

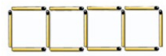
Materials

Practice Tasks

The practice tasks consisted of 14 × 2 task sets of corresponding items (14 for AR and 14 for CMR, respectively). Each set had 10 sub-tasks. The practice task sets used in this study were chosen randomly from a larger pool of 28 task sets, designed to lead students toward using AR and CMR, respectively (**Figures 1A,B**). The AR tasks were designed to be similar to tasks found in standard mathematic textbooks. For each AR task, both a solution method (algorithm) and an example of how it should be applied were provided (**Figure 1A**). For the CMR tasks, no further guidance, such as an algorithm or example, was given (**Figure 1B**). In all CMR task sets the third subtask was to construct a formula (**Figure 1C**). Students were given 4 min to complete each of the 14 task sets and if a participant finished all 10 subtasks, the software randomly re-sampled new numerical tasks until time ran out. This served to make sure the AR and CMR practice conditions were equally long.

A *Post-test numerical practiced task.*

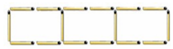
When squares are put in a row, it looks like the figure on the right, 13 matches are needed for four squares.



How many matches are needed to get 100 squares in a row?

B *Post-test numerical transfer task.*

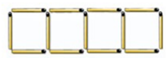
When rectangles are put in a row, it looks like the figure on the right, 16 matches are needed for three squares.



How many matches are needed to get 100 rectangles in a row?

C *Post-test formula practiced task.*

When squares are put in a row, it looks like the figure on the right, 13 matches are needed for four squares.

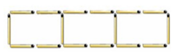


If x is the number of squares put in a row and y is the number of matches needed to build the squares.

How could you describe y as a function of x?

D *Post-test formula transfer task.*

When rectangles are put in a row, it looks like the figure on the right, 16 matches are needed for three squares.



If x is the number of rectangles put in a row and y is the number of matches needed to build the rectangles.

How could you describe y as a function of x?

FIGURE 2 | Examples of test tasks and how they were presented to the students on their laptop screen. **(A,C)** Practiced test tasks and **(B,D)** transfer test task.

Post-test Tasks

There were 21 post-test tasks, 14 of which had the same layout as the CMR practice tasks (but using different numbers) and were denoted as "numerical practiced task" and "formula practiced task" (**Figures 2A,C**). In addition, seven tasks differed from the practice session tasks, which were denoted as "numerical transfer tasks" and "formula transfer tasks" (**Figures 2B,D**). The transfer post-test tasks shared underlying solution ideas with the practice tasks, but could not be solved using the same formulas. The distinction between transfer test tasks and practiced test tasks is further described in Jonsson et al. (2020a; experiment 1). The time limit for the post-test tasks was 4 min. More extensive descriptions of both practiced tasks and test tasks can be found in Jonsson et al. (2014), Norqvist et al. (2019a), and Jonsson et al. (2020a) as well as in Supplementary Material provided with the Jonsson et al.'s (2020a) study.

Working Memory Measures

The working memory measures included were operation span (Unsworth and Engle, 2005), block span, and digit span assessing the central executive, spatial short term memory and phonological short term memory, respectively (Baddeley, 2003). In the operation span task, participants are instructed to do mathematical calculations. After each calculation, they are asked to maintain a letter (displayed for 800 ms) in their memory. They are then presented with a new mathematical task and asked to maintain both the previous and the new letter in their memory. After a full set is completed (each set contains three to seven letters), the participants are asked to identify the letters in the order they were presented. There were three sets of each size and the participants score was the sum of all correctly recalled sets (Unsworth and Engle, 2005). Operation span was administered via computer and self-paced. In the block span task participants were instructed to remember squared blocks presented on a computer screen in 4 × 4 matrices separated by an interstimulus interval of 1 s. The squares were presented as sequences of squares increasing in difficulty—from two squares, three squares, four squares.... up to a limit of 16 squares. After a delay of 2 s participants were prompted to tap on the squares in the same order as they were presented. The total number of perfectly recalled sequences was used as the dependent variable. In the digit span task, numbers between 1 and 9 were presented on the computer screen in random order with an interstimulus interval of 1 s. After a delay of 2 s, participants were prompted to recall the numbers in the same order as they were presented. The test started with a two-digit sequence and increased by one digit as long as the participants managed to repeat the correct sequence. The highest sequence length was used as dependent measure., See Jonsson et al. (2020b) for extensive descriptions of the tasks and their psychometric properties.

Need-for-Cognition

Need for Cognition was measured by the *Mental Effort Tolerance Questionnaire* (METQ; Dornic et al., 1991), a Swedish adaptation of the original NFC Scale by Cacioppo and Petty (1982). The METQ consists of 30 items that are rated on a 5-point Likert-like scale (from 1 = strongly disagree to 5 = strongly agree). 12 items indicate positive and 18 items negative attitudes toward engaging in cognitive activity. The negative attitude items are scored reversely. An example of a positive attitude item from the METQ scale is "It is important to ponder upon why things work as they do" (Dornic et al., 1991, p. 316). Stenlund and Jonsson (2017) evaluated the psychometric properties of the 30-item METQ scale and found good internal consistency ($\alpha = 0.88$) and test-retest reliability ($r = 0.88$). The high internal consistency and high test-re-test reliability indicate that the full 30 item NFC scale is a valid and reliable measure.

The working memory tasks and METQ, were selected due to their known associations with math performance and mathematical problem-solving strategies tasks (e.g., Beilock et al., 2007; Gonthier and Roulin, 2020) as well as their good psychometric properties. See Jonsson et al. (2020b) for extensive descriptions of the tasks and their psychometric properties.

Procedure

In a between-group design, the participants were randomly assigned to either the AR or CMR groups (N = 72 and 65, respectively). The working memory measures and the NFC survey were completed 1 week before the practice session, and there was 1 week between the practice and post-test sessions.

During the training session students worked individually, receiving mathematics tasks and submitting answers through a computer. We recognize that both cooperative and individual learning can be valuable (e.g., Cross, 2009; OECD, 2017; Parveen et al., 2017) in ordinary classrooms. The individual approach in this study was motivated by the ambition to link individual measures of working memory and NFC to mathematical practice and posttest performance. After a student submitted an answer, the correct answer was displayed. No such feedback was given after the formula construction tasks (the third CMR task). This was to prevent the CMR task from turning into an AR task, as the students could then memorize the formula and apply it to later subtasks instead of constructing their own solution.

For the post-test session, the practiced and transfer tasks could be further split into numerical and formula tasks. In the formula tasks for both practiced and transfer tasks, the students were asked to write down the formula (**Figures 2C,D**). The practiced tasks were presented before the transfer tasks. The first task for both practiced and transfer tasks was a formula task and the second a numerical task.

Both the practice and the post-test sessions were conducted in the students' classroom. No teacher or peer support was available, but the students were offered the assistance of a simple virtual calculator displayed on the screen of their laptops. The software used automatically corrected and saved the students' answers during both the practice and post-test sessions. For additional examples and descriptions of the tasks used in this study, see Norqvist et al. (2019a).

Statistical Analyses

In Jonsson et al. (2020a, experiment 1) the statistical analyses showed that training with CMR tasks was superior to training with AR tasks on all four types of test tasks: retrieving the formula from memory for both practiced- and transfer tasks and solving numerical practiced- and transfer tasks. In order to reduce the number of models, we collapsed the four test tasks (two practiced and two transfer tasks) used in Jonsson et al. (2020a, experiment 1) to a composite overall measure of performance, denoted as composite test performance (C-TP).

The working memory measures were used as indicators of a latent WMC factor, while the items in the NFC scale, with a Chronbachs alpha of 0.89, were collapsed to form a composite score of NFC.

First, the descriptive information of the study sample was summarized followed by zero-order correlations between all the variables included in the analyses (see **Tables 1**, **2**). Second, to confirm the AR-CMR group differences found in Jonsson et al. (2020a, experiment 1), an initial *t*-test of the composite test scores was conducted. Third, three structural equation models (SEM) investigated the effects of WMC and NFC on C-TP (the dependent variable). The first model included all participants, the second and third analyzed CMR and AR groups separately. Due to the known correlation between WMC and NFC (e.g., Stenlund and Jonsson, 2017; Gonthier and Roulin, 2020), the models covary the latent factor WMC with NFC. Three fit indices were used to evaluate the models, including the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and χ^2 divided by degrees of freedom. To attain an acceptable fit for CFI, the value must be equal to or greater than 0.95 (Browne and Cudeck, 1989). RMSEA values need to be equal to or less than 0.06 to attain a good model fit and 0.08 for a reasonable fit (Browne and Cudeck, 1989; Hu and Bentler, 1999). Note that the sample sizes used in the group specific analyses could be regarded as low (Kline, 2013). However, Tanaka (1987) argued that a sample size of 50 could be enough when the model is simple. The models in this study contain only one exogenous latent factor, one exogenous manifest variable and one endogenous variable. The data were analyzed using SPSS (IBM Corporation, Armonk, NY, United States) and AMOS 27 (Arbuckle, 2016) with bias-corrected percentile method as bootstrapping procedure.

Ethical Considerations

The data used in this study were obtained as part of a research project that has been approved by the Regional Ethical Review Board in Umeå. The process of collecting the data followed current principles and guidelines as specified by the Swedish Research Council. Written informed consent was obtained from each participant.

RESULTS

Descriptive statistics and correlations between the continuous variables can be seen in **Tables 1**, **2**, respectively. All continuous variables were approximately normally distributed, with values below 0.81 for both skewness and kurtosis. No values outside a third interquartile range were detected. *T*-tests confirmed that the groups were equal with respect to NFC, operation span, digit span and block span, all p's > 0.17), meaning that the two groups can be considered to be equal when it comes to working memory and NFC. The correlations were significant, except for the correlation between block span and NFC (see **Table 2**). The initial *t*-test confirmed as expected that participants in the CMR group outperformed their counterparts in the AR group $t(135) = 3.44, p < 0.001$.

TABLE 1 | Descriptive statistics for the continuous variables.

	C-TP	Operation span	Block span	Digit span	NFC
CMR	0.297 (0.216)	32.231 (16.668)	13.754 (2.616)	3.108 (1.047)	102.776 (16.340)
AR	0.179 (0.182)	30.875 (16.152)	13.466 (2.959)	3,278 (1,224)	99.139 (14.674)

Mean values with standard deviation in the parentheses. CMR, Creative Mathematical Reasoning group; AR, Algorithmic Reasoning group: C-TP, Composite Test Performance; NFC, Need for Cognition.

TABLE 2 | Pearson's correlations.

Variables	1	2	3
1. O span	—		
2. Digit span	0329***	—	
3. Block span	0.388***	0.185*	—
4. NFC	0.301***	0.190*	$0.08P^{ns}$

****p < 0.0001; *p < 0.05.*

Figures 3A–C shows the SEM models with regression weights for the overall model (a), the CMR group (b) and the AR group (c), separately. The results of standardized and unstandardized beta weights, standard error and p-values from the SEM analyses accompanied by bootstrapping (95% CI) and p-values can be seen in **Table 3**. The overall model indicated reasonable fit with CFI = 0.975, RMSEA = 0.066, $\chi^2/df = 1.60$, $p = 0.172$, explaining 42% of the variance for C-TP. The model fit for CMR was excellent; CFI = 1.00, RMSEA = 0.000, $\chi^2/df = 0.81$, $p = 0.516$, explaining 50% of the variance for C-TP. Model fit was a bit lower for AR; CFI = 0.925, RMSEA = 0.105, $\chi^2/df = 1.78$, $p = 0.129$, explaining 35% of the variance for C-TP. The direct effect of WMC on C-TP was almost identical across groups. The most apparent difference was that the NFC > C-TP path was significant for the CMR model ($\beta = 0.26$) but not for the AR model ($\beta = 0.00$) (see **Table 3** for details). However, constraining the NFC > C-TP path and performing a Boostrapping, bias-corrected percentile significant test did not reach a significant between group difference, $p = 0.15$.

DISCUSSION

How to help students better develop a conceptual understanding of mathematics is under scrutiny and is regarded as an important question (e.g., Loveless, 2004; Lithner, 2008, 2017). One suggested solution is to help students build conceptual understanding by constructing their own solution methods, denoted using *CMR* (Lithner, 2008, 2017). CMR is often contrasted against the more common method based on imitative reasoning, *AR*. Several previous publications have shown that practicing with CMR tasks when students construct the solution is superior to AR (Jonsson et al., 2014, 2016, 2020a; Norqvist et al., 2019b).

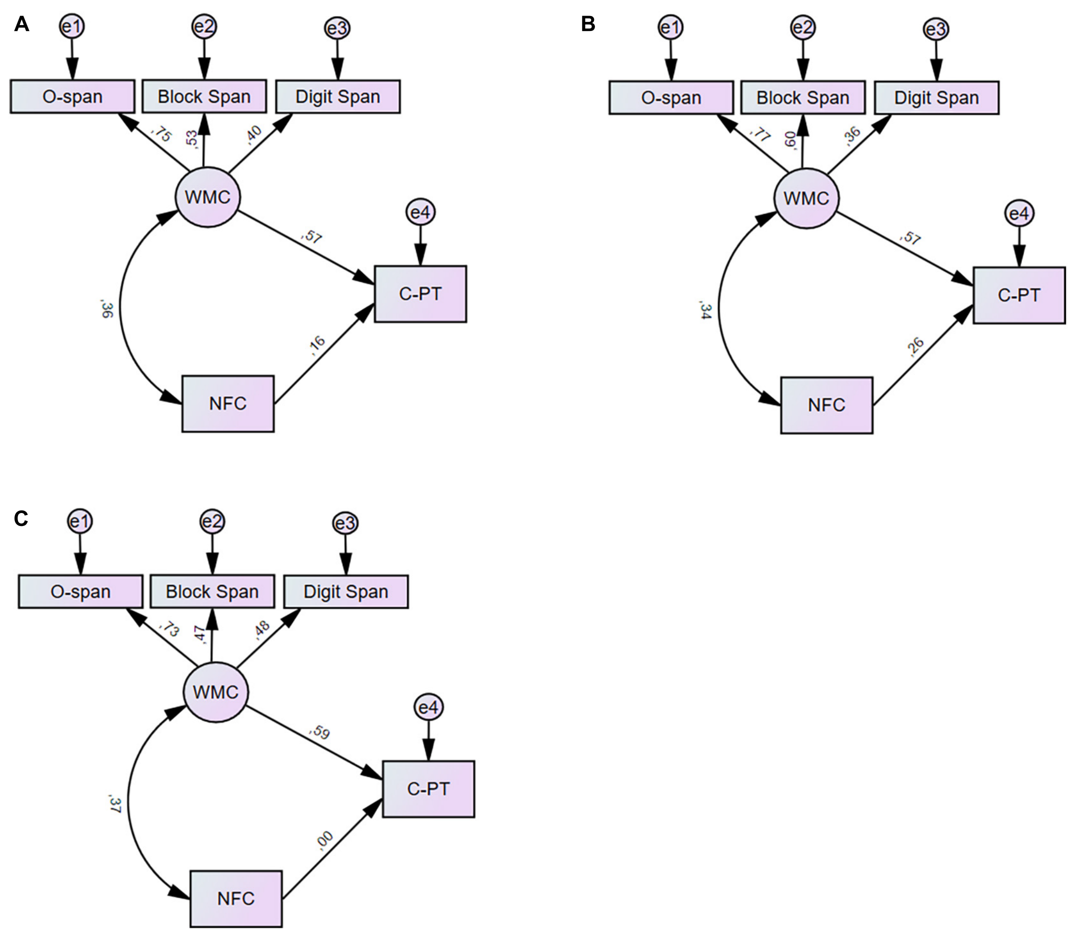


FIGURE 3 | The figure shows the standardized regression weights for both groups **(A)**, CMR **(B)** and AR **(C)**, separately. C-PT, composite test performance; WMC, Working memory capacity; NFC, Need for Cognition.

TABLE 3 | Path analyses with test task performance as dependent variable.

					Bootstrapping (BC 95% CI)		
Overall	**β**	***B***	**S.E**	***p***	**Lower**	**Higher**	***p***
WMC → C-TP	0.571	0.259	0.076	<0.001	0.132	0.576	0.001
NFC → C-TP	0.163	0.002	0.001	0.059	0.000	0.005	0.108
WMC → Digit span	0.400*						
WMC → O-span	0.749	26.773	7.364	<0.001	17.035	53.329	0.001
WMC → Block span	0.533	3.255	0.951	<0.001	1.742	6.849	0.001
CMR group							
WMC → C-TP	0.572	0.325	0.141	0.021	0.148	1.049	0.002
NFC → C-TP	0.263	0.003	0.002	0.021	0.000	0.008	0.037
WMC → Digit span	0.364*						
WMC → O-span	0.774	33.801	13.963	0.015	15.498	160.732	0.001
WMC → Block span	0.601	4.120	1.756	0.019	1.729	16.225	0.001
AR group							
WMC → C-TP	0.594	0.185	0.068	0.007	0.072	1.186	0.005
NFC → C-TP	0.003	0.000	0.002	0.980	−0.004	0.003	0.970
WMC → Digit span	0.478*						
WMC → O-span	0.735	20.256	6.781	0.003	10.382	52.447	0.001
WMC → Block span	0.601	2.371	0.914	0.009	0.679	10.786	0.013

*BC, bias corrected; 2,000 bootstrap samples; β, Standardized regression weight; B, Unstandardized regression weight; P, Significance of Estimates; *Constrained parameter.*

However, to what extent intrinsic cognitive motivation influences performance has not been investigated. Here we extended a previous publication (Jonsson et al., 2020a, experiment 1) by assessing the influence of NFC and WMC on math performance independent of group and separately for CMR and AR groups. To reduce the number of parameters, we collapsed the four dependent measures used in Jonsson et al. (2020a, experiment 1) to a composite score (C-TP), assessing participants overall performance. The initial analyses of the psychometric properties showed that all continuous variables were normally distributed and that the groups were equal regarding the cognitive ability measures and NFC. In line with previous studies, it was hypothesized that practicing with CMR tasks should be superior to practicing with AR tasks on subsequent test performance. It was hypothesized that NFC would be predictive of performance for the CMR group but not for the AR group. It was also hypothesized that WMC would predict performance for both groups.

The initial t-test of group difference based on the composite score of the four dependent variables used in Jonsson et al. (2020a, experiment 1) was significant. Hence participants in the CMR group outperformed their counterparts in the AR group, as indicated in **Table 1**, confirming hypothesis 1. This result also replicated other previous findings (Jonsson et al., 2014, 2016; Norqvist et al., 2019b), adding to a growing pile of evidence showing the positive effects of encouraging students to train creative mathematical reasoning.

The second hypothesis was confirmed, showing that the measure of NFC did predict mathematical performance following CMR—but not AR training. This finding is in line with the argument that NFC support selection of more complex and accurate problem-solving strategies (Rudolph et al., 2018; Gonthier and Roulin, 2020). To note is that the group comparison for the NFC > C-TP path did not reach significance. However, it seems likely that this is a question of power. In addition, in all three SEM analyses, we covary NFC and WMC, thereby controlling for the combined effects of NFC and WMC.

The third hypothesis, that WMC would predict mathematical performance on the post-test independent of group was also confirmed. The main effect of WMC is in line with established research on the effects of cognitive abilities on mathematical performance (e.g., Campos et al., 2013; Peng et al., 2019). The fact that the effect of WMC was obtained independent of group indicates that using CMR is not only for the cognitively stronger students. However, the positive correlation between WMC, and NFC, and the effect of NFC on CMR tasks implies that the motivation to engage in cognitively strenuous tasks is higher among those with higher WMC. From a didactical perspective, it is therefore critical to allow, provide time, and encourage all students to struggle with mathematical problems to create their own task solutions. Thereby, CMR training could be accessible and effective even for students who lack the motivation to engage in cognitively strenuous mathematical tasks.

Limitations and Future Research

The psychometric properties, tight SEM models, and hypothesis-driven analyses are strengths. With that said, the significant effects of NFC must be interpreted with caution, partly due to the relatively low sample size and that this is the first study that focused on NFC and creative mathematical reasoning. Another important note is that the sample was restricted to upper secondary students. Since NFC is known no develop over time, and the correlation with WMC is relatively high, the external validity in terms of generalizability to younger students is difficult to assess.

We hope that this first study on the influence of intrinsic cognitive motivation regarding creative and algorithmic mathematical reasoning will encourage researchers to conduct more studies. Considering the developmental paths of both NFC and cognitive ability, a longitudinal within-subject approach would be desirable.

Although more research is needed, we emphasize the need to provide time and opportunities for struggle with creative mathematical tasks, thereby enhancing students conceptual understanding. With that said, we have in previous studies discussed the potential of combining the CMR approach with other validated methods that are designed to facilitate mathematical understanding, such as worked example, self-explanation and retrieval practice. Regarding retrieval practice and CMR, we have in a recent publication (Stillesjö et al., 2021) demonstrated common neurocognitive long-term memory effects by using functional magnetic brain imaging (fMRI). The brain imaging data indicate that active learning conditions, such as CMR and retrieval practice engage a shared brain network with higher functional brain activity for these learning methods when compared to more passive such as re-study and AR, despite dissimilar study material (math problems for CMR and Swahili vocabulary for retrieval practice). These findings are argued to be related to the formation and reactivation of semantic representations and raise the question and potential of combining retrieval practice with CMR. It is also interesting to discuss the potential to integrate CMR with cooperative learning. Indeed, an initial study focusing on collaborative learning using CMR tasks has, as pointed out above, been conducted (Granberg and Olsson, 2015). Designing situations which invite to cooperative struggle with CMR tasks seems feasible and a productive way to move forward. However, the effects of combining CMR with retrieval practice or cooperative learning is at the end of the day an empirical question.

CONCLUSION

In summary, this study demonstrates that training with CMR tasks yields better mathematical performance than AR tasks and that cognitive abilities strongly affect mathematical performance independent of group. These results add to a stable pattern of CMR, showing good effects on mathematical performance and strengthening its viability as an educational strategy. Although WMC was a significant and robust predictor, the effects were equally strong in both groups. The influence of NFC on performance for those that had practiced with CMR tasks seems logical in relation to the structure of CMR tasks and the NFC construct.

DATA AVAILABILITY STATEMENT

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

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Regional Ethics Committee at Umeå University. 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

BJ, LK, JL, and JM came up with the idea for the study and jointly contributed to the study's conceptualization, and revised the manuscript for important intellectual content. BJ performed the statistical analysis and wrote the first draft of the manuscript, whereby all authors contributed to the manuscript and read and approved the submitted version.

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REFERENCES

Andersson, U., and Lyxell, B. (2007). Working memory deficit in children with mathematical difficulties: a general or specific deficit? *J. Exp. Child Psychol.* 96, 197–228. doi: 10.1016/j.jecp.2006.10.001

Arbuckle, J. (2016). *IBM® SPSS® Amos^{TM} User's Guide*. Chicago, IL: SmallWaters.

Ashcraft, M. H., and Krause, J. A. (2007). Working memory, math performance, and math anxiety. *Psychon. Bull. Rev.* 14, 243–248. doi: 10.3758/BF03194059

Baddeley, A. (2003). Working memory and language: an overview. *J. Commun. Disord.* 36, 189–208. doi: 10.1016/s0021-9924(03)00019-4

Battista, M. (2001). "Research and reform in mathematics education," in *The Great Curriculum Debate: How Should We Teach Reading and Math*, ed. T. Loveless (Washington, DC: Brookings Institution Press).

Beilock, S. L., Rydell, R. J., and McConnell, A. R. (2007). Stereotype threat and working memory: mechanisms, alleviation, and spillover. *J. Exp. Psychol. Gen.* 136, 256–276. doi: 10.1037/0096-3445.136.2.256

Bergqvist, E. (2007). Types of reasoning required in university exams in mathematics. *J. Math. Behav.* 26, 348–370. doi: 10.1016/j.jmathb.2007.11.001

Bergqvist, T., and Lithner, J. (2012). Mathematical reasoning in teachers' presentations. *J. Math. Behav.* 31, 252–269. doi: 10.1016/j.jmathb.2011.12.002

Blair, C., Gamson, D., Thorne, S., and Baker, D. (2005). Rising mean IQ: cognitive demand of mathematics education for young children, population exposure to formal schooling, and the neurobiology of the prefrontal cortex. *Intelligence* 33, 93–106. doi: 10.1016/j.intell.2004.07.008

Boesen, J., Helenius, O., Bergqvist, E., Bergqvist, T., Lithner, J., Palm, T., et al. (2014). Developing mathematical competence: from the intended to the enacted curriculum. *J. Math. Behav.* 33, 72–87. doi: 10.1186/s40594-017-0089-9

Boesen, J., Lithner, J., and Palm, T. (2010). The relation between types of assessment tasks and the mathematical reasoning students use. *Educ. Stud. Math.* 75, 89–105. doi: 10.1186/s12913-016-1423-5

Browne, M. W., and Cudeck, R. (1989). Single sample cross-validation indices for covariance structures. *Multivariate Behav. Res.* 24, 445–455. doi: 10.1207/s15327906mbr2404_4

Bruine, de Bruin, W., McNair, S. J., Taylor, A. L., Summers, B., and Strough, J. (2015). "Thinking about numbers is not my idea of fun":need for cognition mediates age differences in numeracy performance. *Med. Decis. Making* 35, 22–26. doi: 10.1177/0272989X14542485

Cacioppo, J. T., and Petty, R. E. (1982). The need for cognition. *J. Pers. Soc. Psychol.* 42, 116–131. doi: 10.1037/0022-3514.42.1.116

Campos, I. S., Almeida, L. S., Ferreira, A. I., Martinez, L. F., and Ramalho, G. (2013). Cognitive processes and math performance: a study with children at third grade of basic education. *Eur. J. Psychol. Educ.* 28, 421–436. doi: 10.1007/s10212-012-0121-x

Carroll, J. B. (1993). *Human Cognitive Abilities: a Survey of Factor-Analytic Studies*. Cambridge: Cambridge University Press. doi: 10.1017/CBO9780511571312

Cross, D. I. (2009). Creating optimal mathematics learning environments: combining argumentation and writing to enhance achievement. *Int. J. Sci. Math. Educ.* 7, 905–930. doi: 10.1007/s10763-008-9144-9

Dornic, S., Ekehammar, B., and Laaksonen, T. (1991). Tolerance for mental effort: self-ratings related to perception, performance and personality. *Pers. Individ. Differ.* 12, 313–319. doi: 10.1016/0191-8869(91)90118-u

Elias, S. M., and Loomis, R. J. (2002). Utilizing need for cognition and perceived self-efficacy to predict academic performance1. *J. Appl. Soc. Psychol.* 32, 1687–1702. doi: 10.1111/j.1559-1816.2002.tb02770.x

Engle, R. W., Kane, M. J., and Tuholski, S. W. (1999). Individual differences in working memory capacity and what they tell us about controlled attention, general fluid intelligence, and functions of the prefrontal cortex. *Models of Working Memory: Mechanisms of Active Maintenance and Executive Control*, eds A. Miyake and P. Shah (Cambridge: Cambridge University Press). doi: 10.1017/CBO9781139174909.007

Fleischhauer, M., Enge, S., Brocke, B., Ullrich, J., Strobel, A., and Strobel, A. (2010). Same or different? clarifying the relationship of need for cognition to personality and intelligence. *Pers. Soc. Psychol. Bull.* 36, 82–96. doi: 10.1177/0146167209351886

Floyd, R. G., Evans, J. J., and McGrew, K. S. (2003). Relations between measures of cattell-horn-carroll (CHC) cognitive abilities and mathematics achievement across the school-age years [Review]. *Psychol. Sch.* 40, 155–171. doi: 10.1002/pits.10083

Furnham, A., and Thorne, J. D. (2013). Need for cognition. *J. Individ. Differ.* 34, 230–240. doi: 10.1027/1614-0001/a000119

Fyfe, E. R., and Rittle-Johnson, B. (2017). Mathematics practice without feedback: a desirable difficulty in a classroom setting. *Instr. Sci.* 45, 177–194. doi: 10.1007/s11251-016-9401-1

Gollub, J. P. (2002). *Learning and Understanding: Improving Advanced Study of Mathematics and Science in U.S. High Schools*. Washington, DC: National Academy Press.

Gonthier, C., and Roulin, J.-L. (2020). Intraindividual strategy shifts in Raven's matrices, and their dependence on working memory capacity and need for cognition. *J. Exp. Psychol. Gen.* 149, 564–579. doi: 10.1037/xge0000660

Granberg, C., and Olsson, J. (2015). ICT-supported problem solving and collaborative creative reasoning: Exploring linear functions using dynamic mathematics software. *J. Math. Behav.* 37, 48–62. doi: 10.1016/j.jmathb.2014.11.001

Hiebert, J., and Grouws, D. A. (2007). "The effects of classroom mathematics teaching on students' learning," in *Second Handbook of Research on Mathematics Teaching and Learning*, ed. F. K. Lester (Charlotte: Information Age Publishing).

Hill, B. D., Foster, J. D., Elliott, E. M., Shelton, J. T., McCain, J., and Gouvier, W. D. (2013). Need for cognition is related to higher general intelligence, fluid intelligence, and crystallized intelligence, but not working memory. *J. Res. Pers.* 47, 22–25. doi: 10.1016/j.jrp.2012.11.001

Hill, B. D., Foster, J. D., Sofko, C., Elliott, E. M., and Shelton, J. T. (2016). The interaction of ability and motivation: average working memory is required for Need for Cognition to positively benefit intelligence and the effect increases with ability. *Pers. Individ. Differ.* 98, 225–228. doi: 10.1016/j.paid.2016.04.043

Hu, L. T., and Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. *Struct. Equ. Modeling Multidisciplinary J.* 6, 1–55. doi: 10.1080/10705519909540118

Jäder, J., Lithner, J., and Sidenvall, J. (2019). Mathematical problem solving in textbooks from twelve countries. *Int. J. Math. Educ. Sci. Technol.* 51, 1120–1136. doi: 10.1080/0020739X.2019.1656826

Jonsson, B., Granberg, C., and Lithner, J. (2020a). Gaining mathematical understanding: the effects of creative mathematical reasoning and cognitive proficiency. *Front. Psychol.* 11:574366. doi: 10.3389/fpsyg.2020.574366

Jonsson, B., Kulaksiz, Y. C., and Lithner, J. (2016). Creative and algorithmic mathematical reasoning: effects of transfer-appropriate processing and effortful struggle. *Int. J. Math. Educ. Sci. Technol.* 47, 1206–1225. doi: 10.1080/0020739x.2016.1192232

Jonsson, B., Norqvist, M., Liljekvist, Y., and Lithner, J. (2014). Learning mathematics through algorithmic and creative reasoning. *J. Math. Behav.* 36, 20–32. doi: 10.1016/j.jmathb.2014.08.003

Jonsson, B., Wiklund-Hörnqvist, C., Stenlund, T., Andersson, M., and Nyberg, L. (2020b). A learning method for all: the testing effect is independent of cognitive ability. *J. Educ. Psychol.* 113, 972–985. doi: 10.1037/edu0000627

Karlsson, W. L., Lithner, J., Jonsson, B., Liljekvist, Y., Norqvist, M., et al. (2015). Learning mathematics without a suggested solution method: Durable effects on performance and brain activity. *Trends Neurosci. Educ.* 4, 6–14. doi: 10.1016/j.tine.2015.03.002

Kline, P. (2013). *Handbook of Psychological Testing*. Milton Park: Routledge. doi: 10.4324/9781315812274

Lithner, J. (2008). A research framework for creative and imitative reasoning. *Educ. Stud. Math.* 67, 255–276. doi: 10.1007/s10649-007-9104-2

Lithner, J. (2017). Principles for designing mathematical tasks that enhance imitative and creative reasoning. *ZDM* 49, 937–949. doi: 10.1007/s11858-017-0867-3

Loveless, T. (2004). *The Great Curriculum Debate: How Should We Teach Reading and Math?* Washington, DC: Brookings Institution Press.

Norqvist, M., Jonsson, B., Lithner, J., Qwillbard, T., and Holm, L. (2019b). Investigating algorithmic and creative reasoning strategies by eye tracking. *J. Math. Behav.* 55:100701. doi: 10.1016/j.jmathb.2019.03.008

Norqvist, M., Jonsson, B., and Lithner, J. (2019a). Eye-tracking data and mathematical tasks with focus on mathematical reasoning. *Data Brief* 25:104216. doi: 10.1016/j.dib.2019.104216

OECD (2017). *PISA 2015 Results (Volume V): Collaborative Problem Solving, PISA*. Paris: OECD Publishing.

Parveen, Q., Yousuf, M. I., and Mustafa, S. (2017). An experimental study on the effect of cooperative learning on students' academic achievement and students' perceptions towards cooperative learning. *Anthropologist* 27, 69–76.

Peng, P., Wang, T., Wang, C., and Lin, X. (2019). A meta-analysis on the relation between fluid intelligence and reading/mathematics: effects of tasks, age, and social economics status. *Psychol. Bull.* 145, 189–236. doi: 10.1037/bul0000182

Raven, J., Raven, J. C., and Court, J. H. (2003). *Manual for Raven's Progressive Matrices and Vocabulary Scales*. San Antonio, TX: Harcourt Assessment.

Rudolph, J., Greiff, S., Strobel, A., and Preckel, F. (2018). Understanding the link between need for cognition and complex problem solving. *Contemp. Educ. Psychol.* 55, 53–62. doi: 10.3138/jvme.37.2.165

Sandra, D. A., and Otto, A. R. (2018). Cognitive capacity limitations and need for cognition differentially predict reward-induced cognitive effort expenditure. *Cognition* 172, 101–106. doi: 10.1016/j.cognition.2017.12.004

Shelton, J. T., Elliott, E. M., Matthews, R. A., Hill, B. D., and Gouvier, W. D. (2010). The relationships of working memory, secondary memory, and general fluid intelligence: working memory is special. *J. Exp. Psychol. Learn. Mem. Cogn.* 36, 813–820. doi: 10.1037/a0019046

Shield, M., and Dole, S. (2013). Assessing the potential of mathematics textbooks to promote deep learning. *Educ. Stud. Math.* 82, 183–199. doi: 10.1007/s10649-012-9415-9

Skolverket (2019). *Läroplan för Grundskolan, Förskoleklassen och Fritidshemmet 2011 : Reviderad 2019*. Sweden: Skolverket.

Stenlund, T., and Jonsson, B. (2017). Assessing the willingness to elaborate among young students: psychometric evaluation of a swedish need for cognition scale [original research]. *Front. Educ.* 2:2. doi: 10.3389/feduc.2017.00002

Stillesjö, S., Karlsson Wirebring, L., Andersson, M., Granberg, C., Lithner, J., Jonsson, B., et al. (2021). Active math and grammar learning engages overlapping brain networks. *Proc. Natl. Acad. Sci. U.S.A.* 118:e2106520118. doi: 10.1073/pnas.2106520118

Strobel, A., Behnke, A., Gärtner, A., and Strobel, A. (2019). The interplay of intelligence and need for cognition in predicting school grades: a retrospective study. *Pers. Individ. Differ.* 144, 147–152. doi: 10.1016/j.paid.2019.02.041

Stylianides, A. J., and Stylianides, G. J. (2007). Learning mathematics with understanding: a critical consideration of the learning principle in the principles and standards for school mathematics. *Mathematics Enthusiast* 4, 103–114.

Tanaka, J. S. (1987). "How big is big enough?": sample size and goodness of fit in structural equation models with latent variables. *Child Dev.* 58, 134–146. doi: 10.2307/1130296

Unsworth, N., and Engle, R. W. (2005). Working memory capacity and fluid abilities: examining the correlation between operation span and raven. *Intelligence* 33, 67–81. doi: 10.1016/j.intell.2004.08.003

Weissgerber, S. C., Reinhard, M.-A., and Schindler, S. (2018). Learning the hard way: need for cognition influences attitudes toward and self-reported use of desirable difficulties. *Educ. Psychol.* 38, 176–202. doi: 10.1080/01443410.2017.1387644

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Working Memory and Its Mediating Role on the Relationship of Math Anxiety and Math Performance: A Meta-Analysis

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It is well established that math anxiety has a negative relationship with math performance (MP). A few theories have provided explanations for this relationship. One of them, the Attentional Control Theory (ACT), suggests that anxiety can negatively impact the attentional control system and increase one's attention to threat-related stimuli. Within the ACT framework, the math anxiety (MA)—working memory (WM) relationship is argued to be critical for math performance. The present meta-analyses provides insights into the mechanisms of the MA—MP relation and the mediating role of WM. Through database searches with pre-determined search strings, 1,346 unique articles were identified. After excluding non-relevant studies, data from 57 studies and 150 effect sizes were used for investigating the MA—MP correlation using a random-effects model. This resulted in a mean correlation of $r = -0.168$. The database search of WM as a mediator for the MA—MP relation revealed 15 effects sizes leading to a descriptive rather than a generalizable statistic, with a mean indirect effect size of −0.092. Overall, the results confirm the ACT theory, WM does play a significant role in the MA—MP relationship.

Keywords: math anxiety, math performance, meta-analysis, working memory, Attentional Control Theory (ACT)

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INTRODUCTION

It is well established that there is a negative relationship between math anxiety (MA) and math performance (MP; Namkung et al., 2019). There are a few theories that explain how MA affects MP. One that has gained a steady foothold in the literature is the Attentional Control Theory (ACT; Eysenck et al., 2007), which stipulates that anxiety can deplete cognitive resources, which is vital for computing math-related problems. Unexpectedly, there are no systematic literature studies that have explicitly looked at (I) the relationship between MA and WM, and (II) the mediating effect of working memory (WM) on the relationship of MA predicting MP, despite the ACT being the dominant theory. In line with the ACT, the literature points out that MA can deprive WM resources that are needed for complex math computation (see Ashcraft and Krause, 2007 for an overview). This systematic literature study and meta-analysis address these research gaps by synthesizing research that has studied the MA—WM link and WM's mediating effect on the MA—MP relationship.

Math Anxiety, Working Memory and Performance

MA, which has been of concern for social science researchers since at least the 1950's (Dreger and Aiken, 1957), is commonly defined as feelings of fear, apprehension and tension that interfere when performing math-related activities (Ashcraft, 2002). Math is the single most strenuous subject in the school curriculum which can cause emotions comparable to phobia (Ashcraft and Ridley, 2005), and has been shown to correlate with other types of anxieties, such as test anxiety (Kazelskis et al., 2000; Ashcraft, 2002). Although the two constructs have in some cases shown to correlate strongly with each other, it has been possible to distinguish one from the other through confirmatory factor analysis (Kazelskis et al., 2000).

Ramirez et al. (2018) suggested three potential explanations for MA. The first is framed as the *deficit theory* in which poor math skills explain MA. Ma and Xu (2004) conducted a longitudinal study and found that lower math achievement predicted higher MA. The second is framed as a genetic predisposition. Wang et al. (2014) studied a sample of 514 twin-siblings ($m = 12.25$ years), and their results suggested that ~40% of the variation in MA is due to genetic predispositions, the variation left is caused by environmental factors specific to the child. The third is framed as socio-environmental factors, arguing that children in the lower grades can inherit some of their parents MA, though only if their MA parents reported to frequently support their child (Maloney et al., 2015). On the other hand, Vukovic et al. (2013b) reported that parental involvement in their child's learning significantly reduced MA, which led to an increase in MP (the phenomena was observed in algebraic and word problems, not whole arithmetic problems).

Ashcraft and Moore (2009) propose a risk-factor model of MA which consists of (I) deficits in MP (deficit theory), (II) lack of motivation and (III) weak WM. WM becomes a more relevant factor once the child faces more complex math than single digit arithmetical tasks. Although the developmental aspect of MA is still in need of more research, especially in younger participants to better understand the onset and progression of MA, some studies have found early indications of MA. For example, Mononen et al. (2021) found that MA growth was negatively related to growth in MP in participants as young as 6-year-olds. Another perspective is to what extent MA can arise as soon as formal school is introduced (Maloney and Beilock, 2012). Ashcraft and Moore's (Ashcraft and Moore, 2009) review suggests that MA strengthens in middle school, and peaks around grade 9 or 10.

Concerning the MA—MP link, two diametrically opposite models have been researched in attempts to identify the causality between the two variables (Carey et al., 2016). (I) The Deficit Theory, assuming that poor MP causes MA, was supported in Passolunghi's (2011) study, where children with math learning disabilities exhibited higher MA. In a longitudinal study of Finnish students in grade 3–5, Sorvo et al. (2019) found that arithmetic achievement predicted MA one year later, MA on the other hand, didn't predict later math achievement. The opposing theory, (II) the Debilitating Anxiety Model implies that MA leads to poorer MP. These models combined suggest a reciprocal model (Carey et al., 2016). Other longitudinal studies have provided evidence of reciprocal effects, (Ma and Xu, 2004; Gunderson et al., 2018). Although the relationship between MA and MP may be of a reciprocal nature, in the current study we approached this relationship from the Debilitating Anxiety model by adopting the ACT. Further research is necessary to better understand the MA—MP relation, potentially by addressing influences of individual differences. For instance, Chang and Beilock (2016) discuss the reciprocal relationship between MA and MP and whether individual differences can explain the MA—MP relationship, such as (a) variations in individual cognitive, affective, and motivational factors and (b) environmental factors that consist of teachers and parental MA, and student's perceived classroom environment. In the present study, we focus on WM, a subconstruct of cognition. We use our WM to retrieve the information needed to solve math tasks, keep relevant information about the salient problem, and inhibit irrelevant information.

According to Baddeley and Hitch's (1974) definition of WM, the construct comprises an attentional control system (the central executive), a modality-free processor able to monitor, plan, manipulate information, and select strategies to complete the tasks at hand. This control system is accompanied by two sub-systems: the visuospatial sketchpad and the phonological loop. The WM model has proven to be long-lasting and is referenced in a wide range of research areas (Baddeley, 2010). An additional component was subsequently proposed, namely the episodic buffer, which supposedly is a passive, multimodal storage system that integrates with the subsidiary systems as well as the long-term memory in holding episodic information (Baddeley, 2000). Working memory has consistently been shown to predict math performance (Swanson and Kim, 2007; De Smedt et al., 2009; Wiklund-Hörnqvist et al., 2016). If the math task induces anxiety, the ability of our working memory to maintain information online, and store and retrieve information from long-term memory will be reduced (Ashcraft and Kirk, 2001; Ramirez et al., 2013). Hence, the cognitive processing associated with the to-be-solved mathematical task in combination with math anxiety can overload the working memory system which, consequently, will reduce one's MP. This fits well with the ACT proposition, though one important detail that is vital to the ACT is that anxiety affects processing efficiency (effort spent on a task in relation to performance effectiveness) to a further extent than performance effectiveness (quality of performance; Eysenck et al., 2007). According to the ACT, anxiety impairs attentional processes relevant to the WM, and thereafter redistributing attentional resources on either internal or external stimuli. Internal consisting of worrying thoughts, external of irrelevant distractors threatening to the on-going task.

When reviewing the literature of the MA—WM relationship, the findings varied considerably. Whereas some studies found the MA—WM correlation to be 0.079 and 0.081, respectively (Ching, 2017; Pappas et al., 2019), others found the correlation to be −0.43 and −0.4, respectively (Witt, 2012; Soltanlou et al., 2019). Moreover, in Ashcraft and Kirk's (2001) experiments, the authors found that their subjects WM-scores significantly declined as

MA increased, though only in WM-tests containing numerical information, not in language-based tests ($r_{\text{letter-span}} = -0.2$; $r_{\text{computation-span}} = -0.4$). This is certainly interesting in respect of the utilization of measurement instruments for analyzing the MA—WM link. These differences in effect sizes may also vary as a function of age.

There have been gender differences reported, though to what degree gender can moderate relationships of MA—MP or MA—WM is unclear. Females have displayed higher MA than their male counterparts (Hembree, 1990; Hopko, 2003). In longitudinal studies, Geary et al. (2019) found that MP predicted future MA in females but not males, and in contrast Ma and Xu (2004) found that MP predicted higher MA in males compared to females. Regarding WM, there have been reports of males scoring better at visuospatial measures but not verbal (Robert and Savoie, 2006). Further, Maloney et al. (2012) found that spatial ability mediated the gender—MA relationship.

Previous Meta-Analyses

Hembree (1990) conducted one of the first, if not the first, meta-analysis on the correlation between MA and MP (high school students $r = -0.34$; college students $r = -0.31$). Later, Ma (1999) synthesized correlations from 26 studies focusing on samples from elementary and high schools ($r = -0.27$). More recently, Namkung et al. (2019), Zhang et al. (2019) and Barroso et al. (2021) pooled correlations of MA and math performance from 223, 131 and 49 studies and found moderate negative correlations ($r = -0.28$; $r = -0.34$; $r = -0.3$). Altogether research has established a robust negative relationship between MA and MP. This is especially of concern as Fan et al. (2019) found, through latent profile analysis on PISA-data, that 22% of US and Korean students and 10% of Finnish students belonged to a high MA profile. Peng et al. (2016) conducted a meta-analysis on the WM—MP relationship from 110 studies and found a moderate correlation ($r = 0.35$). However, the correlation for typically math performing participants was $r = 0.34$, while participants with math difficulties and other cognitive disorders displayed a correlation of $r = 0.52$. Regarding the WM domains, the use of composite measures of WM had a larger correlation with MP ($r = 0.38$) than isolated WM-domains alone (verbal WM: $r = 30$; visuospatial WM: $r = 0.31$), most likely because these tasks include computational requirements which are predictive of MP, both in the visuospatial and the phonological domains (Swanson and Kim, 2007). Moreover Liang et al. (2021) showed that children in the first grade depended more on visuospatial ability than verbal WM, while fifth graders relied on both WM domains in MP situations. These results highlight the progressive and domain specific aspects of WM's influence on MP.

The Current Study

Though many studies have researched the MA—MP relation, there are still gaps that need to be investigated to better understand the relationship between the two variables. Following the tenets of the ACT, the available executive function resources are depleted as a consequence of MA, and fewer resources are left to the designated task. Lowered WM capacity and diminished executive control following MA will affect performance. For anxious individuals, a worrying stimulus acts as a distractor by reducing the cognitive resources required for successful performance. Conversely, higher WM capacity can act as a protective factor. Although these theories have support from empirical studies, there would be a lot to gain from synthesizing the existing research in order to present a mean correlation. With the ACT setting as the basic framework, we posed two research questions (RQ), assessing the strength of the association between MA and WM and potential mediating effect of WM: (RQ1) what is the mean correlation between MA and WM? (RQ2) what is the mean indirect effect between MA and MP while accounting for WM as a mediator?

METHODS

Literature Search

The following databases were employed for our search task: Web of Science, Google Scholar, APAPsycNet, Scopus, ProQuest, and the meta-database EBSCO(host)[1]. No restrictions were applied on the dates for when the research-articles were published (earliest possible date until 25th October 2020). A search string was developed by looking up synonyms with various thesauruses. After running pilot-searches the final search-string resulted in the following:

("math* achievement" OR "math* performance" OR "math* success" OR "math* score" OR "arithmet*" OR "calculation" OR "math* ability")
AND
("math* anxiety" OR "math* worry")
AND
("working memory" OR "short term memory" OR "spatial" OR "phonological loop" OR "memory span" OR "digit span" OR "cognit*")

The same search string was used in all the aforementioned databases except for Google Scholar as the character limit was exceeded[2]. The search resulted in 1,901 articles which were imported to the reference management tool EndNote x9. Hand-searched references, which gained an additional 8 articles to the collection, were also imported to EndNote. The initial search accumulated 1,909 articles. After duplicates were removed 1,346 unique articles were reviewed on a title and abstract level.

Study Criteria

After an initial screening of abstracts, the articles were assessed in full-text. To be included in the full-text analysis, the article had to be peer-reviewed, published, written in English and comprise all three variables of interest: MA, WM, and MP. Further, the results had to include either (or both) a correlation between MA and WM, or a mediation analysis where WM was set to mediate

[1]EBSCO(host) included the following databases: Academic Search Premier, APA Psycinfo, Business Source Premier, CINAHL, ERIC, MEDLINE, SocINDEX and SPORTDiscus.
[2]The following were excluded in Google Scholar: "calculation," "math* ability," "memory span" and "digit span".

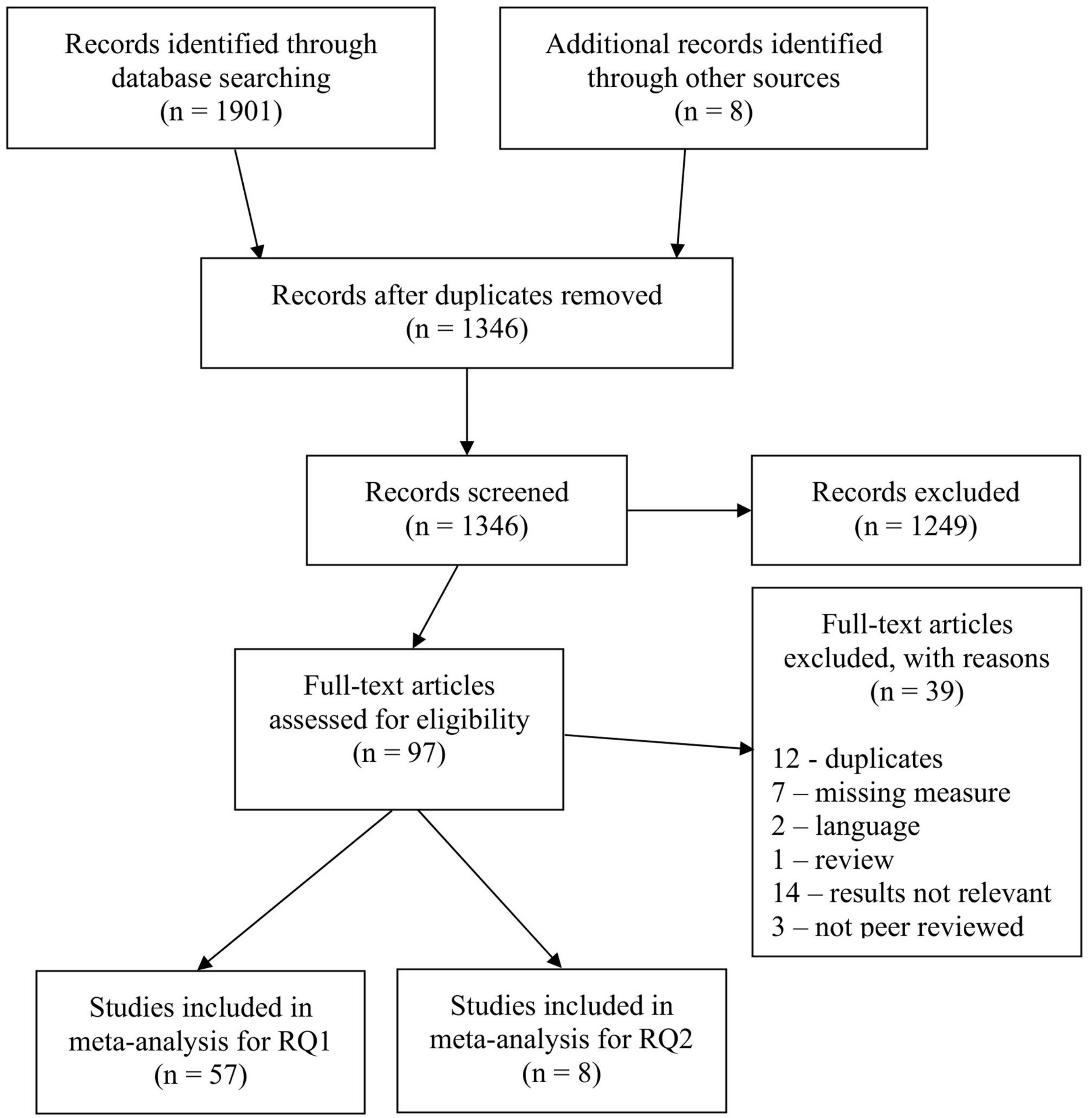

FIGURE 1 | Flowchart of literature search. Based on PRISMA from Moher et al. (2009).

the MA—MP relationship. See **Figure 1** for a flowchart of the literature search procedure.

MA is usually conceptualized as two-dimensional, having one affective and one cognitive component (Ho et al., 2000). Regarding MA and the affective dimension, instruments such as MARS (Richardson and Suinn, 1972), different varieties of the MARS, and the AMAS (Hopko et al., 2003) were included in the study. These measurements are designed to capture feelings of nervousness when facing mathematically challenging situations. Regarding MA and the cognitive worry dimension, only the *Faces Pain Scale* instruments (Bieri et al., 1990) have been used in studies of MA (e.g., Trezise and Reeve, 2014a,b). Other measures of anxieties, such as test anxiety, were not considered to meet the MA-criteria and were consequently excluded from the literature review.

Following the Baddeley and Hitch (1974) WM model, the study included measures of the central executive (e.g., operation span), and the sub-systems: phonological loop (e.g., digit span) and visuospatial sketch pad (e.g., Corsi block span). See **Table 1** for examples of these measures. Moreover, by extension a categorization into one of the four categories: (1) visuospatial, (2) phonological, (3) central executive + phonological, or (4) central executive + visuospatial was conducted. To qualify into categories one and two, the test must measure verbal or visual memory without applying strains on the central executive. To qualify for categories three or four, the test should require the participants to utilize either spatial or phonological abilities, and simultaneously manipulate information or steer their attention to a second, concurrent task.

MP was essentially measured in every article that measured MA and WM, these tests differed somewhat. The majority of the studies used standardized math tests, such as the quantitative reasoning ability from the Woodcock-Johnson III-battery (e.g., Miller and Bichsel, 2004). Other tests were researcher's self-designed math test (e.g., Novak and Tassell, 2017) or ordinary class exams (e.g., Alamolhodaei, 2009). Working memory has been shown to predict a broad range of math outcomes, even when other cognitive factors are controlled for (see Raghubar et al., 2010 for an overview), However task differences have been observed. When comparing types of math skill with WM, Peng et al.'s (2016) meta-analysis revealed that word-problem solving and whole-number calculations correlated the strongest with WM ($r = 0.37$; $r = 0.35$), while geometry differed significantly from the aforementioned, displaying a weaker correlation with WM ($r = 0.23$).

Coding and Interrater Reliability

To measure the reliability of the screening process, the first author read all abstracts and the second author read 40% of the abstracts, this allowed us to calculate a reliability statistic. The Cohen's kappa, an interrater reliability measure, was calculated with the following formula $k = (P_o - P_e)/(1 - P_e)$ and resulted in an adequate reliability $k = 0.83$ (Cooper et al., 2019). Any disagreements were revisited and discussed by both authors until consensus was achieved. From the abstract screening process, 1,249 articles were excluded leaving 97 articles eligible for full-text assessment.

The first and second author assessed all 97 articles in full text, if articles didn't present relevant results they were excluded. The reliability coefficient for the second comparison was $k = 0.79$. Similar to the first comparison, both authors revisited the articles that were subject for disagreements, in order to discuss and resolve any ambiguities. The first and second authors extracted and independently double coded all of the study's variables, this was in accordance with Cooper et al.'s (2019) recommendations. The study information included variables, such as sample size, sample characteristics, effect sizes, measurement instruments and country, which were all coded into an Excel workbook. Sample size was used to calculate study weights and variances (within study variance) for the effect sizes. Sample size was also needed to calculate the tau-squared (τ^2), which functioned as a between study variance-measure (Borenstein et al., 2009). All the coded information was compared between the two authors, and any inconsistencies were revisited and discussed. If an inconsistency remained uncertain it was brought up under meetings and assessed by all five authors.

Analysis

The correlation measure Pearson's r for MA and WM was used for the meta-analysis in RQ1. The correlations were transformed into Fisher's z effect sizes and variances. As for studies that reported multiple effect sizes based on the same sample, a mean effect size and variance was calculated for the dependent effect sizes. The dependent effects were correlated and estimated with

TABLE 1 | Examples of the most common instruments measuring working memory.

Component of WM	Name	Description	References
Phonological	Digit span forward	Participants read back increasingly longer sequences of numbers in the same order as the examiner presented.	Imbo and Vandierendonck, 2007; Buelow and Frakey, 2013; Ramirez et al., 2013; Ashkenazi and Danan, 2017; Skagerlund et al., 2019; Geary et al., 2020
Visuo-spatial	Corsi block test	A sequence of blocks in a quadrant (consisting of blocks) are shown to the participant who later must reproduce the same sequence in the right order.	Trezise and Reeve, 2014a,b; Guthrie and Vallee-Tourangeau, 2018; Lauer et al., 2018; Trezise and Reeve, 2018; Soltanlou et al., 2019; Wang et al., 2020
Central executive + phonological	Operation SPAN	Requires participants to hold information while performing concurrent arithmetic calculations.	Hoffman, 2010; Novak and Tassell, 2015; Novak and Tassell, 2017; Juniati and Budayasa, 2020
	Digit span backwards	Participants read back increasingly longer sequences of numbers in the reverse order of what the examiner presented.	Alamolhodaei, 2009; Alikamar et al., 2013; Georges et al., 2016; Braham and Libertus, 2018; Passolunghi et al., 2019
Central executive + visuo-spatial	Mental rotation	The task is to decide if a given 3D figure is identical or a mirror image of the displayed alternative answers.	Casey et al., 1997; Delgado and Prieto, 2008; Hart et al., 2017; Likhanov et al., 2017; Lauer et al., 2018; Sokolowski et al., 2019
	Corsi block backwards	Participants reproduce a pattern of blocks in a quadrant in the reverse order.	Ashkenazi and Danan, 2017; Soltanlou et al., 2019

WM, working memory.

the robust variance estimation (RVE) method with the R-package Robumeta (Fisher and Tipton, 2015). A problem with treating dependent effect sizes that are positively correlated with each other as independent effects, is that the analysis can overestimate the precision and underestimate the error of the mean effect (Borenstein et al., 2009). With this in mind, a mean effect size for dependent effects was computed. The variance for each mean effect size considered the within-study correlation between the outcomes (ρ). Depending on how ρ is specified it can affect the estimation of the between-study variance (τ^2), the mean error and the actual effect size. The ρ was specified to 0.8 as it was expected that the effect sizes would be correlated with each other. A sensitivity analysis revealed that the analysis was robust over the whole range of estimates of ρ (0–1).

Sub-group analyses (on age, school level, WM domain, verbal- and numerical tests) were performed with the Meta-package in R (Schwarzer, 2007) in accordance with Harrer et al.'s (2021) guide. In the sub-group analysis, moderator variables with multiple categories were transformed into dummy variables, dichotomous variables didn't require transformation. In the sub-group analysis, each effect size was treated as an independent effect.

Regarding the second aim for this study, whether working memory mediates the relationship between math anxiety and math performance, standardized regression coefficients from such models were extracted if reported. In some cases, only unstandardized coefficients were reported. We then used reported descriptive information of means and standard deviations to transform the statistics into standardized coefficients. The main analysis was to compute a summary effect with confidence intervals of the indirect effect, which was calculated by multiplying path a by path b (see **Figure 2**). Some studies answering RQ2 reported multiple effect sizes. As in RQ1, the RVE method was employed to balance the weights of the studies containing multiple effects. ρ was specified to 0.8. A sensitivity analysis showed that the estimated mean effect and the τ^2 was slightly affected over the span of 0–1, though within reasonable limits.

The RVE used employed a random-effects model. The rationales for using random-effects model rather than fixed-effect model for answering RQ1 were: (I) the samples originated from different populations as samples varied by age, country, and other factors. (II) A test of heterogeneity was significant ($p < 0.001$) and the I^2-index (I^2 = total heterogeneity/total observed variability), a statistic that can offer an indication of the degree of heterogeneity, resulted in 75.6% heterogeneity, which can be considered a high value (Higgins et al., 2003). Regarding the analysis for RQ2, there was evidence of some heterogeneity ($I^2 = 47$ %) in addition to the varied samples. This also suggested that a random-effects model would be appropriate.

Potential bias in our data was analyzed by fitting a funnel plot (**Figure 4**) to the data for subsequent visual inspection. Egger's

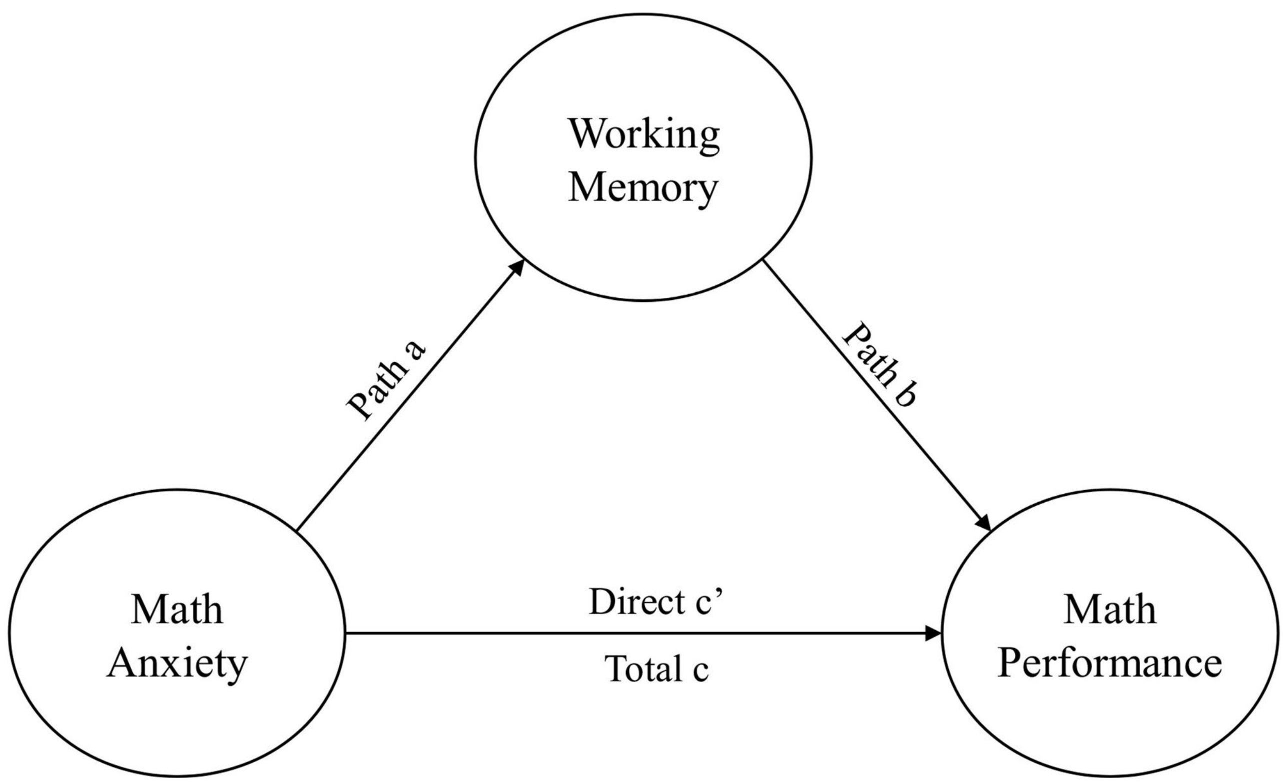

FIGURE 2 | Mediation model.

TABLE 2 | Mean correlation and sub-group analysis on the MA—WM relationship.

Subcategory	Effect sizes	r	95 % CI.	τ^2	Between group statistics	
					Q	*p*-value
Mean correlation[a]	150	−0.168	[−0.203; −0.133]	0.0123		
Age					23.16	<0.0001
Child < 12 year	29	−0.101	[−0.148; −0.053]	0.0098		
Child ≤ > 12 year	29	−0.126	[−0.161; −0.090]	0.0044		
Child ≥ 12 year	92	−0.219	[−0.251; −0.188]	0.0166		
School level					14.02	0.0029
Primary	42	−0.113	[−0.150; −0.075]	0.0085		
High school	39	−0.205	[−0.257; −0.153]	0.0235		
University	64	−0.202	[−0.238; −0.165]	0.0134		
WM category					9.27	0.0547
Visuospatial	33	−0.185	[−0.228; −0.142]	0.0103		
Phonological	20	−0.125	[−0.162; −0.087]	0.0015		
Phono + CE	63	−0.204	[−0.247; −0.161]	0.0218		
Visuo + CE	31	−0.167	[−0.215; −0.118]	0.0134		
Verbal WM-test					1.85	0.1738
Verbal based test	80	−0.192	[−0.224; −0.159]	0.0161		
No Verbal elements	70	−0.159	[−0.193; −0.124]	0.0139		
Numerical based test					5.91	0.0151
Numeric	64	−0.212	[−0.251; −0.173]	0.0177		
Non-numeric	86	−0.152	[−0.181; −0.123]	0.0123		

[a] *Estimated with robust variance estimation method in a random effects model, standard error = 0.0181. WM, working memory; MA, math anxiety; CE, central executive.*

regression test was carried out for assessing asymmetry in the funnel plot. The inverse of the standard errors was applied to the vertical axis as it's usually the recommended practice for bias-detection in meta-analysis (Sterne and Egger, 2001). This brings studies with larger sample sizes to the top of the funnel and smaller closer to the bottom.

Sub-Group Analysis

The fairly high level of heterogeneity gave reason to investigate whether certain variables affected the MA—WM relationship. The sub-groups that were chosen were based on sample characteristics and the large amount and diversity of the WM measures. These consisted of age, school-level, WM-domain, and type of WM-test. Age was categorized into participants (I) <12 years, (II) ≥12 years, (III) samples consisting of participants around the age 12. The decision for our cut-off value of 12-years for the age-variable, was based partly on earlier research that has found MA to increase in the early teens (Ashcraft and Moore, 2009), and partly on a related earlier meta-analysis' age grouping (Caviola et al., 2017). School level consisted of (I) primary school, (II) high school, (III) university. WM-domains consisted of: (I) visuospatial, (II) phonological, (III) visuospatial + central executive and (IV) phonological + central executive. WM-tests were divided into (I) verbally based and (II) tests without verbal elements. WM-tests were also divided based on their numerical attributes into either (I) numerical tests, or (II) non-numerical tests.

RESULTS

Mean Correlation Working Memory—Math Anxiety

To answer RQ1 effect sizes were pooled from a total of 57 articles, 66 unique samples comprising of 16,589 participants and 150 correlation coefficients. The mean correlation between MA and WM was −0.168 with confidence intervals on the 95% level ranging from −0.203 to −0.133 (see **Table 2**). The sub-group analysis of age, school level, and numerical based WM-tests were all significant, $p < 0.001$, $p < 0.01$, and $p < 0.05$, respectively.

Participant Age

Age was one of the clearest moderating variables. Participants of under the age of 12 had a weak MA—WM correlation ($r = -0.101$, 95 % C.I. [−0.148; −0.053]). Participants around the age of 12 (samples that ranged from under 12 to over 12), had a slightly stronger MA—WM relationship ($r = -0.126$, 95 % C.I. [−0.161; −0.090]). Participants over the age of 12 exhibited the strongest MA—WM relationship ($r = -0.219$, 95 % C.I. [−0.251; −0.188]) which was significantly stronger than the two other age groups ($p < 0.001$). A meta-regression analysis was carried out with participant mean age as the predictor of the relationship. This resulted in a small, significant effect ($\beta = -0.005$, std. error = 0.002, $p < 0.01$). Further, the MA—WM correlation increased in strength from primary to high-school ($r = -0.113$; $r = -0.205$). The correlation didn't significantly differ from high school to university ($r = -0.205$; $r = -0.202$).

Regarding the gender aspect, there was not enough available data for investigating differences between males and females (number of effect sizes: males = 2; females = 12) in the MA—WM relation. This would be of interest for future research as previous research has shown that females experience higher levels of MA compared to males (Hembree, 1990).

Working Memory Category and Tests

A between-group analysis revealed a marginal main effect of WM categories ($p = 0.055$). Descriptively, this effect can be seen in **Table 2**, represented by almost non-overlapping confidence intervals. Hence, the phonological ($r = -0.125$, 95 % C.I. [−0.162; −0.087]) and phonological + central executive domain's ($r = -0.205$, 95 % C.I. [−0.247; −0.161]) confidence intervals (95%) overlapped with only one thousandths decimal point. A meta-regression analysis revealed that phonological domain predicted the MA—WM correlation ($\beta = 0.064$, std. error = 0.036, $p < 0.05$). No other WM category revealed significant effects, neither sub-group analysis nor meta-regression analysis. The analysis of verbal WM tests revealed no main effect while the analysis of numerical tests revealed a main effect ($p < 0.05$), with a stronger MA—WM correlation for numerical tests ($r = -0.212$) compared to non-numerical tests ($r = -0.152$). See **Table 2** for details.

Mean Correlation of Indirect Effect

As for RQ2, 10 studies reportedly measured the mediation model of interest (see **Figure 2**). However, one study didn't report the necessary statistics for the analysis, as their aim was more focused on the gender aspect, though they did mention that MA failed to show an indirect or a direct effect on MP in a model accounting for WM, other parallel mediators, and covariates. A second study was dropped because the reported statistics were out of proportion and couldn't be transformed into standardized values. Though in the same study, the authors reported a significant indirect effect of MA predicting MP while accounting for WM. A sample size of 1,824 participants from eight studies with a total of 15 effect sizes of the indirect effects of MA predicting MP while accounting for WM as a mediator, were synthesized with the RVE method and resulted in a significant negative indirect effect ($r = -0.092$, $p < 0.05$) between MA predicting MP while accounting for WM. See **Table 3** for details.

Funnel Plot Analysis

A funnel plot with study effect sizes for RQ1 was analyzed (see **Figure 3**). Visual inspection of the effect sizes in relation to the funnel suggested the data wasn't normally distributed as effect sizes occurred outside the funnel. Egger's regression test for asymmetry was significant ($p < 0.001$) confirming the asymmetric data. It's possible that the data suffers from small-study effects as stronger effects are seen in smaller studies with larger standard errors (Rücker et al., 2011). A bias-corrected analysis in the form of a trim-and-fill method can function as a sensitivity analysis (Peters et al., 2007). Adding 27 effect sizes, to mirror the extremes, into the funnel plot ($n = 173$) lowered the average correlation to −0.136, while remaining significant (95 % C.I. −0.164 to −0.108, $p < 0.001$). A meta-regression was performed on publication year which suggested that the effect slightly decreases with more recent publications ($\beta = 0.008$, $SE = 0.003$, $p < 0.001$).

TABLE 3 | Mean correlation of the indirect effect.

Studies	Effect sizes	Estimate	Std. Error	95 % C.I.	τ^2
8	15	−0.0923	0.0326	[−0.169; −0.0152]	0.00426

Indirect effect of math anxiety predicting math performance while accounting for working memory as a mediator.

DISCUSSION

This meta-analysis investigated the relationship between MA and WM, and the mediating effect of WM on the relationship of MA predicting MP. The results based on 66 unique samples showed that MA had a significant negative correlation with WM ($r = -0.168$), which according to Hemphill (2003), is interpreted as a small effect size. This relationship varied significantly as a function of age, school level, WM category and whether WM tests were numerically based or not. Furthermore, a significant indirect effect (−0.092) of MA on MP through WM was found based on eight unique samples. There has been plenty of research reporting the MA—WM statistic, though these effect sizes have varied from study to study. A synthesized correlation of MA—WM has been reported in Namkung et al. (2019) which contrasts our study as they found a non-significant correlation between the two variables MA and WM ($r = -0.08$), though their study-focus was on the MA—MP correlation. The current study presents a mean correlation on the MA—WM link, based on synthesized effect sizes from published, peer reviewed research.

Participant Characteristics

There was a clear age effect in the MA—WM relationship, as older participants displayed a stronger negative MA—WM relationship. This was also mirrored in the school-level analyses. From primary school to high school the MA—WM relationship grew stronger, leveling off in high school and remained static throughout university. These results are in line with Ashcraft and Moore's (Ashcraft and Moore, 2009) suggestion that MA peaks around grade 10, and levels off shortly after. Moreover, the age-effect in the MA—WM correlation in the present study and the MA—MP correlation in Zhang et al.'s (2019) meta-analysis is up to high school level very similar. With the exception that University students displayed a lower MA—MP correlation than high school students, in their study.

Working Memory

The WM measures selected were based on Baddeley and Hitch's (1974) model and thus were categorized into phonological, visuospatial or combinations of the central executive and the phonological or visuospatial sub-systems. Between-group analysis, between phonological—MA and phonological + centra executive—MA, revealed a marginal significant main effect ($p = 0.055$; **Table 2**), as indicated by almost separated confidence intervals (95%). This in combination with the meta-regression analysis showing that the phonological domain predicted the relationship of MA—WM, indicate that the phonological domain might differ from the rest. The phonological + central executive measures correlated more strongly with MA ($r = -0.205$) compared to tests measuring solely the phonological loop ($r = -0.125$). These results are interesting from the perspective of the ACT, which theorizes that anxiety functions as a distractor that depletes cognitive resources required for cognitively demanding problems. Just like its predecessor, the processing efficiency theory (Eysenck and Calvo, 1992), the ACT emphasizes that anxiety has a greater impact on the executive component of working memory. The interpretation of our results can to some extent support the idea, that anxiety affects short term memory storage and attentional processes to a greater extent compared to short term memory storage alone. This is however not applied to our results of the visuospatial domain as most of the C.I. in visuospatial and visuospatial + central executive overlapped, indicating that the correlation was fairly similar.

Working Memory as a Mediator

The debilitating anxiety model suggests that anxiety can cause deficiencies in math performance. Deficits in MP caused by MA can fully or at least partly be mediated by cognitive processes. Indeed, our results showing a significant negative indirect effect of MA on MP via WM, support the ACT. When one experiences worrying thoughts, working memory resources are spent on irrelevant stimuli, thus, limiting the processing capacity required for performing the math problems at hand. Regarding RQ1 our sub-group analysis on numerical-based WM-tests supports Ashcraft and Kirk's (2001) findings that MA correlates more strongly with WM if the WM-measures are numerical. This implies that numbers *per se* can trigger anxiety to large extent and thus deplete cognitive processing resources. But why is higher MA significantly associated with lower WM, when looking at non-numerical WM measures? An explanation could potentially be found in the lack of construct independence. Although MA is defined as a feeling of nervousness in a math-related context (Ashcraft, 2002), its relative high correlation with test anxiety (Kazelskis et al., 2000), indicates associations to other forms of anxieties. Indeed, studies have found that MA relates moderately to strongly with state anxiety, ($r = 0.30$, Hopko, 2003), general anxiety ($r =$

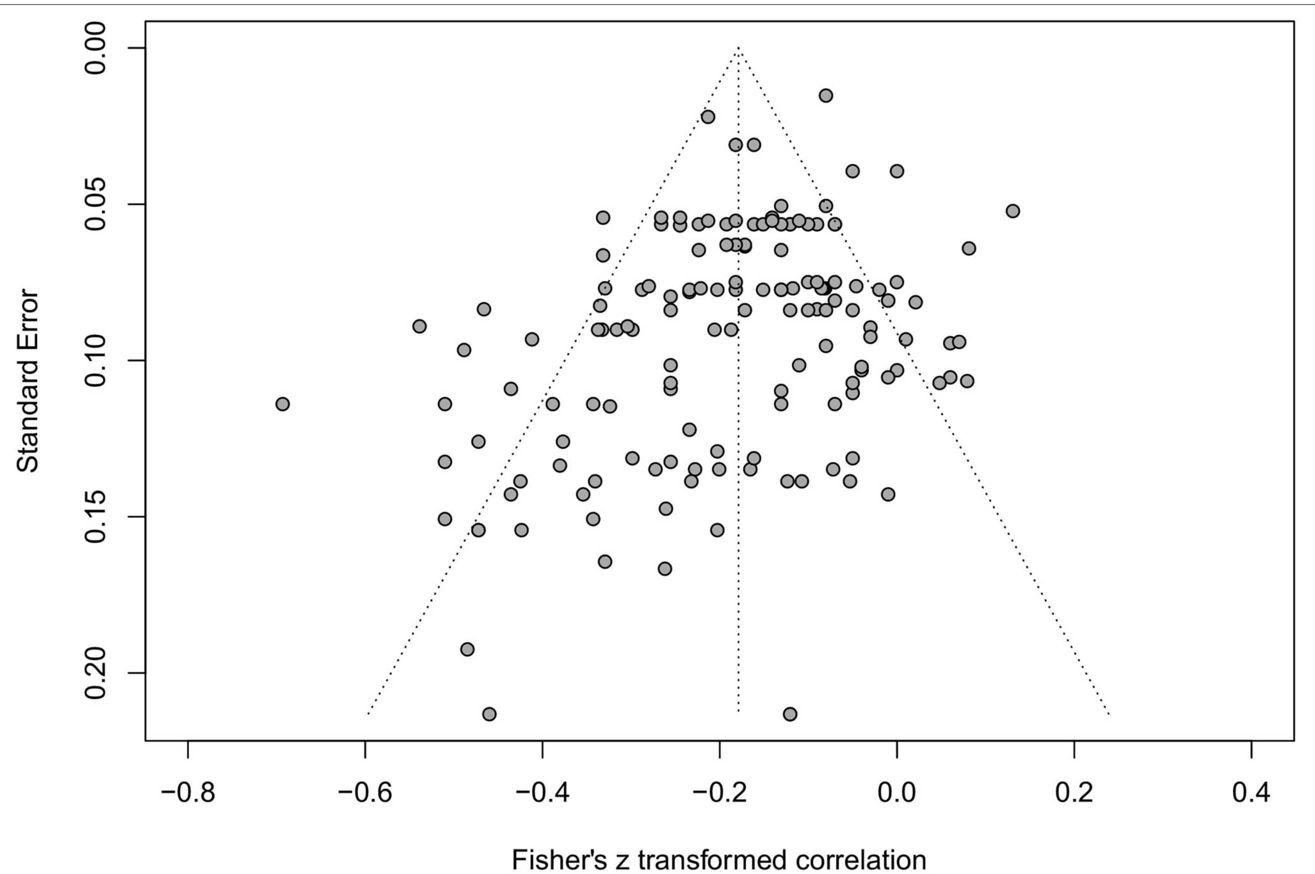

FIGURE 3 | Funnel plot of the math anxiety—working memory effects.

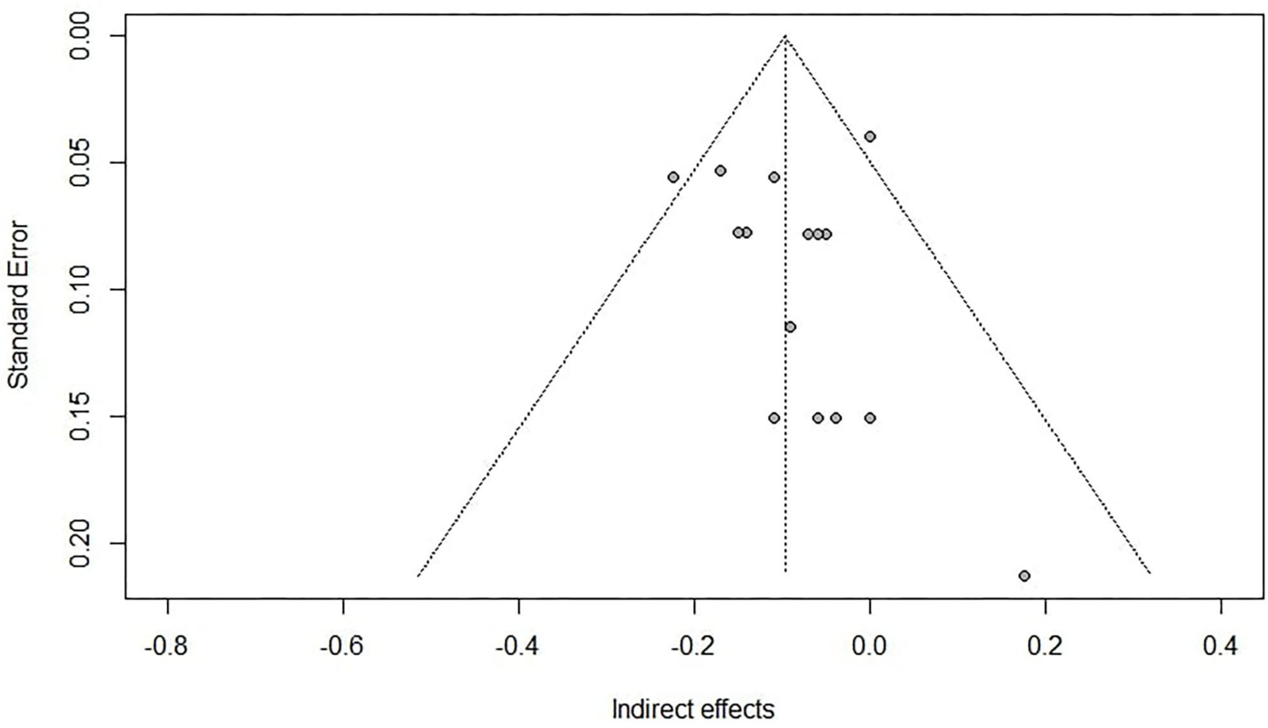

FIGURE 4 | Funnel plot of indirect effects.

0.5, Llabre and Suarez, 1985) and test anxiety ($r = 0.687$, O'Leary et al., 2017).

Limitation

The results from the funnel plot (**Figure 4**) with some studies outside the funnel in combination with Egger's regression test for asymmetry and the trim-and-fill method that lowered the average correlation indicated a publication bias. Especially as the current study only collected peer-reviewed, published studies, which can be seen as a limitation as some research (e.g., theses) will be left out. However, the effect sizes collected for our meta-analysis were seldom the main aim in the included literature. These effect sizes were most often found in sections where descriptive information or background variables were presented, typically not being an object of publication bias- providing a counterargument for publication bias. Moreover, a meta-regression revealed that publication date predicted the MA—WM relationship, which partly could explain the asymmetry in the funnel plot. With respect to the heterogeneity that characterizes the data (Higgins et al., 2003) we opted for implementing a random-effects model for RQ1. For instance, the data involves a vast and diverse measurement for both MA and WM, and the results show evidence of how the relationship increases in strength as the population grows older (**Table 2**). Imputing new data for bias-reasons may not be the answer in this case. As the τ^2 was significant, it is not always good practice to correct for this type of bias as the chances of unreliable results increase (Peters et al., 2007).

Regarding RQ2, an evident problem had to be addressed, namely the small number of studies answering the research question. This challenged the external validity and is considered a limitation. The reader should regard the results for RQ2 as descriptive and not prescriptive.

CONCLUSION

This study presents a robust significant negative relationship between MA—WM confirming the relevance of the ACT. A significant indirect effect from MA predicting MP while accounting for WM is also shown, though this relationship should be interpreted with caution as there was a limited number of studies answering this question. Researchers should be aware of what type of WM-measure is used and whether the instrument is of numerical nature or not, which could impact on the MA participants. Further, our results suggest that WM-measures of both the phonological and executive components have a stronger association with MA than phonological storage processes alone, which also is stated in the ACT. We recognize that there is still a shortage of data for determining the precision and certainty of the indirect effect that MA has on MP. This question still requires further investigation. Lastly, there is the age aspect to the MA—WM relationship. Our results indicate that somewhere between primary and high school the relationship develops in strength and levels off in university. This protracted development may be connected to younger children experiencing less MA than older (Wigfield and Meece, 1988; Ashcraft and Moore, 2009). If that is the case, the findings of this study highlight the importance of early interventions to suppress anxieties that can have detrimental effects on math performance and be pertinent to general cognitive processing abilities.

DATA AVAILABILITY STATEMENT

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

AUTHOR CONTRIBUTIONS

JK and BJ came up with the idea for the study. JF, ES, JK, HE, and BJ jointly contributed to the study's conceptualization and revised the manuscript for important intellectual content. JF performed the statistical analysis and wrote the first draft of the manuscript. All authors contributed to the manuscript and read and approved the submitted version.

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REFERENCES

*Alamolhodaei, H. (2009). A working memory model applied to mathematical word problem solving. *Asia Pacific Educ. Rev.* 10, 183–192. doi: 10.1007/s12564-009-9023-2

*Alikamar, M. A., Alamolhodaei, H., and Radmehr, F. (2013). The role of metacognition on effect of working memory capacity on students' mathematical problem solving. *Eur. J. Child Dev. Educ. Psychopathol.* 1, 125–139. doi: 10.30552/ejpad.v1i3.11

*Allen, M., and Vallee-Tourangeau, F. (2016). Interactivity defuses the impact of mathematics anxiety in primary school children. *Int. J. Sci. Math. Educ.* 14, 1553–1566. doi: 10.1007/s10763-015-9659-9

Ashcraft, M. H. (2002). Math anxiety: personal, educational, and cognitive consequences. *Curr. Dir. Psychol. Sci.* 11, 181–185. doi: 10.1111/1467-8721.00196

*Ashcraft, M. H., and Kirk, E. P. (2001). The relationships among working memory, math anxiety, and performance. *J. Exp. Psychol.* 130:224. doi: 10.1037/0096-3445.130.2.224

Ashcraft, M. H., and Krause, J. A. (2007). Working memory, math performance, and math anxiety. *Psychonom. Bull. Rev.* 14, 243–248. doi: 10.3758/BF03194059

Ashcraft, M. H., and Moore, A. M. (2009). Mathematics anxiety and the affective drop in performance. *J. Psychoeduc. Assess.* 27, 197–205. doi: 10.1177/0734282908330580

Ashcraft, M. H., and Ridley, K. S. (2005). "Math anxiety and its cognitive consequences," in *Handbook of Mathematical Cognition*, ed J. I. Campbell (New York, NY: Psychology Press), 315–327.

*Ashkenazi, S., and Danan, Y. (2017). The role of mathematical anxiety and working memory on the performance of different types of arithmetic tasks. *Trends Neurosci. Educ.* 7, 1–10. doi: 10.1016/j.tine.2017.05.001

Baddeley, A. (2000). The episodic buffer: a new component of working memory? *Trends Cogn. Sci.* 4, 417–423. doi: 10.1016/S1364-6613(00)01538-2

Baddeley, A. (2010). Working memory. *Curr. Biol.* 20, R136–R140. doi: 10.1016/j.cub.2009.12.014

Baddeley, A. D., and Hitch, G. (1974). Working memory. *Psychol. Learn. Motiv.* 8, 47–89. doi: 10.1016/S0079-7421(08)60452-1

*Barroso, C., Ganley, C. M., Hart, S. A., Rogers, N., and Clendinning, J. P. (2019). The relative importance of math- and music-related cognitive and affective factors in predicting undergraduate music theory achievement. *Appl. Cogn. Psychol.* 33, 771–783. doi: 10.1002/acp.3518

Barroso, C., Ganley, C. M., McGraw, A. L., Geer, E. A., Hart, S. A., and Daucourt, M. C. (2021). A meta-analysis of the relation between math anxiety and math achievement. *Psychol. Bull.* 147:134. doi: 10.1037/bul0000307

Bieri, D., Reeve, R. A., Champion, G. D., Addicoat, L., and Ziegler, J. B. (1990). The faces pain scale for the self-assessment of the severity of pain experienced by children: development, initial validation, and preliminary investigation for ratio scale properties. *Pain* 41, 139–150. doi: 10.1016/0304-3959(90)90018-9

Borenstein, M., Hedges, L. V., Higgins, J. P., and Rothstein, H. R. (2009). *Introduction to Meta-Analysis*. Hoboken, NJ: John Wiley & Sons. doi: 10.1002/9780470743386

*Braham, E. J., and Libertus, M. E. (2018). When approximate number acuity predicts math performance: the moderating role of math anxiety. *PLoS ONE* 13:e0195696. doi: 10.1371/journal.pone.0195696

*Buelow, M. T., and Frakey, L. L. (2013). Math anxiety differentially affects WAIS-IV arithmetic performance in undergraduates. *Arch. Clin. Neuropsychol.* 28, 356–362. doi: 10.1093/arclin/act006

Carey, E., Hill, F., Devine, A., and Szücs, D. (2016). The chicken or the egg? The direction of the relationship between mathematics anxiety and mathematics performance. *Front. Psychol.* 6:1987. doi: 10.3389/fpsyg.2015.01987

*Cargnelutti, E., Tomasetto, C., and Passolunghi, M. C. (2017). The interplay between affective and cognitive factors in shaping early proficiency in mathematics. *Trends Neurosci. Educ.* 8–9, 28–36. doi: 10.1016/j.tine.2017.10.002

*Casey, M. B., Nuttall, R. L., and Pezaris, E. (1997). Mediators of gender differences in mathematics college entrance test scores: a comparison of spatial skills with internalized beliefs and anxieties. *Dev. Psychol.* 33, 669–680. doi: 10.1037/0012-1649.33.4.669

Caviola, S., Carey, E., Mammarella, I. C., and Szucs, D. (2017). Stress, time pressure, strategy selection and math anxiety in mathematics: a review of the literature. *Front. Psychol.* 8:1488. doi: 10.3389/fpsyg.2017.01488

Chang, H., and Beilock, S. L. (2016). The math anxiety-math performance link and its relation to individual and environmental factors: a review of current behavioral and psychophysiological research. *Curr. Opin. Behav. Sci.* 10, 33–38. doi: 10.1016/j.cobeha.2016.04.011

*Ching, B. H.-H. (2017). Mathematics anxiety and working memory: longitudinal associations with mathematical performance in Chinese children. *Contemp. Educ. Psychol.* 51, 99–113. doi: 10.1016/j.cedpsych.2017.06.006

Cooper, H., Hedges, L. V., and Valentine, J. C. (2019). *The Handbook of Research Synthesis and Meta-Analysis*. New York, NY: Russell Sage Foundation. doi: 10.7758/9781610448864

*Daneshamooz, S., Radmehr, F., Alamolhodaei, H., and Mohajer, M. (2011). The effects of sleep duration on predictive factors of mathematical performance. *ARPN J. Sci. Technol.* 2, 283–291.

De Smedt, B., Janssen, R., Bouwens, K., Verschaffel, L., Boets, B., and Ghesquière, P. (2009). Working memory and individual differences in mathematics achievement: a longitudinal study from first grade to second grade. *J. Exp. Child Psychol.* 103, 186–201. doi: 10.1016/j.jecp.2009.01.004

*Delgado, A. R., and Prieto, G. (2008). Stereotype threat as validity threat: the anxiety-sex-threat interaction. *Intelligence* 36, 635–640. doi: 10.1016/j.intell.2008.01.008

*Douglas, H. P., and LeFevre, J. A. (2017). Exploring the influence of basic cognitive skills on the relation between math performance and math anxiety. *J. Numerical Cogn.* 3, 642–666. doi: 10.5964/jnc.v3i3.113

Dreger, R. M., and Aiken, L. R. Jr (1957). The identification of number anxiety in a college population. *J. Educ. Psychol.* 48:344. doi: 10.1037/h0045894

Eysenck, M. W., and Calvo, M. G. (1992). Anxiety and performance: the processing efficiency theory. *Cogn. Emot.* 6, 409–434. doi: 10.1080/02699939208409696

Eysenck, M. W., Derakshan, N., Santos, R., and Calvo, M. G. (2007). Anxiety and cognitive performance: attentional control theory. *Emotion* 7:336. doi: 10.1037/1528-3542.7.2.336

Fan, X., Hambleton, R. K., and Zhang, M. (2019). Profiles of mathematics anxiety among 15-year-old students: a cross-cultural study using multi-group latent profile analysis. *Front. Psychol.* 10:1217. doi: 10.3389/fpsyg.2019.01217

*Ferguson, A. M., Maloney, E. A., Fugelsang, J., and Risko, E. F. (2015). On the relation between math and spatial ability: the case of math anxiety. *Learn. Individ. Dif.* 39, 1–12. doi: 10.1016/j.lindif.2015.02.007

Fisher, Z., and Tipton, E. (2015). *Robumeta: An R-package for robust variance estimation in meta-analysis*. arxiv [preprint].arxiv:1503.02220.

*Ganley, C. M., and Vasilyeva, M. (2014). The role of anxiety and working memory in gender differences in mathematics. *J. Educ. Psychol.* 106:105. doi: 10.1037/a0034099

*Geary, D. C., Hoard, M. K., Nugent, L., Chu, F., Scofield, J. E., and Ferguson Hibbard, D. (2019). Sex differences in mathematics anxiety and attitudes: concurrent and longitudinal relations to mathematical competence. *J. Educ. Psychol.* 111, 1447–1461. doi: 10.1037/edu0000355

*Geary, D. C., Hoard, M. K., Nugent, L., and Scofield, J. E. (2020). In-class attention, spatial ability, and mathematics anxiety predict across-grade gains in adolescents' mathematics achievement. *J. Educ. Psychol.* doi: 10.1037/edu0000487

*Georges, C., Hoffmann, D., and Schiltz, C. (2016). How math anxiety relates to number-space associations. *Front. Psychol.* 7:1401. doi: 10.3389/fpsyg.2016.01401

Gunderson, E. A., Park, D., Maloney, E. A., Beilock, S. L., and Levine, S. C. (2018). Reciprocal relations among motivational frameworks, math anxiety, and math achievement in early elementary school. *J. Cogn. Dev.* 19, 21–46. doi: 10.1080/15248372.2017.1421538

*Guthrie, L. G., and Vallee-Tourangeau, F. (2018). Numbers in action: individual differences and interactivity in mental arithmetic. *Cogn. Process.* 19, 317–326. doi: 10.1007/s10339-018-0856-7

Harrer, M., Cuijpers, P., Furukawa, T. A., and Ebert, D. D. (2021). *Doing Meta-Analysis With R: A Hands-On Guide*. Boca Raton, FL; London: Chapmann; Hall/CRC Press. doi: 10.1201/9781003107347

*Hart, S., Daucourt, M., and Ganley, C. (2017). Individual differences related to college students' course performance in calculus II. *J. Learn. Anal.* 4, 129–153-129–153. doi: 10.18608/jla.2017.42.11

*Hartwright, C. E., Chung Yen, L., Sella, F., Inuggi, A., Santos, F. H., González-Salinas, C., et al. (2018). The neurocognitive architecture of individual differences in math anxiety in typical children. *Sci. Rep.* 8, 1–10. doi: 10.1038/s41598-018-26912-5

Hembree, R. (1990). The nature, effects, and relief of mathematics anxiety. *J. Res. Math. Educ.* 21, 33–46. doi: 10.2307/749455

Hemphill, J. F. (2003). Interpreting the magnitudes of correlation coefficients. *Am. Psychol.* 58, 78–80. doi: 10.1037/0003-066X.58.1.78

Higgins, J. P., Thompson, S. G., Deeks, J. J., and Altman, D. G. (2003). Measuring inconsistency in meta-analyses. *BMJ* 327, 557–560. doi: 10.1136/bmj.327.7414.557

Ho, H. Z., Senturk, D., Lam, A. G., Zimmer, J. M., Hong, S., Okamoto, Y., et al. (2000). The affective and cognitive dimensions of math anxiety: A cross-national study. *J. Res. Math. Educ.* 31, 362–379. doi: 10.2307/749811

*Hoffman, B. (2010). 'I think I can, but I'm afraid to try': the role of self-efficacy beliefs and mathematics anxiety in mathematics problem-solving efficiency. *Learn. Individ. Dif.* 20, 276–283. doi: 10.1016/j.lindif.2010.02.001

Hopko, D. R. (2003). Confirmatory factor analysis of the math anxiety rating scale–revised. *Educ. Psychol. Measure.* 63, 336–351. doi: 10.1177/0013164402251041

Hopko, D. R., Mahadevan, R., Bare, R. L., and Hunt, M. K. (2003). The abbreviated math anxiety scale (AMAS) construction, validity, and reliability. *Assessment* 10, 178–182. doi: 10.1177/1073191103010002008

*Imbo, I., and Vandierendonck, A. (2007). The development of strategy use in elementary school children: working memory and individual differences. *J. Exp. Child Psychol.* 96, 284–309. doi: 10.1016/j.jecp.2006.09.001

*Juniati, D., and Budayasa, I. K. (2020). Working memory capacity and mathematics anxiety of mathematics undergraduate students and its effect on mathematics achievement. *J. Educ. Gifted Young Sci.* 8, 279–291. doi: 10.17478/jegys.653518

*Justicia-Galiano, M. J., Martin-Puga, M. E., Linares, R., and Pelegrina, S. (2017). Math anxiety and math performance in children: the mediating roles of working memory and math self-concept. *British J. Educ. Psychol.* 87, 573–589. doi: 10.1111/bjep.12165

Kazelskis, R., Reeves, C., Kersh, M. E., Bailey, G., Cole, K., Larmon, M., et al. (2000). Mathematics anxiety and test anxiety: separate constructs? *J. Exp. Educ.* 68, 137–146. doi: 10.1080/00220970009598499

*Kucian, K., Zuber, I., Kohn, J., Poltz, N., Wyschkon, A., Esser, G., et al. (2018). Relation between mathematical performance, math anxiety, and affective priming in children with and without developmental dyscalculia. *Front. Psychol.* 9:263. doi: 10.3389/fpsyg.2018.00263

*Kyttala, M., and Bjorn, P. M. (2014). The role of literacy skills in adolescents' mathematics word problem performance: controlling for visuo-spatial ability and mathematics anxiety. *Learn. Individ. Dif.* 29, 59–66. doi: 10.1016/j.lindif.2013.10.010

*Lauer, J. E., Esposito, A. G., and Bauer, P. J. (2018). Domain-specific anxiety relates to children's math and spatial performance. *Dev. Psychol.* 54, 2126–2138. doi: 10.1037/dev0000605

Liang, Z., Dong, P., Zhou, Y., Feng, S., and Zhang, Q. (2021). Whether verbal and visuospatial working memory play different roles in pupil's mathematical abilities. *Br. J. Educ. Psychol. e*12454. doi: 10.1111/bjep.12454

*Likhanov, M., Zakharov, I., Kuzmina, Y., Budakova, A., Vasin, G., Malykh, S., et al. (2017). "Maths anxiety does not moderate the link between spatial and maths ability," in *Icpe 2017: International Conference on Psychology and Education* (Moscow). doi: 10.15405/epsbs.2017.12.21

Llabre, M. M., and Suarez, E. (1985). Predicting math anxiety and course performance in college women and men. *J. Counsel. Psychol.* 32:283. doi: 10.1037/0022-0167.32.2.283

Ma, X. (1999). A meta-analysis of the relationship between anxiety toward mathematics and achievement in mathematics. *J. Res. Math. Educ.* 30, 520–540. doi: 10.2307/749772

Ma, X., and Xu, J. (2004). The causal ordering of mathematics anxiety and mathematics achievement: a longitudinal panel analysis. *J. Adolesc.* 27, 165–179. doi: 10.1016/j.adolescence.2003.11.003

*Maldonado Moscoso, P. A., Anobile, G., Primi, C., and Arrighi, R. (2020). Math anxiety mediates the link between number sense and math achievements in high math anxiety young adults. *Front. Psychol.* 11:1095. doi: 10.3389/fpsyg.2020.01095

Maloney, E. A., and Beilock, S. L. (2012). Math anxiety: who has it, why it develops, and how to guard against it. *Trends Cogn. Sci.* 16, 404–406. doi: 10.1016/j.tics.2012.06.008

Maloney, E. A., Ramirez, G., Gunderson, E. A., Levine, S. C., and Beilock, S. L. (2015). Intergenerational effects of parents' math anxiety on children's math achievement and anxiety. *Psychol. Sci.* 26, 1480–1488. doi: 10.1177/0956797615592630

Maloney, E. A., Waechter, S., Risko, E. F., and Fugelsang, J. A. (2012). Reducing the sex difference in math anxiety: the role of spatial processing ability. *Learn. Individ. Dif.* 22, 380–384. doi: 10.1016/j.lindif.2012.01.001

*Miller, H., and Bichsel, J. (2004). Anxiety, working memory, gender, and math performance. *Pers. Individ. Dif.* 37, 591–606. doi: 10.1016/j.paid.2003.09.029

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., and Prisma Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *PLoS Med.* 6:e1000097. doi: 10.1371/journal.pmed.1000097

Mononen, R., Niemivirta, M., Korhonen, J., Lindskog, M., and Tapola, A. (2021). Developmental relations between mathematics anxiety, symbolic numerical magnitude processing, and arithmetic skills from first to second grade. *Cogn. Emot.* doi: 10.1080/02699931.2021.2015296. [Epub ahead of print].

Namkung, J. M., Peng, P., and Lin, X. (2019). The relation between mathematics anxiety and mathematics performance among school-aged students: a meta-analysis. *Rev. Educ. Res.* 89, 459–496. doi: 10.3102/0034654319843494

*Necka, E. A., Sokolowski, H. M., and Lyons, I. M. (2015). The role of self-math overlap in understanding math anxiety and the relation between math anxiety and performance. *Front. Psychol.* 6:1543. doi: 10.3389/fpsyg.2015.01543

*Novak, E., and Tassell, J. (2015). Using video game play to improve education-majors' mathematical performance: an experimental study. *Comput. Hum. Behav.* 53, 124–130. doi: 10.1016/j.chb.2015.07.001

*Novak, E., and Tassell, J. L. (2017). Studying preservice teacher math anxiety and mathematics performance in geometry, word, and non-word problem solving. *Learn. Individ. Dif.* 54, 20–29. doi: 10.1016/j.lindif.2017.01.005

*Núñez-Peña, M. I., Suárez-Pellicioni, M., Guilera, G., and Mercadé-Carranza, C. (2013). A Spanish version of the short Mathematics Anxiety Rating Scale (sMARS). *Lean. Individ. Dif.* 24, 204–210. doi: 10.1016/j.lindif.2012.12.009

O'Leary, K., Fitzpatrick, C. L., and Hallett, D. (2017). Math anxiety is related to some, but not all, experiences with math. *Front. Psychol.* 8:2067. doi: 10.3389/fpsyg.2017.02067

*Orbach, L., Herzog, M., and Fritz, A. (2020). State- and trait-math anxiety and their relation to math performance in children: the role of core executive functions. *Cognition* 200:104271. doi: 10.1016/j.cognition.2020.104271

*Pappas, M. A., Polychroni, F., and Drigas, A. S. (2019). Assessment of mathematics difficulties for second and third graders: cognitive and psychological parameters. *Behav. Sci.* 9, 76–76. doi: 10.3390/bs9070076

Passolunghi, M. C. (2011). Cognitive and emotional factors in children with mathematical learning disabilities. *Int. J. Disabil.* 58, 61–73. doi: 10.1080/1034912X.2011.547351

*Passolunghi, M. C., Cargnelutti, E., and Pellizzoni, S. (2019). The relation between cognitive and emotional factors and arithmetic problem-solving. *Educ. Stud. Math.* 100, 271–290. doi: 10.1007/s10649-018-9863-y

Peng, P., Namkung, J., Barnes, M., and Sun, C. (2016). A meta-analysis of mathematics and working memory: moderating effects of working memory domain, type of mathematics skill, and sample characteristics. *J. Educ. Psychol.* 108:455. doi: 10.1037/edu0000079

Peters, J. L., Sutton, A. J., Jones, D. R., Abrams, K. R., and Rushton, L. (2007). Performance of the trim and fill method in the presence of publication bias and between? study heterogeneity. *Stat. Med.* 26, 4544–4562. doi: 10.1002/sim.2889

*Prast, E. J., Van de Weijer-Bergsma, E., Miocevic, M., Kroesbergen, E. H., and Van Luit, J. E. H. (2018). Relations between mathematics achievement and motivation in students of diverse achievement levels. *Contemp. Educ. Psychol.* 55, 84–96. doi: 10.1016/j.cedpsych.2018.08.002

*Prevatt, F., Welles, T. L., Li, H., and Proctor, B. (2010). The contribution of memory and anxiety to the math performance of college students with learning disabilities. *Learn. Disabil. Res. Pract.* 25, 39–47. doi: 10.1111/j.1540-5826.2009.00299.x

*Rabab'h, B., and Veloo, A. (2015). Spatial visualization as mediating between mathematics learning strategy and mathematics achievement among 8th grade students. *Int. Educ. Stud.* 8, 1–11. doi: 10.5539/ies.v8n5p1

Raghubar, K. P., Barnes, M. A., and Hecht, S. A. (2010). Working memory and mathematics: a review of developmental, individual difference, and cognitive approaches. *Learn. Individ. Dif.* 20, 110–122. doi: 10.1016/j.lindif.2009.10.005

*Ramirez, G., Gunderson, E., Levine, S., and Beilock, S. (2013). Math anxiety, working memory, and math achievement in early elementary school. *J. Cogn. Dev.* 14, 187–202. doi: 10.1080/15248372.2012.664593

Ramirez, G., Shaw, S. T., and Maloney, E. A. (2018). Math anxiety: past research, promising interventions, and a new interpretation framework. *Educ. Psychol.* 53, 145–164. doi: 10.1080/00461520.2018.1447384

Richardson, F. C., and Suinn, R. M. (1972). The mathematics anxiety rating scale: psychometric data. *J. Counsel. Psychol.* 19:551. doi: 10.1037/h0033456

Robert, M., and Savoie, N. (2006). Are there gender differences in verbal and visuospatial working-memory resources? *Eur. J. Cogn. Psychol.* 18, 378–397. doi: 10.1080/09541440500234104

Rücker, G., Carpenter, J. R., and Schwarzer, G. (2011). Detecting and adjusting for small-study effects in meta-analysis. *Biometr. J.* 53, 351–368. doi: 10.1002/bimj.201000151

Schwarzer, G. (2007). Meta: an R package for meta-analysis. *R News* 7, 40–45.

*Semeraro, C., Giofre, D., Coppola, G., Lucangeli, D., and Cassibba, R. (2020). The role of cognitive and non-cognitive factors in mathematics achievement: the importance of the quality of the student-teacher relationship in middle school. *PLoS ONE* 15:e0231381. doi: 10.1371/journal.pone.0231381

*Shaw, S. T., Pogossian, A. A., and Ramirez, G. (2020). The mathematical flexibility of college students: the role of cognitive and affective factors. *Br. J. Educ. Psychol.* 90, 981–996. doi: 10.1111/bjep.12340

*Skagerlund, K., Östergren, R., Västfjäll, D., and Träff, U. (2019). How does mathematics anxiety impair mathematical abilities? Investigating the link between math anxiety, working memory, and number processing. *PLoS ONE* 14:e0211283. doi: 10.1371/journal.pone.0211283

*Sokolowski, H. M., Hawes, Z., and Lyons, I. M. (2019). What explains sex differences in math anxiety? A closer look at the role of spatial processing. *Cognition* 182, 193–212. doi: 10.1016/j.cognition.2018.10.005

*Soltanlou, M., Artemenko, C., Dresler, T., Fallgatter, A. J., Ehlis, A. C., and Nuerk, H. C. (2019). Math anxiety in combination with low visuospatial memory impairs math learning in children. *Front. Psychol.* 10:89. doi: 10.3389/fpsyg.2019.00089

Sorvo, R., Koponen, T., Viholainen, H., Aro, T., Räikkönen, E., Peura, P., et al. (2019). Development of math anxiety and its longitudinal relationships with arithmetic achievement among primary school children. *Learn. Individ. Dif.* 69, 173–181. doi: 10.1016/j.lindif.2018.12.005

Sterne, J. A., and Egger, M. (2001). Funnel plots for detecting bias in meta-analysis: guidelines on choice of axis. *J. Clin. Epidemiol.* 54, 1046–1055. doi: 10.1016/S0895-4356(01)00377-8

Swanson, L., and Kim, K. (2007). Working memory, short-term memory, and naming speed as predictors of children's mathematical performance. *Intelligence* 35, 151–168. doi: 10.1016/j.intell.2006.07.001

*Tomasetto, C., Morsanyi, K., Guardabassi, V., and O'Connor, P. A. (2020). Math anxiety interferes with learning novel mathematics contents in early elementary school. *J. Educ. Psychol.* 113, 315–29. doi: 10.1037/edu0000602

*Trezise, K., and Reeve, R. A. (2014a). Cognition-emotion interactions: patterns of change and implications for math problem solving. *Front. Psychol.* 5:840. doi: 10.3389/fpsyg.2014.00840

*Trezise, K., and Reeve, R. A. (2014b). Working memory, worry, and algebraic ability. *J. Exp. Child Psychol.* 121, 120–136. doi: 10.1016/j.jecp.2013.12.001

*Trezise, K., and Reeve, R. A. (2018). Patterns of anxiety in algebraic problem solving: a three-step latent variable analysis. *Lean. Individ. Dif.* 66, 78–91. doi: 10.1016/j.lindif.2018.02.007

*Vallée-Tourangeau, F., Sirota, M., and Vallée-Tourangeau, G. (2016). Interactivity mitigates the impact of working memory depletion on mental arithmetic performance. *Cogn. Res.* 1:26. doi: 10.1186/s41235-016-0027-2

*Valle-Tourangeau, F., Sirota, M., and Villejoubert, G. (2013). Reducing the impact of math anxiety on mental arithmetic: the importance of distributed cognition. *Proc. Annu. Meet. Cogn. Sci. Soc.* 35, 3615–3620.

*Vukovic, R. K., Kieffer, M. J., Bailey, S. P., and Harari, R. R. (2013a). Mathematics anxiety in young children: concurrent and longitudinal associations with mathematical performance. *Contemp. Educ. Psychol.* 38, 1–10. doi: 10.1016/j.cedpsych.2012.09.001

Vukovic, R. K., Roberts, S. O., and Green Wright, L. (2013b). From parental involvement to children's mathematical performance: the role of mathematics anxiety. *Early Educ. Dev.* 24, 446–467. doi: 10.1080/10409289.2012.693430

Wang, Z., Hart, S. A., Kovas, Y., Lukowski, S., Soden, B., Thompson, L. A., et al. (2014). Who is afraid of math? Two sources of genetic variance for mathematical anxiety. *J. Child Psychol. Psychiatry* 55, 1056–1064. doi: 10.1111/jcpp.12224

*Wang, Z., Rimfeld, K., Shakeshaft, N., Schofield, K., and Malanchini, M. (2020). The longitudinal role of mathematics anxiety in mathematics development: issues of gender differences and domain-specificity. *J. Adolesc.* 80, 220–232. doi: 10.1016/j.adolescence.2020.03.003

Wigfield, A., and Meece, J. L. (1988). Math anxiety in elementary and secondary school students. *J. Educ. Psychol.* 80:210. doi: 10.1037/0022-0663.80.2.210

Wiklund-Hörnqvist, C., Jonsson, B., Korhonen, J., Eklöf, H., and Nyroos, M. (2016). Untangling the contribution of the subcomponents of working memory to mathematical proficiency as measured by the national tests: a study among Swedish third graders. *Front. Psychol.* 7:1062. doi: 10.3389/fpsyg.2016.01062

*Witt, M. (2012). The impact of mathematics anxiety on primary school children's working memory. *Eur. J. Psychol.* 8, 263–274. doi: 10.5964/ejop.v8i2.458

*Wu, S. S., Chen, L., Battista, C., Smith Watts, A. K., Willcutt, E. G., and Menon, V. (2017). Distinct influences of affective and cognitive factors on children's non-verbal and verbal mathematical abilities. *Cognition* 166, 118–129. doi: 10.1016/j.cognition.2017.05.016

*Zhang, J., Cheung, S. K., Wu, C. G., and Meng, Y. X. (2018). Cognitive and affective correlates of Chinese children's mathematical word problem solving. *Front. Psychol.* 9:2357. doi: 10.3389/fpsyg.2018.02357

Zhang, J., Zhao, N., and Kong, Q. P. (2019). The relationship between math anxiety and math performance: a meta-analytic investigation. *Front. Psychol.* 10:1613. doi: 10.3389/fpsyg.2019.01613

*Studies included in our meta-analyses (n = 56).

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Reducing Math Anxiety in School Children: A Systematic Review of Intervention Research

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Recent studies indicate that math anxiety (MA) can already be found in school-aged children. As early MA depicts a potential risk for developing severe mathematical difficulties and impede the socio-emotional development of children, distinct knowledge about how to reduce MA in school-aged children is of particular importance. Therefore, the goal of this systematic review is to summarize the existing body of research on MA interventions for children by identifying the approaches, designs, and characteristics as well as the effects of the interventions.

Keywords: math anxiety, intervention, review, school, children

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1 INTRODUCTION

In the last decade, a considerable amount of research focused on math anxiety (MA). Ramirez et al. (2018) sum up results of across 65 countries that participated in the 2012 PISA survey and highlight that "33% of 15-year-old students, on average, reported feeling helpless when solving math problems" (p.146). In accordance with the high prevalence in this age group, the majority of existing studies addressed MA in adolescents and young adults. However, more recent research described MA as early as in primary school children (Ramirez et al., 2013; Cargnelutti et al., 2017; Gunderson et al., 2018; Sorvo et al., 2019; Primi et al., 2020) and highlighted negative impacts of early MA on their short- and long-term development and performance in mathematics (Sorvo et al., 2017; Namkung et al., 2019; Zhang et al., 2019; Barroso et al., 2021). However, until now little attention has been paid to the investigation of interventions aiming at the reduction of MA in children (Passolunghi et al., 2020). The paper at hand aims to systematically review the existing literature on interventions and approaches that target to reduce MA in school-aged children.

2 THEORETICAL BACKGROUND

2.1 Definition of MA

MA can generally be defined as an "anxiety that interferes with manipulation of numbers and the solving of mathematical problems in a wide variety of ordinary life and academic situations" (Richardson and Suinn, 1972, p.551). There is, however, no consensus on the exact operationalization of MA in the field (e.g., Dowker et al., 2016). One important step towards a more precise definition and operationalization of MA is offered by the distinction of MA into trait and state anxiety. According to Spielberger (1972) trait anxiety refers to a relatively enduring individual disposition to feel anxious, whereas state anxiety refers to temporary and situational feelings of anxiety. Current MA studies either assess anxiety in math-related situations using hypothetical/retrospective questions (e.g., "How anxious would you feel if . . . ") or assess anxiety about failure in math (e.g., "How worried are you if you have problems with . . . "). The first type of question allows assumptions about state-like MA as not administered within the actual situation, the second type of question provides indications about trait MA (Sorvo et al., 2017; Orbach et al., 2019). Considering empirical discrepancies between MA self-reports (see questions above) and real-time assessments (Bieg, 2013), nowadays more studies apply questionnaires assessing state-MA within the actual mathematical situation (e.g., Vanbecelaere et al., 2021).

2.2 Explaining MA in Children

The development of MA and its relation to math performance has been investigated in only a few longitudinal studies (Sorvo et al., 2019). According to these studies different etiological pathways have been suggested (Carey et al., 2017; Sorvo et al., 2019) and it has been assumed that the MA-performance link is bidirectional (Carey et al., 2016; Foley et al., 2017). In other words, MA can be considered as both the cause and the outcome of poor math performance (Young et al., 2012).

Accordingly, MA could be elicited or increased over time because of math difficulties that often originate in early school years (Ramirez et al., 2018). Ramirez et al. (2018) define this as *reduced competency account* and explain this link in two ways: A first explanation might be seen in lower numerical/spatial abilities which lead to underperformance in math and consequently to MA. Barroso et al. (2021) describe this association as the "deficit model" of MA (p.136). Ramirez et al. (2018) further summarize, that a second explanation could be seen in avoidance behavior that amplifies the development of math difficulties and consequent MA. In line with this, Ashcraft and Moore (2009) state that "avoidance of math is an overriding characteristic of math-anxious individuals" (p. 201). Therefore, experiencing math difficulties might cause a "vicious circle" (Dowker et al., 2016) in which students avoid math-related situations leading to fewer opportunities to improve their math skills. Ramirez et al. (2018) consequently argue, that according to the assumption that MA may be the outcome of poor math performance, "interventions that aim to improve students' math skills may be effective" to reduce MA (p. 156). Consequently, recent studies suggest a positive effect of mathematical interventions (MI) on MA in school children (e.g., Supekar et al., 2015; Passolunghi et al., 2020; Vanbecelaere et al., 2020).

Performance-inhibiting effects might, however, also be caused by MA. Such types of MA might be originally developed from environmental factors (e.g., adult role models: Casad et al., 2015; Lin et al., 2017) and genetic dispositions (Wang et al., 2014; Malanchini et al., 2017). Such MA-related impacts on mathematical performance might be explained by the disruption of executive function processes and working memory (*disruption account*; Ramirez et al., 2018). This disruption may be caused by math-related worries (e.g., negative thoughts and rumination about one's abilities or the consequences of failure). As a result, MA-evoking situations interfere with available cognitive resources (e.g., working memory) (e.g., Ramirez et al., 2013; Pizzie et al., 2020). Therefore, less resources are available for task-related problem-solving processes (e.g., arithmetical strategies). This might lead children either to switch to less sophisticated strategies (e.g., *production deficiencies*) or apply advanced strategies unsuccessfully (e.g., *utilization deficiencies*; Miller and Seier, 1994), both approaches leading to poorer performances. Barroso et al. (2021) summarize such links under the "processing efficiency theory" of MA (p.136). The links between MA and performance might additionally be influenced by the complexity of math tasks that children have to solve and the presence of time pressure. Studies using math assessments including more complex tasks show stronger MA-performance links (Namkung et al., 2019; Zhang et al., 2019). Another stress-evoking factor might be seen in time pressure, as it seems to affect the arousal of children (Caviola et al., 2017a; Orbach et al., 2020). According to the assumption of a disruption of executive functions caused by math-related worries, cognitive-behavioral interventions (CBI) may help children to deal with maladaptive thoughts that e.g., attribute poor math grades to a lack of ability. Recent studies suggest a positive effect of CBI on MA in school children (e.g., Passolunghi et al., 2020).

2.3 Reducing MA in Children

With regard to the described manifold link between MA and mathematical performance, it becomes clear that reducing symptoms of MA might be a relevant approach in supporting children's mathematical development (Passolunghi et al., 2020). At the same time, the multiple explanations of the link between MA and mathematical performance might serve as a diverse foundation for designing appropriate interventional activities (e.g., addressing numerical/spatial abilities, executive functions, math self-concept). Previous work highlighted that the existing body of research can be subsumed into interventions that primarily target mathematical abilities as well as into cognitive-behavioral interventions that target anxiety related cognitions (Dowker et al., 2016). Both directions can thereby be interpreted with regard to the described differential links between MA and mathematical performance.

As described, MI might be of particular relevance in light of the described *reduced competency account* (Ramirez et al., 2018). They aim to break the vicious circle of MA and performance by promoting mathematical performance and thereby increasing math self-concept as well as decreasing MA. In line with this argument Dowker et al. (2016) propose that "interventions for children with mathematical difficulties may go some way toward preventing a vicious spiral, where mathematical difficulties cause anxiety, which causes further difficulties with mathematics" (p. 10). Similarly, math trainings moreover depict exposure interventions. Accordingly, Ramirez et al. (2018) argue that "the avoidance framework under the Reduced Competency Account states that avoidance tendencies may be responsible for the deficits in development (and explains why increased exposure is an effective solution)" (p. 156).

The effects of CBI can be mainly explained with regard to the described *disruption account* (Ramirez et al., 2018). Accordingly, CBI might decline the potential impact of anxiety-related cognitive processes and by that means improve mathematical performance. Dowker et al. (2016) as well as Ramirez et al. (2018) both highlight the potential impact of CBI such as re-appraisal and expressive writing on MA.

3 OBJECTIVE OF THE STUDY AND RESEARCH QUESTIONS

Most of the existing body of research on MA and MA interventions appears to focus on older adolescents and adults, as MA has been previously associated with more complex mathematics. At the same time, MA could already be observed in school-aged children and might be associated with early mathematical functioning and numeracy. Therefore, early identification and intervention of MA seems to be of high relevance to prevent negative developmental outcomes. As research on early MA interventions is limited, the exact conditions and characteristics of successful interventions in school-aged children remain unclear. To our knowledge, no existing work has summarized the existing evidence on the interventional approaches that target MA in childhood. Therefore, the objective of this study is to give an overview of interventional approaches in addressing MA in children and adolescents and to highlight potential characteristics of effective interventions. The study is guided by the following research questions:

1) What are the approaches, designs, and characteristics (e.g., setting, duration) of existing interventions aiming at the reduction of MA in school children?
2) What are the effects of these existing interventions?

Answers to these questions might contribute to the field of MA intervention research, as they might serve as a foundation and orientation for future intervention studies aiming at improving children's emotional well-being and academic development in schools, especially regarding mathematics.

4 METHODS

As MA has been addressed in previous research, we aim to identify characteristics of effective interventions based on the existing body of research. Therefore, we conduct a systematic (scoping) review. Thereby, we will describe the main findings of the included studies and highlight specific components using a narrative approach.

4.1 Search Procedure

To identify all relevant studies, we used a two-step approach. In a first step we conducted a systematic search in the most widely used electronic databases in psychological and educational research. Therefore, we focused on the databases PsycINFO and PubPsych. PubPsych is a multilingual database that includes entries from additional databases, such as PSYNDEX, MEDLINE and ERIC (Educational Resources Information Center). We used the descriptors: math (ematics) anxiety AND intervention OR treatment OR therapy OR program OR training OR tutoring OR support OR strategies OR best practice, AND alleviation as well as its synonyms reduction OR decrease OR remediation. Additionally, a German translation of the descriptors was used. To prevent the exclusion of relevant studies at an early stage no filters were used except the exclusion of dissertations as full texts are often difficult to access. We additionally identified studies by hand search, i.e., visually scanning reference lists from relevant studies or theoretical papers. The literature search was conducted in July 2020 and October 2021.

4.1.1 Inclusion and Exclusion Criteria

Studies were eligible for the systematic review if they met all the following inclusion criteria:

- Participants received intervention or a combination of interventions.
- Participants were assessed with a quantitative and/or qualitative measure of MA.
- Participants were of school-age (5–17 years old).

Studies were not eligible if they met one of the following exclusion criteria:

- The study was no intervention study (e.g., theoretical paper, literature review, meta-analysis, or correlation study).
- Participants did not match the target population (e.g., university students or (pre-service) teachers).
- The study was published in a language other than English or German.

The selection of eligible studies was conducted in two stages. Firstly, we employed an initial screening of titles and abstracts against the inclusion and exclusion criteria. Screening procedures followed PRISMA guidelines (Moher et al., 2009). All studies were screened using the tool for systematic reviews Rayyan (Ouzzani et al., 2016). Rayyan is an open access online application that enables a semi-automated collaborative screening process. Secondly, all studies that appeared to meet the inclusion criteria, or when a decision could not be made based on the title and/or abstract, were screened again based on their full texts.

4.2 Study Selection

The described inclusion and exclusion criteria were applied during the selection process (for an overview of the study selection process see **Figure 1**). The initial search in the databases PsycINFO and PubPsych led to the identification of 521 records. Additionally, 13 records were identified by hand search. After removing duplicates, the titles, and abstracts of 479 records were screened for potential eligibility. This step led to the exclusion of 452 records. The full texts of 27 records were consequently assessed for eligibility. As a result, three more records were excluded. These steps led to the inclusion of 24

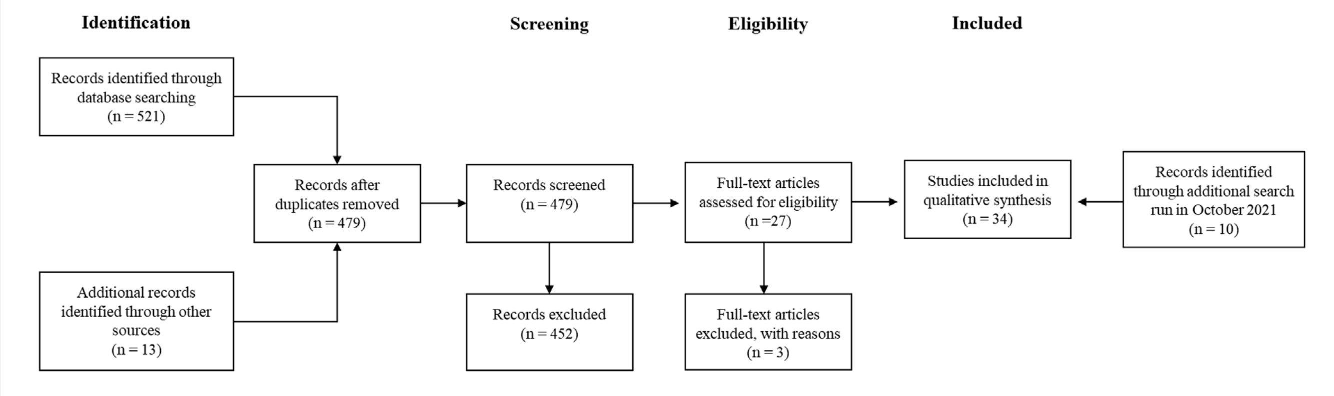

FIGURE 1 | Study selection process following PRISMA guidelines.

records. A second search run was conducted in October 2021 to include most recent studies. This led to the inclusion of ten more studies. The final number of studies for the qualitative synthesis was 34.

4.3 Data Extraction and Coding Procedure

Next to general information about the studies, such as author(s), year of publication, and title, we extracted relevant data to address our specific research questions. Regarding our first research question (approaches, designs, and characteristics of existing interventions) we coded all information given by the author(s) about the study design, interventions, and their respective settings. This included information about the general study approach (quantitative, qualitative, mixed method), the study design (pre-post-test, follow up, control/comparison group), the operationalization of MA, as well as data about sample size and age group of the participants. Regarding the intervention we extracted information about the content as well as the intended goal of the interventions. We also coded the duration of the interventions (overall time span and number of sessions), the duration of single sessions, the intervention mode (computer-based, face-to-face), and the social arrangement (single, partner, small groups, class). Concerning our second research question (effects of these existing interventions) we coded the key results of the studies regarding the effectiveness of the intervention(s) to reduce MA as reported by the authors.

Relevant information has been coded using a spread sheet covering the previously described categories. The number of free text fields has been limited as much as possible to enable an unambiguous extraction and analysis of the data. Preferably fixed text such as yes/no decisions and drop-down lists has been used to code the data. The data extraction spread sheet has been previously piloted and adapted.

5 RESULTS

For a complete overview over all included studies (reference, sample, design, MA measure, operationalization type of MA, intervention, setting, and main findings) see **Table 1**.

5.1 Intervention Approach

Most of the included studies applied either a mathematical intervention (MI) approach (see section I in **Table 1**) or a cognitive-behavioral intervention (CBI) approach (see section II in **Table 1**). Four studies used other interventional approaches that could not clearly assigned to one of these two approaches (see section III in **Table 1**).

5.2 Sample and Study Design

The study samples differed between the two main intervention approaches (MI and CBI) in regards to the age groups of the participants. 82% of the MI studies targeted school age children (6–12 years), whereas 57% of the studies within the CBI approach focused on adolescents (13–17 years). Regarding the sample size and choice of study design there appears to be no systematic difference between MI and CBI studies. The majority of the included studies applied a quantitative study design to examine the effects of various interventions on MA. Thereby, the sample size of the included studies varies strongly, $M = 138$ ($SD = 171$). Whilst some studies used large samples of over 300 participants (Shapka and Keating, 2003; Brandenberger and Moser, 2018; Vanbecelaere et al., 2020), other studies only collected information of approximately 20 participants (Kamann and Wong, 1993; Supekar et al., 2015; Choi-Koh and Ryoo, 2019). Most of the quantitative studies applied a pre-post design and included a control or comparison group. Whilst some studies used a waiting list procedure for the control group (i.e., the group received the same intervention with some time delay after the intervention group), other studies applied alternative interventions (e.g., Shapka and Keating, 2003; Asikhia and Mohangi, 2015) or applied modified version of the actual target intervention (Kramarski et al., 2010; Huang et al., 2014). Four studies additionally followed up on their participants in the intervention and control group (Sheffield and Hunt, 2006; Rauscher et al., 2017; Vanbecelaere et al., 2020; Vanbecelaere et al., 2021). Two of the identified studies applied single-case procedures to address potential effects of interventions on MA. LaGue et al. (2019) applied a multiple baseline approach within an experimental single-case design. Hord et al. (2018) used a qualitative approach to single-case research and focused on

TABLE 1 | Overview of included studies.

Reference	Sample	Design	MA measure	MA operationalization type[a]	Intervention	Setting	Main findings
I – Mathematical Interventions (MI)							
Alanazi (2020)	*n*= 60 School age (6–12 years)	quantitative; pre-post; control group	Math Anxiety Scale for children MASC; Chiu and Henry (1990) (Arabic translation)	Hyp/retro (statelike-MA) and anxiety about failure in math (trait-MA)	Active recreational math games (vs. regular math teaching)	Face-to-face; Small group; 8 weeks; 3 sessions (45 min each) per week	Intervention group obtained lower MA scores and higher math performance than the control group
Arias Rodriguez et al. (2019)	*n* = 42 School age (6–12 years)	quantitative; pre-post; comparison group	Escala de Ansiedade à Matemática (Math Anxiety Scale) EAM; Carmo (2008)	Hyp/retro (statelike-MA)	Numeracy musical training Da Silva et al. (2017) (Low vs. average achieving students)	Face-to-face; Small group; 8 weeks; 1 session (40 min) per week	Both groups obtained lower MA scores and higher math performance
Choi-Koh & Ryoo, (2019)	*n* = 25 Adolescence (13–17 years)	quantitative; pre-post; comparison group	Math Anxiety Scale for students (MASS) revised by Ko and Yi (2011)	Hyp/retro (statelike-MA)	Quadratic functions training and Brain Integration in Education program BIE; Kim (2010) (Low MA vs. high MA)	Face-to-face; 3 lessons	Reduction of MA in high MA group; No reduction of MA in low MA group
Hord et al. (2018)	*n* = 2 Adolescence (13–17 years)	qualitative; single case	Field notes, recordings, interviews	Not classifiable	Algebra training, individual support	Face-to-face; Single	One student needed more support to address MA than the other; Both improved math performance
Huang et al. (2014)	*n* = 56 School age (6–12 years)	quantitative; pre-post; control group	Math Anxiety Scale for 1st and 2nd grade students Shie (2006)	No further information	Digital game-based learning with diagnostic feedback (vs. without diagnostic feedback)	Computer; Single; 6 weeks; 2 sessions (40 min each) per week	Both groups obtained lower MA scores and enhanced levels of learning motivation
Jansen et al. (2013)	*n* = 207 School age (6–12 years)	quantitative; pre-post; control group	Math Anxiety Scale for children MASC; Chiu and Henry (1990) (Dutch translation)	Hyp/retro (statelike-MA) and anxiety about failure in math (trait-MA)	Adaptive math training software *Math Garden* Klinkenberg et al. (2011) in three experimental conditions with different pre-set success rates (vs. regular math teaching)	Computer; Class; 6 weeks; 4 sessions (15 min each) per week	All groups obtained lower MA scores; Math performance only improved in the experimental conditions
Kramarski et al. (2010)	*n* = 140 School age (6–12 years)	quantitative; pre-post; control group	Questionnaire adapted from Sarason (1980, 1986) and Midgley et al. (2000)	Hyp/retro (statelike-MA) and anxiety about failure in math (trait-MA)	Self-regulated math learning (SRL) based on the IMPROVE method Mevarech and Kramarski (1997) (vs. no SRL support)	Face-to-face; Class; 4 weeks; 4 h per week	Intervention group obtained lower MA scores and higher math problem solving than the control group
Lavasani et al. (2012)	*n* = 40 School age (6–12 years)	quantitative; pre-post; control group	Math Anxiety Scale (18 items; no further information)	No further information	Cooperative learning (vs. regular math teaching)	Face-to-face; Class; 8 sessions	Intervention group obtained lower MA scores and increased help seeking behavior than the control group
Mehdizadeh et al. (2013)	*n* = 40 Adolescence (13–17 years)	quantitative; pre-post; control group	Math Anxiety Remote Sensing Scale (MARS) by Shokrani (2002)	No further information	Cooperative learning (vs. regular math teaching)	Face-to-face; Small group	Intervention group obtained lower MA scores, higher math performance, and increased help seeking behavior than the control group
Mevarech et al. (1991)	*n* = 149 School age (6–12 years)	quantitative; pre-post; comparison group	Math Anxiety Scale by Mevarech and Rich (1985)	Hyp/retro (statelike-MA) and anxiety about failure in math (trait-MA)	Computer assisted math instruction TOAM system; Hativa et al. (1990) (Cooperative use in pairs vs. individual use)	Computer; Pairs; 20 min per session	Low achieving students in cooperative group obtained lower MA scores and higher math performance

(Continued on following page)

TABLE 1 | (*Continued*) Overview of included studies.

Reference	Sample	Design	MA measure	MA operationalization type[a]	Intervention	Setting	Main findings
							than in individual group; Both groups showed similar math self-concept
Passolunghi et al. (2020)	*n* = 224 School age (6–12 years)	quantitative; pre-post; control group	Abbreviated Math Anxiety Scale (AMAS; Caviola et al., 2017b)	Hyp/retro (statelike-MA)	Calculation strategies training (vs. control training)	Face-to-face; Small group; 8 weeks; 1 session (60 min each) per week	Intervention group obtained lower MA scores and higher math performance than the control group
Rauscher et al. (2017)	*n* = 68 School age (6–12 years)	quantitative; pre-post-follow up; control group	MAI Kohn et al. (2013)	Hyp/retro (statelike-MA)	Adaptive math training Calcularis e.g., Käser et al. (2013) (vs. waiting list vs. control training)	Computer; Single; 6 weeks; 5 sessions (20 min each) per week	Intervention group obtained lower MA scores than waiting list control group; No difference in MA between intervention group and control training group; All groups improved similarly in their attitude towards math and math self-concept
Supekar et al. (2015)	*n* = 28 School age (6–12 years)	quantitative; pre-post; comparison group	Math Anxiety Level SEMA Wu et al. (2012)	Hyp/retro (statelike-MA)	Adaptation of MathWise Fuchs et al. (2013) (Low vs. high MA)	Face-to-face; 8 weeks; Single; 3 sessions (45 min each) per week	Reduction of MA in High MA group; Math performance improved equally in both groups
Tok (2013)	*n* = 55 School age (6–12 years)	quantitative; pre-post; control group	Math Anxiety Scale by Bindak (2005)	Hyp/retro (statelike-MA) and anxiety about failure in math (trait-MA)	Metacognitive strategy training (Know-Want-Learn-Strategy) (vs. regular math teaching)	Face-to-face; Class; 8 weeks; 4 sessions (40 min each) per week	Intervention group showed no reduction of MA but obtained higher math performance and metacognition than the control group
Tok et al. (2015)	*n* = 42 School age (6–12 years)	quantitative; pre-post; control group	Math Anxiety Scale by Bindak (2005)	Hyp/retro (statelike-MA) and anxiety about failure in math (trait-MA)	Teaching math creatively (vs. regular math teaching)	Face-to-face; Class; 6 weeks; 4 sessions (40 min each) per week	Intervention group obtained lower MA scores, higher math performance, and better attitudes towards math than the control group
Vanbecelaere et al. (2020)	*n* = 336 School age (6–12 years)	quantitative; pre-post-follow up; control group	Child Math Anxiety Questionnaire – Revised CMAQ-R; Ramirez et al. (2016) (Flemish adaptation)	Hyp/retro (statelike-MA)	Digital game-based learning in reading and math (vs. regular math teaching)	Computer; 8 weeks; Single; 1–2 sessions (50 min each) per week	Intervention group showed no reduction of MA but performed better in number line estimation and reading competence than the control group
Vanbecelaere et al. (2021)	*n* = 78 School age (6–12 years)	quantitative; pre-post-follow up; comparison group	State-Math Anxiety Questionnaire state-MAQ; e.g., Orbach et al. (2020) (Dutch translation)	State-MA (real-time assessment)	Adaptive educational math game *Number Sense Game*, Maertens et al. (2016) (vs. non-adaptive version)	Computer; 3 weeks; Single; 2 sessions (30 min each) per week	Both groups obtained lower MA scores and improved on early numeracy skills
II – **Cognitive-behavioral Interventions (CBI)**							
Asanjarani and Zarebahramabadi (2021)	*n* = 30 School age (6–12 years)	quantitative; pre-post; control group	Math Anxiety Rating Scale (MARS) by	Hyp/retro (statelike-MA)	Cognitive behavioral therapy based on Chiu and Henry (1990) (vs. control	Face-to-face; Small group; 1	Intervention group obtained lower MA scores and higher

(Continued on following page)

TABLE 1 | (*Continued*) Overview of included studies.

Reference	Sample	Design	MA measure	MA operationalization type[a]	Intervention	Setting	Main findings
			Suinn and Winston (2003)		group not further described)	session (90 min each) per week	math self-concept than the control group
Asikhia and Mohangi (2015)	*n* = 120 Adolescence (13–17 years)	quantitative; pre-post; control group	Math Anxiety Rating Scale – Revised MARS-R, Plake and Parker (1982)	Hyp/retro (statelike-MA)	Problem solving training (vs. class debate)	Face-to-face; 8 sessions (60 min each)	Intervention group obtained lower MA scores than the control group
Brandenberger and Moser (2018)	*n* = 348 Adolescence (13–17 years)	quantitative; pre-post; control group	Achievement Emotions Questionnaire – Mathematics (AEQ-M) – German Pekrun et al. (2005) (Shortened version)	Hyp/retro (statelike-MA)	Combined student and teacher workshops on e.g., emotions, motivation, learning goals, cooperative learning, and feedback (vs. student workshops only vs. waiting list)	Face-to-face; 38 weeks; Class; 3–4 sessions (45 min each)	All groups obtained lower MA scores; Intervention group reported higher joy of learning than the waiting list control group and the student workshops only group
Collingwood and Dewey (2018)	*n* = 144 School age (6–12 years)	quantitative; pre-post; control group	Scale of Math Anxiety Cavanaugh and Sparrow (2011); Math Anxiety Scale OECD (2005)	Hyp/retro (statelike-MA)	Coping strategies; mindful breathing; self-regulation (vs. waiting list)	Face-to-face; Small group; 4 weeks; 3 sessions (45 min each) per week	Intervention group showed no reduction of MA or enhancement of math self-concept but higher math performance than the control group
Hines et al. (2016)	*n* = 93 Adolescence (13–17 years)	quantitative; pre-post; control group	Math Anxiety Rating Scale MARS, Suinn and Edwards (1982)	Hyp/retro (statelike-MA)	Expressive writing on feelings about math (vs. expressive writing on neutral topic)	Single; 15–30 min a day for 3 days	Intervention group reported reduced levels of general and MA and the control group had a reduction in MA.
Kamann and Wong (1993)	*n* = 20 School age (6–12 years)	quantitative; pre-post; comparison group	Think out loud (self-talk measure)	Not classifiable	Coping strategy training (students with learning disability (LD) vs. students without LD)	Face-to-face; Small group; 6 weeks; 1 session per week	LD group showed increase in positive self-talk compared to group without LD group indicating enhanced coping with MA.
Karimi and Venkatesan (2009)	*n* = 33 Adolescence (13–17 years)	quantitative; pre-post; control group	Math Anxiety Rating Scale MARS, Alexander and Martray (1989)	Hyp/retro (statelike-MA)	Cognitive behavior group therapy (vs. control group not further described)	Face-to-face; Small group; 7.5 weeks; 2 sessions (90 min each) per week	Intervention group obtained lower MA scores than the control group
Kim et al. (2017)	*n* = 138 Adolescence (13–17 years)	quantitative; pre-post; control group	Math Anxiety Rating Scale – Revised MARS-R, Plake and Parker (1982)	Hyp/retro (statelike-MA)	Embodied agent with instructional guidance and anxiety treating messages (vs. embodied agent with instructional guidance only)	Computer; Class; 1 week; 4 sessions (45 min each) per week	Both groups obtained lower MA scores and higher math performance
LaGue et al. (2019)	*n* = 3 Adolescence (13–17 years)	quantitative; single case design with multiple baselines	Fennema-Sherman Math Anxiety Scale – Revised (FSMAS-R: FSANX subscale)	Hyp/retro (statelike-MA)	Mindfulness-based cognitive therapy	Face-to-face; Single; 6 weeks; 2 sessions (45 min each) per week	All three students showed decreased levels of MA.
Passolunghi et al. (2020)	*n* = 224 School age (6–12 years)	quantitative; pre-post; control group	Abbreviated Math Anxiety Scale (AMAS; Caviola et al., 2017b)	Hyp/retro (statelike-MA)	Identifying and coping with MA related feelings (vs. control training)	Face-to-face; Small group; 8 weeks; 1 session (60 min each) per week	Intervention group obtained lower MA scores but no increase in math performance compared to the control group

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TABLE 1 | (*Continued*) Overview of included studies.

Reference	Sample	Design	MA measure	MA operationalization type[a]	Intervention	Setting	Main findings
Ruark (2021)	*n* = 40 Adolescence (13–17 years)	quantitative; pre-post; control group	Modified Abbreviated Math Anxiety Scale (mAMAS; Carey et al., 2017)	Hyp/retro (statelike-MA)	Expressive writing on math homework problems and feelings (vs. expressive writing on homework problems only)	Single; 2 weeks; every day	No reduction of MA in both groups
Ruff and Boes (2014)	*n* = 13 School age (6–12 years)	Mixed-method; pre-post	Math Anxiety Scale for children MASC; Chiu and Henry (1990); Five open ended (self-developed) questions	Hyp/retro (statelike-MA) and anxiety about failure in math (trait-MA)	School counseling (e.g., identifying and expressing feelings; stress reduction, and relaxation)	Face-to-face; Small group; 6 weeks; 2 sessions per weeks	Some students obtained lower MA scores and higher math performance compared to the pre-test; Teachers reported more confidence and participation in math class
Sheffield and Hunt (2006)	*n* = 154 School age (6–12 years)	quantitative; pre-post-follow up; control group	Maths Anxiety Rating Scale for Children MASC, Chiu and Henry (1990)	Hyp/retro (statelike-MA) and anxiety about failure in math (trait-MA)	Systematic desensitization modified from Meichenbaum (1977) (vs. classroom games)	Face-to-face; 1 session; 1 h	Intervention group obtained lower MA scores and higher math performance than the control group
Singh (2016)	*n* = 60 Adolescence (13–17 years)	quantitative; pre-post	Short Math Anxiety Rating Scale (sMARS) based on MARS Richardson and Suinn (1972)	Hyp/retro (statelike-MA)	Behavior modification; Super brain yoga	Face-to-face; 6 weeks	Students obtained lower MA scores and higher math performance compared to the pre-test
III – Other Interventions							
Idris (2006)	*n* = 109 Adolescence (13–17 years)	quantitative; pre-post; control group	Math Anxiety Scale (no further information)	No further information	Graphing calculator (vs. no graphing calculator)	Face-to-face; Class; 10 weeks	Intervention group obtained lower MA scores and higher math performance scores than the control group
Segumpan and Tan (2018)	*n* = 90 Adolescence (13–17 years)	quantitative; pre-post-follow up; control group	Math Self-Efficacy and Anxiety Questionnaire (MSEAQ; May, 2009) (Adapted version)	Hyp/retro (statelike-MA) and anxiety about failure in math (trait-MA)	Flipped classroom (vs. regular math teaching)	Computer and face-to-face; Single and class	Intervention group obtained lower MA scores than the control group; Both groups increased math performance
Shapka and Keating (2003)	*n* = 786 Adolescence (13–17 years)	quantitative; pre-post; control group	Self-reported perceived Math Anxiety and attitude towards math	Hyp/retro (statelike-MA)	Girls-only math teaching (vs. mixed gender teaching)	Face-to-face; Class	No reduction of MA or increase in perceived math competence in intervention group (single sex girls) but higher math performance and course enrolment than in control group (co-ed girls)
Verkijika and De Wet (2015)	*n* = 36 Adolescence (13–17 years)	quantitative	Fennema-Sherman Math Anxiety Scale FSMAS, Kazelskis and Reeves (2002)	Hyp/retro (statelike-MA)	Neuropsychological feedback while playing math computer game (*Math-Mind* game; developed for this study)	Computer; Single; 2 sessions in 2 days; 4 data gathering waves per session	MA was reduced

[a]*Hyp/retro = hypothetical/retrospective questions about anxiety in math-related situations.*

two eighth grade students with learning disabilities using a descriptive, qualitative microanalysis.

5.3 MA Measure

Different quantitative measures have been used to assess the level of MA (for an overview see **Table 1**). Some of the measures have been extensively researched and validated, such as the Math Anxiety Scale for children (MASC; Chiu and Henry, 1990) or the Math Anxiety Rating Scale—Revised (MARS-R; Plake and Parker, 1982). Often measures were translated and/or adapted for the specific contexts and needs of the studies. Some studies used measures that were self-developed or not as commonly known (e.g., Kramarski et al., 2010; Tok et al., 2015; Singh, 2016) Also, qualitative measures such as observational field notes and self-talk recordings have been used (Kamann and Wong, 1993; Hord et al., 2018). According to the differentiations by Sorvo et al. (2017) and Orbach et al. (2019), one study (Vanbecelaere et al., 2021) used a real-time assessment measuring individuals math-related anxiety reaction during a math test situation (state-MA), 19 studies (approx. 54%) applied questionnaires with hypothetical/retrospective questions asking how anxious the individual would feel during a math-related situation (anxiety in math-related situations/statelike-MA) and nine studies (approx. 26%) used questionnaires with hypothetical/retrospective questions about anxiety in math-related situations (statelike-MA) and questions focusing anxiety about failure in math (trait-MA). Two studies used unclassifiable qualitative approaches (Kamann and Wong, 1993; Hord et al., 2018). Four studies provided no clear information about the MA operationalization (Idris, 2006; Lavasani et al., 2012; Mehdizadeh et al., 2013; Huang et al., 2014).

5.4 Intervention Activity

5.4.1 Mathematical Interventions

The MI covered a wide range of different activities and programs, such as educational games or formalized math programs. Due to the amount of activities, only selected studies are presented in more detail below. The study selection does not constitute an evaluation of the quality of the studies. For a comprehensive overview of all MI see the first section of **Table 1**.

Alanazi (2020), Huang et al. (2014), and Vanbecelaere et al. (2021) investigated the effect of educational math games on MA and performance in primary school children. The intervention group in Alanazi (2020) study participated in face-to-face recreational math games (e.g., movement games containing mathematical problems) in addition to their regular math teaching. The comparison group received regular math teaching. The intervention group obtained lower MA scores and higher math performance than the control group. Huang et al. (2014) and Vanbecelaere et al. (2021) applied a digital game-based learning approach. Huang et al. (2014) designed a digital math game to train basic arithmetic operations that provided the children in the intervention group with interactive diagnostic feedback. The children in the comparison group also played the game but without diagnostic feedback. Both groups obtained lower MA scores and enhanced levels of learning motivation. Vanbecelaere et al. (2021) compared an adaptive version with a nonadaptive version of the *Number Sense Game* (Maertens et al., 2016). The Number Sense Game contained two types of exercises, a comparison game and a number line estimation game. Both groups obtained lower MA scores and improved on early numeracy skills.

Jansen et al. (2013), Rauscher et al. (2017), and Supekar et al. (2015) investigated the effect of formalized math training programs on primary school students' math performance and anxiety. Jansen et al. (2013) and Rauscher et al. (2017) applied specific math training software, namely *Math Garden* (Klinkenberg et al., 2011) and *Calcularis* (Käser et al., 2013). In Jansen et al. (2013) study the control group received regular math teaching. Both groups obtained lower MA scores and the math performance only improved in the intervention group. Rauscher et al. (2017) compared the intervention group with two control groups; one was a waiting list group, the other received a control training. The results showed that the intervention group obtained lower MA scores than the waiting list control group, but there was no difference in MA between the intervention group and the control training group. Supekar et al. (2015) examined an adaption of *MathWise* (Fuchs et al., 2013), a training program that aims to improve number knowledge, counting speed and the application of calculation strategies. Comparing children with high MA and low MA levels, the children with high MA significantly decreased their MA. In regards to math performance both groups benefited equally from the training.

5.4.2 Cognitive-Behavioral Interventions

The CBI also included different techniques and activities, such as coping strategy training or expressive writing. Due to the amount of activities, only selected studies are presented in more detail below. The study selection does not constitute an evaluation of the quality of the studies. For a comprehensive overview of all CBI see the second section of **Table 1**.

Collingwood and Dewey (2018), Kamann and Wong (1993), Passolunghi et al. (2020), and Ruff and Boess (2014) investigated the effect of coping strategy trainings on primary school students' MA. Kamann and Wong (1993) examined a coping strategy based on cognitive behavior modification (Meichenbaum, 1977) to reduce MA. They compared children with and without learning disabilities (LD) providing both groups with sample self-instruction statements on cue cards to assist them in applying those statements at each level of the coping process. The LD group showed increased positive self-talk compared to the group without LD indicating enhanced coping with MA. Collingwood and Dewey (2018) examined a multi-dimensional cognitive intervention called *Thinking your problems away* (Martin, 2008) that encouraged (among other things such as self-regulation) the use of positive-self-coping statements based on Kamann and Wong (1993). The control group was a waiting list control group. The intervention group showed no reduction of MA or enhancement of math self-concept but higher math performance than the control group. Passolunghi et al. (2020) trained the primary school children in strategy-based techniques (among others things such as the recognition of emotions) to decrease their MA. These techniques included breathing exercises, safe place visualizations and re-appraisal of negative thoughts based on Ellis and Bernard (2006). The control group received a control training composed of playful activities with comic strips. The intervention group obtained lower MA scores but no increase in math performance compared to the control group.

Hines et al. (2016) and Ruark (2021) investigated the effect of expressive writing on MA in secondary school students. In the intervention group of Hines et al. (2016) study the participants wrote about their math related feelings 15 min a day for 3 days. The control group did the same amount of expressive writing but on a neutral topic. The intervention group reported reduced levels of general anxiety and MA, whereas the control group also indicated reduced levels of MA. The students in Ruark (2021) study wrote about their math homework problems every day for 2 weeks. The intervention group was requested to write about their feelings when encountering problems during math homework for at least 1 minute. The control group wrote about their math homework problems only. Both groups showed no reduction of MA.

5.5 Intervention Mode and Setting

The interventions were either carried out face-to-face (67.6%) or via computer (23.5%). Three studies (8.8%) did not fit into one of the two categories. Segumpan and Tan (2018) used both settings—face-to-face and computer—as they investigated the effect of a Flipped Classroom on secondary school students' MA and performance. In Hines et al. (2016) and Ruark (2021) studies the participants performed expressive writing activities at home without specifications whether to use paper and pencil or a computer.

Within the mathematics intervention approach computers were predominantly used to train basic arithmetic operations in primary school children (e.g., Mevarech et al., 1991; Jansen et al., 2013; Huang et al., 2014; Rauscher et al., 2017). Jansen et al. (2013), Rauscher et al. (2017), and Vanbecelaere et al. (2021) explicitly mentioned the adaptivity of their training software, i.e. the selection of training tasks was regulated by an adaptive algorithm (Klinkenberg et al., 2011). The only study within the CBI approach that utilized computers was Kim et al. (2017). In this study secondary school students were guided through a computer-based learning environment by a so-called embodied agent. The learning environment covered fundamental algebra topics. In the intervention group the embodied agent provided not only instructional guidance (control condition) but also anxiety treating messages. Results indicated that both groups obtained lower MA scores and higher math performance. All other CBI were conducted face-to-face.

The interventions were either held in classrooms (29.4%), small groups (32.4%), or individual settings (26.5%). Four studies (11.8%) did not specify the setting of their intervention. There were no significant differences between the settings in regards to the intervention approach.

5.6 Intervention Length

On average, the included studies applied interventions for M = 7.04 weeks (SD = 6.78). However, the span of the overall duration was large. The interventions ranged between a 1-h session (Sheffield and Hunt, 2006) and one school year (Brandenberger and Moser, 2018). Similarly, the number of training sessions varied between the included studies, M = 10.51 sessions (SD = 7.86). Again, the span of the number of sessions was large. The interventions took between one session (e.g., Sheffield and Hunt, 2006) and 30 sessions (Rauscher et al., 2017). Accordingly, the number of sessions per week differed, M = 2.6 sessions/week (SD = 1.4). Moreover, the duration of the individual session varied, M = 46.82 min (SD = 19.85), ranging from 15 min (e.g., Jansen et al., 2013) to 90 min of intervention time (e.g., Asanjarani and Zarebahramabadi, 2021) in each session.

5.7 Intervention Effects on MA

The intervention effects reported by the authors were mixed. 59% of the studies reported a positive effect of the intervention on MA in the intervention group compared to no effect in the control/comparison group (e.g., Kramarski et al., 2010; Tok et al., 2015; Alanazi, 2020; Passolunghi et al., 2020). In Passolunghi et al. (2020) study math strategy training influenced and improved not only math ability, but also contributed to a decrease in students' MA level. In the same study the cognitive-behavioral MA training showed only effects in reducing MA level, but there was no improvement of math abilities. Verkijika and De Wet (2015) provided evidence that MA could be effectively reduced by means of neuropsychological feedback while playing a math game. LaGue et al. (2019) reported positive effects of mindfulness-based cognitive therapy on students' MA levels using an experimental single-case study design.

21% of the studies found a positive effect of intervention(s) on MA in both the intervention as well as the control/comparison group (e.g., Jansen et al., 2013; Huang et al., 2014; Hines et al., 2016; Kim et al., 2017; Arias Rodriguez et al., 2019). Rauscher et al. (2017) showed that students who trained with the online math training *Calcularis* obtained significant lower MA scored compared the waiting list control group (intervention vs. waiting list control group). When compared to the control group that received a control training MA was, however, reduced equally in both groups (intervention vs. control training). Other studies reported a positive effect of the intervention(s) on MA for certain groups of students, such as highly anxious (Supekar et al., 2015; Choi-Koh and Ryoo, 2019) or low achieving students (e.g., Mevarech et al., 1991).

15% of the studies did not find a positive effect of the intervention on the students' level of MA (e.g., Shapka and Keating, 2003; Tok, 2013; Collingwood and Dewey, 2018; Vanbecelaere et al., 2020). Collingwood and Dewey (2018) reported a positive impact of intervention on the mathematical performance of students in the intervention group, however, no significant impact on the level of MA. Tok (2013) also found increased achievement after teaching students to use the *Know-Want-Learn* strategy as well as improved metacognitive abilities, but no significant impact on MA. Shapka and Keating (2003) did not find evidence that girls-only math teaching would reduce female students' MA in comparison to co-educated math teaching.

The findings did not differ in relation to the applied MA questionnaires. The only study that used a real-time assessment (state-MA) reported a positive effect of a math training on MA, approx. 80% of the studies using questionnaires with hypothetical/retrospective items (statelike-MA/anxiety in math-related situations) reported lower MA after the intervention and approx. 90% of the studies using questionnaires focusing anxiety about failure (trait-MA) and anxiety in math-related situations (statelike-MA) reported lower MA after the intervention.

6 DISCUSSION

The goal of this study was to summarize the existing body of research on MA interventions for school children. Therefore, we conducted a systematic (scoping) review and presented the results in a narrative manner. **Table 1** gives a comprehensive overview of the included studies and their main characteristics. Note that not all studies provided all relevant information.

Generally, the overall number of eligible studies identified in this review was still relatively small, for example compared to general mathematical intervention studies (Reynvoet et al., 2021). Given the potential negative impact of early MA on children's short- and long-term development, one would have expected a greater attention to this field of research. This finding indicates that research on MA interventions is still emerging. The fact that most studies included in this review are relatively recent underpins this assumption. At the same time, the categorization of interventions into either MI or CBI as described in adults, can be similarly found in MA research in children and adolescents. The application of both approaches might be justified by different explanations of the MA-performance link (e.g., the reduced competency account and the disruption account of MA; Ramirez et al., 2018). Our findings do not justify any judgments on potential empirical advantages of either approach, as no direct comparisons of the described effects are possible. Future meta-analyses are required to address this issue. At the same time, our findings give qualitative insights into the existing body of research in MA interventions.

More than half of the included studies primarily focused on math performance rather than MA. Hence, MA was often assessed as an affective covariate but was not necessarily the actual target of the intervention. Despite that, almost half of the included MI still reported a positive side-effect of the intervention on students' MA compared to the control/comparison group. This supports the assumption that MI can reduce anxiety responses, but might also allow children to re-evaluate dysfunctional cognitive beliefs ("I am bad at math") and to stimulate the formation of new basic cognitive assumptions (e.g., increase of math self-concept).

As for the CBI, more than half of the included studies reported a positive effect of the intervention on the level of MA compared to the control/comparison group. At the same time, the effect of CBI on math performance was comparatively low. One possible explanation could be that the physiological arousal that comes with an anxious response (e.g., increased heart rate, faster breathing) can also support performance. Therefore, reducing this arousal through breathing or self-regulation exercises might not always be beneficial to enhance performance. Instead re-appraising the arousal as a sign of challenge or excitement rather than threat, might help children to capitalize on the performance enhancing effects of their physiological response see Biopsychological model of Challenge and Threat, (Blascovich, 2008). Similar effects have already been observed in adults (e.g., Brooks, 2014; Jamieson et al., 2016).

The mixed effects of the MI and CBI on MA and performance might indicate that a combination of both approaches could be most beneficial for school children. This means, on the one hand, to develop sound arithmetic skills that build not only the foundation for more complex math content but would also help children to form a positive math self-concept. On the other hand, combined interventions could also provide children with cognitive-behavioral tools to cope with their anxious thoughts and arousal in math related situations. These tools should, however, take effect models into account, such as the Biopsychological model of Challenge and Threat (Blascovich, 2008), that aim to capture the complex interrelations between cognitive processes and affective, physiological, and behavioral responses.

Furthermore, almost a quarter of the described studies, that either apply MI or CBI, reported positive effects on MA for both the intervention and the control/comparison group. This surprising result raises questions on potential third factors that led to a reduction of MA in these studies, and that have not yet been taken explicitly into account. These third factors could be school- and teaching-related variables that might be associated with the development of MA (e.g., teacher's beliefs). At the same time, the differences between the control groups of the included studies hinder potential discussions of these third factor variables. Of course, methodological issues might explain the non-existing differences between control and intervention groups (e.g., non-randomized controls leading to an unbalanced study design, unknown background interventions). In addition, reductions in the level of MA in both groups might be explained by the applied MA measures. To make differentiated conclusions about impacts of intervention programs on math-related anxiety reactions and/or math anxious cognitive beliefs, it may be useful for future studies to carefully consider the conceptualizations of MA questionnaires. E.g., intervention programs focusing emotional-regulation strategies could benefit from real-time assessments, measuring math-related anxiety reactions (state-MA), whereas studies that incorporate CBI might be more likely to evaluate effects on cognitive beliefs and trait-dispositions. However, to account for all influences, it would be best to consider both situation- and disposition-related approaches.

When comparing the mode and settings of the MI and CBI, it becomes clear that the majority of CBI was based in a one-to-one or small group setting. A classroom-based application of CBI was rare. Hence, future research might try to apply CBI or to combine CBI and MI on a classroom level. Despite the fact that interventions addressing MA are of relevance for students with high levels of MA, all students might profit from adequate strategies targeting anxiety related cognitions.

To conclude, a few limitations of our systematic review need to be mentioned. Firstly, the review only included intervention studies that target MA. This approach might have excluded a range of studies and findings, that highlighted the relevance of potential variables that might also be associated with the development of MA but had not been part of an intervention study (e.g., environmental factors). Secondly, although we tried to capture all relevant information of the included studies as accurate and complete as possible, the transparency within the studies was lacking at times. This implies, that important information might be missing or incomplete for some of the included studies. Especially missing information on the format and duration of the interventions makes it difficult to compare the effectiveness of the different approaches. And thirdly, our review is not a meta-analysis. Insights in described effects are therefore on a descriptive level and do not allow a direct statistical comparison or aggregation of the described effects.

In the end, no clear picture can be drawn yet of how effective MA intervention for school children should look like. However, this literature review still offers valuable insights into the current state in the field of MA intervention research. Both approaches (MI and CBI) show potential positive effects. The findings of this review at hand might therefore serve as an orientation for future research and for the development of effective interventions that aim to reduce MA in children.

DATA AVAILABILITY STATEMENT

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

AUTHOR CONTRIBUTIONS

LO, MB and MB-R drafted the theoretical background. MB and MB-R were responsible for data analysis and discussion of the findings. All authors contributed to the article and approved the submitted version.

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REFERENCES

Alanazi, H. M. N. (2020). The Effects of Active Recreational Math Games on Math Anxiety and Performance in Primary School Children: An Experimental Study. *Mult. J. Edu. Soc. Tec. Sci.* 7 (1), 89–112. doi:10.4995/muse.2020.12622

Alexander, L., and Martray, C. (1989). The Development of an Abbreviated Version of the Mathematics Anxiety Rating Scale. *Meas. Eval. Couns. Develop.* 22 (3), 143–150. doi:10.1080/07481756.1989.12022923

Arias Rodriguez, I., Mendes do Nascimento, J., Voigt, M. F., and Dos Santos, F. H. (2019). Numeracy Musical Training for School Children with Low Achievement in Mathematics. *An Psicol-Spain* 35 (3), 405–416. doi:10.6018/analesps.35.3.340091

Asanjarani, F., and Zarebahramabadi, M. (2021). Evaluating the Effectiveness of Cognitive-Behavioral Therapy on Math Self-Concept and Math Anxiety of Elementary School Students. *Preventing Sch. Fail. Altern. Edu. Child. Youth* 65 (3), 223–229. doi:10.1080/1045988X.2021.1888685

Ashcraft, M. H., and Moore, A. M. (2009). Mathematics Anxiety and the Affective Drop in Performance. *J. Psychoeducational Assess.* 27 (3), 197–205. doi:10.1177/0734282908330580

Asikhia, O. A., and Mohangi, K. (2015). The Use of Problem-Solving Training in Reducing Mathematics Anxiety Among Nigerian Secondary School Students. *Gend. Behav.* 13 (1), 6547–6558.

Barroso, C., Ganley, C. M., McGraw, A. L., Geer, E. A., Hart, S. A., and Daucourt, M. C. (2021). A Meta-Analysis of the Relation between Math Anxiety and Math Achievement. *Psychol. Bull.* 147 (2), 134–168. doi:10.1037/bul0000307

Bieg, M. (2013). Trait And State Academic Emotions: Two Sides Of the Same Coin. Dissertation. Germany: University of Konstanz. Available: https://kops.uni-konstanz.de/handle/123456789/25394 (Accessed January 14, 2022).

Bindak, R. (2005). İlköğretim Öğrencileri Için Matematik Kaygıölçeği [Math Anxiety Scale for Elementary School Students]. *F.Ü. Fen Ve Mühendislik Bilimleri Dergisi* 17 (2), 442–448.

Blascovich, J. (2008). "Challenge and Threat," in *Handbook of Approach and Avoidance Motivation*. Editor A. J. Elliot (New York: Psychology Press), 431–445.

Brandenberger, C. C., and Moser, N. (2018). "Förderung der Lernfreude und Reduzierung der Angst im Mathematikunterricht in der Sekundarstufe 1 [Supporting joy of learning and reducing anxiety in secondary school mathematics classrooms," in *Emotionen und Emotionsregulation in der Schule und Hochschule*. Editors G. Hagenauer, and T. Hascher (Münster: Waxmann).

Brooks, A. W. (2014). Get Excited: Reappraising Pre-performance Anxiety as Excitement. *J. Exp. Psychol. Gen.* 143 (3), 1144–1158. doi:10.1037/a0035325

Carey, E., Hill, F., Devine, A., and Szücs, D. (2016). The Chicken or the Egg? The Direction of the Relationship between Mathematics Anxiety and Mathematics Performance. *Front. Psychol.* 6, 1987. doi:10.3389/fpsyg.2015.01987

Carey, E., Hill, F., Devine, A., and Szűcs, D. (2017). The Modified Abbreviated Math Anxiety Scale: A Valid and Reliable Instrument for Use with Children. *Front. Psychol.* 8, 11. doi:10.3389/fpsyg.2017.00011

Cargnelutti, E., Tomasetto, C., and Passolunghi, M. C. (2017). How Is Anxiety Related to Math Performance in Young Students? A Longitudinal Study of Grade 2 to Grade 3 Children. *Cogn. Emot.* 31 (4), 755–764. doi:10.1080/02699931.2016.1147421

Carmo, J. S. (2008). *Escala de Ansiedade à Matemática [Mathematics Anxiety Scale]*. Unpublished Manuscript. Brazil: Federal University of São Carlos.

Casad, B. J., Hale, P., and Wachs, F. L. (2015). Parent-Child Math Anxiety and Math-Gender Stereotypes Predict Adolescents' Math Education Outcomes. *Front. Psychol.* 6, 1597. doi:10.3389/fpsyg.2015.01597

Cavanagh, R., and Sparrow, L. (2011). "Mathematics Anxiety: Scafolding a New Construct Model," in Mathematics Education Research Group Australasia

(MERGA) Conference Proceedings, Alice Springs, Australia, July 3–7, 2011, 166–173. Available at:https://www.merga.net.au/Public/Public/Publications/Annual_Conference_Proceedings/2011_MERGA_CP.aspx (Accessed January 14, 2022).

Caviola, S., Carey, E., Mammarella, I. C., and Szucs, D. (2017a). Stress, Time Pressure, Strategy Selection and Math Anxiety in Mathematics: A Review of the Literature. *Front. Psychol.* 8, 1488. doi:10.3389/fpsyg.2017.01488

Caviola, S., Primi, C., Chiesi, F., and Mammarella, I. C. (2017b). Psychometric Properties of the Abbreviated Math Anxiety Scale (AMAS) in Italian Primary School Children. *Learn. Individual Differences* 55, 174–182. doi:10.1016/j.lindif.2017.03.006

Chiu, L. -H., and Henry, L. L. (1990). Development and Validation of the Mathematics Anxiety Scale for Children. *Meas. Eval. Couns. Develop.* 23 (3), 121–127.

Choi-Koh, S. S., and Ryoo, B. G. (2019). Differences of Math Anxiety Groups Based on Two Measurements, MASS and EEG. *Educ. Psychol.* 39 (5), 659–677. doi:10.1080/01443410.2018.1543857

Collingwood, N., and Dewey, J. (2018). Thinking Your Problems Away': Can Maths Interventions Be Developed to Address Both the Academic and Affective Aspects of Learning in Primary Aged Children? *Educ. Child Psychol.* 35 (2), 76–92.

Da Silva, E. R., Dos Santos Baldin, M., and Dos Santos, F. H. (2017). Cognitive Effects of Numeracy Musical Training in Brazilian Preschool Children: A Prospective Pilot Study. *Psychol. Neurosci.* 10 (3), 281–296. doi:10.1037/pne0000098

Dowker, A., Sarkar, A., and Looi, C. Y. (2016). Mathematics Anxiety: What Have We Learned in 60 years? *Front. Psychol.* 7, 508. doi:10.3389/fpsyg.2016.00508

Ellis, A., and Bernard, M. E. (Editors) (2006). *Rational-Emotive Behavioral Approaches to Childhood Disorders: Theory, Practice and Research*. Boston, MA: Springer Science & Business Media.

Foley, A. E., Herts, J. B., Borgonovi, F., Guerriero, S., Levine, S. C., and Beilock, S. L. (2017). The Math Anxiety-Performance Link. *Curr. Dir. Psychol. Sci.* 26 (1), 52–58. doi:10.1177/0963721416672463

Fuchs, L. S., Fuchs, D., Schumacher, R. F., and Seethaler, P. M. (2013). "Instructional Intervention for Students with Mathematics Learning Disabilities," in *Handbook of Learning Disabilities*. Editors H. L. Swanson, K. R. Harris, and S. Graham (New York: The Guilford Press), 388–404.

Gunderson, E. A., Park, D., Maloney, E. A., Beilock, S. L., and Levine, S. C. (2018). Reciprocal Relations Among Motivational Frameworks, Math Anxiety, and Math Achievement in Early Elementary School. *J. Cogn. Develop.* 19 (1), 21–46. doi:10.1080/15248372.2017.1421538

Hativa, N., Shapira, R., and Navon, D. (1990). Computer-Managed Practice: Effects on Instructional Methods and on Teacher Adoption. *Teach. Teach. Edu.* 6 (1), 55–68. doi:10.1016/0742-051x(90)90007-r

Hines, C. L., Brown, N. W., and Myran, S. (2016). The Effects of Expressive Writing on General and Mathematics Anxiety for a Sample of High School Students. *Education* 137 (1), 39–45.

Hord, C., Marita, S., Ayaz, S., Tomaro, T. M., Gordon, K., Tunningley, J., et al. (2018). Diverse Needs of Students with Learning Disabilities: A Case Study of Tutoring Two Students in Algebra. *J. Res. Spec. Educ. Needs* 18 (Suppl. 1), 25–35. doi:10.1111/1471-3802.12415

Huang, Y.-M., Huang, S.-H., and Wu, T.-T. (2014). Embedding Diagnostic Mechanisms in a Digital Game for Learning Mathematics. *Education Tech Res. Dev* 62 (2), 187–207. doi:10.1007/s11423-013-9315-4

Idris, N. (2006). Exploring the Effects of TI-84 Plus on Achievement and Anxiety in Mathematics. *Eurasia J. Math. Sci. Tech. Edu.* 2 (3), 66–78. doi:10.12973/ejmste/75465

Jamieson, J. P., Peters, B. J., Greenwood, E. J., and Altose, A. J. (2016). Reappraising Stress Arousal Improves Performance and Reduces Evaluation Anxiety in Classroom Exam Situations. *Soc. Psychol. Personal. Sci.* 7 (6), 579–587. doi:10.1177/1948550616644656

Jansen, B. R. J., Louwerse, J., Straatemeier, M., Van der Ven, S. H. G., Klinkenberg, S., and Van der Maas, H. L. J. (2013). The Influence of Experiencing success in Math on Math Anxiety, Perceived Math Competence, and Math Performance. *Learn. Individual Differences* 24, 190–197. doi:10.1016/j.lindif.2012.12.014

Käser, T., Baschera, G. M., Kohn, J., Kucian, K., Richtmann, V., Grond, U., et al. (2013). Design and Evaluation of the Computer-Based Training Program Calcularis for Enhancing Numerical Cognition. *Front. Psychol.* 4, 489–513. doi:10.3389/fpsyg.2013.00489

Kamann, M. P., and Wong, B. Y. (1993). Inducing Adaptive Coping Self-Statements in Children with Learning Disabilities through Self-Instruction Training. *J. Learn. Disabil.* 26 (9), 630–638. doi:10.1177/002221949302600913

Karimi, A., and Venkatesan, S. (2009). Cognitive Behavior Group Therapy in Mathematics Anxiety. *J. Indian Acad. Appl. Psychol.* 35 (2), 299–303.

Kazelskis, R., and Reeves, C. (2002). The Fennema-Sherman Mathematics Anxiety Scale: An Exploratory Factor Analysis. *Res. Schools* 9 (1), 61–64.

Kim, Y., Thayne, J., and Wei, Q. (2017). An Embodied Agent Helps Anxious Students in Mathematics Learning. *Edu. Tech Res. Dev* 65 (1), 219–235. doi:10.1007/s11423-016-9476-z

Kim, E. J. (2010). A Study on the Development of a Brain Education Program to Improve Self Directed Learning Ability. *Korean J. Youth Stud.* 17 (10), 161–188.

Klinkenberg, S., Straatemeier, M., and van der Maas, H. L. J. (2011). Computer Adaptive Practice of Maths Ability Using a New Item Response Model for on the Fly Ability and Difficulty Estimation. *Comput. Edu.* 57, 1813–1824. doi:10.1016/j.compedu.2011.02.003

Ko, H. K., and Yi, H. S. (2011). Development and Validation of a Mathematics Anxiety Scale for Students. *Asia Pac. Educ. Rev.* 12 (4), 509–521. doi:10.1007/s12564-011-9150-4

Kohn, J., Richtmann, V., Rauscher, L., Kucian, K., Käser, T., Grond, U., et al. (2013). Das Mathematikangstinterview (MAI): Erste Psychometrische Gütekriterien. *Lernen und Lernstörungen* 2 (3), 177–189. doi:10.1024/2235-0977/a000040

Kramarski, B., Weisse, I., and Kololshi-Minsker, I. (2010). How Can Self-Regulated Learning Support the Problem Solving of Third-Grade Students with Mathematics Anxiety? *ZDM Math. Edu.* 42 (2), 179–193. doi:10.1007/s11858-009-0202-8

LaGue, A., Eakin, G., and Dykeman, C. (2019). The Impact of Mindfulness-Based Cognitive Therapy on Math Anxiety in Adolescents. *Preventing Sch. Fail. Altern. Edu. Child. Youth* 63 (2), 142–148. doi:10.1080/1045988X.2018.1528966

Lavasani, M. G., Hejazi, E., and Khandan, F. (2012). The Effect of Cooperative Learning on Mathematics Anxiety and Help Seeking Behavior. *J. Psychol.* 15 (4), 397–411.

Lin, Y., Durbin, J. M., and Rancer, A. S. (2017). Perceived Instructor Argumentativeness, Verbal Aggressiveness, and Classroom Communication Climate in Relation to Student State Motivation and Math Anxiety. *Commun. Edu.* 66 (3), 330–349. doi:10.1080/03634523.2016.1245427

Maertens, B., De Smedt, B., Sasanguie, D., Elen, J., and Reynvoet, B. (2016). Enhancing Arithmetic in Pre-Schoolers with Comparison or Number Line Estimation Training: Does it Matter? *Learn. Instruction* 46, 1–11. doi:10.1016/j.learninstruc.2016.08.004

Malanchini, M., Rimfeld, K., Shakeshaft, N. G., Rodic, M., Schofield, K., Selzam, S., et al. (2017). The Genetic and Environmental Aetiology of Spatial, Mathematics and General Anxiety. *Sci. Rep.* 7 (1), 42218–42311. doi:10.1038/srep42218

Martin, A. J. (2008). Enhancing Student Motivation and Engagement: The Effects of a Multidimensional Intervention. *Contemp. Educ. Psychol.* 33 (2), 239–269. doi:10.1016/j.cedpsych.2006.11.003

May, D. K. (2009). Mathematics Self-Efficacy and Anxiety Questionnaire. Dissertation. Athens: University of Georgia. Available at: https://getd.libs.uga.edu/pdfs/may_diana_k_200908_phd.pdf (Accessed January 14, 2022).

Mehdizadeh, S., Nojabaee, S. S., and Asgari, M. H. (2013). The Effect of Cooperative Learning on Math Anxiety, Help Seeking Behavior. *J. Basic Appl. Scientific Res.* 3 (3), 1185–1190.

Meichenbaum, D. (1977). *Cognitive Behaviour Modification: An Integrative Approach*. New York: Plenum Press.

Mevarech, Z. R., and Kramarski, B. (1997). Improve: A Multidimensional Method for Teaching Mathematics in Heterogeneous Classrooms. *Am. Educ. Res. J.* 34 (2), 365–394. doi:10.3102/00028312034002365

Mevarech, Z. R., and Rich, Y. (1985). Effects of Computer-Assisted Mathematics Instruction on Disadvantaged Pupils' Cognitive and Affective Development. *J. Educ. Res.* 79 (1), 5–11. doi:10.1080/00220671.1985.10885638

Mevarech, Z. R., Silber, O., and Fine, D. (1991). Learning with Computers in Small Groups: Cognitive and Affective Outcomes. *J. Educ. Comput. Res.* 7 (2), 233–243. doi:10.2190/BRCJ-P9K5-9E1D-2ALC

Midgley, C., Kaplan, A., Middleton, M., Maehr, M. L., Urdan, T., Anderman, L. H., et al. (2013). *Manual for the Patterns of Adaptive Learning Scales*. Ann Arbor: University of Michigan.

Miller, P. H., and Seier, W. L. (1994). Strategy Utilization Deficiencies in Children: When, where, and Why. *Adv. child Dev. Behav.* 25, 107–156. Academic Press. doi:10.1016/S0065-2407(08)60051-8

Moher, D., Liberati, A., Tetzlaff, J., and Altman, D. G. (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. *BMJ* 339 (7), b2535–b2536. doi:10.1136/bmj.b2535

Namkung, J. M., Peng, P., and Lin, X. (2019). The Relation between Mathematics Anxiety and Mathematics Performance Among School-Aged Students: A Meta-Analysis. *Rev. Educ. Res.* 89 (3), 459–496. doi:10.3102/0034654319843494

OECD (2005). *PISA 2003 Technical Report*. Paris: OECD Publishing. doi:10.1787/9789264010543-en

Orbach, L., Herzog, M., and Fritz, A. (2019). Relation of State- and Trait-Math Anxiety to Intelligence, Math Achievement and Learning Motivation. *J. Numer. Cogn.* 5 (3), 371–399. doi:10.5964/jnc.v5i3.204

Orbach, L., Herzog, M., and Fritz, A. (2020). Relation of Attention Deficit Hyperactivity Disorder (ADHD) to Basic Number Skills and Arithmetic Fact Retrieval in Children. *Res. Dev. Disabil.* 103, 103697. doi:10.1016/j.ridd.2020.103697

Ouzzani, M., Hammady, H., Fedorowicz, Z., and Elmagarmid, A. (2016). Rayyan-a Web and mobile App for Systematic Reviews. *Syst. Rev.* 5 (210), 210–10. doi:10.1186/s13643-016-0384-4

Passolunghi, M. C., De Vita, C., and Pellizzoni, S. (2020). Math Anxiety and Math Achievement: The Effects of Emotional and Math Strategy Training. *Dev. Sci.* 23, e12964. doi:10.1111/desc.12964

Pekrun, R., Goetz, T., and Frenzel, A. C. (2005). *Academic Emotions Questionnaire–Mathematics (AEQ-M): User's Manual*. Munich: University of Munich, Department of Psychology.

Pizzie, R. G., Raman, N., and Kraemer, D. J. M. (2020). Math Anxiety and Executive Function: Neural Influences of Task Switching on Arithmetic Processing. *Cogn. Affect Behav. Neurosci.* 20 (2), 309–325. doi:10.3758/s13415-020-00770-z

Plake, B. S., and Parker, C. S. (1982). The Development and Validation of a Revised Version of the Mathematics Anxiety Rating Scale. *Educ. Psychol. Meas.* 42 (2), 551–557. doi:10.1177/001316448204200218

Primi, C., Donati, M. A., Izzo, V. A., Guardabassi, V., O'Connor, P. A., Tomasetto, C., et al. (2020). The Early Elementary School Abbreviated Math Anxiety Scale (The EES-AMAS): A New Adapted Version of the AMAS to Measure Math Anxiety in Young Children. *Front. Psychol.* 11, 1014. doi:10.3389/fpsyg.2020.01014

Ramirez, G., Gunderson, E. A., Levine, S. C., and Beilock, S. L. (2013). Math Anxiety, Working Memory, and Math Achievement in Early Elementary School. *J. Cogn. Develop.* 14 (2), 187–202. doi:10.1080/15248372.2012.664593

Ramirez, G., Chang, H., Maloney, E. A., Levine, S. C., and Beilock, S. L. (2016). On the Relationship between Math Anxiety and Math Achievement in Early Elementary School: The Role of Problem Solving Strategies. *J. Exp. Child. Psychol.* 141, 83–100. doi:10.1016/j.jecp.2015.07.014

Ramirez, G., Shaw, S. T., and Maloney, E. A. (2018). Math Anxiety: Past Research, Promising Interventions, and a New Interpretation Framework. *Educ. Psychol.* 53 (3), 145–164. doi:10.1080/00461520.2018.1447384

Rauscher, L., Kohn, J., Käser, T., Kucian, K., McCaskey, U., Wyschkon, A., et al. (2017). Effekte des Calcularis-Trainings. *Lernen und Lernstörungen* 6 (2), 75–86. doi:10.1024/2235-0977/a000168

Reynvoet, B., Vanbecelaere, S., Depaepe, F., and Sasanguie, D. (2021). "Intervention Studies in Math: A Metareview," in *Heterogeneous Contributions to Numerical Cognition*. Editors W. Fias and A. Hanik (Cambridge, MA: Academic Press), 283–308. doi:10.1016/b978-0-12-817414-2.00012-9

Ruark, A. (2021). Expressive Writing as an Intervention for Math Anxiety in Middle School Students. *MLET: J. Middle Level Edu. Tex.* 7 (1), 1.

Ruff, S. E., and Boes, S. R. (2014). The Sum of All Fears: The Effects of Math Anxiety on Math Achievement in Fifth Grade Students and the Implications for School Counselors. *Ga. Sch. Counselors Assoc. J.* 21 (1).

Sarason, I. G. (1980). *Test Anxiety: Theory, Research, and Applications*. Hillsdale: Lawrence Erlbaum.

Sarason, I. G. (1986). "Test Anxiety, Worry, and Cognitive Interference," in *Self-Related Cognitions in Anxiety and Motivation*. Editor R. Schwarzer (Hillslade: Lawrence Erlbaum), 19–35.

Segumpan, L. L. B., and Tan, D. A. (2018). Mathematics Performance and Anxiety of Junior High School Students in a Flipped Classroom. *Eur. J. Educ. Stud.* 4 (12), 1–33. doi:10.5281/ZENODO.1325918

Shapka, J. D., and Keating, D. P. (2003). Effects of a Girls-Only Curriculum during Adolescence: Performance, Persistence, and Engagement in Mathematics and Science. *Am. Educ. Res. J.* 40 (4), 929–960. doi:10.3102/00028312040004929

Sheffield, D., and Hunt, T. (2006). How Does Anxiety Influence Maths Performance and what Can We Do about it? *MSOR Connections* 6 (4), 19–23. doi:10.11120/msor.2006.06040019

Shie, B.-H. (2006). Construction of Mathematics Anxiety Scale for Younger Pupils: Verification of Theoretical Models. Unpublished Master Thesis. Taipei: National Taipei University of Education.

Shokrani, M. (2002). Creation and Validity Recognition of Math Anxiety Scale of Measurement at Secondary School Students in Khomeini Shahr and Investigation of Factors Related to Math Anxiety. Unpublished Master Thesis. Tehran: University of Tehran.

Singh, P. (2016). Management of Mathematics Phobia Among Ninth Standard Students. *Int. J. Indian Psychol.* 3 (2), 69–76. doi:10.25215/0302.043

Sorvo, R., Koponen, T., Viholainen, H., Aro, T., Räikkönen, E., Peura, P., et al. (2017). Math Anxiety and its Relationship with Basic Arithmetic Skills Among Primary School Children. *Br. J. Educ. Psychol.* 87 (3), 309–327. doi:10.1111/bjep.12151

Sorvo, R., Koponen, T., Viholainen, H., Aro, T., Räikkönen, E., Peura, P., et al. (2019). Development of Math Anxiety and its Longitudinal Relationships with Arithmetic Achievement Among Primary School Children. *Learn. Individual Differences* 69, 173–181. doi:10.1016/j.lindif.2018.12.005

Spielberger, C. D. (1972). *Anxiety. Current Trends in Theory and Research*. New York: Academic Press.

Suinn, R. M., Edie, C. A., Nicoletti, J., and Spinelli, P. R. (1972). The MARS, a Measure of Mathematics Anxiety: Psychometric Data. *J. Clin. Psychol.* 28 (6), 373–375. doi:10.1002/1097-4679(197207)28:3+<373:aid-jclp2270280320>3.0.co;2-c

Suinn, R. M., and Edwards, R. (1982). The Measurement of Mathematics Anxiety: The Mathematics Anxiety Rating Scale for Adolescents--MARS-A. *J. Clin. Psychol.* 38 (3), 576–580. doi:10.1002/1097-4679(198207)38:3<576:aid-jclp2270380317>3.0.co;2-v

Suinn, R. M., and Winston, E. H. (2003). The Mathematics Anxiety Rating Scale, a Brief Version: Psychometric Data. *Psychol. Rep.* 92 (1), 167–173. doi:10.2466/pr0.2003.92.1.167

Supekar, K., Iuculano, T., Chen, L., and Menon, V. (2015). Remediation of Childhood Math Anxiety and Associated Neural Circuits through Cognitive Tutoring. *J. Neurosci.* 35 (36), 12574–12583. doi:10.1523/JNEUROSCI.0786-15.2015

Tok, Ş., Bahtiyar, A., and Karalök, S. (2015). The Effects of Teaching Mathematics Creatively on Academic Achievement, Attitudes towards Mathematics, and Mathematics Anxiety. *Int. J. Innovation Sci. Math. Edu.* 23 (4), 1–24.

Tok, Ş. (2013). Effects of the Know-Want-Learn Strategy on Students' Mathematics Achievement, Anxiety and Metacognitive Skills. *Metacognition Learn.* 8 (2), 193–212. doi:10.1007/s11409-013-9101-z

Vanbecelaere, S., Van den Berghe, K., Cornillie, F., Sasanguie, D., Reynvoet, B., and Depaepe, F. (2020). The Effects of Two Digital Educational Games on Cognitive and Non-Cognitive Math and reading Outcomes. *Comput. Edu.* 143, 103680. doi:10.1016/j.compedu.2019.103680

Vanbecelaere, S., Cornillie, F., Sasanguie, D., Reynvoet, B., and Depaepe, F. (2021). The Effectiveness of an Adaptive Digital Educational Game for the Training of Early Numerical Abilities in Terms of Cognitive, Noncognitive and Efficiency Outcomes. *Br. J. Educ. Technol.* 52 (1), 112–124. doi:10.1111/bjet.12957

Verkijika, S. F., and De Wet, L. (2015). Using a Brain-Computer Interface (BCI) in Reducing Math Anxiety: Evidence from South Africa. *Comput. Edu.* 81, 113–122. doi:10.1016/j.compedu.2014.10.002

Wang, Z., Hart, S. A., Kovas, Y., Lukowski, S., Soden, B., Thompson, L. A., et al. (2014). Who Is Afraid of Math? Two Sources of Genetic Variance for Mathematical Anxiety. *J. Child. Psychol. Psychiatry* 55 (9), 1056–1064. doi:10.1111/jcpp.12224

Wu, S. S., Barth, M., Amin, H., Malcarne, V., and Menon, V. (2012). Math Anxiety in Second and Third Graders and its Relation to Mathematics Achievement. *Front. Psychol.* 3 (162), 162. doi:10.3389/fpsyg.2012.00162

Young, C. B., Wu, S. S., and Menon, V. (2012). The Neurodevelopmental Basis of Math Anxiety. *Psychol. Sci.* 23 (5), 492–501. doi:10.1177/0956797611429134

Zhang, J., Zhao, N., and Kong, Q. P. (2019). The Relationship between Math Anxiety and Math Performance: A Meta-Analytic Investigation. *Front. Psychol.* 10, 1613. doi:10.3389/fpsyg.2019.01613

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Retrieval Practice Is Effective Regardless of Self-Reported *Need for Cognition* - Behavioral and Brain Imaging Evidence

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There is an emerging consensus that retrieval practice is a powerful way to enhance long-term retention and to reduce achievement gaps in school settings. Less is known whether retrieval practice benefits performance in individuals with low intrinsic motivation to spend time and effort on a given task, as measured by self-reported *need for cognition* (NFC). Here, we examined retrieval practice in relation to individual differences in NFC by combining behavioral and functional magnetic resonance imaging (fMRI) data. Using a within-subject design, upper-secondary school students ($N = 274$) learned a language-based material (Swahili-Swedish word-pairs), with half of the items by means of retrieval practice with feedback and half by study only. One week later, the students were tested on the word-pairs either in the classroom ($n = 204$), or in a fMRI scanner ($n = 70$). In both settings, a retrieval practice effect was observed across different levels of NFC (high or low). Relatedly, comparable fMRI effects were seen in both NFC subgroups. Taken together, our findings provide behavioral and brain-imaging evidence that retrieval practice is effective also for individuals with lower levels of NFC, which is of direct relevance for educational practice.

Keywords: retrieval practice, testing effect, *need for cognition* (NFC), learning and memory, fMRI, classroom

INTRODUCTION

Recent meta-analytic reviews have demonstrated that active learning methods reduce the achievement gap between academic success and failure (Freeman et al., 2014; Theobald et al., 2020). Similarly, key insights from neuroscience on learning and memory have shown that learning by actively engaging the brain has a direct effect on learning and memory retention (e.g., Mårtensson et al., 2012; Stillesjö et al., 2021). One form of active learning is retrieval practice, where the activity of including test sessions while acquiring new information has been shown to markedly boost long-term retention (i.e., commonly denoted as the testing-effect; e.g., see Roediger and Karpicke, 2006a,b; Roediger and Butler, 2011; Dunlosky et al., 2013; Agarwal et al., 2021; McDermott, 2021; for reviews).

The positive learning effects following retrieval practice have been demonstrated in: (1) young children ranging to older adults (e.g., Fazio and Marsh, 2019), (2) from easy to more complex materials (e.g., Karpicke and Aue, 2015; McDermott, 2021), (3) for both theoretical and practical course subjects (e.g., Dunlosky et al., 2013; Larsen et al., 2013), (4) for students with lower cognitive abilities (e.g., Brewer and Unsworth, 2012; Agarwal et al., 2017; Jonsson et al., 2020) as well as for those (5) with a diversity of learning disabilities (e.g., ADHD; Knouse et al., 2016, Downs syndrome; Starling et al., 2019, dyslexia/development language disorder; Leonard et al., 2019) and (6) to result in better learning outcome compared to other learning active methods [e.g., group discussions (Stenlund et al., 2017) and mind maps (Karpicke and Blunt, 2011)]. Based on the available evidence, it has been argued that retrieval practice is a learning method that is easy to apply and, as such, has high utility for educational practice across ages and course subjects (see also Dunlosky et al., 2013; Moreira et al., 2019, McDermott, 2021; for examples of reviews and meta-analyzes). In spite of this evidence, both students and teachers tend to overlook the beneficial effects of retrieval practice, and instead think of it as a method for evaluation (i.e., summative assessment) than for learning (i.e., formative assessment; McDermott, 2021).

Despite the well-established learning effects retrieval practice has on long term retention, (i.e., the testing effect), less is known about its effect related to individual variations in need for cognition (NFC; Cacioppo et al., 1996). NFC is a personality trait and is defined as "*differences among individuals in their tendency to engage in and enjoy thinking*" (Cacioppo and Petty, 1982, p. 116). High levels of NFC have a positive impact on performance (Weissgerber et al., 2018) and school grades (Grass et al., 2017; Luong et al., 2017; Strobel et al., 2019). Whereas some evidence exists for a positive link between NFC and cognitive ability (e.g., Fleischhauer et al., 2010; Hill et al., 2016), others have proposed that there is no such relationship (e.g., Gärtner et al., 2021). For example, Gärtner et al. (2021) suggest that NFC is a trait that is less characterized by cognitive abilities *per se*, instead they rather stress that the degree of NFC is related to the willingness to invest effort and self-control in the task at hand (see also Sandra and Otto, 2018). Related to NFC, prior behavioral studies have reported that students with lower NFC have a tendency to prefer learning strategies characterized by surface rather than deep learning (e.g., Evans et al., 2003; Sandra and Otto, 2018), or lack engagement in cognitively demanding learning activities (e.g., Gärtner et al., 2021). Moreover, Gonthier and Roulin (2020) further provide evidence that individuals with lower levels of working memory capacity and NFC are more inclined to use less effective learning strategies given the task at hand (see also Evans et al., 2003 for related findings). As such, one challenge within the educational field is to identify and examine whether specific learning methods can reduce the influence intrinsic motivation to spend low cognitive effort on a given task has, and in turn boost learning and retention in individuals with lower NFC. One possible learning method for this purpose could be retrieval practice.

Recently, non-invasive brain imaging methods such as functional magnetic resonance imaging (fMRI) has served as a complementary method to study *how* and *why* retrieval practice benefit long-term retention. For example, activity differences for retrieval practice, relative study, have been observed in a number of cortical (e.g., Keresztes et al., 2014; Jonsson et al., 2020; see van den Broek et al., 2016 for an overview); and subcortical brain regions (e.g., Wing et al., 2013; Liu et al., 2014; Jonker et al., 2018; Wiklund-Hörnqvist et al., 2020) typically associated with semantic processing and retrieval of well-consolidated memory representations (see e.g., Cabeza et al., 2008; Binder and Desai, 2011; Eichenbaum, 2017). For example, Karlsson Wirebring reported higher functional brain activity in the inferior frontal gyrus (IFG) 1 week after retrieval practice. Activity in the IFG is associated with the reinstatement of semantic memory representations stored elsewhere in the brain, including the parietal and temporal cortices (Martin and Chao, 2001; Binder et al., 2009). Repeated retrieval has also been linked to subcortical brain regions such as the hippocampus (Wing et al., 2013; Liu et al., 2014; Vestergren and Nyberg, 2014; Jonker et al., 2018; Wiklund-Hörnqvist et al., 2020). In addition, it was recently suggested that retrieval practice strengthens subsequent memory *via* a dual action of the hippocampus to support retrieval of detailed as well as generalized memory representations (Wiklund-Hörnqvist et al., 2020). The positive learning effects 1 week after retrieval practice was recently demonstrated to be accompanied by higher brain activity in fronto-parietal brain regions independent of cognitive proficiency (Jonsson et al., 2020). However, it still remains unknown if a similar pattern of brain activity following retrieval practice can be observed for individuals reporting different levels of NFC.

We here extend a previously published study (Jonsson et al., 2020) which focused on the retrieval practice effects related to cognitive ability and fMRI data. From the same data set, we here extracted a measure of NFC and examined individual differences in NFC in relation to the retrieval practice effects by combining behavioral and functional brain imaging data. Upper secondary school students ($N = 274$) participated in a learning intervention (study/retrieval practice) in the classroom. The to-be-learned material was foreign language vocabulary (60 Swahili-Swedish word-pairs). In the classroom, students learned half of the word-pairs by study, and the other half by retrieval practice and feedback (correct answer feedback). In both conditions, each word-pair was randomly presented six times, and interleaved between the two conditions. To examine the testing effect, learning was assessed by means of a cued recall test either in the classroom ($n = 204$) or by the use of fMRI ($n = 70$) 1 week after the learning intervention (see **Figures 1**, **2**).

We have for this sample shown that brain activity is higher in several cortical and subcortical brain regions following retrieval practice (Jonsson et al., 2020; Wiklund-Hörnqvist et al., 2020). Several of the identified brain regions, such as the IFG and the hippocampus, have been implicated in retrieval of well-established semantic memories (Martin and Chao, 2001; Binder and Desai, 2011; Eichenbaum, 2017). One possibility is that individuals with high NFC will benefit more from retrieval practice, for example due to being more inclined to use semantic elaboration. If so, this would result in a significant fMRI main-effect of NFC group, for example reflecting higher activity in fronto-parietal brain regions and

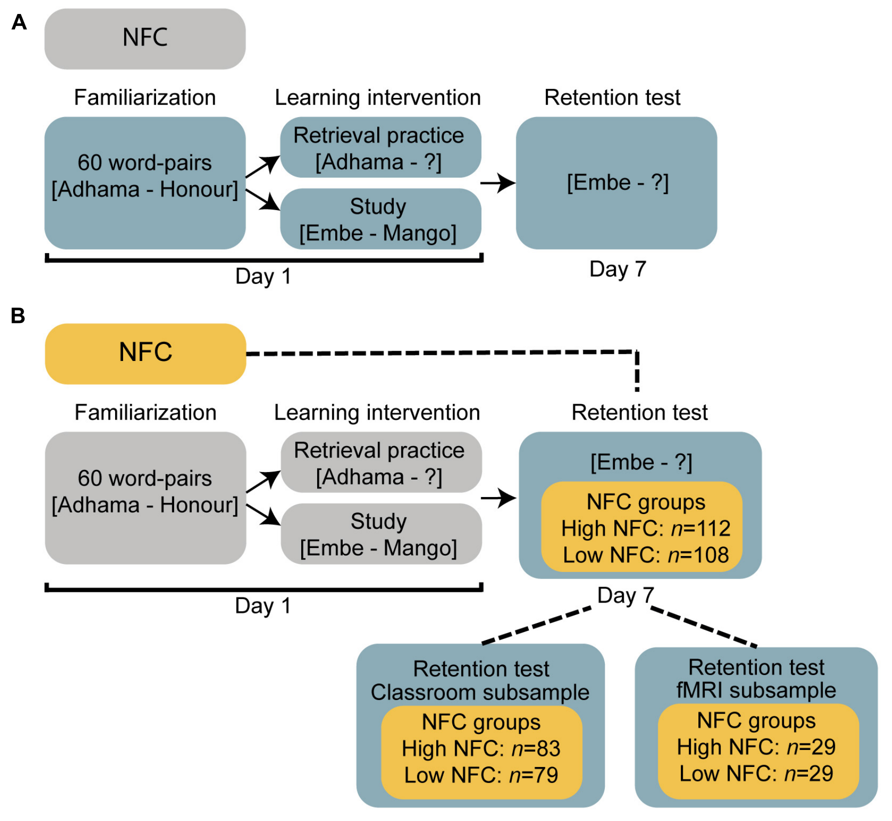

FIGURE 1 | A schematic overview over the **(A)** overall study design and **(B)** related to the low and high NFC groups (yellow).

the hippocampus for high NFC individuals. An alternative possibility is that low NFC individuals will benefit more from retrieval practice, as the difference between a more passive (study) versus an active (retrieval practice) condition will be more marked for these individuals if retrieval practice "automatically" confers semantic elaboration. If so, this would yield a significant interaction effect between learning condition and NFC group, possibly in the IFG and hippocampus. Still another possibility is that retrieval practice will be equally effective regardless of level of NFC. Based on behavioral studies confirming the benefits of retrieval practice across a diversity of factors (see e.g., Roediger and Butler, 2011; Dunlosky et al., 2013; Fazio and Marsh, 2019; Moreira et al., 2019; Jonsson et al., 2020; Agarwal et al., 2021; McDermott, 2021; for overviews), we predicted that we would find support for the latter possibility, i.e., significant testing effects regardless of the level of NFC. If so, this could result in a significant fMRI main-effect (in favor for retrieval practice) with higher brain activity in IFG and hippocampus independent of NFC status. Alternatively, similar behavioral testing effects in individuals with high or low NFC levels could still map on to qualitative and/or quantitative differences in the recruited functional brain networks (i.e., behavioral equivalence does not always correspond to neural equivalence; Sohn et al., 2004). The combination of behavioral and fMRI data allowed us to assess the latter possible outcome.

MATERIALS AND METHODS

Participants

Participants were 274 upper secondary school students (M_{age} = 17.51 years, SD = 0.74; n = 137 girls). All participants were native Swedish speakers, and none reported prior experience with the Swahili language. Prior to the data collection, written informed consent were obtained from the participants in accordance with the Helsinki declaration. For the fMRI subsample (n = 70; 54% girls), all participants were neurologically healthy, right-handed by self-report, had normal or corrected-to-normal vision. For participants (n = 10) who had not yet attained a legal age of majority (18 years.), written informed consent was obtained from the participant and both caregivers.

Materials

Foreign Language Vocabulary

The to-be-learned material was 60 Swahili-Swedish word-pairs translated from Nelson and Dunlosky (1994) and previously used (e.g., Vestergren and Nyberg, 2014; Karlsson Wirebring et al., 2015; Wiklund-Hörnqvist et al., 2017, 2020).

Need for Cognition

Need for cognition was measured by the Mental Effort Tolerance Questionnaire (METQ; Dornic et al., 1991;

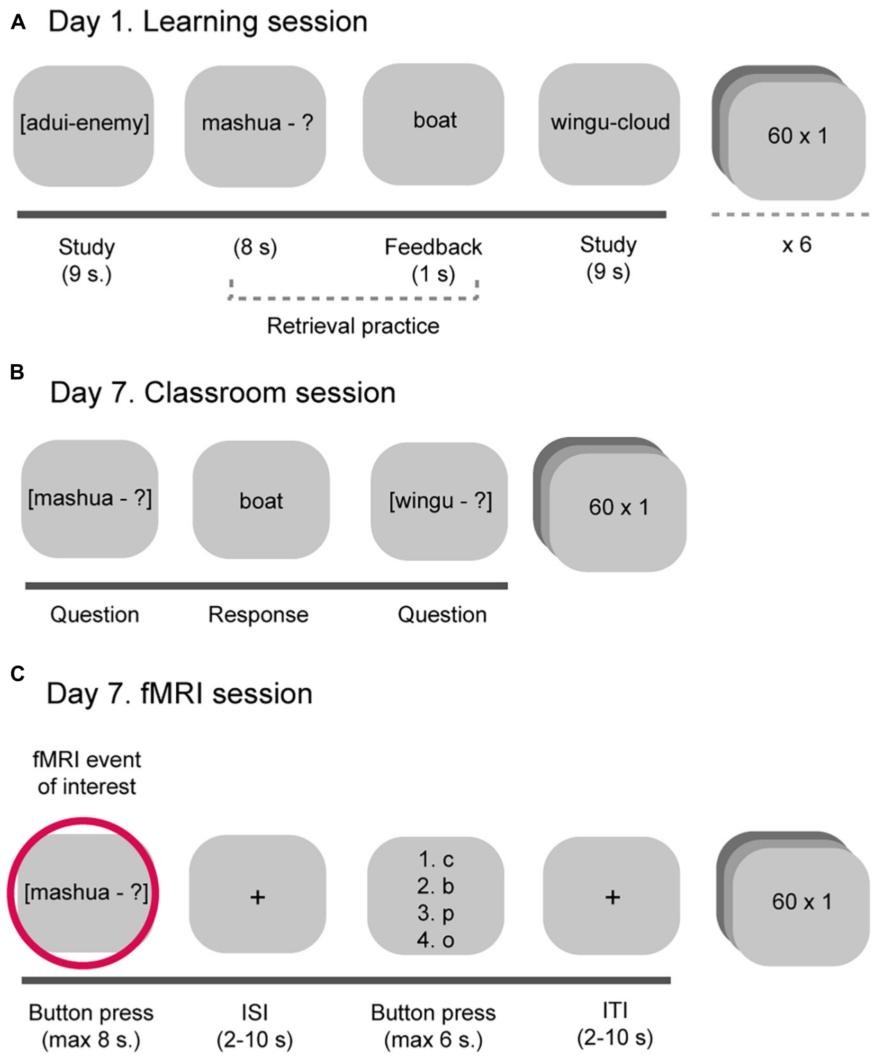

FIGURE 2 | The experimental procedure related to **(A)** the learning intervention (day 1) and the 1 week retention test in the **(B)** classroom and the **(C)** MR scanner.

Stenlund and Jonsson, 2017), which is a Swedish adaptation of the original NFC scale (Cacioppo and Petty, 1982). The METQ encompasses 30 items rated on a 5-point Likert scale (1 = strongly disagree, 3 = neutral, and 5 = strongly agree). Eighteen of the 30 items are reversed scored. The individual NFC score is calculated as the sum of all items, with higher scores as indicative for more NFC. In line with psychometric studies on the Swedish version of METQ, the internal consistency in this study was good, Chronbach's $\alpha = 0.87$ (see Stenlund and Jonsson, 2017 for psychometric evaluation of the Swedish version of METQ).

Procedure

Need for cognition was collected 1–2 weeks prior to the learning intervention (see **Figure 1**). The learning intervention took place over two sessions (learning intervention and a retention test) separated by 1 week. The learning intervention was identical for all participants (see **Figure 2A**). The procedure for the 1 week retention test differed among participants such that the majority of the participants (classroom subsample, $n = 204$) performed the retention test in the classroom in front of their computer (see **Figure 2B**), but a subsample (fMRI subsample, $n = 70$) performed the 1 week retention test in the MR scanner (see **Figure 2C**).

Learning Intervention (Day 1)

The learning intervention was performed in the classroom (see **Figure 2A**). Each student sat in front of their own computer spaced apart from their classmates. First, to familiarize the students with the to-be-learned material, each complete Swahili-Swedish word-pair was presented one by one on the computer screen once. Next, half of the words were learned through study (Adhama – Honor), and the other half through retrieval practice (Bahasha - ?) followed by correct answer feedback (Envelope). Each word-pair was presented six consecutive times, and exposure time for each word was equal in both learning conditions (9 s). To prevent item and order effects, words were randomly interspersed related to learning condition (retrieval practice, study) and each student had a unique learning list.

One Week Retention Test (Day 7)

One week after the learning intervention, learning was assessed by means of a cued recall test either in the classroom ($n = 204$) or by the use of fMRI ($n = 70$). The only difference between the methodologies (classroom and fMRI) for the cued recall test was how students responded (see **Figures 2B,C**). In the classroom, all students were required to type in the corresponding Swedish counterpart using their laptop. In the scanner, students were instead asked to respond by a button press whether they *knew*, *believed they knew* or *did not know* the Swedish counterpart (see **Figure 2C**). Next, a jittered cross-hair appeared on the screen (ISI, 2–10 s). Students were then asked to select among four alternatives to indicate the second letter that corresponded to the second letter in the retrieved Swedish counterpart (right middle finger). The second letter cueing was used to single out correctly remembered words that were successfully retrieved. The position of the correct answer relative to the lures systematically varied to avoid item order effects (see Karlsson Wirebring et al., 2015; Wiklund-Hörnqvist et al., 2017, 2020; Jonsson et al., 2020; Stillesjö et al., 2021). Next followed a jittered crosshair (ITI, 2–10 s) before the presentation of the next cue appeared on the screen. The fMRI session lasted for ∼ 45 min, and ended with structural images.

Statistical Analyzes Related to Need for Cognition

One of the purposes with the study was to delineate the association between NFC and performance 1 week after the learning intervention, and a second purpose was to use fMRI data to further complement behavioral data related to the first purpose. As such, individual scores on NFC were analyzed both at the individual (i.e., continuous variable) and split into subgroups based on NFC levels (i.e., high NFC group, low NFC group).

First, independent of learning condition, students ($N = 274$) performance 1 week after the learning intervention was correlated with the individual NFC score. Next, to further evaluate whether individual levels of NFC influences the testing effect, students were divided into high and low NFC groups. The high NFC group ($n = 112$) was defined as the 40% individuals with the highest NFC scores ($M = 116.13$, $SD = 7.73$; range $NFC_{score} = 106–138$). The low NFC group ($n = 108$) was defined as the 40% individuals with the lowest NFC scores ($M = 87.43$, $SD = 8.75$; range $NFC_{score} = 58–97$; see **Figure 1B**). The motivation to divide the sample into 40% high and 40% low NFC individuals, and to exclude 20% in the middle, was related to us wanting to separate the groups of interest. We therefore avoided using under/above the median to define "low" or "high" NFC individuals (but see **Supplementary Figures 1A,B** for an illustration including all participants).

Next, as the fMRI subsample ($n = 70$) already was included in the high and low NFC groups related to the behavioral analyzes (see **Table 1** for descriptive statistics and **Figure 1B**), we re-run the ANOVA on the fMRI data.

TABLE 1 | Descriptive statistics related to the testing effect, NFC scores for the different subsamples.

	NFC score		RP	S	TE
Sample	***M***	**SD**	***M* (SD)**	***M* (SD)**	***p***
Overall ($N = 274$)	101.99	14.87	0.46 (0.27)	0.30 (0.24)	<0.001
Subsample					
Classroom ($n = 204$)	101.82	15.22	0.48 (0.28)	0.32 (0.25)	<0.001
fMRI ($n = 70$)	102.46	13.90	0.41 (0.23)	0.25 (0.20)	<0.001

NFC, Need for cognition; RP, Retrieval practice; S, Study; TE, testing effect.

Image Acquisition

Images were acquired on a 3.0 T whole-body scanner (MR 750, GE Medical Systems) equipped with a head coil. T2* weighted images were collected with a single-shot GE-EPI sequence for BOLD imaging. The parameters used for the data collection were: echo time, 30 ms; repetition time, 2,000 ms; flip angle, 90°; FOV, 248 × 248 mm; acquisition matrix 96 × 96 (reconstructed to 128 × 128 and hence 1.95 mm resolution); and slice thickness, 3.4 mm (37 slices acquired). Ten dummy scans were collected to allow equilibrium of the fMRI signal, and discarded before the start of the data collection. T1-weighted structural images were obtained for each participant. Cushions within the head coil were used to minimize head movements during scanning, and headphones and earplugs were used to reduce scanner noise. All stimuli were presented to the participants through a mirror attached to the head coil, and run from a PC through E-prime version 2.0 (Psychology Software Tools). Participants' responses were collected with a four-key button keypad (Lumitouch fMRI optical response keypads, Photon Control).

Functional data were preprocessed in SPM 12 and run through an in-house program (DataZ). Preprocessing of all images included: Correction for slice-timing, and head movements were corrected with realign and unwarp. Segmentation was done for all T1-images, and a group specific mean template and individual flow fields were created with the DARTEL algorithm (Ashburner, 2007). The DARTEL template and flow fields were used to normalize the images to MNI space (2 mm), and the images were smoothed (8 mm FWHM Gaussian filter kernel).

Functional Magnetic Resonance Imaging Data Analysis

A 2 (learning condition: Retrieval practice vs. Study) × 2 (NFC group: High NFC vs. low NFC) ANOVA was set up to examine patterns of brain activity change during retrieval practice in relation to self-reported NFC.

At the first level, for each student, individual general linear models were estimated. The model included separate regressors of interest (items learned through retrieval practice, items learned through study), and the six movement parameters were included as covariates of no interest. All regressors except the movement parameters were convolved with a hemodynamic response function. The design was event-related, and the duration was set to zero. Two t-contrast images were defined to evaluate brain activity specifically related to retrieval practice and study.

Second, to test for an interaction effect between learning conditions (retrieval practice, study) and NFC groups, a whole-brain 2 (retrieval practice, study) × 2 (high NFC, low NFC) ANOVA was performed. All students' individual t-contrasts related to retrieval practice and study defined at the first level were inserted in the ANOVA. Peak activity related to retrieval practice and study in selected brain regions were plotted. The statistical threshold was set to $p < 0.05$ (FWE corrected), and $k > 10$. The ANOVA was also evaluated at a more liberal threshold $p < 0.0001$ (uncorrected) at the voxel level, and $k > 10$ at the cluster level.

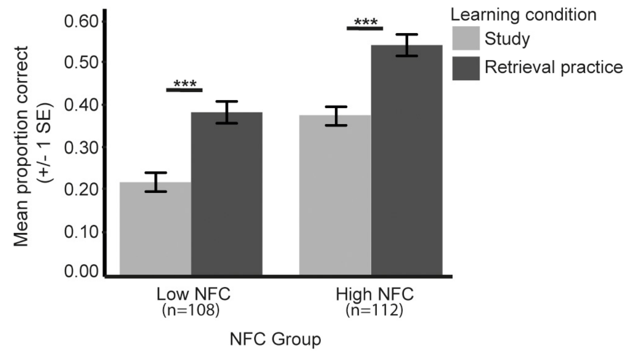

FIGURE 3 | The behavioral testing effects related to the NFC groups. Error bars denote ± 1 SEM. ***$p < 0.001$.

RESULTS

Behavioral Results

A paired t-test confirmed a significant testing effect [$t(273) = 11.97$, $p < 0.001$] meaning that performance was higher following retrieval practice compared to after study (see **Table 1**). Despite the significant testing effect, and independent of learning condition, individual variation in NFC was positively associated with long-term retention (study, $r = 0.24$, $p < 0.001$, retrieval practice, $r = 0.25$, $p < 0.001$).

To further evaluate whether different levels of NFC influences the testing effect, a mixed model ANOVA with learning condition (retrieval practice/study) as within-subject factor and NFC group (high/low) as between-subject factor was performed. Results revealed significant main effects of learning condition [$F(1, 218) = 118.50$, $p < 0.001$] and NFC group [$F(1, 218) = 27.65$, $p < 0.001$], but no significant interaction between NFC group and learning condition ($p = 0.99$; **Figure 3**). This means that independent of NFC group, significant testing effects were again confirmed, but also that the high NFC group ($n = 112$) displayed a higher performance level compared to the low NFC group ($n = 108$). As can be seen in **Figure 3**, the magnitude of the testing effect ([performance retrieval practice – performance study]) was identical for both NFC groups (High NFC: $M_{\mathrm{TE}} = 0.17$, SE = 0.02; Low NFC: $M_{\mathrm{TE}} = 0.17$, SE = 0.02), but the relative gain ([performance retrieval practice/performance study]) after retrieval practice was larger in the low NFC group (1.75) than in the high NFC group (1.44). Running the same analysis for the classroom (low NFC: $n = 79$; high NFC: $n = 83$) and the fMRI subsample (low NFC: $n = 29$; high NFC: $n = 29$) respectively, revealed comparable significant testing effects (p's < 0.001, see **Supplementary Figure 2**). To further control whether the lack of the learning condition × NFC group interaction was plausible, a Bayesian mixed model ANOVA was performed on the whole sample. The analysis revealed a Bayes factor (BF_{10}) of 0.14, providing weak support for a possible significant interaction effect (Lakens et al., 2020).

In sum, the behavioral analyzes showed that retrieval practice results in better long-term retention relative study independent of NFC, and that higher levels of NFC are related to higher performance independent of learning condition.

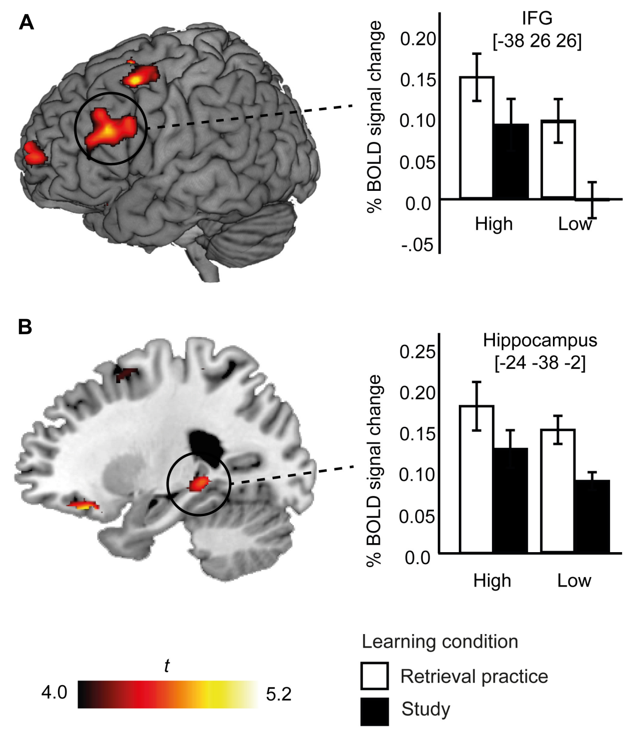

FIGURE 4 | Brain activation related to the two learning condition (retrieval practice and study) × two NFC group (high NFC and low NFC) ANOVA. Brain activity more engaged after retrieval practice > study is illustrated in selected brain regions (**A**, the left IFG [−38 26 26] and **B**, the left hippocampus [−24 −38 −2]). BOLD activity for the retrieval practice and study conditions is plotted separately for the NFC groups (high and low). White bars represent the retrieval practice condition. Black bars represent the study condition. Error bars denote ± 1 SEM.

Imaging Results

As expected, independent of performance (see **Supplementary Figure 3**), and in line with our previous analyzes of partly the same dataset (Jonsson et al., 2020), there was a significant main effect of condition, such that cued recall of items initially acquired by means of retrieval practice versus study engaged several left-lateralized cortical and subcortical brain regions (**Figures 4A,B**). There was no significant main effect of NFC group, but at the more lenient statistical threshold a main effect of NFC was observed in left precentral gyrus, (see **Supplementary Figure 4**).

The main focus of the imaging analysis was to evaluate if there was an interaction between initial learning condition (retrieval practice, study) and level of NFC. No significant interaction effect was found at the FWE corrected level, and not even at the more lenient statistical threshold ($p < 0.0001$, $k > 10$). Thus, differences in brain activity 1 week after acquisition by means of retrieval practice or study were independent of level of NFC. This outcome is illustrated for two regions from the main effect; the left IFG and hippocampus (**Figures 4A,B**). As can be seen, the difference in fMRI activity during cued recall of information acquired by retrieval practice versus study was of a comparable magnitude in the high and low NFC groups. To further control for possible interactions in the IFG and hippocampus, *post hoc* analyzes were performed. Beta values for the IFG and hippocampus from the main effect of condition were extracted for each participant and inserted in a 2 (retrieval practice, study) × 2 (low NFC, high NFC) ANOVA. No interactions were detected (left IFG: $p = 0.25$; left hippocampus = 0.73, respectively).

DISCUSSION

Using a within-subject design, we here combined behavioral methods with brain imaging to investigate the retrieval practice effects in relation to NFC among upper-secondary school students. A significant behavioral testing effect was confirmed for the whole sample, and dividing participants into low and high NFC groups revealed identical TEs in both groups, suggesting that retrieval practice seems to protect against lower levels of NFC. Imaging data further validated the behavioral observations, such that the difference in fMRI activity during cued recall of information acquired by retrieval practice versus study was of a comparable magnitude in the high and low NFC groups.

Our results clearly show that while NFC positively influences performance in general, it is unrelated to the magnitude of the testing effect. Evidence exists showing that retrieval practice, as a learning method, protects against acute stress (Smith et al., 2016; Pastötter et al., 2020), reduces test anxiety (i.e., examinations, see e.g., Agarwal et al., 2014; Szőllősi et al., 2017), reduces mind wandering (Szpunar et al., 2013) and has shown to be unrelated to different levels of cognitive abilities (Brewer and Unsworth, 2012; Agarwal et al., 2017; Bertilsson et al., 2020; Jonsson et al., 2020). Both NFC and the testing effect has each been studied extensively for their potential in memory and learning (e.g., Evans et al., 2003; Dunlosky et al., 2013; Sandra and Otto, 2018; Moreira et al., 2019; Strobel et al., 2019; Gonthier and Roulin, 2020; McDermott, 2021), but less is known of the association between the two. We here demonstrate that retrieval practice can boost learning and retention in individuals with lower NFC, possibly by enforcing active and deeper learning. Speculatively, retrieval practice as a learning method might prevent surface learning by requiring the learner to actively engage in the task at hand. As such, the learning method in itself might compensate for the lack of motivation and willingness to invest cognitive effort in a given task (Gärtner et al., 2021).

The present brain imaging results further extend the behavioral findings by showing that how the brain activates 1 week after learning with retrieval practice is comparable between different levels of NFC in upper-secondary school students. The lack of an interaction effect, as indicated by similar pattern of brain activity between NFC groups, further supports the finding that retrieval practice had an equal effect on the brain regardless of NFC. In addition, the significant main effect of retrieval practice (relative study) was evident in the left IFG and the left hippocampus. Such findings might support the idea that retrieval practice in itself prevents surface learning (Craik and Lockhart, 1972) as it requires the learner to actively engage in the task at hand, and more efficiently allocates the attention to stored memory representations regardless of NFC.

Both IFG and the hippocampus are well-established as brain regions implicated in learning and memory (e.g., Eichenbaum, 2017), and particularly in the retrieval of well-consolidated semantic memory representations (Martin and Chao, 2001; Salami et al., 2010, Binder and Desai, 2011). For example, a key role for the IFG in learning and memory is related to allocation of cognitive control for successful retrieval of memory representations stored elsewhere (Salami et al., 2010). In our prior fMRI studies we found support for that retrieval practice, as measured across three consecutive tests with (Wiklund-Hörnqvist et al., 2017) or without feedback (Karlsson Wirebring et al., 2015), reduces demands on left prefrontal brain regions implicated in cognitive control functions. Retrieval practice has also been found to increase hippocampal activity related to detailed and generalized memory representations 1 week after learning (Wiklund-Hörnqvist et al., 2020).

Taken together, our findings align with the positive learning effects retrieval practice has shown to have for students with lower cognitive abilities [e.g., working memory capacity (Agarwal et al., 2017) cognitive proficiency (Jonsson et al., 2020); general fluid intelligence (Brewer and Unsworth, 2012)], maintain executive control and prevents mind wandering during lectures (Szpunar et al., 2013). Those findings echo well with our brain imaging results related to NFC, which entails that brain regions in the IFG and hippocampus seems to be equally engaged for low and high NFC groups following retrieval practice. With that in mind, the general effectiveness of retrieval practice likely triggers neurocognitive mechanisms involved in enabling access to stored memory representations to a higher degree compared to study (Antony et al., 2017), regardless of NFC. Thus, combining behavioral data with brain imaging provide a unique window into the learning brain not possible to detect by behavioral data alone.

CONCLUSION

In conclusion, we here provide behavioral and neurocognitive evidence that retrieval practice is effective for learning in the classroom regardless of levels of NFC. These results are promising for the educational field as they clearly demonstrate that learning by retrieval practice can limit the influence the willingness to invest cognitive effort has on performance, by boosting learning and retention in lower as well as high NFC individuals.

DATA AVAILABILITY STATEMENT

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

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Regional Ethical Review board, Umeå, Sweden. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

CW-H and SS wrote the first draft of the manuscript. LN, BJ, and CW-H designed the research. CW-H performed the research. CW-H, SS, and MA analyzed the data. CW-H, SS, MA, BJ, and LN wrote sections of the manuscript. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2021.797395/full#supplementary-material

Supplementary Figure 1 | (A) The behavioral testing effect related to NFC group (high NFC and low NFC) reported in the article (i.e., **Figure 3**) along with an illustration of performance for the excluded intermediate NFC group (i.e., the 20% in the middle; patterned bars). Error bars denote ± 1 SEM., and **(B)** a plot for the association of each individual's testing effect with their NFC score.

Supplementary Figure 2 | The behavioral testing effect related to NFC group (high NFC and low NFC) and the different subsamples (classroom, fMRI). Error bars denote ± 1 SEM. ***$p < 0.001$.

Supplementary Figure 3 | The overlap (yellow) in functional brain activity from the 2 × 2 ANOVA (main effect retrieval practice > study; red) and the group *t*-test controlling for performance differences (retrieval practice > study; green). For illustrative purposes, the effects are shown at a more lenient statistical threshold (uncorrected $p < 0.0001$ at the voxel level, and $k > 10$ at the cluster level).

Supplementary Figure 4 | The main-effect of NFC group in the precentral gyrus [−48 4 32] at a more lenient statistical threshold (uncorrected $p < 0.0001$ at the voxel level, and $k > 10$ at the cluster level). Blue bars represent the retrieval practice condition. Red bars represent the study condition. Error bars denote ± 1 SEM.

REFERENCES

Agarwal, P. K., D'Antonio, L., Roediger, H. L., McDermott, K. B., and McDaniel, M. A. (2014). Classroom-based programs of retrieval practice reduce middle school and high school students' test anxiety. *J. Appl. Res. Mem. Cogn.* 3, 131–139. doi: 10.1016/j.jarmac.2014.07.002

Agarwal, P. K., Finley, J. R., Rose, N. S., and Roediger, H. L. (2017). Benefits from retrieval practice are greater for students with lower working memory capacity. *Memory* 25, 764–771. doi: 10.1080/09658211.2016.1220579

Agarwal, P. P., Nunes, L. D., and Blunt, J. R. (2021). Retrieval practice consistently benefits student learning: a systematic review of applied research in schools and classrooms. *Educ. Psychol. Rev.* 30, 641–656. doi: 10.1007/s10648-021-09595-9

Antony, J. W., Ferreira, C. S., Norman, K. A., and Wimber, M. (2017). Retrieval as a fast route to memory consolidation. *Trends Cogn. Sci.* 21, 573–576. doi: 10.1016/j.tics.2017.05.001

Ashburner, J. (2007). A fast diffeomorphic image registration algorithm. *NeuroImage* 38, 95–113. doi: 10.1016/j.neuroimage.2007.07.007

Bertilsson, F., Stenlund, T., Wiklund-Hörnqvist, C., and Jonsson, B. (2020). Retrieval practice: beneficial for all students or moderated by individual differences. *Psychol. Learn. Teach.* [Epub ahead of print]. doi: 10.1177/1475725720973494

Binder, J. R., and Desai, R. H. (2011). The neurobiology of semantic memory. *Trends Cogn. Sci.* 15, 527–536. doi: 10.1016/j.tics.2011.10.001

Binder, J. R., Desai, R. H., Graves, W. W., and Conant, L. L. (2009). Where is the semantic system? A critical review and meta-analysis of 120 functional neuroimaging studies. *Cereb. Cortex* 19, 2767–2796. doi: 10.1093/cercor/bhp055

Brewer, G. A., and Unsworth, N. (2012). Individual differences in the effects of retrieval from long-term memory. *J. Mem. Lang.* 66, 407–415. doi: 10.1016/j.jml.2011.12.009

Cabeza, R., Ciaramelli, E., Olson, I. R., and Moscovitch, M. (2008). Parietal cortex and episodic memory: an attentional account. *Nat. Rev. Neurosci.* 9, 613–625. doi: 10.1038/nrn2459

Cacioppo, J. T., and Petty, R. E. (1982). The need for cognition. *J. Pers. Soc. Psychol.* 42, 116–131.

Cacioppo, J. T., Petty, R. E., Feinstein, J. A., and Jarvis, W. B. G. (1996). Dispositional differences in cognitive motivation: the life and times of individuals varying in need for cognition. *Psychol. Bull.* 119, 197–253.

Craik, F. I. M., and Lockhart, R. S. (1972). Levels of processing: a framework for memory research. *J. Verbal Learn. Verbal Behav.* 11, 671–684.

Dornic, S., Ekehammar, B., and Laaksonen, T. (1991). Tolerance for mental effort: self-ratings related to perception, performance and personality. *Pers. Individ. Diff.* 12, 313–319. doi: 10.1016/0191-8869(91)90118-U

Dunlosky, J., Rawson, K. A., Marsh, E. J., Nathan, M. J., and Willingham, D. T. (2013). Improving students' learning with effective learning techniques. *Psychol. Sci. Public Interest* 14, 4–58. doi: 10.1177/1529100612453266

Eichenbaum, H. (2017). Memory: organization and control. *Annu. Rev. Psychol.* 68, 19–45. doi: 10.1146/annurev-psych-010416-044131

Evans, C. J., Kirby, J. R., and Fabrigar, L. R. (2003). Approaches to learning, need for cognition, and strategic flexibility among university students. *Br. J. Educ. Psychol.* 73, 507–528. doi: 10.1348/000709903322591217

Fazio, L. K., and Marsh, E. J. (2019). Retrieval-based learning in children. *Curr. Direct. Psychol. Sci.* 28, 111–116. doi: 10.1177/0963721418806673

Fleischhauer, M., Enge, S., Brocke, B., Ullrich, J., Strobel, A., and Strobel, A. (2010). Same or different? Clarifying the relationship of need for cognition to personality and intelligence. *Pers. Soc. Psychol. Bull.* 36, 82–96. doi: 10.1177/0146167209351886

Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., et al. (2014). Active learning increases student performance in science, engineering, and mathematics. *Proc. Natl. Acad. Sci. U.S.A.* 111, 8410–8415. doi: 10.1073/pnas.1319030111

Gärtner, A., Grass, J., Wolff, M., Goschke, T., Strobel, A., and Strobel, A. (2021). No relation of need for cognition to basic executive functions. *J. Pers.* 89, 1113–1125. doi: 10.1111/jopy.12639

Gonthier, C., and Roulin, J.-L. (2020). Intraindividual strategy shifts in Raven's matrices, and their dependence on working memory capacity and need for cognition. *J. Exp. Psychol. Gen.* 149, 564–579. doi: 10.1037/xge0000660

Grass, J., Strobel, A., and Strobel, A. (2017). Cognitive investment sin academic success: the role of need for cognition at university. *Front. Psychol.* 8:790. doi: 10.3389/fpsyg.2017.00790

Hill, B. D., Foster, J. D., Sofko, C., Elliot, E. M., and Shelton, J. T. (2016). The interaction of ability and motivation: average working memory is required for Need for Cognition to positively benefit intelligence and the effect increases with ability. *Pers. Individ. Diff.* 98, 225–228. doi: 10.1016/j.paid.2016.04.043

Jonker, T. R., Dimsdale-Zucker, H., Ritchey, M., Clarke, A., and Ranganath, C. (2018). Neural reactivation in parietal cortex enhances memory for episodically linked information. *Proc. Natl. Acad. Sci. U.S.A.* 115, 11084–11089. doi: 10.1073/pnas.1800006115

Jonsson, B., Wiklund-Hörnqvist, C., Stenlund, T., Andersson, M., and Nyberg, L. (2020). A learning method for all: the testing effect is independent of cognitive ability. *J. Educ. Psychol.* [Epub ahead of print]. doi: 10.1037/edu0000627

Karlsson Wirebring, L., Wiklund-Hörnqvist, C., Eriksson, J., Andersson, M., Jonsson, B., and Nyberg, L. (2015). Lesser neural pattern similarity across repeated tests is associated with better long-term memory retention. *J. Neurosci.* 35, 9595–9602. doi: 10.1523/JNEUROSCI.3550-14.2015

Karpicke, J. D., and Blunt, J. R. (2011). Retrieval practice produces more learning than elaborative studying with concept mapping. *Science* 331, 772–775. doi: 10.1126/science.1199327

Karpicke, J. D., and Aue, W. R. (2015). The testing effect is alive and well with complex materials. *Edu. Psychol. Rev.* 27, 317–326. doi: 10.1007/s10648-015-9309-3

Keresztes, A., Kaiser, D., Kovács, G., and Racsmány, M. (2014). Testing promotes long-term learning via stabilizing activation patterns in a large network of brain areas. *Cereb. Cortex* 24, 3025–3035. doi: 10.1093/cercor/bht158

Knouse, L. E., Rawson, K. A., Vaughn, K. E., and Dunlosky, J. (2016). Does testing improve learning for college students with attention deficit/hyperactivity disorder? *Clin. Psychol. Sci.* 4, 136–143. doi: 10.1177/2167702614565175

Lakens, D., McLatchie, N., Isager, P., Scheel, A. M., and Dienes, Z. (2020). Improving inferences about null effects with Bayes factors and equivalence tests. *J. Gerontol. Ser. B Psychol. Sci. Soc. Sci.* 75, 45–57. doi: 10.1093/geronb/gby065

Larsen, D. P., Butler, A. C., Lawson, A. L., and Roediger, H. L. (2013). The importance of seeing the patient: test-enhanced learning with standardized patients and written tests improves clinical application of knowledge. *Adv. Health Sci. Educ.* 18, 409–425. doi: 10.1007/s10459-012-9379-7

Leonard, L. B., Deevy, P., Karpicke, J., Christ, S., Weber, C., Kueser, J. B., et al. (2019). Adjective learning in young typically developing children and children with developmental language disorder: a retrieval-based approach. *J. Speech Lang. Hear Res.* 62, 4433–4449. doi: 10.1044/2019_JSLHR-L-19-0221

Liu, X. L., Liang, P., Li, K., and Reder, L. M. (2014). Uncovering the neural mechanisms underlying learning from tests. *PLoS One* 9:e92025. doi: 10.1371/journal.pone.0092025

Luong, C., Strobel, A., Wollschläger, R., Greiff, S., Vainikainen, M.-P., and Preckel, F. (2017). Need for cognition in children and adolescents: behavioral correlates and relations to academic achievement and potential. *Learn. Individ. Diff.* 53, 103–113. doi: 10.1016/j.lindif.2016.10.019

Mårtensson, J., Eriksson, J., Bodammer, N. C., Lindgren, M., Johansson, M., Nyberg, L., et al. (2012). Growth of language-related brain areas after foreign language learning. *Neuroimage* 63, 240–244. doi: 10.1016/j.neuroimage.2012.06.043

Martin, A., and Chao, L. L. (2001). Semantic memory and the brain: structure and processes. *Curr. Opin. Neurobiol.* 11, 194–201. doi: 10.1016/S0959-4388(00)00196-3

McDermott, K. (2021). Practicing retrieval facilitates learning. *Annu. Rev. Psychol.* 72, 609–633. doi: 10.1146/annurev-psych-010419-051019

Moreira, B. F. T., Pinto, T. S. S., Starling, D. S. V., and Jaeger, A. (2019). Retrieval practice in classroom settings: a review of applied research. *Front. Educ.* 4:5. doi: 10.3389/feduc.2019.00005

Nelson, T. O., and Dunlosky, J. (1994). Norms of Paired-Associate recall during multitrial learning of Swahili-English translation equivalents. *Memory* 2, 325–335. doi: 10.1080/09658219408258951

Pastötter, B., von Dawans, B., Domes, G., and Frings, C. (2020). The ¨forward testing effect is immune to acute psychosocial encoding/retrieval stress. *Exp. Psychol.* 76, 112–122. doi: 10.1027/1618-3169/a000472

Roediger, H. L., and Butler, A. C. (2011). The critical role of retrieval practice in long-term retention. *Trends Cogn. Sci.* 15, 20–27. doi: 10.1016/j.tics.2010.09.003

Roediger, H. L., and Karpicke, J. D. (2006a). Test-enhanced learning: taking memory tests improves long-term memory. *Psychol. Sci.* 17, 249–255. doi: 10.1111/j.1467-9280.2006.01693.x

Roediger, H. L., and Karpicke, J. D. (2006b). The power of testing memory: basic research and implications for educational practice. *Perspect. Psychol. Sci.* 1, 181–210. doi: 10.1111/j.1745-6916.2006.00012.x

Salami, A., Eriksson, J., Kompus, K., Habib, R., Kauppi, K., and Nyberg, L. (2010). Characterizing the neural correlates of modality-specific and modality-independent accessibility and availability signals in memory using partial-least squares. *NeuroImage* 52, 686–698. doi: 10.1016/j.neuroimage.2010.04.195

Sandra, D. A., and Otto, R. A. (2018). Cognitive capacity limitations and need for cognition differentially predict reward-induced cognitive effort expenditure. *Cognition* 172, 101–106. doi: 10.1016/j.cognition.2017.12.004

Smith, A. M., Floerke, V. A., and Thomas, A. K. (2016). Retrieval practice protects memory against acute stress. *Science* 354, 1046–1048. doi: 10.1126/science.aah5067

Sohn, M. H., Goode, A., Koedinger, K. R., Stenger, V. A., Fissell, K., Carter, C. S., et al. (2004). Behavioral equivalence, but not neural equivalence–neural evidence of alternative strategies in mathematical thinking. *Nat. Neurosci.* 7, 1193–1194. doi: 10.1038/nn1337

Starling, D. S. V., Moreira, B. F. T., and Jaeger, A. (2019). Retrieval practice as a learning strategy for individuals with down syndrome: a preliminary study. *Dement. Neuropsychol.* 13, 104–110. doi: 10.1590/1980-57642018dn13-010012

Stenlund, T., and Jonsson, B. (2017). Assessing the willingness to elaborate among young students: psychometric evaluation of a Swedish need for cognition scale. *Front. Educ.* 2:2. doi: 10.3389/feduc.2017.00002

Stenlund, T., Jönsson, F. U., and Jonsson, B. (2017). Group discussions and test-enhanced learning: individual learning outcomes and personality characteristics. *Educ. Psychol.* 37, 145–156. doi: 10.1080/01443410.2016.1143087

Stillesjö, S., Karlsson Wirebring, L., Andersson, M., Granberg, C., Lithner, J., Jonsson, B., et al. (2021). Active math and grammar learning engages overlapping brain networks. *Proc. Natl. Acad. Sci. U.S.A.* 118:e2106520118. doi: 10.1073/pnas.2106520118

Strobel, A., Behnke, A., Gartner, A., and Strobel, A. (2019). The interplay of intelligence and need for cognition in predicting school grades: a retrospective study. *Pers. Individ. Diff.* 144, 147–152. doi: 10.1016/j.paid.2019.02.041

Szőllősi, Á, Keresztes, A., Novák, B., Szászi, B., Kéri, S., and Racsmány, M. (2017). The testing effect is preserved in stressful final testing environment. *Appl. Cogn. Psychol.* 31, 615–622. doi: 10.1002/acp.3363

Szpunar, K. K., Khan, N. Y., and Schacter, D. L. (2013). Interpolated memory tests reduce mind wandering and improve learning of online lectures. *Proc. Natl. Acad. Sci. U.S.A.* 110, 6313–6317. doi: 10.1073/pnas.1221764110

Theobald, E. J., Hill, M. J., Tran, E., Agrawal, S., Arroyo, E. N., Behling, S., et al. (2020). Active learning narrows achievement gaps for underrepresented students in undergraduate science, technology, engineering, and math. *Proc. Natl. Acad. Sci. U.S.A.* 117, 6476–6483. doi: 10.1073/pnas.1916903117

van den Broek, G., Takashima, A., Wiklund-Hörnqvist, C., Wirebring, L. K., Segers, E., Verhoeven, L., et al. (2016). Neurocognitive mechanisms of the "testing effect": a review. *Trends Neurosci. Educ.* 5, 52–66.

Vestergren, P., and Nyberg, L. (2014). Testing alters brain activity during subsequent restudy: evidence for test-potentiated encoding. *Trends Neurosci. Edu.* 3, 69–80. doi: 10.1016/j.tine.2013.11.001

Weissgerber, S. C., Reinhard, M. A., and Schindler, S. (2018). Learning the hard way: need for cognition influences attitudes toward and self-reported use of desirable difficulties. *Educ. Psychol.* 38, 176–202.

Wiklund-Hörnqvist, C., Andersson, M., Jonsson, B., and Nyberg, L. (2017). Neural activations associated with feedback and retrieval success. *NPJ Sci. Learn.* 2:12. doi: 10.1038/s41539-017-0013-6

Wiklund-Hörnqvist, C., Stillesjö, S., Andersson, M., Jonsson, B., and Nyberg, L. (2020). Retrieval practice facilitates learning by strengthening processing in both the anterior and posterior hippocampus. *Brain Behav.* 2021:e01909. doi: 10.1002/brb3.1909

Wing, E. A., Marsh, E. J., and Cabeza, R. (2013). Neural correlates of retrieval-based memory enhancement: an fMRI study of the testing effect. *Neuropsychologia* 51, 2360–2370. doi: 10.1016/j.neuropsychologia.2013.04.004

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Relations Between Class Competition and Primary School Students' Academic Achievement: Learning Anxiety and Learning Engagement as Mediators

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This study aimed to analyze the relations between class competition and primary school students' academic achievement, considering the possible mediating roles of learning anxiety and learning engagement. Participants were 1,479 primary school students from four primary schools in Zhejiang, China. We analyzed participants' scores for class competition, learning anxiety, and learning engagement and their last two final exam scores. Class competition did not directly predict academic achievement, but indirectly affected academic achievement through learning anxiety and learning engagement. There were three effect paths: (1) class competition negatively predicted academic achievement by increasing learning anxiety; (2) class competition positively predicted academic achievement by promoting learning engagement; and (3) class competition affected academic achievement through multiple mediating effects of learning anxiety and learning engagement. This study highlights the important roles of learning anxiety and learning engagement in class competition and academic achievement, which have theoretical and practical significance.

Keywords: primary school students, class competition, academic achievement, learning anxiety, learning engagement, mediating role

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INTRODUCTION

Competition is a ubiquitous and age-old behavior pattern (Sun et al., 2015), and has become a prevalent problem across countries, cultures, and ethnic groups (Wong et al., 2006). For decades, psychological research has valued the study of competition (Sun et al., 2015). In the field of education, due to the limited high-quality educational resources, plus the driving force of students' life goals, competition has also become a reality that students have to face (Posselt and Lipson, 2016). The primary school stage is the beginning of a person's academic career, and it is also the basis of subsequent learning and future development. Parents often pay much attention to students' academic achievement since children commence primary school life. This is especially reflected in students from some Asian countries such as China (Deng and Zou, 2015). As a result, primary school students may be unknowingly faced with academic competition. Children spend most of their time at school, which, after family, is the most important environment affecting child development (Volk et al., 2015). Because primary school students spend most of their school time in classes, academic competition among students is mainly reflected in class competition (Hu, 2018).

Academic achievement is a key indicator of students' learning conditions, and provides an important basis for determining whether students can enter higher education. In addition, academic achievement is commonly used as a standard to judge the quality of school teaching. Therefore, students' academic achievement receives substantial attention from students, parents and society. Various researchers have proposed that class competition is a critical factor in the education process (John et al., 2003; Ogbuehi and Fraser, 2007), and can have a negative impact on students' academic achievement (Johnson and Johnson, 1994; Ames and Archer, 1988). The pressure perceived by students increases as class competition increases, and many children experience doubt regarding their learning abilities (Sommet et al., 2013). In addition, competitive instruction has been observed to stress the acquisition of low-level information rather than high-level ideas (Sullivan, 1980), which can have a negative impact on children's academic achievement. However, previous studies have reported conflicting results. In some studies, individual competition was reported to have a positive impact on students' academic achievement (Fisher, 1976; Tauer and Harackiewicz, 2004). He et al. (2011) reported a significant positive correlation between class competition and academic achievement. Competition can be divided into benign competition and vicious competition (Horney, 1937; Ryckman et al., 1990), and some researchers (Burguillo, 2010; Olitsky, 2011) have analyzed class competition from a dialectical perspective, and reported that benign competition stimulated students' motivation, promoted individuals to learn from each other, and caused individuals to perform better, but vicious competition resulted in inaccurate cognition, children's loss of correct judgment of their own value, and limit collaboration among students, hinder their progress, and ultimately have negative effects on their academic achievement. However, other researchers have reported that competition has no clear effect on students' academic achievement (Pesout and Nietfeld, 2021) and that class competition cannot predict academic achievement in students (Pang, 2009). Thus, the relation between class competition and academic achievement is complex. Consequently, the effect of class competition on students' academic achievement remains controversial, and its internal mechanisms require further investigation.

Mediating Role of Learning Anxiety

Learning anxiety may be an important factor in the negative relation between class competition and academic achievement. From a psychological perspective, class competition reflects students' and teachers' perceptions regarding the competitive atmosphere in the class or classroom environment (Fraser, 1986). Therefore, class competition is the type of psychological environment that students perceive. Learning anxiety refers to uneasy or unpleasant psychological reflection caused by internal conflict and is a specific state of tension in a student group (Woodman and Hardy, 2001). Learning anxiety is therefore a negative emotion produced by students in the process of learning (Pekrun, 2005).

Relative deprivation theory suggests that students tend to evaluate their academic level based on comparison with other students in the same class (Davis, 1966). Because of differences in learning ability among students, it is inevitable that some students win while other students fail in a competitive situation. Anxiety is triggered when students anticipate that they may fail (Pekrun, 2006). When the level of class competition is low, the pressure caused by students comparing themselves with each other is low, and students learn easily and happily. However, when class competition exceeds a certain level, students' learning pressure increases and they may begin to doubt themselves, which results in negative emotions such as high anxiety (Johnson and Johnson, 1994). Therefore, it follows that class competition may increase students' learning anxiety (Epstein and Harackiewicz, 1992; Quach et al., 2015).

Previous studies confirmed that learning anxiety can lead to poor academic achievement among students (Sariem et al., 2014; Chang and Beilock, 2016; D'Agostino et al., 2021). Emotions have been found to affect a wide range of cognitive processes, including attention, memory storage and retrieval, social judgment, decision making and cognitive problem solving (Clore and Huntsinger, 2009). Students in a state of learning anxiety will exhibit task-irrelevant thinking and a reduction in the cognitive resources available for task purposes, as well as becoming distracted during learning, causing low learning efficiency and a decline in academic achievement (Pekrun et al., 2017). Some researchers have examined the relation between learning anxiety and academic achievement in specific subjects, particularly mathematics. Previous studies reported that mathematics anxiety negatively predicted mathematics achievement (Foley et al., 2017; Wang et al., 2019; Tomasetto et al., 2021). Mathematics anxiety may impair performance by diverting cognitive resources from task-relevant purposes (i.e., a mathematics task) to task-irrelevant aspects (e.g., worry) (Ching, 2017; Ching et al., 2020). Further research revealed that, compared with boys, girls have less fun and more anxiety in mathematics learning (Pekrun and Stephens, 2010; Dowker et al., 2019).

Mediating Role of Learning Engagement

A possible reason for the positive correlation between class competition and academic achievement is the mediating role of learning engagement. Learning engagement is considered to be a positive, fulfilling, and work-related state of mind that is characterized by vigor, dedication, and absorption (Schaufeli et al., 2002b). Vigor is characterized by high levels of energy and mental resilience while working and by the willingness and ability to invest effort in one's work. Dedication is characterized by a sense of significance, enthusiasm, inspiration, pride, and challenge. Absorption is characterized by being fully concentrated and happily engrossed in one's work (Schaufeli et al., 2002a).

Class competition may promote learning engagement (Tauer and Harackiewicz, 2004; Reyes et al., 2012) and enhance students' pressure and motivation in learning. Students will consciously invest in learning to ensure or improve their status among their classmates (Roth et al., 2009). Social learning theory (Bandura, 1978) posits that when many students in a class work hard, they serve as role models with which other students will compare themselves and imitate, promoting their engagement in learning activities (Hasan and Bagde, 2013). Learning engagement is positively correlated with academic achievement (Schaufeli et al., 2002a; Chang and Beilock, 2016). When the level of learning engagement is high, students will actively invest more time and energy in learning activities, and they will also have positive emotional experiences in learning (Schaufeli and Bakker, 2004; Liu et al., 2020), which plays an important role in promoting students' academic achievement (Pietarinen et al., 2014; Bayoumy and Alsayed, 2021).

Relation Between Learning Anxiety and Learning Engagement

Learning anxiety, as a negative emotion in an academic context, may have an adverse effect on students' learning engagement. Studies have shown that students' emotions are critical to their willingness to learn and their volitional control over the learning process (Pekrun, 2005). Positive emotions can stimulate learners' motivation and promote high engagement in learning (Frenzel et al., 2007; Wara et al., 2018), whereas negative emotions (e.g., anxiety) reduce learning efficiency and may even cause serious learning delays (Macher et al., 2012). In addition, learning anxiety means students focus more on threats and failures, which restricts their cognition and activity maps (Fredrickson, 2001) and occupies their limited cognitive resources (Pekrun and Stephens, 2010). In turn, this affects students' processing of current learning tasks (Owens et al., 2012). When students fail to meet the cognitive requirements of academic activities, they gradually develop low learning engagement (Zhen et al., 2017).

Present Study and Hypotheses

Previous studies reported inconsistent findings about the relation between class competition and student academic achievement. We speculated that this may be related to the dual effects of class competition on students. On the one hand, class competition may have a negative effect on students' academic achievement by increasing their learning anxiety; on the other hand, class competition may have a positive effect on their academic achievement by promoting learning engagement. However, few studies have explored this inconsistency and its underlying mechanisms, particularly in class competition among primary school students. Primary school students begin to face competition in the early stages of their learning careers, and investigating the underlying mechanisms is important for understanding the mode of action of class competition, promoting primary school students' physical and mental health, and improving teaching outcomes. Therefore, the current study focused on primary school students to investigate the relation between class competition and academic achievement, as well as the mediating role of learning anxiety and learning engagement. Based on available research results, this study proposed the following hypotheses and a conceptual model (**Figure 1**).

Hypothesis 1 (H1): Class competition will have a direct effect on students' academic achievement.
Hypothesis 2 (H2): Learning anxiety will play a mediating role between class competition and students' academic achievement.

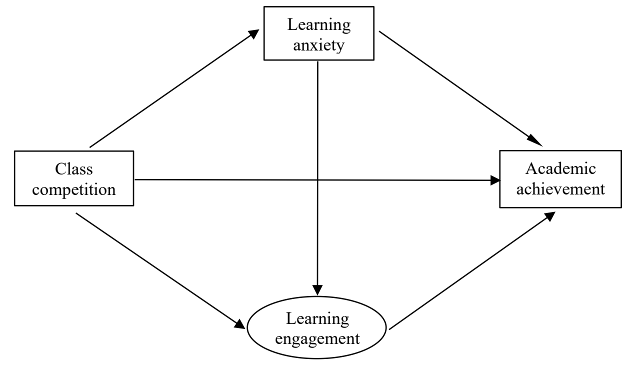

FIGURE 1 | Hypothesis model of the relation between class competition and academic achievement.

Hypothesis 3 (H3): Learning engagement will play a mediating role between class competition and students' academic achievement.
Hypothesis 4 (H4): Learning anxiety and learning engagement will play multiple mediating roles between class competition and students' academic achievement.

MATERIALS AND METHODS

Participants

This survey was conducted in Hangzhou, Zhejiang Province, in Eastern China. We chose four primary schools (two from the city and two from rural areas) to reflect the overall situation of local schools. Considering the limitations of students' psychological level and text understanding ability in grades one and two of primary school, we surveyed 40 classes from grade three to grade six in the four selected schools (10 classes for each grade). In total, 1,645 questionnaires were collected. After summarizing the questionnaire data and students' exam results, and excluding omissions, overfilling, and missing results, data for 1,479 students were included in the analysis (effective rate 89.91%). Participating students were aged 8–13 years (M = 10.592 years; standard deviation = 1.204 years), 46.1% of them were girls, and 53.9% were boys.

Measuring Instruments

Class Competition

Class competition is often regarded as a dimension of class environment. The most influential class environmental measurement scale has mainly been used to examine classes in schools in western countries (Fraser et al., 1982; Moos and Trickett, 1987). In the Chinese cultural context, classes in Chinese schools are very different to those in western countries. To ensure cultural applicability, this study chose the "My Class" scale compiled by Chinese researchers (Jiang, 2004). Previous studies have confirmed that this scale has good reliability and validity among Chinese students (Zhang et al., 2006). The scale consists of five dimensions, including teacher-student relationships, classmate relationships, order and discipline, class competition, and learning burden, with a total of 38 items. Among these dimensions, the class competition dimension consists of seven items (e.g., "Everyone is afraid of falling behind in learning" and "In order not to be surpassed by others, no one dares to relax in learning"). Responses are on a 5-point Likert-type scale from 1 (completely disagree) to 5 (completely agree), and the average score of the seven items was used as a student's perceived class competition score. Higher scores indicate greater competition. The Cronbach's alpha value for the class competition scale in this study was 0.682.

Learning Anxiety

The learning anxiety scale used in this study was derived from the Mental Health Diagnostic Test compiled by Zhou (1991), which has been widely used in thousands of primary and secondary schools in more than 20 provinces and cities in China, with high reliability and validity (Ding and Li, 2017; Hu et al., 2019). The learning anxiety subscale of the test scale has a total of 15 items (e.g., "When the teacher asks questions to the class, I feel uneasy about asking myself," "I have dreamed about being reprimanded by parents or teachers because of my poor grades"). Responses were provided on a 5-point Likert-type scale from 1 (completely disagree) to 5 (completely agree), and the average score of the items was used as a student's perceived learning anxiety score. Higher scores indicate greater learning anxiety. The Cronbach's alpha value for the learning anxiety scale in this study was 0.887.

Learning Engagement

The Chinese version of the learning engagement scale in this study was translated and revised by Fang et al. (2008). The original scale was developed by Schaufeli et al. (2002a,b). The Chinese version of the scale has been reported to have good reliability and validity (Fang et al., 2008; Shi et al., 2013). The scale includes three dimensions and has a total of 17 items. Items 1–6 belong to the vitality dimension, items 7–11 to the dedication dimension, and items 12–17 to the concentration dimension. Examples of items are: "Even if my study is not smooth, I am not discouraged and can persevere" and "When I study, I forget everything around me." Responses are provided on a 5-point Likert-type scale from 1 (completely disagree) to 5 (completely agree), and the average score of the 17 items was used as a student's perceived learning engagement score. Higher scores indicate greater learning engagement. In this study, the three dimensions and the total scale had good reliability (vitality: Cronbach's $\alpha = 0.849$; dedication: Cronbach's $\alpha = 0.861$; concentration: Cronbach's $\alpha = 0.881$; total scale: Cronbach's $\alpha = 0.938$). The structural validity indicators were: χ^2 (111) = 466.467, comparative fit index (CFI) = 0.975, Tucker–Lewis index (TLI) = 0.970, root mean square error of approximation (RMSEA) with 90% confidence interval (CI) = 0.047 (0.042–0.051), and standardized root mean squared residual (SRMR) = 0.024.

Academic Achievement

The indicators of academic achievement used in this study were based on four subjects: Chinese, mathematics, English, and science (full score for each course: 100 points). These four subjects are recognized as the main subjects in primary school in China and usually serve as an important reference to reflect the academic achievement of primary school students. In the current study, class competition refers to the overall feelings of students about the competitive atmosphere of the class, and not specifically to the feelings of competition in a certain subject. Therefore, the academic achievement of the students in this study also refers to the overall learning situation of the students, not that of a certain subject, so students' academic achievement is calculated based on the average scores of the four subjects of Chinese, mathematics, English, and science. To ensure that the indicators of academic achievement were robust, we adopted the results of the last two final exams.

Procedures

This study was first approved by the Ethics Committee of Hangzhou Normal University. We then applied to the administrative department for each selected school and obtained permission to conduct the study. Written informed consent was obtained from students' parents before the investigation. After receiving consent, paper-and-pencil questionnaires were administered to students in class by trained graduate students who were majoring in psychology. It took approximately 20 min to complete the questionnaires. Students' academic achievement data were provided by teachers at each school.

Data Analysis

After the survey data were recovered, SPSS version 24.0 was used to test the valid sample data for missing completely at random (MCAR) data. The MCAR test results were: $\chi^2 = 1254.895$, df = 1206, $p = 0.160 > 0.05$, and the missing value was completely random. The Harman's single-factor test was used to control the common method biases, and the first factor without rotation explained 24.44% of the variance, which was less than the critical value of 40%. Therefore, there were no obvious common method biases in this study. Descriptive statistics and correlations were calculated using SPSS version 24.0. A structural equation model and bias-corrected bootstrap test were then performed using Mplus version 7.0 to verify the mediating role of learning anxiety and learning engagement between class competition and academic achievement as well as to analyze the effect path.

RESULTS

Descriptive Statistics and Correlation Analysis

The descriptive statistics and Pearson's correlations among the variables are presented in **Table 1**. The average class competition score for primary school students was 3.16 points (range 1–5), indicating that the class competition atmosphere of primary school students was in a moderate level. In terms of relevance, class competition was significantly positively correlated with learning anxiety and learning engagement, learning engagement was significantly positively correlated with academic achievement, and learning anxiety was significantly

TABLE 1 | Descriptive statistics and correlation analysis for each variable.

	1	2	3	4
1. Class competition	–			
2. Learning anxiety	0.205***	–		
3. Learning engagement	0.213***	-0.141***	–	
4. Academic achievement	−0.008	−0.190***	0.213***	
Range	1–5	1–5	1–5	0–100
Mean	3.16	3.25	3.52	83.52
Standard deviation	0.79	0.93	0.93	11.31
Male–female difference	5.018***	−3.092**	−0.130	−2.417*
Urban–rural difference	−3.905***	−4.735***	−1.641	4.519***

*$p < 0.05$, **$p < 0.01$, and ***$p < 0.001$.

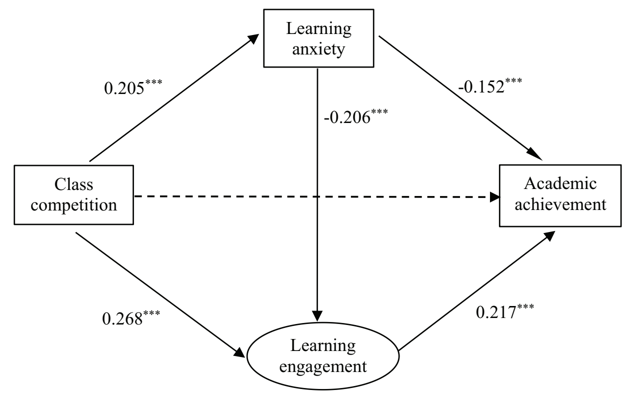

FIGURE 2 | Mediation effect model of class competition on academic achievement. ***$p < 0.001$.

negatively related to learning engagement and academic achievement. There was no significant correlation between class competition and academic achievement.

Further analysis revealed that in addition to learning engagement, the three variables of class competition, learning anxiety, and academic achievement exhibited significant differences by gender and urban–rural dimensions. Regarding gender, the average class competition score of boys was significantly higher than that of girls, and the average learning anxiety and academic achievement scores of boys were significantly lower than those of girls. Regarding the urban–rural dimension, the average class competition and learning anxiety scores of urban students were lower than those of rural students, but the average academic achievement score of urban students was significantly higher than that of rural students.

Mediating Effect Analysis of Learning Anxiety and Learning Engagement

As mentioned earlier, the results revealed no significant correlation between class competition and academic achievement. This finding raises the question of whether or not class competition has an effect on academic achievement. Some methodologists believe that whether independent variables and dependent variables are significantly correlated does not constitute a prerequisite for the existence of mediating effects (Collins et al., 1998; Shrout and Bolger, 2002; Preacher et al., 2007). A simulation study by Rucker et al. (2011) revealed that in nearly half of all simulation conditions, the relation between the independent variable and the dependent variable was not significant, but there was a significant mediating effect. Therefore, it is necessary to further analyze mediating effects despite the lack of a significant correlation between students' perceived class competition and their academic achievement.

The starting theoretical model (**Figure 1**) showed a good fit to the empirical data: $\chi^2(6) = 29.135$, CFI = 0.992, TLI = 0.981, RMSEA (90% CI) = 0.051 (0.033–0.070), and SRMR = 0.014. The results indicated that the effect of class competition on academic achievement was not significant, but learning anxiety and learning engagement fully mediated the relation between class competition and academic achievement (**Figure 2**).

Finally, we used a bias-corrected bootstrap method to test whether the mediating effects described above were significant. In general, if the 95% CI does not include 0, the mediating effect is considered to be significant at the 0.05 level (Preacher and Hayes, 2008). The results revealed that the mediating effects of learning anxiety and learning engagement were significant, and class competition affected academic achievement through the three possible paths: class competition had a negative effect on academic achievement through increasing learning anxiety, a positive effect on academic achievement through promoting learning engagement, and a chain effect on academic achievement through learning anxiety *via* learning engagement (**Table 2**).

DISCUSSION

The Current Situation of Main Variables

The results in **Table 1** show that the average class competition score of primary school students in the current study was 3.16 points (score range: 1–5), indicating that primary school classes had a clear competitive atmosphere. In China, many parents expect their children to be among the best in class rankings (Deng and Zou, 2015). Students with advantages in class competition are often favored by teachers and tend to have greater influence in the student group, while students with disadvantages in class competition have difficulty in becoming influential figures in the class (Warren et al., 2005). According to the relative deprivation theory (Davis, 1966), individuals' sense of relative deprivation arises from comparison with others, and their sense of competition will be stimulated when perceiving inferior position. Given the combined effects of pressure from parents, teachers and other factors, primary school students are increasingly likely to experience Competition (Liu et al., 2020).

Regarding the gender differences in class competition, learning anxiety, and academic achievement among primary school students revealed in the current results, we believe that, in addition to boys being more sensitive to the competitive atmosphere (Volk et al., 2006), the high familial expectations in traditional Chinese culture concerning the academic achievement and future careers of male children in particular

TABLE 2 | Bias-corrected bootstrap test on mediating effects.

Paths	Standardized estimates	95% confidence interval	
		Lower	Upper
Class competition-academic achievement	−0.025	−0.080	0.028
Class competition-learning anxiety-academic achievement	−0.031***	−0.047	−0.018
Class competition-learning engagement-academic achievement	0.058***	0.040	0.078
Class competition-learning anxiety-learning engagement-academic achievement.	−0.009***	−0.014	−0.006

****p < 0.001.*

may also increase boys' sense of competitive pressure. This is consistent with the conclusion of a previous study that boys' perception of the class competition atmosphere is higher than that of girls (Li et al., 2019). Emotion-related characteristics of girls (Pekrun and Stephens, 2010) may explain why girls' learning anxiety was higher than that of boys in the current results. Boys have been reported to exhibit significantly lower levels of school adaptation and lower learning consciousness compared with girls (Zhang et al., 2014; Liu et al., 2020), which may explain why the academic achievement of girls in primary school is higher than that of boys.

The differences between urban and rural students in class competition, learning anxiety and academic achievement may be related to the imbalance between urban and rural education in China. Compared with urban students, rural students have fewer employment channels, and changing their employment trajectory through studying hard is often the only option for rural children's future development. As Pettigrew et al. (2008) pointed out, individuals' socioeconomic status significantly affects their sense of relative deprivation, and those with lower social status and less political influence experience stronger sense of relative deprivation, and strive to change the *status quo*. Compared with urban students, rural students have a stronger sense of relative deprivation, which further intensifies competition in class and increases their learning anxiety. However, because the quality of teachers and teaching facilities in rural schools lags behind that in urban areas, the education received by rural students is significantly worse than that of urban students (Sang et al., 2009). This reality may be the main reason why rural students' academic achievement is not as good as that of urban students.

Direct Effect of Class Competition on Academic Achievement

This study investigated the mechanism of the effect of class competition on academic achievement among primary school students by establishing a multiple mediating model for the first time. The results revealed that class competition had no significant direct effect on students' academic achievement, which failed to support H1. A previous study reported that class competition had different effects on students with different levels of academic achievement, such that students with good grades felt the pressure brought by competition, leading them to study harder and achieve better grades, whereas students with poor grades lacked self-confidence, causing their learning enthusiasm and motivation to be further decreased by repeated failures in class competition, leading to worse grades (Zimmerman, 2003). The polarization of academic achievement caused by class competition counteracts the effect of class competition on academic achievement to some degree, which may explain the absence of a significant correlation between these two variables in the current study.

The results of this study were inconsistent with the findings of many previous studies (Ames and Archer, 1988; Sommet et al., 2013). We believe that these discrepancies may have arisen because most previous research focused on students from junior high schools, senior high schools, and universities, whereas we investigated primary school students. Students' perception of the classroom psychological environment is reported to vary across education stages (Zhang et al., 2014), and their academic achievement is the result of interactions among many factors, including their family background and school environment (Feng et al., 2019). Therefore, it is understandable that the relation between class competition and academic achievement in this study differed from that reported in previous studies.

Mediating Roles of Learning Anxiety and Learning Engagement

The current findings indicate that class competition can be a "double-edged sword" for academic achievement through the intermediating variables of learning anxiety and learning engagement. These findings supported H2 and H3. Class competition negatively affected students' academic achievement by increasing their learning anxiety, which was consistent with conclusions drawn by Sariem et al. (2014) and D'Agostino et al. (2021). According to Lewin's field theory (Lewin, 1936), individuals' mental activity and behaviors are closely related with the environment they live. For students who daily live in a competitive atmosphere, the pressure of comparison and potential failures leads them to feel uneasy and anxious about learning outcomes. Anxiety is experienced particularly strongly when control over the outcome of a competition seems impossible (Pekrun, 2006). The conclusion that class competition can negatively affect students' academic achievement by increasing their learning anxiety may serve as a reminder for teachers and parents to pay attention to the learning-related emotions of primary school students. Reducing class competition and alleviating students' learning anxiety *via* home–school cooperation may enable students to study in a relaxed and happy state, thereby improving their learning outcomes.

Conversely, the current results also revealed that class competition positively affected students' academic achievement by promoting their learning engagement, which was consistent with the results of several previous studies (Roth et al., 2009; Reyes et al., 2012; Bayoumy and Alsayed, 2021). The pressure of class competition means that students who want to satisfy their needs for academic achievement or class status have to increase their learning engagement by using certain strategies (e.g., listening carefully in class and reviewing spontaneously after class) to achieve better grades. One study found no significant correlation between learning engagement and academic achievement (Shernoff, 2010). We propose that this finding may have arisen because students with good grades master fast learning skills, thereby reducing their learning time. In contrast, students with poor grades do not have a good foundation for those skills, and it remains difficult for them to achieve good grades even if they struggle and invest more time (Phuntsho and Dhendup, 2020). This highlights the need for teachers to pay attention to students' learning foundations, learning style, and learning habits, and to guide students to adopt a learning method that suits their specific characteristics. Furthermore, Schaufeli et al. (2002b) divided learning engagement into three dimensions (vitality, dedication, and concentration). In the current study, we did not perform comprehensive analyses of the specific roles of these three dimensions in the relation between class competition and academic achievement. This question should be addressed in future research.

The current study revealed that class competition negatively affected students' academic achievement through multiple mediating effects of learning anxiety and learning engagement. This finding supported H4 and also revealed another possible path by which class competition indirectly affected academic achievement (i.e., class competition positively affected students' learning anxiety, learning anxiety negatively affected learning engagement, and learning engagement positively predicted academic achievement). Therefore, the effects of class competition on academic achievement may be determined by learning anxiety and learning engagement. This conclusion further demonstrated the close relation between learning anxiety and learning engagement. As Kindermann (1993) noted, learning engagement is essentially students' emotional engagement in learning activities. The control value theory proposed by Pekrun (2006) also details this process: emotions can affect students' academic achievement by influencing their motivation and effort, their use of learning strategies and self-regulation, and the availability of cognitive resources needed for learning and performance. Some researchers in the field of psychology verified the impact of learning anxiety on personal values and individual behavioral input through empirical research and follow-up surveys (Gao et al., 2021). Class competition can affect academic achievement through multiple mediating effects of learning anxiety and learning engagement, which reflects the chain relation among the four variables and demonstrates another way in which learning anxiety and learning engagement play a mediating role between class competition and academic achievement.

Limitations and Contributions

Several limitations of the current study should be acknowledged. First, the sample was selected from four primary schools in Hangzhou, Zhejiang Province, China. However, the educational and cultural contexts in China differ from those in other countries, and further research should examine a wider range of samples to include students in different cultural contexts. Second, this study mainly focused on individual students' perceptions of the competitive atmosphere in class. However, classes with different levels of competition may have different effects on students. Therefore, in future studies, multilevel modeling should be adopted to model class-level effects. Third, this study focused on the relation between students' overall feelings about class competition and students' learning anxiety, learning engagement and academic achievement, which are not specific to individual subjects. However, the relations between the four variables may vary between different subjects. Thus, relevant research for specific disciplines should be carried out in future research. Fourth, although the reliability of the class competition scale in this study was acceptable, it is still low, and the survey process should be further improved. In addition, because this was a cross-sectional study, the causal direction of the hypothesized effects should be confirmed in longitudinal research.

Despite these limitations, the current study has important theoretical implications and practical value. From a theoretical perspective, this study expanded the research on competition among primary school students and also provides a theoretical explanation for the inconsistent effects of class competition on academic achievement. From a practical perspective, the existence of class competition is inevitable. The results of this study can guide teachers in taking effective measures to enable students to strengthen their learning engagement levels actively in an atmosphere of benign competition. At the same time, our findings suggest that teachers should pay close attention to students' psychological states and create cooperative classroom learning environments at an appropriate stage to give students appropriate encouragement, thereby reducing the negative effects of class competition and avoiding learning anxiety (Okebukola, 1986). In addition, teachers should guide students to improve their learning methods and form good learning habits, thereby improving learning engagement and promoting a high level of academic achievement.

CONCLUSION

The current study focused on primary school students to investigate the relation between class competition and academic achievement, as well as the mediating roles of learning anxiety and learning engagement. The following three findings were highlighted. First, the class competition atmosphere of primary school students we investigated was in a moderate level. Except learning engagement, class competition, learning anxiety, and academic achievement exhibited significant differences in gender and urban–rural residence. Second, class competition did not have a direct relation with academic achievement. Third, class competition was significantly negatively correlated with academic achievement *via* learning anxiety, whereas was positively correlated with academic achievement *via* learning engagement. Besides, class competition was negatively associated with academic achievement *via* the multiple mediating roles of learning anxiety and learning engagement.

DATA AVAILABILITY STATEMENT

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

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Academic Ethics Committee of Jing Hengyi School of Education, Hangzhou Normal University. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

GL and RZ developed the research project, with the contribution of XW and ZL. ZL prepared the data set. XW carried out the data analysis. ZL reviewed the literature. GL and RZ reviewed and edited the manuscript. All authors contributed to the article and approved the submitted version.

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REFERENCES

Ames, C., and Archer, J. (1988). Achievement goals in the classroom: students' learning strategies and motivation processes. *J. Educ. Psychol.* 80, 260–267. doi: 10.1037/0022-0663.80.3.260

Bandura, A. (1978). The self system in reciprocal determinism. *Am. Psychol.* 33, 344–358. doi: 10.1037/0003-066X.33.4.344

Bayoumy, H., and Alsayed, S. (2021). Investigating relationship of perceived learning engagement, motivation, and academic performance among nursing students: a multisite study. *Adv. Med. Educ. Pract.* 12, 351–369. doi: 10.2147/AMEP.S272745

Burguillo, J. C. (2010). Using game-theory and competition-based learning to stimulate student motivation and performance. *Comput. Educ.* 55, 566–575. doi: 10.1016/j.compedu.2010.02.018

Chang, H., and Beilock, S. L. (2016). The math anxiety-math performance link and its relation to individual and environmental factors: a review of current behavioral and psychophysiological research. *Curr. Opin. Behav. Sci.* 10, 33–38. doi: 10.1016/j.cobeha.2016.04.011

Ching, B. H. (2017). Mathematics anxiety and working memory: longitudinal associations with mathematical performance in Chinese children. *Contemp. Educ. Psychol.* 51, 99–113. doi: 10.1016/j.cedpsych.2017.06.006

Ching, B. H., Kong, K. H. C., Wu, H. X., and Chen, T. T. (2020). Examining the reciprocal relations of mathematics anxiety to quantitative reasoning and number knowledge in Chinese children. *Contemp. Educ. Psychol.* 63:101919. doi: 10.1016/j.cedpsych.2020.101919

Clore, G. L., and Huntsinger, J. R. (2009). How the object of affect guides its impact. *Emot. Rev.* 1, 39–54. doi: 10.1177/1754073908097185

Collins, L. M., Graham, J. W., and Flaherty, B. P. (1998). An alternative framework for defining mediation. *Multivar. Behav. Res.* 33, 295–312. doi: 10.1207/s15327906mbr3302_5

D'Agostino, A., Spagnolo, F. S., and Salvati, N. (2021). Studying the relationship between anxiety and school achievement: evidence from PISA data. *Stat. Methods Appl.* doi: 10.1007/s10260-021-00563-9

Davis, J. A. (1966). The campus as a frog pond: an application of the theory of relative deprivation to career decisions of college men. *Am. J. Sociol.* 72, 17–31. doi: 10.2307/2775756

Deng, Y. C., and Zou, J. Q. (2015). From hierarchy and hierarchical consciousness to achievement anxiety and academic competition. *J. Hubei Eng. Univ.* 35, 76–79.

Ding, Y., and Li, X. P. (2017). Mental health of high-grade pupils in poverty-stricken areas of Shanxi Province, China. *J. Health Psychol.* 25, 140–144. doi: 10.13342/j.cnki.cjhp.2017.01.033

Dowker, A., Cheriton, O., Horton, R., and Mark, W. (2019). Relationships between attitudes and performance in young children's mathematics. *Educ. Stud. Math.* 100, 211–230. doi: 10.1007/s10649-019-9880-5

Epstein, J. A., and Harackiewicz, J. M. (1992). Winning is not enough: the effects of competition and achievement orientation on intrinsic interest. *Pers. Soc. Psychol. Bull.* 18, 128–138. doi: 10.1177/0146167292182003

Fang, L. T., Shi, K., and Zhang, F. H. (2008). Research on reliability and validity of Utrecht work engagement scale-student. *Chin. J. Clin. Psychol.* 16, 618–620. doi: 10.16128/j.cnki.1005-3611.2008.06.023

Feng, X., Xie, K., Gong, S., Gao, L., and Cao, Y. (2019). Effects of parental autonomy support and teacher support on middle school students' homework effort: homework autonomous motivation as mediator. *Front. Psychol.* 10:612. doi: 10.3389/fpsyg.2019.00612

Fisher, J. E. (1976). Competition and gaming: an experimental study. *Simulat. Gaming* 7, 321–328. doi: 10.1177/003755007673007

Foley, A. E., Herts, J. B., Borgonovi, F., Guerriero, S., Levine, S. C., and Beilock, S. L. (2017). The math anxiety-performance link: a global phenomenon. *Curr. Dir. Psychol. Sci.* 26, 52–58. doi: 10.1177/0963721416672463

Fraser, B. J. (1986). *Classroom Environment*. London: Croom Helm Ltd.

Fraser, B. J., Anderson, G. J., and Walberg, H. J. (1982). *Assessment of Learning Environments: Manual for Learning Environment Inventory (LEI) and My Class Inventory(MCI)*. Perth, WA: Western Australia Institute of Technology.

Fredrickson, B. L. (2001). The role of positive emotions in positive psychology: the broaden-and-build theory of positive emotions. *Am. Psychol.* 56, 218–226. doi: 10.1037/0003-066x.56.3.218

Frenzel, A. C., Pekrun, R., and Goetz, T. (2007). Perceived learning environment and students' emotional experiences: a multilevel analysis of mathematics classrooms. *Learn. Instr.* 17, 478–493. doi: 10.1016/j.learninstruc.2007.09.001

Gao, L. J., Huang, F. L., Wu, X. X., Liao, F. Q., and Chen, X. B. (2021). Characteristics and relationship of attachment relationships and coping styles of adolescents with emotional behavior problems. *Psychol. Mon.* 16, 12–13+8. doi: 10.19738/j.cnki.psy.2021.16.005

Hasan, S., and Bagde, S. (2013). The mechanics of social capital and academic performance in an Indian college. *Am. Sociol. Rev.* 78, 1009–1032. doi: 10.1177/0003122413505198

He, L. X., Zhang, Q., and Wang, C. K. (2011). The relationship between competition-cooperation and academic achievement: a mediator role of academic self-concept. *Psychol. Explor.* 31, 172–175.

Horney, K. (1937). *The Neurotic Personality of Our Time*. New York, NY: W.W. Norton & Co.

Hu, Q. J., Liang, W. M., Zhang, Y. L., Zhang, X. X., Chen, M., Xing, L., et al. (2019). Mental health condition of primary school students in Dongguan, China. *J. Health Psychol.* 27, 923–928. doi: 10.13342/j.cnki.cjhp.2019.06.014

Hu, Z. P. (2018). Kernel collaborative representation classification based on adaptive dictionary learning. *Int. J. Intell. Inform. Syst.* 7:15. doi: 10.11648/j.ijiis.20180702.11

Jiang, G. R. (2004). Class environment in the Chinese school system: structure and measurement. *Psychol. Sci.* 27, 839–843. doi: 10.16719/j.cnki.1671-6981.2004.04.018

John, P., Buerck, T. M., and Elliott, P. (2003). Learning environment and learning styles: nontraditional student environment and success in an internet-based versus a lecture-based computer science course. *Learn. Environ. Res.* 6, 137–155. doi: 10.1023/A:1024939002433

Johnson, D. W., and Johnson, R. T. (1994). *Learning Together and Alone. Cooperative, Competitive, and Individualistic Learning*, 4th Edn. Boston, MA: Allyn and Bacon.

Kindermann, T. A. (1993). Natural peer groups as contexts for individual development: the case of children's motivation in school. *Dev. Psychol.* 29, 970–977. doi: 10.1037/0012-1649.29.6.970

Lewin, K. (1936). *Principles of Topological Psychology*. New York, NY: Mc Graw-Hill.

Li, B. L., Gao, T., Deng, L. Y., Chen, J. J., and Ni, H. (2019). The mediation effect of core self-evaluation between class environment and academic stress among middle school students —the moderation effect of gender. *Psycholol. Dev. Educ.* 35, 192–202. doi: 10.16187/j.cnki.issn1001-4918.2019.02.08

Liu, H. R., Yao, M. L., and Li, J. (2020). Chinese adolescents' achievement goal profiles and their relation to academic burnout, learning engagement, and test anxiety. *Learn. Indiv. Differ.* 83–84:101945. doi: 10.1016/j.lindif.2020.101945

Macher, D., Paechter, M., Papousek, I., and Ruggeri, K. (2012). Statistics anxiety, trait anxiety, learning behavior, and academic performance. *Eur. J. Psychol. Educ.* 27, 483–498. doi: 10.1007/s10212-011-0090-5

Moos, R. H., and Trickett, E. J. (1987). *Classroom Environment Scale Manual*, 2nd Edn. Palo Alto, CA: Consulting Psychologists Press.

Ogbuehi, P. I., and Fraser, B. J. (2007). Learning environment, attitudes and conceptual development associated with innovative strategies in middle-school mathematics. *Learn. Environ. Res.* 10, 101–114. doi: 10.1007/s10984-007-9026-z

Okebukola, P. A. (1986). Reducing anxiety in science classes: an experiment involving some models of class interaction. *Educ. Res.* 28, 146–149. doi: 10.1080/0013188860280211

Olitsky, S. (2011). The role of fictive kinship relationships in mediating classroom competition and supporting reciprocal mentoring. *Cult. Stud. Sci. Educ.* 6, 883–894. doi: 10.1007/s11422-011-9363-1

Owens, M., Stevenson, J., Hadwin, J. A., and Norgate, R. (2012). Anxiety and depression in academic performance: an exploration of the mediating factors of worry and working memory. *Sch. Psychol. Int.* 33, 433–449. doi: 10.1177/0143034311427433

Pang, H. B. (2009). An investigation on the correlation between junior middle school students' class environment and academic achievement. *Psychol. Sci.* 32, 742–744. doi: 10.16719/j.cnki.1671-6981.2009.03.065

Pekrun, R. (2005). Progress and open problems in educational emotion research. *Learn. Instr.* 15, 497–506. doi: 10.1016/j.learninstruc.2005.07.014

Pekrun, R. (2006). The control-value theory of achievement emotions: assumptions, corollaries, and implications for educational research and practice. *Educ. Psychol. Rev.* 18, 315–341. doi: 10.1007/s10648-006-9029-9

Pekrun, R., Lichtenfeld, S., Marsh, H. W., Murayama, K., and Goetz, T. (2017). Achievement emotions and academic performance: longitudinal models of reciprocal effects. *Child Dev.* 88, 1653–1670. doi: 10.1111/cdev.12704

Pekrun, R., and Stephens, E. J. (2010). Achievement emotions: a control-value approach. *Soc. Pers. Psychol. Compass* 4, 238–255. doi: 10.1111/j.1751-9004.2010.00259.x

Pesout, O., and Nietfeld, J. (2021). The impact of cooperation and competition on metacognitive monitoring in classroom context. *J. Exp. Educ.* 89, 237–258. doi: 10.1080/00220973.2020.1751577

Pettigrew, T. F., Christ, O., Wagner, U., Meertens, R. W., van Dick, R., and Zick, A. (2008). Relative deprivation and intergroup prejudice. *J. Soc. Issues* 64, 385–401. doi: 10.1111/j.1540-4560.2008.00567.x

Phuntsho, U., and Dhendup, R. (2020). The relationship between school climate, student engagement, and academic achievement in higher secondary school. *Bhutan J. Res. Dev. Autumn* 9, 98–131. doi: 10.13140/RG.2.2.28798.00327/2

Pietarinen, J., Soini, T., and Pyhältö, K. (2014). Students' emotional and cognitive engagement as the determinants of well-being and achievement in school. *Int. J. Educ. Res.* 67, 40–51. doi: 10.1016/j.ijer.2014.05.001

Posselt, J. R., and Lipson, S. K. (2016). Competition, anxiety, and depression in the college classroom: variations by student identity and field of study. *J. Coll. Stud. Dev.* 57, 973–989. doi: 10.1353/csd.2016.0094

Preacher, K. J., and Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behav. Res. Methods* 40, 879–891. doi: 10.3758/BRM.40.3.879

Preacher, K. J., Rucker, D. D., and Hayes, A. F. (2007). Addressing moderated mediation hypotheses: theory, methods, and prescriptions. *Multivar. Behav. Res.* 42, 185–227. doi: 10.1080/00273170701341316

Quach, A. S., Epstein, N. B., Riley, P. J., Falconier, M. K., and Fang, X. (2015). Effects of parental warmth and academic pressure on anxiety and depression symptoms in Chinese adolescents. *J. Child Fam. Stud.* 24, 106–116. doi: 10.1007/s10826-013-9818-y

Reyes, M. R., Bracket, M. A., River, S. E., White, M., and Salovey, P. (2012). Classroom emotional climate, student engagement, and academic achievement. *J. Educ. Psychol.* 104, 700–712. doi: 10.1037/a0027268

Roth, G., Assor, A., Niemiec, C. P., Ryan, R. M., and Deci, E. L. (2009). The emotional and academic consequences of parental conditional regard: comparing conditional positive regard, conditional negative regard, and autonomy support as parenting practices. *Dev. Psychol.* 45, 1119–1142. doi: 10.1037/a0015272

Rucker, D. D., Preacher, K. J., Tormala, Z. L., and Petty, R. E. (2011). Mediation analysis in social psychology: current practices and new recommendations. *Soc. Pers. Psychol. Compass* 5, 359–371. doi: 10.1111/j.1751-9004.2011.00355.x

Ryckman, R. M., Hammer, M., Kaczor, L. M., and Gold, J. A. (1990). Construction of a hypercompetitive attitude scale. *J. Pers. Assess.* 55, 630–639. doi: 10.1080/00223891.1990.9674097

Sang, G. Y., Valcke, M., van Braak, J., and Tondeur, J. (2009). Investigating teachers' educational beliefs in Chinese primary schools: socioeconomic and geographical perspectives. *Asia Pac. J. Teach. Educ.* 37, 363–377. doi: 10.1080/13598660903250399

Sariem, C. N., Fwangshak, F. D., Shalkur, D., and Adeniyi, M. A. (2014). Factors affecting academic performance of pharmacy students in the University of Jos, Nigeria. *J. Pharm. Bioresour.* 11, 85–92. doi: 10.4314/jpb.v11i2.8

Schaufeli, W. B., and Bakker, A. B. (2004). Job demands, job resources, and their relationship with burnout and engagement: a multi-sample study. *J. Organ. Behav.* 25, 293–315. doi: 10.1002/job.248

Schaufeli, W. B., Salanova, M., González-Romá, V., and Bakker, A. B. (2002b). The measurement of engagement and burnout: a two sample confirmatory factor analytic approach. *J. Happiness Stud.* 3, 71–92. doi: 10.1023/A:1015630930326

Schaufeli, W. B., Martinez, I. M., Pinto, A. M., Salanova, M., and Bakker, A. B. (2002a). Burnout and engagement in university students a cross-national study. *J. Cross Cult. Psychol.* 33, 464–481. doi: 10.1177/0022022102033005003

Shernoff, D. J. (2010). Engagement in after-school programs as a predictor of social competence and academic performance. *Am. J. Community Psychol.* 45, 325–337. doi: 10.1007/s10464-010-9314-0

Shi, L. S., Chen, Y. M., Hou, X., and Gao, F. Q. (2013). Social economic status and study engagement: the mediating effects of academic self-efficacy among junior high school students. *Psychol. Dev. Educ.* 29, 71–78. doi: 10.16187/j.cnki.issn1001-4918.2013.01.006

Shrout, P. E., and Bolger, N. (2002). Mediation in experimental and nonexperimental studies: new procedures and recommendations. *Psychol. Methods* 7, 422–445. doi: 10.1037//1082-989X.7.4.422

Sommet, N., Pulfrey, C., Butera, F., and Ozakinci, G. (2013). Did my M.D. really go to university to learn? Detrimental effects of numerus clausus on self-efficacy, mastery goals and learning. *PLoS One* 8:84178. doi: 10.1371/journal.pone.0084178

Sullivan, E. (1980). "Can values be taught?," in *Moral Development and Socialization*, eds M. Windmiller, N. Lamber, and E. Turiel (Boston, MA: Allyn and Bacon).

Sun, Z., Bai, T., Yu, W., Zhou, J., Zhang, M., and Shen, M. (2015). Attentional bias in competitive situations: winner does not take all. *Front. Psychol.* 6:1469. doi: 10.3389/fpsyg.2015.01469

Tauer, J. M., and Harackiewicz, J. M. (2004). The effects of cooperation and competition on intrinsic motivation and performance. *J. Pers. Soc. Psychol.* 86, 849–861. doi: 10.1037/0022-3514.86.6.849

Tomasetto, C., Morsanyi, K., Guardabassi, V., and O'Connor, P. A. (2021). Math anxiety interferes with learning novel mathematics contents in early elementary school. *J. Educ. Psychol.* 13, 315–329. doi: 10.1037/edu0000602

Volk, A., Craig, W., Boyce, W., and King, M. (2006). Adolescent risk correlates of bullying and different types of victimization. *Int. J. Adolesc. Med. Health* 18, 575–586. doi: 10.1515/ijamh.2006.18.4.575

Volk, A. A., Cioppa, V. D., Earle, M., and Farrell, A. H. (2015). "Social competition and bullying: an adaptive socioecological perspective," in *Evolutionary Perspectives on Social Psychology. Evolutionary Psychology*, eds V. Zeigler-Hill, L. Welling, and T. Shackelford (Cham: Springer).

Wang, Y. H., Yang, Z. X., Zhang, Y. B., Wang, F. M., Liu, T., and Xin, T. (2019). The effect of social-emotional competency on child development in western China. *Front. Psychol.* 10:1282. doi: 10.3389/fpsyg.2019.01282

Wara, E., Aloka, P. J., and Odongo, B. C. (2018). Relationship between emotional engagement and academic achievement among Kenyan secondary school students. *Acad. J. Interdiscipl. Stud.* 7, 107–118. doi: 10.2478/ajis-2018-0011

Warren, K., Schoppelrey, S., Moberg, D. P., and McDonald, M. (2005). A model of contagion through competition in the aggressive behaviors of elementary school students. *J. Abnorm. Child Psychol.* 33, 283–292. doi: 10.1007/s10802-005-3565-5

Wong, P. T., Wong, L. C., and Scott, C. (2006). "Beyond stress and coping: the positive psychology of transformation," in *Handbook of Multicultural Perspectives on Stress and Coping*, eds P. T. P. Wong and L. C. J. Wong (Boston, MA: Springer).

Woodman, T., and Hardy, L. (2001). "Stress and anxiety," in *Handbook of Research on Sport Psychology*, eds R. Singer, H. A. Hausenblas, and C. M. Janelle (New York, NY: Wiley), 290–318.

Zhang, C. M., Zou, H., and Hou, K. (2006). The relations among respecting behaviors, personalities and class environment of primary school children. *Psychol. Dev. Educ.* 3, 16–22. doi: 10.16187/j.cnki.issn1001-4918.2006.03.004

Zhang, G. Z., Liang, Z. B., Deng, H. H., and Lu, Z. H. (2014). Relations between perceptions of school climate and school adjustment of adolescents: a longitudinal study. *Psychol. Dev. Educ.* 30, 371–379. doi: 10.16187/j.cnki.issn1001-4918.2014.04.019

Zhen, R., Liu, R., Ding, Y., Wang, J., Liu, Y., and Xu, L. (2017). The mediating roles of academic self-efficacy and academic emotions in the relation between basic psychological needs satisfaction and learning engagement among Chinese adolescent students. *Learn. Individ. Differ.* 54, 210–216. doi: 10.1016/j.lindif.2017.01.017

Zhou, B. C. (1991). *Mental Health Diagnostic Test (MHT)*. Shanghai: East China Normal University Press.

Zimmerman, D. J. (2003). Peer effects in academic outcomes: evidence from a natural experiment. *Rev. Econ. Stat.* 85, 9–23. doi: 10.2307/3211619

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Relationships Between Mathematics Performance and Attitude to Mathematics: Influences of Gender, Test Anxiety, and Working Memory

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Many studies have indicated that mathematics anxiety, and other negative attitudes and emotions toward mathematics, are pervasive and are associated with lower mathematical performance. Some previous research has suggested that working memory is related to both mathematics anxiety and mathematics. Moreover, both gender and chosen course of study (sciences vs. humanities) appeared likely to influence students' attitudes to mathematics. In the present study, 40 university undergraduates completed a battery of assessments investigating working memory, attitude to mathematics, test anxiety. and mental and written arithmetic. Attitudes to mathematics were significantly associated with the other variables: working memory, test anxiety, and both measures of mathematical performance. The other variables were not strongly associated with one another. There were no gender differences in mathematical performance, but females exhibited more negative attitudes to mathematics and higher test anxiety than males. After controlling for test anxiety, there ceased to be significant gender differences in attitudes to mathematics. Science students had more positive attitudes to mathematics than humanities students, but the groups did not differ in test anxiety, Science students were better at written but not mental arithmetic. They were also better at working memory, but this was not a significant covariate when the groups were compared on mathematical performance and attitudes to mathematics The results are discussed, with particular focus on implications for future research on influences on mathematics anxiety.

Keywords: mathematical performance, attitudes to mathematics, test anxiety, working memory, gender differences, adults

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INTRODUCTION

Numerous studies indicate that attitudes to mathematics are often highly negative, ranging from boredom to severe fear and anxiety. Mathematics anxiety has been defined as "feelings of tension or anxiety that interfere with the manipulating of numbers or the solving of mathematical problems" (Richardson and Suinn, 1972). Estimates of the frequency of mathematics anxiety range from 11% (Betz, 1978) to 68% (Richardson and Suinn, 1972). The frequency of mathematics anxiety will depend both on the nature of the sample and on how "mathematics anxiety" is defined, but even the lower estimates suggest that it is significant problem for many. Moreover, even people who do not have mathematics anxiety as such may have negative attitudes to mathematics and regard it as boring, a waste of time, too difficult for them, and/or irrelevant to their own lives (see Fennema and Sherman, 1976).

Many studies have also found that mathematics anxiety and other negative attitudes to mathematics are associated correlationally, with poorer performance in mathematics (e.g., Hembree, 1990; Ma and Kishor, 1997; Maloney et al., 2011; Carey et al., 2016; Dowker et al., 2016; Zhang et al., 2019; Abín et al., 2020).

This does not mean that the direction of causation is always from anxiety or negative attitudes to performance. Weaknesses in mathematics may cause failures and other negative experiences, which then lead to anxiety and other negative attitudes (Núñez-Peña and Suárez-Pellicioni, 2014). It is generally thought now that there is a bidirectional relationship between attitudes and performance. For example, Maloney and Beilock (2012) propose that a combination of social factors and pre-existing mathematical difficulties results a negative attitude to mathematics. This in turn impedes subsequent performance in mathematics, resulting in a vicious circle.

This study also investigates; the possible relationship between attitude to mathematics and working memory. There are some studies that suggest that mathematics anxiety may impair performance by overloading working memory (Eysenck and Calvo, 1992; Ashcraft and Kirk, 2001). Beilock and DeCaro (2007) found that, in studies of mathematics anxiety, there was only a correlation between mathematics anxiety and mathematics performance when the task given required significant use of working memory resources. Ashcraft and Kirk (2001) supported this idea by finding that people with higher mathematics anxiety demonstrated lower working memory than people with less mathematics anxiety, particularly in tasks involving calculation. Caviola et al. (2012) suggested, similarly, that if anxiety affects working memory, it should have an especially strong effect on arithmetic, as mathematics requires working memory. Vukovic et al. (2013) drew together these ideas and showed that, in a longitudinal study of 113 children, the relationship between mathematics anxiety and performance is greater in those with poorer working memory abilities. This study will examine the relationships between working memory, mathematics anxiety, and mathematical performance in adults.

Some apparent "mathematics anxiety" may in fact reflect a less specific anxiety about academic subjects and especially about tests and examinations. There is usually found to be a high correlation between mathematics anxiety and test anxiety, with typical correlations ranging from 0.3 to 0.5 (Hembree, 1990; Ashcraft et al., 1998). However, mathematics anxiety is not *just* a form of test anxiety, studies generally show a higher correlation between different measures of mathematics anxiety (0.5–0.8) than between mathematics anxiety and test anxiety or general anxiety (Dew et al., 1983; Hembree, 1990; Ashcraft and Ridley, 2005).

A number of studies have attempted to investigate and disentangle the interrelationships between mathematics performance, mathematics anxiety, working memory, and sometimes other characteristics. These studies have given interesting but sometimes somewhat conflicting results. For example, structural equation modeling has been used to obtain a finer-grained analysis of the relationships between mathematical performance, mathematics anxiety, working memory, and other cognitive skills, sometimes producing somewhat contrasting results. Skagerlund et al. (2019) used structural equation modeling to analyze the interrelationships between mathematics anxiety, mathematical performance, and working memory. They found three separate pathways from mathematics anxiety to mathematical performance: a direct effect of mathematics anxiety on performance; an indirect effect *via* effects on symbolic number processing; and an indirect effect *via* effects on working memory. Douglas and Lefevre (2018) also used structural equation modeling to investigate the interrelationships between the above variables and the mathematics-related skills of quantity processing and spatial processing. Although all these variables were correlated, no direct link was found between mathematics anxiety and either quantity processing, spatial processing or working memory; nor were the relationships between the latter abilities and mathematics performance indirectly affected by working memory.

Meta-analyses have been used to combine the results of numerous studies in order to obtain more precise and detailed information about the relationships between mathematics anxiety and mathematical performance and factors that may contribute to such relationships. Zhang et al. (2019) and Barroso et al. (2021) carried out meta-analyses, both of which showed a moderate consistent negative correlation between mathematics anxiety and mathematical performance. The relationship was strongest in secondary school pupils and lowest in children in grades 3 to 5 and in college students. Zhang et al. (2019) also examined the effects of other demographic and methodological variables and found that the relationship between mathematics anxiety and performance was stronger for Asian than European students and was strongest among studies that used a custom test and studies that assessed problem-solving skills. A meta-analysis by Caviola et al. (2021) indicated that both mathematics anxiety and test anxiety were negatively associated with mathematical performance. Working memory had a weak moderating effect on these relationships. Namkung et al. (2019) carried out a meta-analysis specifically of studies of school age pupils and found that the relationship between mathematics anxiety and performance was strongest when the mathematics anxiety measures included both affective and cognitive components; when the mathematics performance measures involved formal assessments that influenced or reflected school grades; and when the mathematics performance measures involved advanced and/or multi-step arithmetic.

One consistent finding from most previous studies is that there are significant gender differences in attitudes to mathematics. Most studies indicate that females show higher mathematics anxiety than males (e.g., Hembree, 1990; Miller and Bichsel, 2004; Devine et al., 2012; Ganley and Vasilyeva, 2014; Sarfo et al., 2020; Wang, 2020; Xie et al., 2020; Delage et al., 2021). Some studies have shown such gender differences even in children in the early years of primary school (Szczygiel, 2020), though many studies have not found such a difference (e.g., Harari et al., 2013; Ching, 2017; Mononen et al., 2021). Most of the studies (with a few exceptions) do not show gender differences in mathematical *performance*. Spelke (2005) reported that in countries where girls have equal education and opportunities, there is no significant gender difference in mathematics performance. Some studies suggest that mathematics anxiety has different effects on performance in males and in females, but the studies give conflicting results as to the direction of the gender difference. Hembree (1990) and Miller and Bichsel (2004) found that mathematics anxiety affected performance more in males than in females. Devine et al. (2012) found on the other hand that after controlling for test anxiety, mathematics anxiety had an independent effect on mathematics performance in girls but not in boys. Hembree (1990) drew attention to the lack of conclusive agreement across studies, as to relationship between gender, mathematics anxiety, and mathematical performance, which Birgin et al. (2010) later attributed to the lack of consistent measurement of mathematics anxiety. The current study, therefore, intends to further investigate the influence of gender on mathematics performance and on a measure related to mathematics anxiety while controlling for test anxiety.

The current study also intends to investigate the relationship between attitude to mathematics and degree subject of study. Betz (1978) found that correlations between mathematics anxiety and performance in university students differed according to course as well as gender. Ashcraft (2002) suggested that correlations between mathematics anxiety and performance could be because those that have higher levels of mathematics anxiety avoid situations involving mathematics, which may mean avoiding certain areas of study, and, thus, gain less practice in mathematics. Thus, the current study intends to investigate how gender and subject of study interact with any relationships between mathematics performance and mathematics anxiety. We tentatively propose that science students may have higher working memory than humanities students, because their area of study may require more short-term mental mathematical and logical calculations, as compared with analyses of long-term information. Popescu et al. (2019), found that mathematics graduate students scored higher on backward digit span and on another working memory task (forward letter span) than humanities graduate students.

The current study investigates relationships between all these variables; attitudes to mathematics, mathematics performance, gender, degree subject, and working memory. The participants in the study were Oxford University students and therefore could be assumed to exclude those with extremely poor mathematical performance (entry requirements usually include a high grade in mathematics at GCSE or equivalent). Therefore, it was decided to use a mathematics attitude measure that did not focus solely on negative attitudes, but included both enjoyment and anxiety. The measure chosen was Aiken's (1974) Mathematics Enjoyment Scale. This also had the advantage of not being very time-consuming, though this also comes with the disadvantage of not being able to include several different factors. Because many of the questions are in fact about anxiety, the construct measured will be termed Mathematics Enjoyment/Anxiety.

Given previous findings about the complicated relationships between mathematics anxiety, test anxiety, and mathematics performances anxiety, mathematics performance (e.g., Devine et al., 2012), a standard measure of test anxiety was also included. The measures of mathematics performance were chosen because they both included only topics that are covered in compulsory school mathematics courses. Thus, it is unlikely that the specific content learnt in the degree would be an additional factor influencing mathematics performance. The decision to use a numerical working memory test seemed most appropriate to the field of mathematics anxiety as this tests working memory for numbers, which is required in mathematics.

Our predictions were (1) that mathematics performance would correlate with both attitudes to mathematics and working memory; (2) that both mathematics anxiety and working memory would be independent predictors of mathematics performance in a multiple regression; (3) that general test anxiety would correlate with both mathematics performance and attitudes to mathematics; (4) that mathematics performance measures and test anxiety would be independent predictors of mathematics anxiety; (5) that females would show more mathematics anxiety and more test anxiety than males; (6) that males and females would not differ in actual mathematical performance or in working memory; (7) that gender differences in mathematical performance would reduce after controlling for test anxiety; (8) that science students would perform better than humanities students on mathematics measures; (9) that science students would show higher mathematics anxiety than humanities students; (10) that science students would show higher working memory than humanities students; and (11) that differences between science and humanities students would reduce after controlling for working memory.

MATERIALS AND METHODS

Design

A between-participants design was used. The grouping factors were gender (male vs. female) and subject of study (sciences vs. humanities). There were five dependent variables: two different mathematics test scores, digit span, mathematics anxiety, and test anxiety. Participants were selected to ensure equal numbers of participants falling into each of the grouping categories.

Participants

Participants were 40 University Undergraduates aged 18–25. Ten were males studying sciences, 10 females studying sciences, 10 males studying humanities, and 10 females studying humanities. University subjects were classed as sciences or humanities on the basis of the division in which the university classed them: sciences if classed in the Medical Sciences division or Mathematical, Physical and Life Sciences division; and humanities if classed in the Humanities division or Social Sciences division.

Participants were recruited through advertisement *via* email and social media and through social contacts and word-of-mouth. They were given an information sheet about the tasks that they would be given and then signed a consent form.

Ethical approval was sought and granted by the Central University Research Ethics Committee of Oxford University.

Tasks

Attitude Measures

1. A measure of Test Anxiety. The measure used was Sarason's (1977) Test Anxiety Scale. This had been shown to have test–retest reliability scores in the 0.80 (Zeidner and Matthews, 2003). It has also been found to correlate well with other test anxiety scales, indicating good concurrent validity. In the present study, Cronbach's alpha for this measure was 0.91.
2. A measure of attitudes to mathematics. The measure used was Aiken's (1974) Mathematics Enjoyment scale. This test had a Cronbach alpha of 0.95 in Aiken's (1974) original study; 0.88 in Watson's (1983) validation; and 0.87 in the sample tested in the present study. Both Aiken (1974) and Watson's (1983) obtained highly significant correlations with a range of measures of mathematical performance and attitudes to mathematics, indicating good concurrent validity.

Working Memory Test

3. WAIS Digit Span subtest. This was taken from the Wechsler Adult Intelligence Scale-IV (Wechsler, 2008). This involves repeating strings of numbers forward and backward. For the purpose of the present study, the Backward Digit Span was used, as this is a purer measure of *working memory*.

Mathematics Tests

4. WAIS Arithmetic subtest (Wechsler, 2008). This was taken from the Wechsler Adult Intelligence Scale-III. It is an orally presented test of word problem-solving with an oral response. The scaled score was the measure used in the analysis. Cronbach's alpha was 0.9 both in the original standardization and in the present study.
5. Test 2 of Hitch's (1978a) Numerical Abilities Tests. This was a written test, involving mathematical questions on fractions, decimals, percentages, and arithmetic functions. Participants were given up to 20 min to complete this without a calculator. In the original study, the split-half reliability computed by the Spearman–Brown formula was 0.97. In the present study, Cronbach's alpha was 0.95.

Procedure

Participants were asked to read an information sheet and sign a consent form and were then told the tasks they were going to complete. Participants were given these tasks in a quiet room with only the researcher present. They were first given the Backward Digit Span and WAIS Arithmetic test (Wechsler, 2008). They were then given the Test Anxiety scale and then the Mathematics Enjoyment Scale, untimed. These were presented on paper, and participants were asked to complete them by hand. Finally, participants were given the Written mathematics test. The decision was made to put the Written mathematics test last, so that self-perceived performance on it would not impact responses given on the attitude measures.

Analysis

IBM SPSS Version 25 was used to analyze the data (SPSS, IBM, 2017).

RESULTS

Scaled scores were coded for Arithmetic using the scoring guide in the WAIS scoring manual (Wechsler, 2008). Since only Backward Digit Span and not Forward Digit Span was included in the analyses for this study, no scaled score was coded for Digit Span.

Arithmetic raw scores ranged from 12 to 21 ($M = 17.93$, $SD = 1.94$) and scaled scores from 10 to 17 ($M = 8.45$, $SD = 2.3$). Written mathematics test scores ranged from 19/40 to 40/40 ($M = 33.25$, $SD = 6.03$). Backward Digit Span scores ranged from 5 to 13 ($M = 20.30$, $SD = 3.94$). Test anxiety scores ranged from 4 to 27 ($M = 15.15$, $SD = 5.13$). Mathematics Anxiety/Enjoyment scores ranged from 12 to 48 ($M = 25.58$, $SD = 11.53$).

Pearson's Correlations

Pearson's correlations were examined between Arithmetic scaled score, Written Mathematics test score, Backward Digit Span, Test Anxiety, and Mathematics Anxiety/Enjoyment. These correlations are shown in **Table 1**. The correlation between Arithmetic scaled score and Written mathematics test score did not reach significance ($p = 0.07$). Backward Digit Span correlated significantly with Arithmetic scaled score, but not with Written mathematics test score. Mathematics Anxiety/Enjoyment correlated significantly with all the other variables: positively with test anxiety and negatively with backward digit span, arithmetic scaled score and written Mathematics test score. Test anxiety only correlated with Mathematics Anxiety/Enjoyment.

Multiple Regressions

An entry-type multiple regression was carried out with Arithmetic scaled score as the dependent variables, and Backward Digit Span, Test Anxiety and Mathematics Anxiety/Enjoyment as the predictors. R^2 was 0.17. The model did not explain a significant amount of the variance [$F(3,36) = 2,5$; $p = 0.07$]. None of the individual predictors was significant for Arithmetic scaled score: Neither Backward Digit Span, $\beta = 0.22$, $t(3, 37) = 1.26$,

$p = 0.217$; Test Anxiety, $\beta = -0.038$, $t(3,37) = -1.69$, $p = 0.834$, nor Mathematics Anxiety/Enjoyment, $\beta = -0.28$, $t(3,37) = -1.45$, $p = 0.15$ proved significant.

Another entry-type multiple regression was carried out with Written mathematics test score as the dependent variable, and Backward Digit Span, Test Anxiety and Mathematics Anxiety/Enjoyment as the predictors. R^2 was 0.14. The model did not explain a significant amount of the variance [$F(3,36) = 1{,}97$; $p = 0.135$]. None of the individual predictors was significant for Written mathematics test score: Neither Backward Digit Span, $\beta = 0.17$, $t(3, 37) = 0.95$, $p = 0.347$; Test Anxiety, $\beta = -0.33$, $t(3,37) = -0.18$, $p = 0.838$, nor Mathematics Anxiety/Enjoyment, $\beta = -0.266$, $t(3,37) = -136$, $p = 0.18$ proved significant.

Another entry-type multiple regression was carried out with Mathematics Anxiety/Enjoyment score as the dependent variable, and Backward Digit Span, Test anxiety and Arithmetic scaled score as the predictors. R^2 was 0.42. The model explained a highly significant amount of the variance [$F(3,36) = 8{,}81$; $p < 0.001$]. Backward Digit Span was a highly significant predictor $\beta = -0.385$, $t(3, 37) = -2.79$, $p = 0.008$; as was Test Anxiety, $\beta = 0.462$, $t(3,37) = 3.51$; $p = 0.001$. Arithmetic scaled score was not a significant predictor, $\beta = 0.199$, $t(3,37) = -1.45$; $p = 0.156$.

Another entry-type multiple regression was carried out with Mathematics Anxiety/Enjoyment score as the dependent variable, and Backward Digit Span, Test anxiety and Written mathematics test score as the predictors. R^2 was 0.41. The model explained a highly significant amount of the variance [$F(3,36) = 8{,}32$; $p < 0.001$]. Backward Digit Span was a highly significant predictor $\beta = -0.4$, $t(3, 37) = -2.95$, $p = 0.006$; as was Test Anxiety, $\beta = 0.466$, $t(3,37) = 3.55$; $p = 0.001$. Written mathematics test score was not a significant predictor, $\beta = -0.18$, $t(3,37) = 1.36$; $p = 0.183$.

Analyses of Variance

A two-factor between-participants Analysis of Variance was then conducted, with Gender (Male vs. Female) and Subject of Study (Science vs. Humanities) as the grouping factors and Arithmetic scaled score, Written mathematics test score. Backward Digit Span, Test Anxiety, and Mathematics Anxiety/Enjoyment as the dependent variables.

As **Table 2** indicates, there were significant gender differences in both Test Anxiety and Mathematics Anxiety: females scored higher on both. There were no significant gender differences in either mathematical performance measure or on Backward Digit Span. There were significant course differences, with

TABLE 1 | Pearson's correlations for arithmetic scaled score, written mathematics test score, backward digit span, test anxiety, and mathematics anxiety/enjoyment.

	Arithmetic Scaled Score	Written mathematics	Backward Digit Span	Test Anxiety	Math. Anxiety/ Enjoyment
Arithmetic Scaled Score	–	0.26 ($p = 0.1$)	0.3 ($p = 0.06$)	0.09 ($p = 0.46$)	−0.379* ($p = 0.016$)
Written Mathematics	–	–	0.27 ($p = 0.1$)	−0.12 ($p = 0.47$)	−0.344* ($p = 0.03$)
Backward Digit Span	–	–	–	0.163 ($p = 0.316$)	−0.37* ($p = 0.018$)
Test Anxiety	–	–	–	–	0.423** ($p = 0.007$)

*$p < 0.05$; **$p < 0.01$.

TABLE 2 | Results of analysis of variance with gender and course as grouping factors and arithmetic scaled score, written mathematics test score, backward digit span.

Source	Dependent Variable	df	Mean Square	*F*	Sig.	Partial Eta Squared
Gender	Arithmetic Scaled Score	(1,36)	0.625	0.182	0.672	0.005
	Written Mathematics	(1,36)	6.400	0.217	0.644	0.006
	Backward Digit Span	(1,36)	0.100	0.020	0.889	0.001
	Test Anxiety	(1,36)	108.900	4.477	0.041	0.111
	Mathematics Anxiety/ Enjoyment	(1,36)	632.025	6.722	0.014	0.157
Course	Arithmetic Scaled Score	(1,36)	3.025	0.883	0.354	0.024
	Written Mathematics	(1,36)	348.100	11.807	0.002	0.247
	Backward Digit Span	(1,36)	22.500	4.480	0.041	0.111
	Test Anxiety	(1,36)	0.100	0.004	0.949	0.000
	Mathematics Anxiety/ Enjoyment	(1,36)	950.625	10.110	0.003	0.219
Gender * Course	Arithmetic Scaled Score	(1,36)	0.025	0.007	0.932	0.000
	Written Mathematics	(1,36)	1.600	0.054	0.817	0.002
	Backward Digit Span	(1,36)	2.500	0.498	0.485	0.014
	Test Anxiety	(1,36)	2.500	0.103	0.750	0.003
	Mathematics Anxiety/ Enjoyment	(1,36)	216.225	2.300	0.138	0.060

Test anxiety and mathematics anxiety/enjoyment as the dependent variables.

moderate effect size, for Written Mathematics (science students did better) and Mathematics Anxiety (humanities students scored higher), and one with lower effect size for Backward Digit Span (science students had longer spans). There were no significant interactions between course and gender. However, it should be noted that although **Table 3** supports the lack of interaction between course and gender regarding the mean Mathematics Anxiety/Enjoyment scores, the standard deviation was much lower for male science students than for female science students or for humanities students of either gender.

In order to investigate whether Test Anxiety was driving the results for gender differences and similarities, a one-way ANOVA was carried out, with Gender as the grouping factor, Test Anxiety as a covariate, and Arithmetic scaled score, Written mathematics test score, Backward Digit Span, and Mathematics Anxiety/Enjoyment as the dependent variables. Test Anxiety proved to be a significant covariate for Mathematics Anxiety/Enjoyment, $F(1, 37) = 5.07$, $p = 0.03$, $\eta_p^2 = 0.12$. There were now no significant gender differences in any variable, including Mathematics Anxiety/Enjoyment.

In order to investigate whether working memory was driving the results for course differences, a similar one-way ANOVA was carried out, with Course as the grouping factor, Backward Digit Span as a covariate, and Arithmetic scaled score, Written mathematics test score, Test Anxiety, and Mathematics Anxiety. Backward Digit Span was not a significant covariate for any of the dependent variables. Course differences continued to be significant for Written mathematics test score, $F(1, 37) = 5.07$, $p = 0.004$, $\eta_p^2 = 0.201$ and for Mathematics Anxiety/Enjoyment, $F(1, 37) = 5.11$, $p = 03$, $\eta_p^2 = 0.121$.

As the ANOVAs may have been somewhat underpowered due to the small sample size, they were supplemented with Bayesian analyses. **Table 4** shows a Bayesian independent samples test for gender comparisons for Arithmetic scaled score, Written mathematics test score, Backward Digit Span, Test Anxiety, and Mathematics Anxiety/Enjoyment.

As can be seen, the Bayes factor was high, favoring the null hypothesis, for the mathematical performance measures and Backward Digit Span, but much lower, giving greater support to the alternative hypothesis, for both anxiety measures.

Table 5 shows a Bayesian independent samples test for course comparisons for Arithmetic scaled score, Written mathematics test score, Backward Digit Span, Test Anxiety, and Mathematics Anxiety/Enjoyment.

As can be seen, the Bayes factor was high, favoring the null hypothesis, for Arithmetic Scaled Score and Test Anxiety, but much lower, giving greater support to the alternative hypothesis, for Written Mathematics, Backward Digit Span, and Mathematics Anxiety/Enjoyment. Thus, the results of the Bayesian analyses are concordant with those of the Analyses of Variance.

TABLE 3 | Scores by gender and course for arithmetic (scaled score), written mathematics, backward digit span, test anxiety, and mathematics anxiety/enjoyment.

	Gender	Course	Mean	Std. Deviation	N
Arithmetic Scaled Score	Male	Science	14.4000	1.26491	10
		Hum.	13.8000	2.25093	10
		Total	14.1000	1.80351	20
	Female	Science	14.1000	1.66333	10
		Hum.	13.6000	2.06559	10
		Total	13.8500	1.84320	20
	Total	Science	14.2500	1.44641	20
		Hum.	13.7000	2.10513	20
		Total	13.9750	1.80438	40
Written Mathematics	Male	Science	36.80	3.521	10
		Hum.	30.50	6.721	10
		Total	33.65	6.141	20
	Female	Science	35.60	4.502	10
		Hum.	30.10	6.332	10
		Total	32.85	6.046	20
	Total	Science	36.20	3.982	20
		Hum.	30.30	6.359	20
		Total	33.25	6.029	40
Backward Digit Span	Male	Science	8.90	1.524	10
		Hum.	7.90	2.514	10
		Total	8.40	2.088	20
	Female	Science	9.50	2.121	10
		Hum.	7.50	2.635	10
		Total	8.50	2.544	20
	Total	Science	9.20	1.824	20
		Hum.	7.70	2.515	20
		Total	8.45	2.298	40
Test Anxiety	Male	Science	13.20	3.706	10
		Hum.	13.80	4.290	10
		Total	13.50	3.914	20
	Female	Science	17.00	6.515	10
		Hum.	16.60	4.766	10
		Total	16.80	5.559	20
	Total	Science	15.10	5.515	20
		Hum.	15.20	4.641	20
		Total	15.15	5.031	40
Mathematics Anxiety/ Enjoyment	Male	Science	14.4000	1.89737	10
		Hum.	28.8000	11.24278	10
		Total	21.6000	10.77717	20
	Female	Science	27.0000	10.77033	10
		Hum.	32.1000	11.40614	10
		Total	29.5500	11.10938	20
	Total	Science	20.7000	9.92127	20
		Hum.	30.4500	11.15194	20
		Total	25.5750	11.52898	40

DISCUSSION

The results of this study confirm our first hypothesis and support many previous studies (Hembree, 1990; Ma and Kishor, 1997; Carey et al., 2016; Dulaney et al., 2017; Skagerlund et al., 2019; Zhang et al., 2019; Abín et al., 2020; Barroso et al., 2021; Caviola et al., 2021) in suggesting that there are some significant relationships between attitudes and performance. A mathematics anxiety and enjoyment measure correlated significantly with two different measures of mathematics: the WAIS Arithmetic subtest (Wechsler, 2008), which mainly tested oral arithmetic problem-solving involving relatively simple calculations and Hitch's (1978a) Numerical Abilities Test 2, which mainly tested written, more complex calculations, and the understanding of fractions and percentages. The fact that it correlated with both simpler and more complex calculations suggests that its effect may be broader than that proposed by

TABLE 4 | Bayes factor independent sample test for differences between male and females (method = rouder)[a].

	Mean Difference	Pooled Std. Error Difference	Bayes Factor[b]	*t*	df	Sig.(2-tailed)
Arithmetic Scaled Score	−0.2500	0.57663	3.962	−0.434	38	0.667
Written Mathematics	−0.80	1.927	3.990	−0.415	38	0.680
Backward Digit Span	0.10	0.736	4.269	0.136	38	0.893
Test Anxiety	3.30	1.520	0.596	2.171	38	0.036
Mathematics Anxiety/ Enjoyment	7.9500	3.46097	0.476	2.297	38	0.027

[a]*Assumes unequal variance between groups.*
[b]*Bayes factor: Null vs. alternative hypothesis.*

TABLE 5 | Bayes factor independent sample test for differences between science and humanities students (Method = Rouder)[a].

	Mean Difference	Pooled Std. Error Difference	Bayes Factor[b]	*t*	df	Sig. (2-tailed)
Arithmetic Scaled Score	−0.5500	0.57113	2.870	−0.963	38	0.342
Written Mathematics	−5.90	1.678	0.035	−3.517	38	0.001
Backward Digit Span	−1.50	0.695	0.608	−2.159	38	0.037
Test Anxiety	0.10	1.612	4.297	0.062	38	0.951
Mathematics Anxiety/ Enjoyment	9.7500	3.33764	0.137	2.921	38	0.006

[a]*Assumes unequal variance between groups.*
[b]*Bayes factor: Null vs. alternative hypothesis.*

Abín et al. (2020), whose results suggested that mathematics anxiety is related to complex but not simple arithmetic, though it must be remembered that Abín et al. (2020) used different measures to ours for both mathematics performance and mathematics anxiety. The meta-analysis by Namkung et al. (2019) also suggested that mathematics anxiety is much more related to complex than simple arithmetic.

As predicted mathematics performance, correlated with working memory; but this only applied to Arithmetic scaled score and not to performance on the written arithmetic test. This may reflect the fact that verbal rehearsal is likely to be more important to oral than written arithmetic (Hitch, 1978b). Also as predicted, Test Anxiety correlated significantly with Mathematics Anxiety/Enjoyment. However, contrary to predictions, it did not correlate with either of with the mathematics measures. It also did not correlate with the working memory measure.

Contrary to predictions, neither working memory, test anxiety nor Mathematics Anxiety/Enjoyment was a significant independent predictor of either of the mathematics measures in multiple regressions. On the other hand, both working memory and test anxiety, but neither of the mathematics performance measures, were significant predictors of Mathematics Anxiety/Enjoyment.

Thus, the mathematics performance measures seemed to be relatively independent of working memory (though this did correlate with Arithmetic scaled score), test anxiety, and even of one another. This differs somewhat from the findings of some other studies, which found stronger influences on mathematical performance of test anxiety (Devine et al., 2012) of working memory (Skagerlund et al., 2019; Caviola et al., 2021) and especially of mathematics anxiety (Ma and Kishor, 1997; Dulaney et al., 2017; Skagerlund et al., 2019; Zhang et al., 2019; Barroso et al., 2021; Caviola et al., 2021). The findings here probably correspond most to those of Douglas and LeFevre (2018), who found relatively limited influence of working memory on other factors and their interrelationships. However, Mathematics Anxiety/Enjoyment did, as pointed out earlier, *correlat*e with all the other variables, even though it did not *independently* predict and was not *independently* predicted by most of them, and it was independently predicted by both working memory and test anxiety. The fact that working memory was a significant independent predictor of attitudes to mathematics, to a greater extent than actual mathematical performance, is one of the most striking findings of the present study. Future research should investigate the direction of causation. It has tended to be assumed that mathematics anxiety interferes with working memory, but it is also possible that working memory weaknesses contribute to mathematics anxiety by increasing the frequency of instances of distraction, confusion, and private and public failures.

As predicted, the ANOVA showed that females and males did not differ in measures of mathematics performance, but females showed more negative attitudes to mathematics, as well as higher levels of test anxiety. These findings are consistent with numerous previous findings, for example, Devine et al. (2012). The lack of a gender difference in performance supports ideas that differences in mathematics anxiety are not explainable by actual poorer performance and may result from exposure to gender stereotypes. They may also reflect differences in academic performance anxiety more generally, a possibility supported by the finding that gender differences in mathematics anxiety ceased to be significant when test anxiety was introduced as a covariate. Future studies should investigate differences in attitudes to and anxiety about academic subjects other than mathematics, including subjects, such as English, where females are generally regarded as higher performing than males. It may also be that different science subjects may be associated with different levels of mathematics anxiety and enjoyment. Some sciences are known to be predominantly chosen by female students (e.g., biology and psychology) and others to be predominantly chosen by male students (e.g., physics and engineering), and it is possible that the latter are seen as "more mathematical."

The study partially supported the hypothesis that science students would perform better at mathematics than humanities students; they scored higher on the written mathematics test than humanities students, but the two groups of students did not differ in Arithmetic scaled score. Science students reported more positive attitudes to mathematics than did humanities students. This finding is unsurprising because, not only are high level mathematical skills required for entry onto most science degree courses, but those who enjoy mathematics are more likely to select such courses. However, the difference in attitudes was very striking, especially as all the participants, as students at a highly selective university, would have needed to have good mathematics qualifications at 16+, and therefore, people with strongly negative attitudes would have been less likely to be participants in the first place. Unlike the gender difference, this difference applied to mathematics anxiety only, and not to general test anxiety. It is also notable that, though there was no significant course–gender interaction for mean mathematics anxiety scores, male science students appeared to be more homogeneous in their (lack of) mathematics anxiety than the other groups, showing a very low standard deviation.

One of the most striking findings was that science students had longer digit spans, implying better working memory, than the humanities students. It would be of interest to investigate whether this is the case for all sciences or just for some and whether humanities students might do better on tests of long-term memory, as their subjects may involve less need for keeping track of ongoing experimental results and more need to remember information long-term. The present findings are consistent with those of Popescu et al. (2019), who found that mathematics graduate students scored higher on backward digit span and on another working memory task (forward letter span) than humanities graduate students.

Despite the differences in working memory between people doing science and humanities courses, working memory was not driving the differences between courses, as it was not a significant covariate in the ANOVA comparing students taking different courses on attitude and performance measures; and the course differences in written arithmetic and Mathematics Enjoyment/Anxiety were not affected by its inclusion as a covariate.

The most significant limitation to the present study is of course the relatively small sample of 40 participants. Most findings were either clearly significant or non-significant, and there were few of the borderline and near-significant results that can result from underpowering, with the exception of the 0.3 correlation ($p = 0.06$) between Arithmetic Scaled Score and Backward Digit Span, However, it is still possible that some potentially significant associations were not found due to the relatively small sample size and that this may partially explain the limited number of independent predictors found. Future studies should attempt to replicate the findings with larger sample.

Ideally, such a sample should also be more diverse. As is commonly true of studies of adults, the results may be to some degree biased by the fact that the available participants were university students. Thus, it is likely that they were more able mathematically and had more positive attitudes than the general population. For example, no participant obtained an Arithmetic scaled score lower than 10, which represents average performance. It would be desirable to study relationships between mathematics attitudes, mathematics performance, and working memory in a larger and more varied, less self-selected sample; though in any sample, people with severe levels of mathematics anxiety are more likely to decline to participate. The participants in this study were informed in advance about what the study would involve, including a mathematics task. This was deemed necessary for ethical reasons, as important for obtaining informed consent; but it may have deterred people with high levels of mathematics anxiety.

It would also be desirable for future studies to include measures of motivation, which may help to explore the possibility that there is not always a simple linear negative relationship between mathematics performance and mathematics anxiety. Macher et al. (2015) have suggested that anxiety may not always be associated with poor performance, at least in the case of statistics anxiety. They proposed that statistics anxiety may on the one hand, both disrupt performance on the other hand may increase motivation to avoid failure, leading for example to greater preparation for examinations. Wang et al. (2015) found that the relationship between mathematics anxiety and mathematics performance could vary with students' level of intrinsic motivation toward mathematics. Students with low intrinsic motivation showed a negative relationship between mathematics anxiety and performance. Students with high intrinsic motivation showed an inverted U-shaped relationship between mathematics anxiety and performance: performing best when moderately anxious and least well when either highly anxious or showing very little anxiety.

In any case, it seems that the relationship between mathematics anxiety and mathematical performance is not always simple, especially if motivation is included as a variable. Wang et al. (2018) carried out a further study of over 900 high school students, including profile analysis of combinations of dimensions of mathematics anxiety and mathematics motivation. They found eight different profiles, with different types of associations with mathematics achievement and engagement. For instance, the highest achieving students reported modest examination-related mathematics anxiety and high mathematics motivation, while the most engaged students reported both high examination-related mathematics anxiety and high mathematics motivation.

As stated in the Introduction, the use of Aiken (1974) Mathematics Enjoyment Scale had the advantages of taking relatively little time and of measuring positive as well as purely negative reactions to mathematics, which reduced the chance of ceiling effects in a relatively mathematically able population. However, one problem with the use of a single scale to measure attitudes and emotions toward mathematics is that it makes it more difficult to differentiate between the effects on mathematical performance, and interactions with working memory, of different attitudes and emotions regarding mathematics. In the present paper, "attitudes to mathematics," "mathematics anxiety," and "mathematics enjoyment/anxiety" have been used almost interchangeably to refer to negative reactions to mathematics. The use of more diverse measures might facilitate a more nuanced analysis. Since some other studies have suggested that positive emotions toward mathematics predict performance, even after controlling for anxiety (Pinxten et al., 2014; Villavicencio and Bernardo, 2016), it would be interesting to investigate whether different aspects of attitudes and emotions regarding mathematics have different effects on mathematics performance This could involve having separate scales for mathematics anxiety and mathematics enjoyment, and/or incorporating and investigating a range of components of mathematics anxiety and other attitudes and emotions, as is done to varying degrees in, for example, the Mathematics Anxiety Rating Scale (Richardson and Suinn, 1972) and the Fennema-Sherman mathematics attitude scales (Fennema and Sherman, 1976).

There is also the question of how closely attitudes and emotional reactions to mathematics are related, and which of these has the strongest relationship to mathematical performance. Some researchers have suggested that mathematics anxiety has both a cognitive dimension (performance anxiety) and an affective dimension (fearful emotional reactions to mathematical stimuli; Wigfield and Meece, 1988; Sorvo et al., 2017). Some studies suggest that the cognitive dimension is not strongly related to mathematical performance before secondary school age, while the affective dimension is already significantly related to performance in the primary school years (Sorvo et al., 2017). Interestingly, Chen et al. (2018) found that, in a group of elementary school children, attitudes to mathematics were not associated with affective-motivational brain areas, which may indicate that, at least in the early stages of development, attitudes to mathematics are distinct from emotions. It may also indicate that, as several studies have suggested, younger children have more positive attitudes to mathematics than older children and adults and have relatively low levels of mathematics anxiety (e.g., Hembree, 1990; Dowker et al., 2012; Szczygieł and Pieronkiewicz, 2021). Chen et al. (2018) found that in elementary school children, the positive attitudes were associated with enhanced hippocampal activation. They proposed that positive attitudes might influence memory processes in mathematics. Therefore, they suggested that attitudes might influence memory processes during learning activities and task solving.

Some studies have suggested that self-rating may be a stronger predictor of mathematical performance than either anxiety or enjoyment in both primary and secondary school children (Dowker et al., 2012; Van der Beek et al., 2017). It can be difficult to determine the causal direction: part of the relationship could be because individuals are in fact estimating their performance accurately and may for example be rating their performance on the basis of previous test scores. However, even in longitudinal studies, confidence seems to predict future performance (Pinxten et al., 2014). Therefore, future studies should include measure of confidence/self-rating in mathematics.

Therefore, it would be useful to replicate the current study in school children, preferably longitudinally and starting in primary school, to see how the relationships between these variables change over time, as suggested by Vukovic et al. (2013). An important aim would be to see if there is a particular point in childhood where the relationship between mathematics anxiety and mathematics performance typically begin to show a strong correlation. If so, it would be desirable to intervene in either mathematics performance or mathematics anxiety or both, before the development of a vicious circle, which may be hard to break; and, if possible, to create a virtuous circle instead. For example (Supekar et al., 2015) found that a mathematics intervention for young children not only improved mathematical performance but reduced anxiety. There are still fewer interventions for mathematics anxiety than for mathematical performance, and it is important to do more work on developing them (Moustafa et al., 2021). It may be that one next step would be to develop interventions simultaneously targeting both performance and anxiety.

To summarize: the results of the present study suggest that mathematics anxiety is correlated with both simple oral arithmetic and complex written arithmetic, but that it ceases to be a significant predictor of either type of arithmetic when test anxiety and working memory are included with it in a multiple regression. However, test anxiety was neither a significant correlate nor significant independent predictor of either mathematics measure. Working memory was a significant independent predictor of oral but not written arithmetic. In multiple regressions with mathematics anxiety as the dependent variable, it was significantly predicted by both working memory and test anxiety, but not by either measure of mathematical performance. There were no gender differences in oral or written arithmetic or in working memory, but females showed more test anxiety and more mathematics anxiety. There were signs that test anxiety was driving the gender differences in mathematics anxiety, as gender differences in mathematics anxiety ceased to be significant when test anxiety was included as a covariate. As regards course, science students had lower mathematics anxiety than humanities students, but the groups did not differ in test anxiety, Science students were better at written but not mental arithmetic. They were also better at working memory, but this was not a significant covariate and did not appear to be influencing the group differences in written mathematics and mathematics anxiety.

DATA AVAILABILITY STATEMENT

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

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Central University Research Ethics Committee, Oxford University. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

AD was predominantly responsible for designing the study and HS for carrying out the experiments. All authors contributed equally to analyses and wrote the article.

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REFERENCES

Abín, A., Núñez, J. C., Rodríguez, C., Cueli, M., García, T., and Rosário, P. (2020). Predicting mathematics achievement in secondary education: The role of cognitive, motivational, and emotional variables. *Front. Psychol.* 11:876. doi: 10.3389/fpsyg.2020.00876

Aiken, L. R. (1974). Two scales of attitude toward mathematics. *J. Res. Math. Educ.* 5, 67–71. doi: 10.5951/jresematheduc.5.2.0067

Ashcraft, M. H. (2002). Math anxiety: personal, educational, and cognitive consequences. *Curr. Dir. Psychol. Sci.* 11, 181–185. doi: 10.1111/1467-8721.00196

Ashcraft, M. H., and Kirk, E. P. (2001). The relationships between working memory, math anxiety and performance. *J. Exp. Psychol. General* 130, 224–237. doi: 10.1037/0096-3445.130.2.224

Ashcraft, M. H., Kirk, E. P., and Hopko, D. (1998). "On the cognitive consequences of mathematics anxiety," in *The Development of Mathematical Skills*. ed. C. Donlan (Hove: Erlbaum), 175–196.

Ashcraft, M. H., and Ridley, K. S. (2005). "Math anxiety and its cognitive consequences: a tutorial review," in *The Handbook of Mathematical Cognition*. ed. J. I. D. Campbell (New York, NY: Psychology Press), 315–327.

Barroso, C., Ganley, C. M., McGraw, A. L., Geer, E. A., Hart, S. A., and Daucourt, M. C. (2021). A meta-analysis of the relation between math anxiety and math achievement. *Psychol. Bull.* 147, 134–168. doi: 10.1037/bul0000307

Beilock, L. S., and DeCaro, M. S. (2007). From poor performance to success under stress: working memory, strategy selection, and mathematical problem solving under pressure. *J. Exp. Psychol.* 33, 983–998. doi: 10.1037/0278-7393.33.6.983

Betz, N. E. (1978). Prevalence, distribution, and correlates of math anxiety in college students. *J. Couns. Psychol.* 25, 441–448. doi: 10.1037/0022-0167.25.5.441

Birgin, O., Baloglu, M., Catlioglu, H., and Gurbuz, R. (2010). An investigation of mathematics anxiety among sixth through eighth grade students in Turkey. *Learn. Individ. Differ.* 20, 654–658. doi: 10.1016/j.lindif.2010.04.006

Carey, E., Hill, F., Devine, A., and Szucs, D. (2016). The chicken or the egg? The direction of the relationship between mathematics anxiety and mathematics performance. *Front. Psychol.* 6:1987. doi: 10.3389/fpsyg.2015.01987

Caviola, S., Mammarella, I. C., Lucangeli, D., and Cornoldi, C. (2012). The involvement of working memory in children's exact and approximate mental additions. *J. Exp. Child Psychol.* 112, 141–160. doi: 10.1016/j.jecp.2012.02.005

Caviola, S., Toffalini, E., Giofre, D., Ruiz, J. M., Szucs, D., and Mammarrella, I. C. (2021). Math performance and academic anxiety forms, from sociodemographic to cognitive aspects: A meta-analysis on 906, 311 participants. *Educ. Psychol. Rev.* 1–37. doi: 10.1007/s10648-021-09618-5

Chen, L., Bae, S. R., Battista, C., Qin, S., Chen, T., Evans, T. M., et al. (2018). Positive attitude toward math supports early academic success: behavioral evidence and neurocognitive mechanisms. *Psychol. Sci.* 29, 390–402. doi: 10.1177/0956797617735528

Ching, B. H.-H. (2017). Mathematics anxiety and working memory: longitudinal associations with mathematical performance in Chinese children. *Contemp. Educ. Psychol.* 51, 99–113. doi: 10.1016/j.cedpsych.2017.06.006

Delage, V., Trudel, G., Retanal, F., and Maloney, A. (2021). Spatial anxiety and spatial ability: Mediators of gender differences in math anxiety. *J. Exp. Psychol. General*. doi: 10.1037/xge0000884 [Epub Ahead of Print]

Devine, A., Fawcett, K., Szucs, D., and Dowker, A. (2012). Gender differences in mathematics anxiety and the relation to mathematics performance while controlling for test anxiety. *Brain Behav. Func.* 8:33. doi: 10.1186/1744-9081-8-33

Dew, K., Galassi, J., and Galassi, M. (1983). Mathematics anxiety: some basic issues. *J. Couns. Psychol.* 30, 443–446. doi: 10.1037/0022-0167.30.3.443

Douglas, H. P., and LeFevre, J.-A. (2018). Exploring the influence of basic cognitive skills on the relation between math performance and math anxiety. *J. Num. Cognit.* 3, 642–666. doi: 10.5964/jnc.v3i3.113

Dowker, A., Bennett, K., and Smith, L. (2012). Attitudes to mathematics in primary school children. *Child Dev. Res.* 2012:124939. doi: 10.1155/2012/12493

Dowker, A., Sarkar, A., and Looi, C. Y. (2016). Mathematics anxiety: what have we learned in 60 years? *Front. Psychol.* 7:508. doi: 10.3389/fpsyg.2016.00508

Dulaney, F., Herts, J. B., Borgonov, F., and Beilock, S. (2017). The math anxiety-performance link: a global phenomenon. *Curr. Dir. Psychol. Sci.* 26, 52–58. doi: 10.1177/0963721416672463

Eysenck, M. W., and Calvo, M. G. (1992). Anxiety and performance: the processing efficiency theory. *Cognit. Emot.* 6, 409–434. doi: 10.1080/02699939208409696

Fennema, E., and Sherman, J. A. (1976). Fennema-Sherman mathematics attitudes scales; instruments designed to measure attitudes towards the learning of mathematics by females and males. *J. Res. Math. Educ.* 7:324. doi: 10.2307/748467

Ganley, C. M., and Vasilyeva, M. (2014). The role of anxiety and working memory in gender differences in mathematics. *J. Educ. Psychol.* 106, 105–120. doi: 10.1037/a0034099

Harari, R. R., Vukovic, R. K., and Bailey, S. P. (2013). Mathematics anxiety in young children: An exploratory study. *J. Exp. Educ.* 81, 538–555. doi: 10.1080/00220973.2012.727888

Hembree, R. (1990). The nature, effects, and relief of mathematics anxiety. *J. Res. Math. Educ.* 21, 33–46. doi: 10.2307/74945

Hitch, G. J. (1978a). Numerical abilities of industrial apprentices. *Br. J. Occup. Psychol.* 51, 163–176. doi: 10.1016/0010-0285(78)90002-6

Hitch, G. J. (1978b). The role of short-term working memory in arithmetic. *Cogn. Psychol.* 10, 302–323. doi: 10.1016/0010-0285(78)90002-6

Ma, X., and Kishor, N. (1997). Assessing the relationship between attitude toward mathematics and achievement in mathematics: a meta-analysis. *J. Res. Math. Educ.* 28, 26–47. doi: 10.2307/749662

Macher, D., Papousek, I., Ruggeri, K., and Paechter, M. (2015). Statistics anxiety and performance: blessings in disguise. *Front. Psychol.* 6:1116. doi: 10.3389/fpsyg.2015.01116

Maloney, E. A., Ansari, D., and Fugelsang, J. A. (2011). The effect of mathematics anxiety on the processing of numerical magnitude. *Q. J. Exp. Psychol.* 64, 10–16. doi: 10.1080/17470218.2010.533278

Maloney, E. A., and Beilock, S. L. (2012). Math anxiety: who has it, why it develops, and how to guard against it. *Trends Cogn. Sci.* 16, 404–406. doi: 10.1016/j.tics.2012.06.008

Miller, H., and Bichsel, J. (2004). Anxiety, working memory, gender, and math performance. *Personal. Individ. Differ.* 37, 591–606. doi: 10.1016/j.paid.2003.09.029

Mononen, M., Niemvirta, M., Koponen, J., Lindskog, M., and Tapola, A. (2021). Developmental relations between mathematics anxiety, symbolic numerical magnitude processing and arithmetic skills from first to second grade. *Cognit. Emotion*, 1–21. doi: 10.1080/02699931.2021.2015296, [Epub Ahead of Print]

Moustafa, A. A., Al-Emadi, A. A., and Megreya, A. M. (2021). The need to develop an individualized intervention for mathematics anxiety. *Front. Psychol.* 12:723289. doi: 10.3389/fpsyg.2021.723289

Namkung, J. M., Peng, P., and Lin, X. (2019). The relation between mathematics anxiety and mathematics performance among school-aged students: A meta-analysis. *Rev. Educ. Res.* 89, 459–496. doi: 10.3102/2F0034654319843494

Núñez-Peña, M. I., and Suárez-Pellicioni, M. (2014). Less precise representation of numerical magnitude in high math-anxious individuals: an ERP study of the size and distance effects. *Biol. Psychol.* 103, 176–183. doi: 10.1016/j.biopsycho.2014.09.004

Pinxten, M., Marsh, H., De Fraine, B., Vane den Noortgate, W., and Van Danne, J. (2014). Enjoying mathematics or feeling competent in mathematics? Reciprocal effects on mathematics achievement and perceived math effort expenditure. *Br. J. Educ. Psychol.* 84, 152–174. doi: 10.1111/bjep.12028

Popescu, T., Sader, E., Schaer, M., Thomas, A., Terhune, D. B., Dowker, A., et al. (2019). The brain-structural correlates of mathematical expertise. *Cortex* 114, 140–150. doi: 10.1016/j.cortex.2018.10.009

Richardson, F., and Suinn, R. (1972). The mathematics anxiety rating scale: psychometric data. *J. Counsel. Psychol.* 19, 551–554. doi: 10.1037/h0033456

Sarason, I. G. (1977). *The Test Anxiety Scale: Concept and Research*. Washington DC: Hemisphere, 193–216.

Sarfo, J. O., Garcia-Santillan, A., Adusei, H., Mokhanova, V. S., Drushlvak, M., Semenikhina, O., et al. (2020). Gender differences in mathematics anxiety across cultures: A univariate analysis of variance among samples from twelve countries. *Eur. J. Contem. Edu.* 106, 105–120. doi: 10.1037/a0034099

Skagerlund, K., Ostergren, R., Vastfjall, D., and Traff, U. (2019). How does mathematics anxiety impair mathematical abilities? Investigating the link between math anxiety, working memory, and number processing. *PLos One* 14:e0211283. doi: 10.1371/journal.pone.021128

Sorvo, R., Koponen, T., Viholainen, H., Aro, T., Raikkönen, E., Peura, P., et al. (2017). Math anxiety and its relationship with basic arithmetic skills among primary school children. *Br. J. Educ. Psychol.* 87, 309–327. doi: 10.1111/bjep.12151

Spelke, S. E. (2005). Sex differences in intrinsic aptitude for mathematics and science? A critical review. *Am. Psychol.* 60, 950–958. doi: 10.1037/0003-66X.60.9.950

SPSS, IBM (2017). IBM Corp. Released 2017. IBM SPSS Statistics for Windows, Version 25.0. Armonk, NY: IBM Corp.

Supekar, K., Iuculano, T., Chen, L., and Menon, V. (2015). Remediation of childhood math anxiety and associated neural circuits through cognitive tutoring. *J. Neurosci.* 35, 12574–12583. doi: 10.1523/JNEUROSCI.0786-15.2015

Szczygiel, M. (2020). Gender, general anxiety, math anxiety and math achievement in early school-age children. *Issues Edu. Res.* 30, 1126–1142.

Szczygieł, M., and Pieronkiewicz, B. (2021). Exploring the nature of math anxiety in young children: intensity, prevalence, reasons. *Math. Think. Learn.* 1–19. doi: 10.1080/10986065.2021.1882363

Van der Beek, J., Van der Ven, S., Kroesbergen, E., and Leseman, P. (2017). Self-concept mediates the relation between achievement and emotions in mathematics. *Br. J. Educ. Psychol.* 87, 478–495. doi: 10.1111/bjep.12160

Villavicencio, F., and Bernardo, A. (2016). Beyond math anxiety: positive emotions predict mathematics achievement, self-regulation and self-efficacy. *Asia Pacific Edu. Res.* 25, 415–422. doi: 10.1007/s40299-015-0251-4

Vukovic, R. K., Kieffer, M. J., Bailey, S. P., and Harari, R. R. (2013). Mathematics anxiety in young children: concurrent and longitudinal associations with mathematical performance. *Contemp. Educ. Psychol.* 38, 1–10. doi: 10.1016/j.cedpsych.2012.09.001

Wang, L. (2020). Mediation relationships among gender, spatial ability, math anxiety, and math achievement. *Educ. Psychol. Rev.* 32, 1–15. doi: 10.1007/s10648-019-09487-z

Wang, Z., Lukowski, S., Hart, S., Lyons, I. M., Thompson, L., Kovas, Y., et al. (2015). Is math anxiety always bad for math learning? *Psychol. Sci.* 26, 1863–1876. doi: 10.1177/0956797615602471

Wang, Z., Shakeshaft, N., Schofield, K., and Malanchini, M. (2018). Anxiety is not enough to drive me away: a latent profile analysis on math anxiety and math motivation. *PLoS One* 13:e0192072. doi: 10.1371/journal.pone.0192072

Watson, J. (1983). The Aiken attitude to mathematics scales: psychometric data on reliability and discriminant validity. *Educ. Psychol. Meas.* 43, 1247–1253. doi: 10.1177/001316448304300436

Wechsler, D. (2008). *Wechsler Adult Intelligence Scale-Fourth UK Edition*. London: Pearson.

Wigfield, A., and Meece, J. L. (1988). Math anxiety in elementary and secondary school students. *J. Educ. Psychol.* 80, 210–216. doi: 10.1037/0022-0663.80.2.210

Xie, F., Xin, Z. Q., and Zhang, L. (2020). Gender difference of Chinese high school students' math anxiety: The effects of self-esteem, test anxiety and general anxiety. *Sex Roles* 81, 235–244. doi: 10.1007/s11199-018-0982-9

Zeidner, M., and Matthews, G. (2003). "Test anxiety," in *Encyclopedia of Psychological Assessment*. ed. R. Fernandez-Ballesteros (London: Sage), 965–969.

Zhang, J., Zhao, N., and Kong, Q. P. (2019). The relationship between math anxiety and math performance: A meta-analytic investigation. *Front. Psychol.* 10:1613. doi: 10.3389/fpsyg.2019.01613

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Clarifying the Relation Between Epistemic Emotions and Learning by Using Experience Sampling Method and Pre-posttest Design

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Epistemic emotions (surprise, curiosity, enjoyment, confusion, anxiety, frustration and boredom) have an object focus on knowledge or knowledge construction and are thus hypothesized to affect learning outcomes. In the context of upper secondary school science, the present study clarifies this relation by examining the students' pre- and posttest performance (n = 148 students) and their experiences of situational epistemic emotions (n = 1801 experience sampling method observations). As expected, epistemic emotions correlated with both pre- and posttest performance: curiosity and enjoyment correlated positively, and frustration and boredom correlated negatively with the performance. However, based on structural equation modeling, after controlling for the pretest performance, only boredom was found to have a significant negative effect on posttest performance. The findings underline the complexity of the interplay between emotions and learning. Thus, the state versus trait nature of epistemic emotions, and the implications for research and practice are being discussed.

Keywords: epistemic emotions, learning, academic performace, experience sampling method (ESM), pre-posttest design

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INTRODUCTION

Recently, the role of emotions in educational contexts has received increasing interest (e.g., Pekrun et al., 2018). Especially, the entanglement between affect and cognition has been acknowledged (Muis et al., 2021), and the relation between emotions and learning or academic performance has been addressed in numerous studies (e.g., Muis et al., 2015; Efklides, 2017; Camacho-Morles et al., 2021; Sainio et al., 2021). Emotions are typically defined as affective episodes that are caused by a certain stimulus or antecedent, and have an object (Ekman, 1992; Russell, 2003; Shuman and Scherer, 2014). Thus, they are different from moods or attitudes that are typically more stable and long lasting, and do not necessarily have such a clear stimulus nor an object. However, also moods and attitudes are often related to learning or performance (Beege et al., 2018; Cahill et al., 2018). In turn, learning can be defined as a process in which a person acquires new skills, knowledge or understanding, whereas, performance or achievement can be considered as more stationary constructs, reflecting merely the state of a learning process (Gross, 2015).

Considering the nature of emotions as situational constructs and learning as a dynamic process, two things need to be considered when aiming to study the relation between emotions and learning. First, emotions should be measured in the actual learning situations and not, for example, by using retrospective questionnaires (Goetz et al., 2016). Second, if learning is conceptualized as a change in performance (Gross, 2015), it cannot be studied cross-sectionally, but a person's prior knowledge needs to be taken into account. However, despite the vast of amount of research conducted on the relation of emotions and learning-related variables, many of the previous studies have limitations in terms of using only the retrospective measures of emotions (e.g., Ainley and Ainley, 2011; Ding and Zhao, 2020) or cross-sectional measures of learning or performance (e.g., Ketonen and Lonka, 2012; Putwain et al., 2021). Moreover, there is a paucity of studies conducted in ecologically valid, real-life classroom settings.

In this regard, the aim of the present study is to discover how situational epistemic emotions relate to students' learning in a real-life upper secondary school science context. The objective is to examine the relationship between students' self-reported, real-time experience sampling method (ESM) data about epistemic emotions and their pre- and posttest scores measuring their performance and learning.

Epistemic Emotions

Academic emotions are defined as emotions occurring in educational settings or relating to learning, studying or other academic activities (Pekrun et al., 2018). Based on their antecedents or object focuses, Pekrun et al. (2018) further classify academic emotions into four categories. First, achievement emotions have their stimuli or object focus in success or achievement in academic tasks. Second, topic emotions relate to the actual topics being studied. Third, social emotions occur in educational contexts similar to any other context in people's life; they relate to social relationships, such as those between students and teachers or among peers. And fourth, epistemic emotions have an object focus in knowledge or knowledge construction, and thus relate directly to the learning process itself.

Epistemic emotions, such as surprise, curiosity, enjoyment, confusion, anxiety, frustration and boredom, typically occur in situations where new information is contradictory to student's previous conceptions and experiences, where cognitive representations are questioned or new understandings are developed (Pekrun et al., 2017, 2018). Epistemic emotions can also occur simultaneously or in sequences (Bosch and D'Mello, 2017). Learning new skills or contents can feel enjoyable and interesting. However, if the novel information is incongruous or contradictory, a student may feel surprise or confusion. If confusion is not resolved, it may lead to anxiety or frustration. In turn, if anxiety or frustration persists, a student can eventually get bored and withdraw oneself from the learning situation. Instead, if the cognitive discrepancy that caused the confusion in the first place is resolved, a student may again experience enjoyment and curiosity (Bosch and D'Mello, 2017; Pekrun et al., 2018). Thus, in learning situations, epistemic emotions can give rise to a complex interplay between cognitive and affective factors.

It is worth noting that the four subcategories of academic emotions described above are not clean-cut nor mutually exclusive. Instead, a certain emotion can represent various subcategories depending on its stimuli or object. For example, enjoyment of meeting friends in the class would be a social emotion, but enjoyment of learning new things would appear as an epistemic emotion. Likewise, anxiety for a forthcoming exam is an achievement emotion, but anxiety aroused by a cognitive discrepancy is an epistemic emotion.

In addition to categorizing academic emotions based on their stimuli or objects, emotions can be also categorized by their valence and activation (Pekrun et al., 2018). In the case of epistemic emotions, curiosity and enjoyment can be considered as positive activating emotions. That is, they are experienced as pleasant or positive, and they are associated with high arousal and activation. In turn, confusion, frustration and anxiety are considered as negative activating emotions, entailing an unpleasant, negative valence and activating nature. Boredom, in turn, represents a negative deactivating emotion. Surprise is considered as an activating emotion, but its valence is more ambiguous. Depending on a situation, surprise can be experienced as a positive, negative or neutral affective experience (Muis et al., 2015; Pekrun et al., 2017).

Science Learning

In general, two types of knowledge or learning can be distinguished: the propositional knowledge of knowing *that*, and the procedural knowledge of knowing *how* (e.g., Siegel, 1998). In the context of science education, these are often referred as disciplinary core ideas and scientific practices, respectively (National Research Council, 2012). However, in science learning these core ideas and practices are often deeply intertwined. When constructing scientific knowledge and developing understanding about scientific phenomena, both are necessarily needed. Thus, also the concept of *epistemic practices* is often used in the context of science learning to emphasize that understanding science implies understanding on how scientific explanations are being generated and scientific knowledge being developed (e.g., Duschl, 2008). Furthermore, Kelly and Licona (2018) define epistemic practices as "socially organized and interactionally accomplished ways that members of a group propose, communicate, evaluate, and legitimize knowledge claims" (p. 140). Thus, science lessons can provide versatile learning situations in which students can experience a variety of epistemic emotions.

The Hypothesized Relation Between Emotions and Learning

Based on the model by Muis et al. (2015), epistemic emotions are aroused by cognitive incongruity, and influence learning outcomes through different learning strategies. Also, a number of other studies have indicated this relation between epistemic emotions, learning strategies and performance described in the Muis et al. (2015) model. First, positive activating emotions of enjoyment (Ainley and Ainley, 2011; Obergriesser and Stoeger, 2020; Camacho-Morles et al., 2021; Putwain et al., 2021) and curiosity (Gruber et al., 2014; Wade and Kidd, 2019), in addition to surprise (Chiu et al., 2014; Muis et al., 2018) and confusion (D'Mello et al., 2014; Muis et al., 2018), are related to positive learning outcomes through deep-processing learning strategies, such as elaboration and critical thinking (Muis et al., 2015, 2021). Also, surprise can have an indirect effect on learning strategies by inducing curiosity and confusion (Vogl et al., 2019). Some studies suggest that confusion is beneficial for learning only at appropriate levels, but if it goes unresolved, it can also detract from learning (D'Mello and Graesser, 2012; Schneider et al., 2016). Second, negative activating emotions of anxiety (Ketonen and Lonka, 2012; Putwain et al., 2021) and frustration (Bosch and D'Mello, 2017) are related to negative learning outcomes through shallow processing strategies, such as maintenance rehearsal (Muis et al., 2015). And third, a negative deactivating emotion of boredom (Mann and Robinson, 2009; Pekrun et al., 2014; Tze et al., 2016; Camacho-Morles et al., 2021) impairs the use of any learning strategies, thus also leading to negative learning outcomes (Muis et al., 2015).

Based on the research reviewed above, the effect of emotions on performance seems evident. Furthermore, some research shows that performance can also influence students' emotional experiences. For example, Sainio et al. (2021) found that students with learning difficulties tend to experience more negative academic emotions than students without such difficulties. Also, previous research suggests that academic emotions can play a mediating role between learning difficulties and achievement (Sainio et al., 2019). Thus, it seems that prior knowledge can influence how students perceive new, and often complex, information, thus arousing varying emotional experiences in them. Together these findings suggest a reciprocal relationship between emotions and performance, and a possible mediating role of emotions in learning processes.

Although a number of studies have been carried out on the relation between emotions and learning-related variables, most of them have used only cross-sectional measures of performance (Mann and Robinson, 2009; Ketonen and Lonka, 2012; Bosch and D'Mello, 2017; Ding and Zhao, 2020; Putwain et al., 2021) and/or retrospective measures of emotions (Mann and Robinson, 2009; Ainley and Ainley, 2011; D'Mello et al., 2014; Pekrun et al., 2014; Sainio et al., 2019, 2021; Ding and Zhao, 2020). Thus, albeit providing valuable and solid evidence on the existing relations between affects and performance, these studies give very little, if any, information about the relation between the emotional experiences in the actual learning situations and the change in performance (i.e., learning). In addition, studies that use situational measures of emotions are typically conducted under highly controlled, laboratory experimental conditions (e.g., Chiu et al., 2014; D'Mello et al., 2014; Gruber et al., 2014; Muis et al., 2015, 2018; Wade and Kidd, 2019; Obergriesser and Stoeger, 2020). While experimental laboratory studies provide an important perspective on situational emotions and learning, their ecological validity is limited, since students' affective experiences in experimental settings may differ from those in real-life classroom setting. In experimental settings, the arousal of emotions is typically manipulated. Instead, authentic classroom situations are ought to arouse more natural range of emotions in students. To our knowledge, there are no prior studies conducted in a real-life classroom setting that take into account both prior knowledge to examine learning progress, and the situational nature of emotions.

The Current Study

In the present study, we examine how epistemic emotions relate to students' performance and learning, in the context of upper secondary school science, by analyzing real-time ESM data about situational epistemic emotions with pre- and posttest scores measuring performance. We conceptualize pretest performance as prior knowledge and posttest performance as learning outcome. We aim to investigate the relations between emotions, performance and learning both correlationally, and by a causal model. The causal model enables us to examine the effect of situational epistemic emotions on learning outcomes after controlling for prior knowledge, as well as investigate the mediating role of epistemic emotions in the learning process, as depicted in **Figure 1**.

Based on the Muis et al. (2015) model and on previous research, we posed the following hypotheses:

H1 (correlational relations):

Situational epistemic emotions are correlated with prior knowledge and learning outcome. Situational surprise, curiosity, enjoyment, and confusion have a positive relation; and situational anxiety, frustration and boredom have a negative relation with performance. We also expect prior knowledge to correlate positively with learning outcome.

H2 (causal model):

Prior knowledge predicts situational epistemic emotions, and situational epistemic emotions in turn predict learning outcome. Epistemic emotions also mediate the effect of the prior knowledge on the learning outcome. Situational surprise, curiosity, enjoyment and confusion have a positive relation with prior knowledge and learning outcome; and situational anxiety, frustration and boredom have a negative relation with prior knowledge and learning outcome. We also expect learning outcome to be positively predicted by prior knowledge.

MATERIALS AND METHODS

Context and Participants

The data for this study was collected in Finnish upper secondary school physics classes during autumn 2019. The participants of the study (n = 148) were first year upper secondary school students from six classes, from two schools located in the Helsinki metropolitan area. A total of 64 students responded to the background questionnaire. Based on this incomplete information, students were on average 15.90 (SD = 0.56; range between 15 and 18) years old; and, 73.4% of the students identified themselves as female and 25.0% as male. Furthermore, 92.2% of the students were Finnish native speakers. In the Finnish education system, students start the first year of upper secondary level typically at the age of 15 to16 and, in Finland, females are

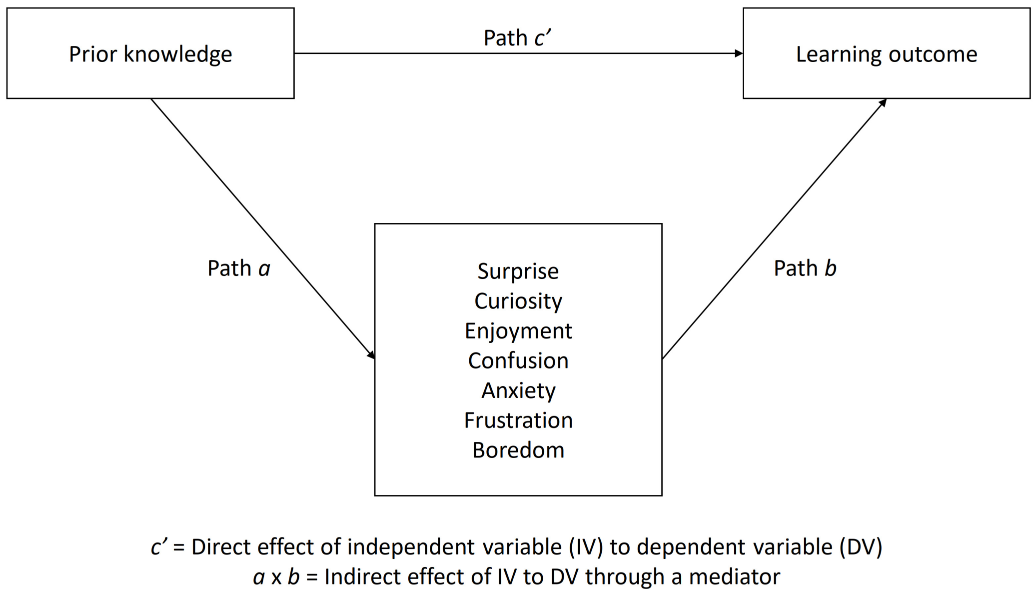


FIGURE 1 | A conceptual model in which the effect of the prior knowledge on the learning outcome is mediated by situational epistemic emotions.

slightly overrepresented among upper secondary school students, 58.2% in 2019 (Official Statistics in Finland, 2020).

In each of the participating classes, the data collection was conducted during a study period of six or seven consecutive lessons (á 75 min). There were typically three physics lessons per week, so the data collection lasted for 2 to 3 weeks for one class. The study period familiarized students with the models that describe the movement of objects with constant and changing velocity, as well as with a model (Newton's second law) describing the reasons behind the changes in motion. Instruction followed the Finnish core curriculum (Finnish National Board of Education, 2016), in which disciplinary core ideas and scientific practices (National Research Council, 2012) are emphasized.

In this study, student anonymity was carefully maintained, and informed consent was required from all the participants. Participation was voluntary. Research activities and data collection were planned together with teachers in order to disturb the schoolwork as little as possible.

Measures and Data Collection

Performance

Students' prior knowledge and learning outcomes in a study period were evaluated using a pre-posttest design. The pretest was conducted just before the study period to measure students' prior knowledge on the topic, and the posttest was conducted after the study period as part of the course exam, to measure the learning outcome. The exact same test served as both a pretest and a posttest, and it covered the disciplinary core ideas and scientific practices related to force and motion phenomena, i.e., the topics covered during the study period. In the test, understanding of the following disciplinary core ideas were measured: velocity, acceleration, force, and Newton's laws. In addition, the understanding of following scientific practices were tested: asking questions; planning and carrying out investigations; analyzing and interpreting data; developing and using models; and engaging in argument from evidence. The test was co-designed together with science education researchers and in-service physics teachers within the teacher-researcher partnership (Schneider et al., 2020; Juuti et al., 2021). The test was further developed through pilot studies and teacher reflection.

Both in pre- and posttest, students had 30 min time to complete the test. The test included altogether 13 questions. Although all items aimed to measure both understanding of disciplinary core ideas and scientific practices, each item was designed to focus either on core ideas (6 items; see an example of a test item in **Figure 2**) or practices (7 items; see an example of a test item in **Figure 3**). Thus, both types of knowledge were needed for answering the questions. There were three multiple choice items and ten open answer items. The test was conducted in Finnish, in a computer-based platform.

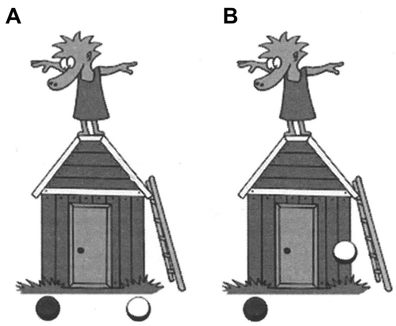
The maximum score of the test was 26. Before the assessment of the students' answers, a criteria-based scoring manual was constructed and revised after preliminary review of the answers. In the manual, typical right answers and also wrong answers were described. The right answers were constructed according to the curriculum aims in order to increase the validity of the coding. All the answers were compared to correct or incorrect answers in the coding manual to further increase the validity of the coding. All assessment was done based on those criteria by science education researchers.

Epistemic Emotions

Data on students' experiences of situational epistemic emotions was gathered using ESM (Goetz et al., 2016). Students filled out an ESM questionnaire on the basis of beeps coming to their smartphones during science lessons. The smartphones were for

The test item:

The cartoon character simultaneously drops two heavy balls of equal size. The darker ball is twice as heavy as the white ball. Which of the options below is correct?



a) Figure A is correct. The mass of an object does not affect the force with which the Earth attracts the object.

b) Figure A is correct. All objects fall in the same way if the air resistance is low compared to the weights of the balls.

c) Figure B is correct. The ground attracts the black ball more strongly, so it is the first to hit the ground. In addition, the air resistance slows down the lighter ball more.

d) Figure B is correct. The ground attracts the black ball more strongly, but the air resistance is equal for both balls because they are the same size.

e) Figure B is correct. The mass affects the falling of the objects, but air resistance has no effect when the objects are the same size.

Correct answer and coding:

Maximum scores: 1

1 score is given for a correct answer: b).

0 scores are given for any other answer.

FIGURE 2 | An example of a multiple-choice test item focusing on disciplinary core ideas (gravitational acceleration).

research use only and thus collected no personal data outside the questionnaire. The smartphones were preprogrammed to beep randomly, three times per every science lesson in the study period, however, simultaneously for each student. Thus, during the study period, each student received 18 or 21 opportunities to answer the ESM questionnaire, depending on if the teacher used six or seven lessons to cover the contents of Newtonian mechanics. This resulted in altogether 1801 answered ESM questionnaires. Each ESM questionnaire included identical items on social, emotional, and contextual aspects. In the questionnaire, epistemic emotions were measured using a modified seven-item short version of The Epistemically-Related Emotions Scales (Pekrun et al., 2017) in which students were asked: "What do you think about the activity you did? Did you feel you were... surprised/curious/excited/confused/anxious/frustrated/bored?". It should be noted that according to The Epistemically-Related Emotions Scales, the emotion of enjoyment is measured with a single item of excitement (Pekrun et al., 2017). A four-point Likert scale with the response categories from 1 = *not at all* to 4 = *very much* was used. The questionnaire was conducted in Finnish. The ESM data collection design used in this study is described in more detail by Schneider et al. (2016) and by Vilhunen et al. (2021).

Analyses

The correlational relation of the epistemic emotions and test performance was examined by bivariate Pearson correlations, conducted with IBM SPSS Statistics 26.0. The data of this study is measured at two levels: pre- and posttest performance are measured at the student level (i.e., between level), and epistemic emotions are measured at the situational level (i.e., within level). Thus, the aggregated mean values of epistemic emotions were used for the correlation analyses.

To examine the effect of epistemic emotions on the learning outcome after controlling for the prior knowledge, a parallel mediation analysis was conducted with Mplus 8.3 (Muthén and Muthén, 2017), in which a multilevel structural equation modeling (MSEM) framework was applied (Preacher et al., 2010). In a parallel mediation model all the mediating variables, in this case epistemic emotions, are included in the same model. The

The test item:

Watch the video about sledging. http://youtube.com/watch?v=3pk8gOFgmnw

Pose two questions that can be used to examine the relations between the measurable variables related to the phenomenon in the video.

Correct answer and coding:

Maximum scores: 4 (2+2)

2 scores are given for a question that examines the relation between two relevant and measurable variables. For example, "What is the correlation between the mass of the sledge (how many people in the sledge) and the time it takes to go down?" or "What is the correlation between the base area of the sledge and the time it takes to go down?"

1 score is given for

- a question that can be answered with "very much/little" or "yes/no". For example, "How much does the surface area influence the acceleration?"

- an obvious statement without a question term. For example, "The mass influences the acceleration".

0 scores are given for a question with one variable and a simple answer. For example, "How long does the way downhill take?" or "Is the velocity constant?"

FIGURE 3 | An example of an open answer test item focusing on scientific practices (formulation of questions and recognizing of problems).

ESM data of this study is hierarchical, meaning the situational observations are nested within students. Since each student answered to an ESM questionnaire multiple times, the data is clustered, and the observations are not independent. Thus, a multilevel approach is needed to take into account the nesting of the data. First, the intraclass correlations (ICC) for the epistemic emotions were calculated, to examine the level of the nestedness. Second, a two-level parallel mediation analysis was conducted to estimate the direct and indirect effects between prior knowledge, epistemic emotions and learning outcomes. In our model, both pre and posttest performance were measured at the person level (i.e., single measure, level 2) and epistemic emotions were measured at the situation level (i.e., repeated measures, level 1), leading to a 2-1-2 design (Preacher et al., 2010). The model includes two cross-level effects: a 2-1 part (the effect of pretest performance on epistemic emotions) and a 1-2 part (the effect of epistemic emotions on posttest performance). Both parts of the model were examined simultaneously and furthermore, the direct and indirect multivariate pathways were estimated. Since the predictor (pretest performance) and dependent variable (posttest performance) were measured at the between level, and only mediators (epistemic emotions) were measured at the within level, all the interpretations of the model were done on a between level. The mediator residuals were allowed to covary both in the within and between level, leading to a perfect model fit (RMSEA = 0.00; CFI = 1.00; TLI = 1.00). All variables were standardized into z-scores before the analysis.

RESULTS

Descriptive Statistics and Bivariate Correlations

The descriptive statistics of the variables are shown in **Table 1**. The ICCs of the emotions were all high and statistically significant. This indicates high similarity between observations within students and rationalizes the use of multilevel approach in subsequent analyses.

As expected, results of the correlation analyses (**Table 2**) show a significant association between pretest and posttest performance. Furthermore, positive epistemic emotions of curiosity and excitement were found to correlate positively to pre- and posttest performance, measuring prior knowledge and learning outcomes, correspondingly. In addition, negative epistemic emotions of frustration and boredom were found to correlate negatively with the pre- and posttest performance.

TABLE 1 | Descriptive statistics of the observed variables.

	$n_{between}$	n_{within}	*M*	*SD*	*ICC*
Pretest performance	136		9.70	4.09	
Posttest performance	141		12.38	4.19	
Surprise	148	1800	1.77	0.82	0.391***
Curiosity	148	1797	2.29	0.86	0.348***
Excitement	148	1798	2.32	0.88	0.510***
Confusion	148	1798	1.93	0.90	0.415***
Anxiety	148	1796	1.66	0.84	0.508***
Frustration	148	1799	1.95	0.94	0.379***
Boredom	148	1799	2.28	0.94	0.377***

*$n_{between}$, the number of students; n_{within}, the number of ESM observations; the maximum score of the pretest and the posttest was 26, epistemic emotions were measured at the Likert scale from 1 to 4; *** $p < 0.001$.*

In contradiction to our hypotheses, surprise, confusion, and anxiety had no statistically significant correlation with performance measures.

Also, epistemic emotions correlated with each other. Surprise had a statistically significant positive correlation with all the other emotions. Mainly, positive emotions correlated positively with each other and negatively with negative emotions, and vice versa. However, curiosity was found to correlate positively with confusion and anxiety.

The Causal Model

According to the MSEM (**Figure 4**), the pretest performance was the strongest predictor of the posttest performance, as expected. Pretest performance also predicted significantly all other epistemic emotions except surprise. Students' with high scores in the pretest experienced higher levels of curiosity and excitement, and lower levels of confusion, anxiety, frustration, and boredom during the study period. However, after accounting for the effect of pretest performance in the model, only boredom appeared as a significant ($p < 0.05$) predictor of posttest performance. Other epistemic emotions were not found to have a significant effect on posttest performance, which was contradictory to our hypotheses. Furthermore, according to mediation analysis, none of the situational epistemic emotions appeared as a statistically significant mediator between pretest performance and posttest performance (**Table 3**).

DISCUSSION

In this study, we examined how epistemic emotions are related to upper secondary school students' prior knowledge and learning outcomes in science, and both if and how they mediate performance during a study period. The results of the study are based on data collected with summative pre- and posttests, and with real-time ESM observations, capturing the situational nature of the epistemic emotions experienced in the authentic classroom learning situations.

The Interplay Between Epistemic Emotions and Learning

As hypothesized, we found positive epistemic emotions (curiosity and enjoyment) to correlate positively with performance, and negative epistemic emotions (frustration and boredom) to correlate negatively with performance. This finding is consistent with previous literature (Ainley and Ainley, 2011; Gruber et al., 2014; Pekrun et al., 2014; Muis et al., 2015; Bosch and D'Mello, 2017), and thus further confirms the association between epistemic emotions and performance. However, the emotion of surprise was not found to correlate with performance, even though the results of some previous, experimental studies suggest the existing relation between surprise and learning (Chiu et al., 2014; Muis et al., 2018). On the other hand, surprise can also have an indirect effect on performance by inducing other epistemic emotions, as suggested in previous research (Vogl et al., 2019). Indeed, in our data, surprise correlates positively with all other epistemic emotions. The relation with both positive and negative emotions also indicates the neutral or changing valence of this emotion. Also, previous research suggests that epistemic surprise can be considered as a positive, negative, or neutral emotion (Muis et al., 2015; Pekrun et al., 2017). Especially, surprise is relatively strongly correlated with other activating emotions, and as Pekrun et al. (2017, p. 1272) discuss, "emotions during epistemic activities are primarily linked along the arousal dimension of emotion rather than

TABLE 2 | Bivariate pearson correlations of the observed variables.

	1	2	3	4	5	6	7	8
1 Pretest performance	–							
2 Posttest performance	0.613***	–						
3 Surprise	−0.029	−0.019	–					
4 Curiosity	0.273**	0.248**	0.365***	–				
5 Excitement	0.305***	0.251**	0.277***	0.569***	–			
6 Confusion	−0.136	−0.081	0.416***	0.108***	−0.063**	–		
7 Anxiety	−0.165	−0.120	0.326***	0.097***	−0.060*	0.502***	–	
8 Frustration	−0.221*	−0.179*	0.263***	−0.073**	−0.209***	0.537***	0.515***	–
9 Boredom	−0.235**	−0.280**	0.055*	−0.212***	−0.331***	0.319***	0.247***	0.485***

*For calculating the Pearson correlations between performance measures and emotions, the aggregated mean values (n = 148) of emotions were used. Correlations between the emotions are calculated on a within level (n = 1793–1799). * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.*

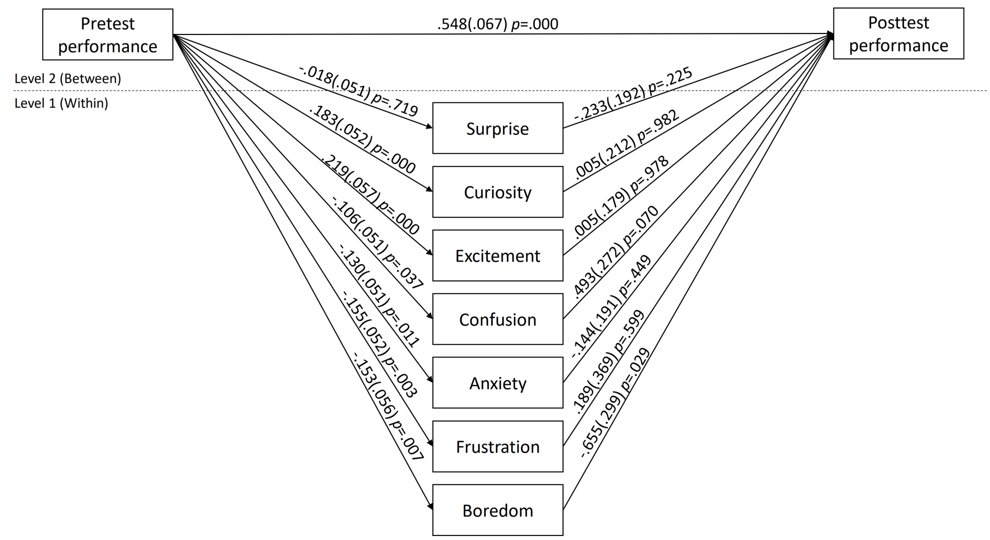


FIGURE 4 | The MSEM with epistemic emotions as parallel mediators between prior knowledge and learning outcome. Regression coefficients correspond to standardized parameter estimates β (standard errors S.E. in parentheses). The mediator residuals were allowed to covary both in the within and between level, the arrows representing the residual covariance were omitted for clarity.

the valence dimension." Interestingly, in our study, we also found a statistically significant ($p < 0.05$) correlation between surprise and a deactivating emotion of boredom. However, the correlation coefficient of 0.055 can be considered very low, indicating only a minimal, if any, interrelation between these constructs. Furthermore, negatively valenced emotions of confusion and anxiety did not correlate significantly with test performance, even though they correlate relatively strongly with other negatively valenced epistemic emotions that have a negative relation to performance. However, confusion and anxiety also have a positive correlation with curiosity, which may indicate that all these emotions occur simultaneously in situations, where curiosity is triggered by new knowledge, but high cognitive demands also cause confusion and anxiety. This finding is in line with those of previous studies indicating a positive correlation between curiosity, confusion and anxiety (Pekrun et al., 2017; Trevors et al., 2017; Di Leo et al., 2019).

Using MSEM, we estimated the effect of epistemic emotions on the change in performance, and their mediating role in the learning process. As expected, prior knowledge (the pretest performance) was the strongest predictor of the learning outcome (the posttest performance). Taking this into account, boredom was found to be the only epistemic emotion having a significant effect on learning outcome. So, the more bored students are when studying, less likely they are to learn. However, even boredom did not reach statistical significance as a *mediator* from prior knowledge to learning outcome. These results are in line with and complement the previous findings on the negative relation of boredom and learning (Pekrun et al., 2014; Tze et al., 2016). Since other epistemic emotions than boredom were not found to have an effect on learning outcome, our hypothesis on causal relations was only partly supported. This finding is further discussed in the following sections.

TABLE 3 | Total and indirect effects of the parallel mediation model.

	Posttest performance		
Pretest performance	**β**	***S.E.***	***p***
Total effect ($c = c' + a \times b$)	0.592	0.066	0.000
Indirect effects ($a \times b$)			
via surprise	0.004	0.013	0.733
via curiosity	0.001	0.039	0.982
via excitement	0.001	0.039	0.978
via confusion	−0.052	0.041	0.202
via anxiety	0.019	0.026	0.476
via frustration	−0.029	0.056	0.600
via boredom	0.100	0.059	0.088

Trait Versus State Emotions in Learning Processes

Based on MSEM conducted in this study, only boredom has an effect on learning outcomes after controlling for prior knowledge. Even though curiosity, enjoyment and frustration correlated strongly with both pre- and posttest performance, they did not relate to change in performance during the study period. However, also the correlation with performance can tell us something about their relation to learning. Students with high situational experiences of curiosity and enjoyment and low experiences of frustration performed better already in the pretest and, due to strong autoregression, also in the posttest. This means that, at some point, these students have either learned more due to a tendency to experience high curiosity and enjoyment and low frustration, or they have developed a tendency to have these emotional experiences due to their previous performance. This leads us to a question about trait versus state nature of epistemic emotions.

Even though emotions are typically defined as affective states (Ekman, 1992; Russell, 2003; Shuman and Scherer, 2014), some students may have a trait-like disposition to experience certain types of emotional states, as discussed also previously for example by Graham and Taylor (2014). And, this trait-type dispositional enjoyment, curiosity or frustration can have an effect on students' performance and situational emotions. Or, perhaps state-type situational emotions become trait-type through performance related feedback and appraisals. Based on previous literature, also interest can develop from a state-type situational interest to a trait-like individual interest (Hidi and Renninger, 2006). Thus, we suppose that this could happen also with other affective factors, such as epistemic emotions in this case. However, trait-like emotions come by definition close to attitudes and should then not be called emotions at all (Shuman and Scherer, 2014). On the other hand, also attitudes can play an important role in learning (Cahill et al., 2018), and thus should not be ignored.

Implications for Research and Practice

The findings of the present study clearly suggest that the relations between emotions and performance look very different depending on whether they are examined correlationally or with causal models. This implies that, when interested specifically in situational emotions and learning as a longitudinal construct, cross-sectional measures of performance or retrospective measures of emotions do not provide an adequate basis for the examination of this relation. It is essential to account for students' prior knowledge when interested in learning processes, to actually be able to detect the change in performance, and further, make some causal inferences. Furthermore, emotions should be measured in the particular situations of interest. Otherwise, if retrospectively measured, they may reflect more on students' moods or attitudes than the actual situational experiences.

Based on the mediation analysis, none of the epistemic emotions mediated the effect of prior knowledge on learning outcome. This implies that there is likely to exist yet undiscovered mediators (Zhao et al., 2010). Based on a relatively strong correlational relations between some epistemic emotions and performance measures, we also argue, that there is another variable (or variables) that have an effect on both situational emotions and performance. We assume that, for example moods or attitudes, which are concepts closely related to emotions, can have an effect on the constructs measured in this study. Also, this finding underlines the importance of controlling for trait-like affective variables when interested specifically on situational emotions. Thus, further studies regarding the effects of different affective variables on learning would be worthwhile.

Taken together, the findings of the present study corroborate the existing relations between epistemic emotions and learning. This implies that the role of emotions should be acknowledged also in everyday educational practices, as well as in teacher training and educational policymaking. Especially the detrimental effect of boredom on learning should be considered. Thus, to engage students in active science learning is an important mission for all practitioners (e.g., Schneider et al., 2020). Previous research shows that in classroom situations, epistemic emotions can be managed for example by instructional activities (Vilhunen et al., 2021): orienting and engaging activities can be implemented to arouse curiosity and enjoyment in students, whereas to avoid the occurrence of boredom, teacher talk should be limited or restrained. However, further research should be undertaken to investigate how to engage students to curiously study science, and to tackle boredom.

Limitations

By definition, epistemic emotions have an object focus on knowledge or knowledge construction. In this study, we investigated seven emotions described as epistemic by Pekrun et al. (2017). However, in our questionnaire students were first asked to think about the activity they were doing, and then to indicate the extent to which they felt surprised, curious, excited, confused, anxious, frustrated or bored, and not what the object of their emotion was. Thus, the emotions being studied were not necessarily *epistemic* in nature. For example, emotions such as enjoyment or anxiety may often have an object focus on something different than the knowledge processed in a given situation (e.g., in the topic or achievement). Some emotions, such as confusion and curiosity can be regarded as more likely to have an object focus on knowledge itself.

The ESM data in this study was collected three times, at random times, during each science lesson of the study period. Researchers and teachers together considered this to be the maximum number of beeps per lesson, in order to disturb the instruction as little as possible. However, emotions typically occur in episodes of varying length (Verduyn et al., 2009), which most probably leads to a situation in which not all the emotional episodes are captured in the ESM data. We suppose this to be the case especially with surprise, which is a relatively short-lived emotion (Horstmann, 2006; Noordewier et al., 2016). Surprise had no significant relation with performance or learning in our data. To capture more detailed data on emotions, data collection should be more intensive (e.g., focusing on facial expressions) or focused on predetermined points of the instruction.

The data collection of this study took place during one predetermined study period of six to seven lessons. This 2 to 3 week period can be considered as a relatively short time to find a significant change in performance, and thus detect learning. On the other hand, that is the time, when students are taught this specific content about Newtonian mechanics, and thus the time when students are supposed to learn these skills and knowledge. Thus, we consider these few weeks to be a sufficient time to detect learning on this particular topic.

The generalizability of these results is subject to certain limitations. First, all the data is gathered within upper secondary school physics courses, in the context of studying Newtonian mechanics, and in one geographically limited area in Finland. A more versatile data collection, including for example different school subjects or participants from different backgrounds, would give results that are more generalizable. Second, the sample size of this study is relatively small, thus leaving open the possibility that repeating the study might give us slightly different results. Furthermore, this implies that even though in our causal model we did not find significant path coefficients in most of the cases, a claim about non-causality cannot be made. Especially, the role of confusion in learning processes should be studied further with versatile research settings and methods: in our study, the regression coefficient from pretest performance to situational confusion was negative (and significant), but the regression coefficient from situational confusion to posttest performance was positive (but not significant, $p = 0.07$). This underlines the complexity of the interplay between learning and situational confusion (D'Mello et al., 2014).

CONCLUSION

In summary, the purpose of the current study was to examine the relation between situational epistemic emotions and performance both correlationally and by a causal model, to address important gaps in the literature concerning the longitudinal nature of learning processes and the experiences of epistemic emotions in the real-life classroom contexts. We used a pre-posttest design to examine students' learning during the study period, and ESM to capture the situational nature of the epistemic emotions in an ecologically valid science-learning environment. The relevance of emotions in the learning context is clearly supported by the findings. Positive epistemic emotions of curiosity and enjoyment were found to correlate positively with students' pre- and posttest performance, whereas the negative epistemic emotions of frustration and boredom had an opposite relation. However, MSEM revealed that after controlling for the prior knowledge, only boredom had a significant effect on learning outcomes, which raises important questions about the state versus trait nature of epistemic emotions. Finally, we see the need for further studies to examine the situational factors influencing learning, and to clarify the dynamic relations between epistemic emotions and academic performance.

DATA AVAILABILITY STATEMENT

The datasets presented in this article are not readily available due to ethical and privacy restrictions. Requests to access the datasets should be directed to EV, elisa.vilhunen@helsinki.fi.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Ethical Review Board in the Humanities and Social and Behavioral Sciences, University of Helsinki. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

EV: conceptualization, methodology, formal analysis, investigation, and writing the original draft. MT: methodology, investigation, and reviewing and editing the manuscript. JL and KS-A: conceptualization, reviewing and editing the manuscript, project administration, and funding acquisition. KJ: conceptualization, methodology, reviewing and editing the manuscript, supervision, project administration, and funding acquisition. All authors contributed to the article and approved the submitted version.

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REFERENCES

Ainley, M., and Ainley, J. (2011). Student engagement with science in early adolescence: the contribution of enjoyment to students' continuing interest in learning about science. *Contemp. Educ. Psychol.* 36, 4–12. doi: 10.1016/j.cedpsych.2010.08.001

Beege, M., Schneider, S., Nebel, S., Häßler, A., and Rey, G. D. (2018). Mood-affect congruency. Exploring the relation between learners' mood and the affective charge of educational videos. *Comput. Educ.* 123, 85–96. doi: 10.1016/j.compedu.2018.05.001

Bosch, N., and D'Mello, S. (2017). The affective experience of novice computer programmers. *Int. J. Artif. Intell. Educ.* 27, 181–206. doi: 10.1007/s40593-015-0069-5

Cahill, M. J., McDaniel, M. A., Frey, R. F., Hynes, K. M., Repice, M., Zhao, J., et al. (2018). Understanding the relationship between student attitudes and student learning. *Phys. Rev. Phys. Educ. Res.* 14:010107. doi: 10.1103/PhysRevPhysEducRes.14.010107

Camacho-Morles, J., Slemp, G. R., Pekrun, R., Loderer, K., Hou, H., and Oades, L. G. (2021). Activity achievement emotions and academic performance: a meta-analysis. *Educat. Psychol. Rev.* 33, 1051–1095. doi: 10.1007/s10648-020-09585-3

Chiu, M., Chou, C., Wu, W., and Liaw, H. (2014). The role of facial microexpression state (FMES) change in the process of conceptual conflict. *Br. J. Educ. Technol.* 45, 471–486. doi: 10.1111/bjet.12126

Di Leo, I., Muis, K. R., Singh, C. A., and Psaradellis, C. (2019). Curiosity…Confusion? Frustration! The role and sequencing of emotions during mathematics problem solving. *Contemp. Educ. Psychol.* 58, 121–137. doi: 10.1016/j.cedpsych.2019.03.001

Ding, Y., and Zhao, T. (2020). Emotions, engagement, and self-perceived achievement in a small private online course. *J. Comput. Assis. Learn.* 36, 449–457. doi: 10.1111/jcal.12410

D'Mello, S., and Graesser, A. (2012). Dynamics of affective states during complex learning. *Learn. Instruc.* 22, 145–157. doi: 10.1016/j.learninstruc.2011.10.001

D'Mello, S., Lehman, B., Pekrun, R., and Graesser, A. (2014). Confusion can be beneficial for learning. *Learn. Instruc.* 29, 153–170. doi: 10.1016/j.learninstruc.2012.05.003

Duschl, R. (2008). Science education in three-part harmony: balancing conceptual, epistemic, and social learning goals. *Rev. Res. Educat.* 32, 268–291. doi: 10.3102/0091732X07309371

Efklides, A. (2017). Affect, epistemic emotions, metacognition, and self-regulated learning. *Teach. College Rec.* 119, 1–22.

Ekman, P. (1992). An argument for basic emotions. *Cogn. Emot.* 6, 169–200.

Finnish National Board of Education (2016). *National Core Curriculum for General Upper Secondary Schools 2015*. New Delhi: National Board of Education.

Goetz, T., Bieg, M., and Hall, N. C. (2016). "Assessing academic emotions *via* the experience sampling method," in *Methodological Advances in Research on Emotion and Education*, eds M. Zembylas and P. A. Schutz (Netherland: Springer), 245–258. doi: 10.1007/978-3-319-29049-2_19

Graham, S., and Taylor, A. Z. (2014). "An attributional approach to emotional life in the classroom," in *International Handbook of Emotions in Education*, eds R. Pekrun and L. Linnenbrink-Garcia (New York, NY: Routledge), 96–119. doi: 10.4324/9780203148211-11

Gross, R. D. (2015). *Psychology: the Science of Mind and Behaviour*, 7th Edn. New York, NY: McGraw-Hill Higher Education.

Gruber, M. J., Gelman, B. D., and Ranganath, C. (2014). States of curiosity modulate hippocampus-dependent learning *via* the dopaminergic circuit. *Neuron* 84, 486–496. doi: 10.1016/j.neuron.2014.08.060

Hidi, S., and Renninger, K. A. (2006). The four-phase model of interest development. *Educ. Psychol.* 41, 111–127. doi: 10.1207/s15326985ep4102_4

Horstmann, G. (2006). Latency and duration of the action interruption in surprise. *Cogn. Emot.* 20, 242–273. doi: 10.1080/02699930500262878

Juuti, K., Lavonen, J., Salonen, V., Salmela-Aro, K., Schneider, B., and Krajcik, J. (2021). A teacher–researcher partnership for professional learning: co-designing project-based learning units to increase student engagement in science classes. *J. Sci. Teach. Educ.* 32, 625–641. doi: 10.1080/1046560X.2021.1872207

Kelly, G. J., and Licona, P. (2018). "Epistemic practices and science education," in *History, Philosophy and Science Teaching. Science: Philosophy, History and Education*, ed. M. Matthews (Netherland: Springer), doi: 10.1007/978-3-319-62616-1_5

Ketonen, E., and Lonka, K. (2012). Do situational academic emotions predict academic outcomes in a lecture course? *Proc. Soc. Behav. Sci.* 69, 1901–1910. doi: 10.1016/j.sbspro.2012.12.144

Mann, S., and Robinson, A. (2009). Boredom in the lecture theatre: an investigation into the contributors, moderators and outcomes of boredom amongst university students. *Br. Educ. Res. J.* 35, 243–258. doi: 10.1080/01411920802042911

Muis, K. R., Chevrier, M., Denton, C. A., and Losenno, K. M. (2021). Epistemic emotions and epistemic cognition predict critical thinking about socio-scientific issues. *Front. Educ.* 6:669908. doi: 10.3389/feduc.2021.669908

Muis, K. R., Pekrun, R., Sinatra, G. M., Azevedo, R., Trevors, G., Meier, E., et al. (2015). The curious case of climate change: testing a theoretical model of epistemic beliefs, epistemic emotions, and complex learning. *Learn. Instruct.* 39, 168–183. doi: 10.1016/j.learninstruc.2015.06.003

Muis, K. R., Sinatra, G. M., Pekrun, R., Winne, P. H., Trevors, G., Losenno, K. M., et al. (2018). Main and moderator effects of refutation on task value, epistemic emotions, and learning strategies during conceptual change. *Contemp. Educ. Psychol.* 55, 155–165. doi: 10.1016/j.cedpsych.2018.10.001

Muthén, L. K., and Muthén, B. O. (2017). *Mplus. User's guide*. Los Angeles, CA: Muthén & Muthén.

National Research Council (2012). *A Framework for K-12 Science Education: Practices, Crosscutting Concepts, and Core Ideas*. Washington, DC: National Academies Press.

Noordewier, M. K., Topolinski, S., and Van Dijk, E. (2016). The temporal dynamics of surprise. *Soc. Personal. Psychol. Compass* 10, 136–149. doi: 10.1111/spc3.12242

Obergriesser, S., and Stoeger, H. (2020). Students' emotions of enjoyment and boredom and their use of cognitive learning strategies – How do they affect one another? *Learn. Instruct.* 66:101285. doi: 10.1016/j.learninstruc.2019.101285

Official Statistics in Finland (2020). *Upper Secondary General Education 2019*. Europe: Statistics Finland.

Pekrun, R., Hall, N. C., Goetz, T., and Perry, R. P. (2014). Boredom and academic achievement: testing a model of reciprocal causation. *J. Educat. Psychol.* 106, 696–710. doi: 10.1037/a0036006

Pekrun, R., Muis, K. R., Frenzel, A. C., and Götz, T. (2018). *Emotions at School*. England, UK: Routledge, doi: 10.4324/9781315187822

Pekrun, R., Vogl, E., Muis, K. R., and Sinatra, G. M. (2017). Measuring emotions during epistemic activities: the epistemically-related emotion scales. *Cogn. Emot.* 31, 1268–1276. doi: 10.1080/02699931.2016.1204989

Preacher, K. J., Zyphur, M. J., and Zhang, Z. (2010). A general multilevel SEM framework for assessing multilevel mediation. *Psychol. Methods* 15, 209–233. doi: 10.1037/a0020141

Putwain, D. W., Schmitz, E. A., Wood, P., and Pekrun, R. (2021). The role of achievement emotions in primary school mathematics: control–value antecedents and achievement outcomes. *Br. J. Educ. Psychol.* 91, 347–367. doi: 10.1111/bjep.12367

Russell, J. A. (2003). Core affect and the psychological construction of emotion. *Psychol. Rev.* 110, 145–172. doi: 10.1037/0033-295X.110.1.145

Sainio, P., Eklund, K., Ahonen, T., and Kiuru, N. (2019). The role of learning difficulties in adolescents' academic emotions and academic achievement. *J. Learn. Disabil.* 52, 287–298. doi: 10.1177/0022219419841567

Sainio, P., Eklund, K., Hirvonen, R., Ahonen, T., and Kiuru, N. (2021). Adolescents' academic emotions and academic achievement across the transition to lower secondary school: the role of learning difficulties. *Scand. J. Educ. Res.* 65, 385–403. doi: 10.1080/00313831.2019.1705900

Schneider, B., Krajcik, J., Lavonen, J., and Salmela-Aro, K. (2020). *Learning Science: the Value of Crafting Engagement in Science Environments*. New Haven, US: Yale University Press.

Schneider, B., Krajcik, J., Lavonen, J., Salmela-Aro, K., Broda, M., Spicer, J., et al. (2016). Investigating optimal learning moments in U.S. and Finnish science classes. *J. Res. Sci. Teach.* 53, 400–421. doi: 10.1002/tea.21306

Shuman, V., and Scherer, K. R. (2014). "Concepts and structures of emotions," in *International Handbook of Emotions in Education*, eds R. Pekrun and L. Linnenbrink-Garcia (England, UK: Routledge), 13–35. doi: 10.4324/9780203148211.ch2

Siegel, H. (1998). "Knowledge, truth and education," in *Education, Knowledge and Truth: Beyond the Postmodern Impasse*, ed. D. Carr (England, UK: Routledge), 19–36.

Trevors, G. J., Muis, K. R., Pekrun, R., Sinatra, G. M., and Muijselaar, M. M. (2017). Exploring the relations between epistemic beliefs, emotions, and learning from texts. *Contemp. Educ. Psychol.* 48, 116–132. doi: 10.1016/j.cedpsych.2016.10.001

Tze, V. M., Daniels, L. M., and Klassen, R. M. (2016). Evaluating the relationship between boredom and academic outcomes: a meta-analysis. *Educ. Psychol. Rev.* 28, 119–144. doi: 10.1007/s10648-015-9301-y

Verduyn, P., Delvaux, E., Van Coillie, H., Tuerlinckx, F., and Van Mechelen, I. (2009). Predicting the duration of emotional experience: two experience sampling studies. *Emotion* 9:83. doi: 10.1037/a0014610

Vilhunen, E., Tang, X., Juuti, K., Lavonen, J., and Salmela-Aro, K. (2021). "Instructional activities predicting epistemic emotions in Finnish upper secondary school science lessons: combining experience sampling and video observations," in *Engaging with Contemporary Challenges Through Science Education Research. Contributions from Science Education Research*, Vol. 9, eds O. Levrini, G. Tasquier, T. G. Amin, L. Branchetti, and M. Levin (Netherland: Springer), 317–329. doi: 10.1007/978-3-030-74490-8_25

Vogl, E., Pekrun, R., Murayama, K., Loderer, K., and Schubert, S. (2019). Surprise, curiosity, and confusion promote knowledge exploration: evidence for robust effects of epistemic emotions. *Front. Psychol.* 10:2474. doi: 10.3389/fpsyg.2019.02474

Wade, S., and Kidd, C. (2019). The role of prior knowledge and curiosity in learning. *Psych. Bull. Rev.* 26, 1377–1387. doi: 10.3758/s13423-019-01598-6

Zhao, X., Lynch, J. G., and Chen, Q. (2010). Reconsidering Baron and Kenny: myths and truths about mediation analysis. *J. Consumer Res.* 37, 197–206. doi: 10.1086/651257

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State Boredom Partially Accounts for Gender Differences in Novel Lexicon Learning

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Gender plays an important role in various aspects of second language acquisition, including lexicon learning. Many studies have suggested that compared to males, females are less likely to experience boredom, one of the frequently experienced deactivating negative emotions that may impair language learning. However, the contribution of boredom to gender-related differences in lexicon learning remains unclear. To address this question, here we conducted two experiments with a large sample of over 1,000 college students to explore the relationships between gender differences in boredom and lexicon learning. In Experiment 1, a cohort of 527 participants (238 males) completed the trait and state boredom scales as well as a novel lexicon learning task without awareness of the testing process. In Experiment 2, an independent cohort of 506 participants (228 males) completed the same novel lexicon learning task with prior knowledge of the testing procedure. Results from both experiments consistently showed significant differences between female and male participants in the rate of forgetting words and the state boredom scores, with female participants performing better than male participants. Furthermore, differences in state boredom scores partially explained differences in the rate of forgetting words between female and male participants. These findings demonstrate a novel contribution of state boredom to gender differences in lexicon learning, which provides new insights into better language-learning ability in females.

Keywords: gender, state boredom, lexicon learning, mediation analysis, trait boredom

INTRODUCTION

Billions of students are learning second (L2) or foreign languages (FLL) every year in the globalized contemporary world. Gender-related differences have been consistently observed in various aspects of language learning. For example, previous research has demonstrated that female learners are likely to perform better than male learners in multiple language learning, such as clearer pronunciation, politer language, better oral communication, and faster vocabulary learning speed (e.g., Gass and Varonis, 1986; Lynn et al., 2005; Van et al., 2015; Ng, 2018; Syafrizal and Putri, 2020).

It is well-known that the success of L2 or FLL depends on learners' emotional status (Krashen, 1981), which includes affective, cognitive, motivational, and peripheral physiological processes. Boredom is one of the most experienced emotions during learning and education (Pekrun, 2006; Goetz and Hall, 2014; Putwain et al., 2018; Li, 2021). According to the Control-Value Theory (CVT), boredom is a deactivating negative emotion resulting from an activity that lacks incentive value and perceived controllability or high control/low-demands conditions implying no sufficient challenge that reduces the incentive value of the activity (Pekrun, 2006). More recently, the Meaning and Attentional Components (MAC) model posits that boredom may result from mismatches between cognitive demands and available mental resources, or mismatches between activities and valued goals (Westgate and Wilson, 2018; Westgate, 2020). Moreover, boredom could hinder academic improvement by affecting perceived meaning (Eastwood et al., 2012; Tam et al., 2021) or disrupting the attention control system in the learners (Suárez-Pellicioni et al., 2016). There is also evidence suggesting that males are more likely to feel bored than females (Watt and Ewing, 1996; Watt and Vodanovich, 1999; Liu et al., 2013). However, scant attention has been paid to the prevalent emotional status of boredom in the L2 and FLL context (Kruk, 2019; Li et al., 2020; Li, 2021), and the same is true for gender differences when it comes to boredom. To date, the contributions of boredom to gender differences in lexicon learning remain unknown.

To address this question, here we conducted two experiments to explore the relationships between gender differences in boredom and lexicon learning in a large sample of over 1,000 college students. In Experiment 1, a cohort of 527 students completed the trait and state boredom scales as well as a lexicon learning task without awareness of the testing process. In Experiment 2, an independent cohort of 506 students completed the same lexicon learning task with prior knowledge of the testing procedure. We expected to observe significant gender differences between male and female participants in the boredom scores, which would contribute to their differences in lexicon learning performance.

LITERATURE REVIEW

Gender Differences in Lexicon Learning

A number of previous studies on gender differences in lexicon learning have shown that gender is a critical variable that influences vocabulary learning performance. Some researchers reported that male students were superior in understanding and using vocabulary (Gass and Varonis, 1986; Lynn et al., 2005). In contrast, others highlighted that compared to male students, female students performed better in vocabulary memorization (Sunderland, 2000; Scheiber et al., 2015), pronunciation (Syafrizal and Putri, 2020), acquisition size, and general proficiency (Gu, 2002). Concerning the semantic fields, female students were better at acquiring vocabulary describing story characters, whereas male students were better at acquiring vocabulary related to sports and geography (Jiménez, 2010). On vocabulary learning strategies, male students tended to use form-focused memory, cognitive processes, and metacognitive monitoring more frequently, while female students possessed a disposition to adopt meaning-focused cognitive strategies and metacognitive planning strategies more frequently (Van et al., 2015; Ng, 2018). In summary, findings on gender differences depend on the aspects examined, and little research has been conducted to examine gender effects on novel lexicon learning achievement.

The observed variability may be explained by the following reasons. The Gender Role Theory posits that prevalent gender stereotypes are culturally shared expectations for gender appropriate behaviors. Females and males acquire appropriate behaviors and attitudes from the sociocultural environment they grow up in (Eagly and Karau, 2002; Bryła-Cruz, 2021). The biological viewpoint suggests that gender difference also depends on cognitive ability and learning style, which are derived from fundamental physiological differences, such as those in the development of the brain or higher-level cortical functions (de Lima Xavier et al., 2019). Regardless of primarily cultural or biological factors, previous educational studies have proven that gender difference manifestly influences students' academic achievements (Główka, 2014).

Considering previous studies, results regarding gender differences in the lexical acquisition are inconclusive. Moreover, most studies have concentrated on the gender differences in pre-university education (e.g., Chee et al., 2005; Aldosari et al., 2017) differences in novel lexicon learning achievement among university students may contribute to our understanding of the whole phenomenon of gender differences in L2 or FLL. The gender gap in favor of L2 or FLL female learners also requires further research in multiple aspects of language competence, including novel lexicon learning.

Gender Differences in Boredom

Boredom can be defined as a dissatisfying state of wanting, but being unable, to engage in the desirable activity (Eastwood et al., 2012). The attention mismatch hypothesis proposes that boredom may occur when there is a mismatch between task requirements and attention ability (Gerritsen et al., 2014). Boredom could be further divided into two subtypes: trait boredom and state boredom (Farmer and Sundberg, 1986). Trait boredom consists of external stimuli and internal stimuli (Vodanovich et al., 2005). An early study of boredom posited that people with increased susceptibility to boredom are less psychosocially developed and thereby have reduced psychosocial abilities to deal with various situations in life (Watt and Vodanovich, 1999). Furthermore, individuals with a high trait of boredom tend to struggle with attention in daily life (Malkovsky et al., 2012) and are more vulnerable to mood disorders like depression (Goldberg et al., 2011). As a chronic tendency to be bored, trait boredom or boredom proneness is also related to various mental health and behavior problems, such as drug use disorder (LePera, 2011), low life meaning (Fahlman et al., 2009) and impulsivity disorders (Malkovsky et al., 2012).

In contrast to trait boredom, state boredom reflects more transient reactions to specific situations, including inattention, time perception, low arousal, high arousal, and disengagement (Liu et al., 2013). State boredom is typically associated with perceptions of time passing by slowly and failures of attention (Pekrun et al., 2010; Eastwood et al., 2012; Hunter and Eastwood, 2016; Westgate, 2020). The perception of meaninglessness or task unimportance is an independent determinant of state boredom (Fahlman et al., 2009; Anusic et al., 2016; Van Tilburg and Igou, 2017b; Chan et al., 2018; Westgate and Wilson, 2018). State boredom may affect individual preference and behavior through stimulation seeking (Van Tilburg and Igou, 2012), awakening curiosity about the environment (Lomas, 2017), or reflecting the self-regulation function of state boredom (Miao and Xie, 2019). Individuals with a high-level state of boredom have been associated with increased hostility (Van Tilburg and Igou, 2012), riskier decisions (Matthies et al., 2012), and poor sustained attention (Westgate, 2020). Taken together, trait boredom and state boredom may reflect different dimensions of boredom and have different effects on language learning.

Most previous studies reported gender-related differences in boredom with males showing greater boredom than females, which may be attributed to differences in personality (Liu et al., 2013) or susceptibility to being bored (Vodanovich and Kass, 1990). For example, compared with females, males are more extroverted, lively and active, and easily bored of learning activities, as they prefer to pursue novel stimulation (Liu et al., 2013). It was reported that female students might experience less boredom due to lacking the ability to perceive interest and significance from the environment (Watt and Vodanovich, 1999), while male students had higher levels of boredom and greater boredom proneness than female students on external stimulation (Von Gemmingen et al., 2003; Vodanovich et al., 2011). Concerning state boredom, previous studies reported that male students yielded significantly higher scores on the state boredom scale (Liu et al., 2013) and different time perceptions than female students (Pawlak et al., 2020).

However, null or even reversed findings on gender differences in boredom have also been reported. For example, McLeod and Vodanovich (1991) and Watt and Ewing (1996) reported no differences between males and females in boredom proneness. Seib and Vodanovich (1998) even reported that males were less likely to experience boredom than females, which may have been due to their inability to self-generate participation. One possible explanation for these discrepant findings is that boredom is multifaceted, and that gender differences may be more pronounced in one subtype of boredom but not the other. Another possible explanation is that gender differences in boredom may not be fully manifested until people reach a particular age level. Nevertheless, more research is necessary to further clarify gender differences in state and trait boredom in large samples and repeatable studies.

Relationships Between Boredom and Learning Performance

It is well-known that learners' emotional status plays an important role in academic performance. As one type of frequently experienced deactivating negative emotional status, boredom is likely to impair learning and academic performance (Pekrun, 2006; Putwain et al., 2018; Kruk and Zawodniak, 2020). The Affective Filtering Hypothesis (Krashen, 1981) posits that language input must pass through an emotional filter before it can be absorbed, and that the stronger the filter, the more language input is suppressed in the brain, leading to poorer achievements in language learning. Numerous empirical studies have reported the negative effects of boredom on academic performance. For example, Frenzel et al. (2007) reported that fifth to tenth graders' boredom levels during math classes correlated negatively with their math achievement. Pekrun et al. (2010) found that undergraduate students' boredom negatively predicted their end-of-year performance. Using a longitudinal design, Ahmed et al. (2013) reported that change in seventh graders' boredom over one school year was negatively associated with math achievement. However, an early study reported small but positive correlations between fifth to ninth graders' boredom and grade point average and test scores (Larson and Richards, 1991), suggesting that the relationships between boredom and academic performance may not always be negative.

Although previous literature has demonstrated gender-related differences in boredom (e.g., Vodanovich and Kass, 1990; Von Gemmingen et al., 2003; Vodanovich et al., 2011; Liu et al., 2013; Pawlak et al., 2020) as well as in language learning (e.g., Sunderland, 2000; Gu, 2002; Lynn et al., 2005; Jiménez, 2010; Scheiber et al., 2015; Ng, 2018), whether gender differences would be similar in subtypes of boredom (i.e., state boredom or trait boredom) remains unclear. Moreover, few if any studies have differentiated the effects of trait boredom and state boredom on language learning and examined the contributions of these boredom subtypes to gender differences in lexicon learning. To address this knowledge gap, the Multidimensional State Boredom Scale (MSBS; Liu et al., 2013) and the Trait Boredom Scale (TBS; Huang et al., 2010) were applied to measure state and trait boredom levels, respectively, in a large sample of college students before they completing a novel lexicon learning task and the tests. Similar to the findings from previous studies, we expected that females would experience less state and trait boredom during the lexicon learning. We also wanted to examine whether state or trait boredom would be a mediator variable for the lexicon learning ability difference between female and male students.

METHODOLOGY

Participants

We recruited a total of 1,070 non-language major students from a college for this study, including 550 participants for Experiment 1 and 520 participants for Experiment 2. Twenty-three participants (4.18%) were excluded from Experiment 1 and fourteen participants (2.69%) were excluded from Experiment 2 due to incompetence or failure to complete the whole study. Data from 1,033 participants were included in the final data analysis, including 527 participants (238 male; mean age = 19.73 ± 2.02 years) for Experiment 1, and 506 participants (228 male; mean age = 19.80 ± 1.45 years) for Experiment 2. All participants reported no history of psychological and psychiatric disorders. There were no differences between male and female participants in age or years of education in both Experiment 1 and Experiment 2 (all $p > 0.1$). The study protocol was approved by the Ethics Committee of Shanghai International Studies University. Participants provided written informed consent before the experiment and received monetary rewards for their participation.

Measures and Materials

The Multidimensional State Boredom Scale (MSBS; Liu et al., 2013) and the Trait Boredom Scale (TBS; Huang et al., 2010) was adopted to assess the participants' levels of state boredom and trait boredom. The MSBS scale includes 24 items divided into five dimensions: (1) *Inattention* refers to having difficulty focusing attention on the current environment or activity. A higher score on this dimension, the harder it is for individuals to concentrate. (2) *Time perception* refers to the excessively slow perception of time. A higher score on this dimension, the more slowly they feel that time passes. (3) *Low arousal* refers to feelings of calmness and depression. This is also a manifestation of negative experiences in the state of boredom. To a certain extent, high state boredom can be reflected by negative emotions. (4) *High arousal* refers to feelings of energy for pleasurable states (e.g., excitement), or tension for unpleasant states (e.g., fear). A higher score on this dimension indicates a higher level of uncontrollable restlessness. (5) *Disengagement* is a lack of participation in current activities and desire to participate in more exciting activities. This emotion could affect people's concentration on their current tasks. All items on the scales are scored from "1 = not agree at all" to "7 = completely agree." A higher total score on the MSBS represents a higher level in the state of boredom. The MSBS scale has a Cronbach's alpha of 0.83 in the present sample, suggesting good internal consistency in the study.

The TBS scale includes 30 items divided into two dimensions: external stimuli and internal stimuli. The former dimension includes four factors: monotony, loneliness, tension, and restraint. The latter dimension consists of two elements: self-control and creativity (Vodanovich et al., 2005). These items are all scored from "1 = not at all" to "5 = completely true." In the current study, we used the total score to measure the individual's boredom proneness. A higher total score indicates a higher level of trait boredom. The TBS scale has a Cronbach's alpha of 0.79 in the present sample, also suggesting good internal consistency in the study.

Pseudoword-Chinese List

The pseudoword-Chinese list was used to measure the result of lexicon learning. The list includes 16 pseudowords, which are coined according to real words and their number of syllables. There are two criteria when selecting pseudowords: (1) eliminating the pseudowords that may lead to the association of real foreign words at a sound or morphological level; (2) using monosyllables, disyllables, trisyllables, and keeping the number of vowels and consonants approximately equal (Gathercole et al., 1991). Each pseudoword is matched with a neutral Chinese meaning. The pseudoword-Chinese list is as follows (see **Table 1**).

Procedure

We first conduct Experiment 1 to explore whether trait boredom, state boredom, or both had a significant effect on novel lexicon learning. Then, we conducted Experiment 2 to replicate the main findings in Experiment 1. To measure the level of boredom of the participants and the effects of novel lexicon learning in Experiment 1 and Experiment 2, we adopted the following experiment process (see **Figure 1**). First, participants' boredom experience was measured with the corresponding boredom scales. After finishing the boredom scales, the pseudoword-Chinese pairs were learned for 15 min, and immediate testing was carried out for about 10 min. Then, participants were arranged to have a 30 min reading. Finally, participants completed a delayed cued recall test in which they were required to write the corresponding Chinese meanings or pseudowords according to the given pseudo-words. The purpose of performing a delayed test as a retest was to measure the relatively stable learning effect (Ke and Dong, 2001). There was a total score of 16 points as one point was given for each correct answer.

At the beginning of learning and tests, participants were asked "How bored are you right now?" with a corresponding Likert scale ranging from 0 (*not at all*) to 8 (*extremely*) presented on the top of the pseudoword list and each test paper. One-way ANOVA analyses were used to confirm that the level of state boredom did not change significantly over the whole process. To rule out the potential confounding factor that the novel lexicon learning task itself may induce boredom, we excluded those participants who reported significant differences in state boredom between the two conditions in the data analyses.

Statistical Analysis

All data were processed and analyzed by using the statistical software SPSS 22.0. Since the difference between the immediate score (the number of correct words) and the delayed score

TABLE 1 | Pseudoword-Chinese list.

Pseudo-word	Chinese	Pseudo-word	Chinese	Pseudo-word	Chinese	Pseudo-word	Chinese
thicult	时间	bidt	坚硬	hond	早	jis	硬件
viulu	下午	deppelate	大的	glitow	飞船	bannow	孩子
blonter	变成	tuwhep	道路	soku	商店	bomme	储存
mef	经历	prindle	告诉	ganner	工作	glisterin	明白

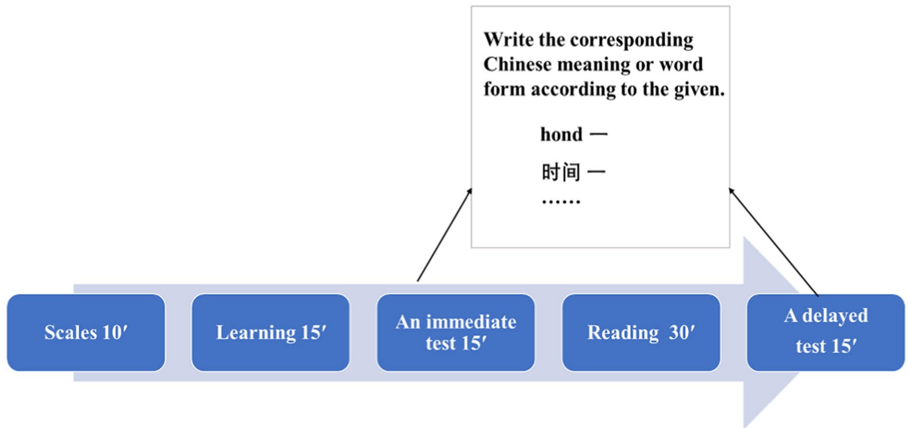

FIGURE 1 | Diagram of the experiment process and the test task.

TABLE 2 | Descriptive statistics and gender differences for MSBS scores, TBS and FRs of participants.

Experiment 1	Males ($n = 238$)	Females ($n = 289$)	*t*	*p*
FRs	0.58 (0.18)	0.51 (0.17)	4.47	<0.001
TBS	92.02 (12.07)	90.65 (16.02)	1.09	>0.05
Internal stimuli	34.85 (5.53)	34.92 (4.86)	−0.15	>0.05
External stimuli	57.17 (11.45)	55.73 (15.25)	1.20	>0.05
MSBS	88.51 (18.05)	82.68 (20.88)	3.37	0.001
Inattention	19.52 (4.76)	14.80 (5.72)	10.13	<0.001
Time perception	16.42 (6.36)	15.70 (6.33)	1.27	>0.05
Low arousal	18.81 (5.54)	19.28 (6.00)	−0.92	>0.05
High arousal	14.14 (4.97)	13.58 (4.36)	1.33	>0.05
Disengagement	19.86 (5.49)	19.13 (5.48)	1.50	>0.05
Experiment 2	**Males ($n = 228$)**	**Females ($n = 278$)**	***t***	***p***
FRs	0.38 (0.22)	0.31 (0.23)	3.57	<0.001
MSBS	86.74 (20.55)	79.53 (21.74)	3.96	<0.001
Inattention	19.63 (4.85)	17.64 (5.47)	4.42	<0.001
Time perception	18.48 (8.49)	18.08 (8.50)	0.53	>0.05
Low arousal	16.43 (5.52)	16.11 (5.42)	0.67	>0.05
High arousal	12.19 (4.86)	12.40 (4.72)	−0.50	>0.05
Disengagement	17.93 (5.46)	16.37 (5.48)	3.27	0.001

MSBS, Multidimensional State Boredom Scale; TBS, Trait Boredom Scale; FRs, Forgetting Rates; Values presented are means (standard deviation).

was not always inversely proportional to the learning effect in our experiments, we calculated the individual word forgetting rate as the effect of novel lexicon learning: Forgetting Rate (FR) = $(\text{score}_{\text{immediate}} - \text{score}_{\text{delayed}})/(\text{score}_{\text{immediate}})$. Higher FRs reflected poorer learning effects. Independent sample t-tests were used for comparing the differences in the studied variables between males and females. Pearson correlation analyses were used to examine the correlations between boredom scores and FRs. A hierarchical multiple regression analysis was conducted to further estimate the effect of gender, state and trait boredom as predictors of FRs. The PROCESS 3.3 program and bootstrap method were employed to verify the mediating effects of boredom.

Based on the literature review, the following four hypotheses were tested in this study: (1) female participants would show better performance (lower FRs) than male participants in the tests after the lexicon learning task; (2) female participants would show lower state and trait boredom than male participants before the learning task; (3) greater state and trait boredom level would be associated with a worse outcome of the lexicon learning task; and (4) state or trait boredom may be a mediator variable for the relationships between gender and lexicon learning.

RESULTS

Gender and Learning Performance

Table 2 provides the descriptive statistics of the male and female groups, as well as the differences in FRs, state boredom scores (inattention, time perception, low arousal, high arousal, and disengagement), and trait boredom scores (external stimuli and internal stimuli) between the groups. Consistent with our hypothesis, the male group showed significantly higher FRs than the female group [Experiment 1: $t(525) = 4.47$, $p < 0.001$; Experiment 2: $t(504) = 3.57$, $p < 0.001$, see **Table 2, Figures 2A,B**], suggesting better performance in female students in the lexicon learning task.

Gender and Boredom

The results also demonstrated distinct gender differences in state boredom. Partly consistent with our hypothesis, the male group showed significantly higher state boredom scores than the female group [Experiment 1: $t(525) = 3.37$, $p = 0.001$; Experiment 2: $t(504) = 3.96$, $p < 0.001$, see **Table 2**; **Figures 2C,D**], suggesting a lower level of state boredom in female students before the lexicon learning task. However, inconsistent with our hypothesis, there were no significant differences between the male and female groups in trait boredom scores, [Experiment 1: $t(525) = 1.09$, $p > 0.05$, see **Table 2**; **Figure 3C**], suggesting a similar level of trait boredom in female and male students before the lexicon learning task.

Correlations Between Boredom and Learning Performance

Consistent with our hypothesis, there were significant positive correlations between the state boredom scores and the FRs in

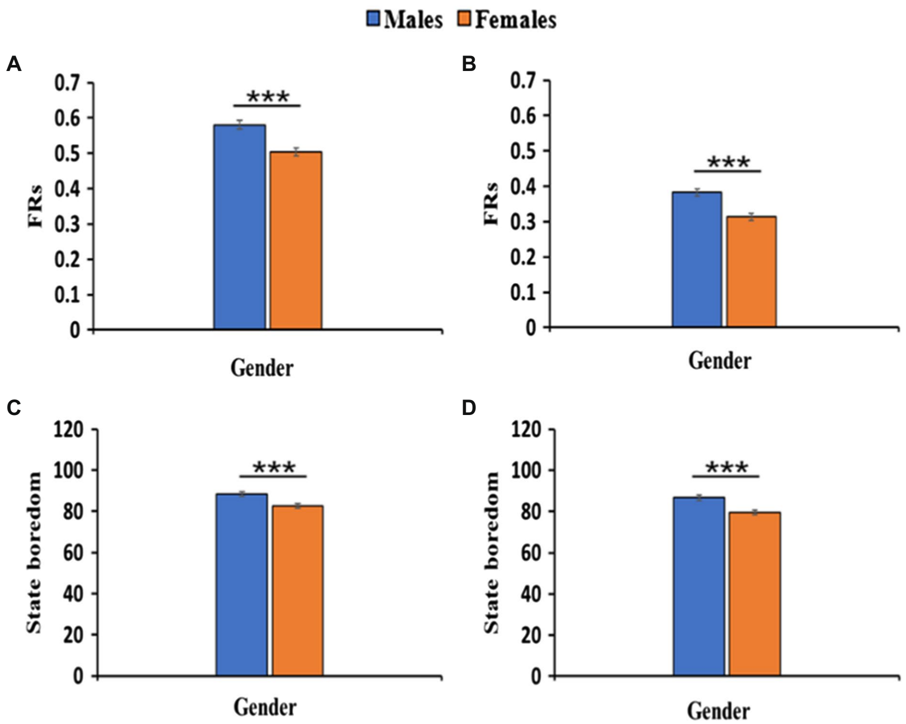

FIGURE 2 | Gender differences for FRs **(A,B)**, scores of state boredom **(C,D)**. ***$p < 0.001$.

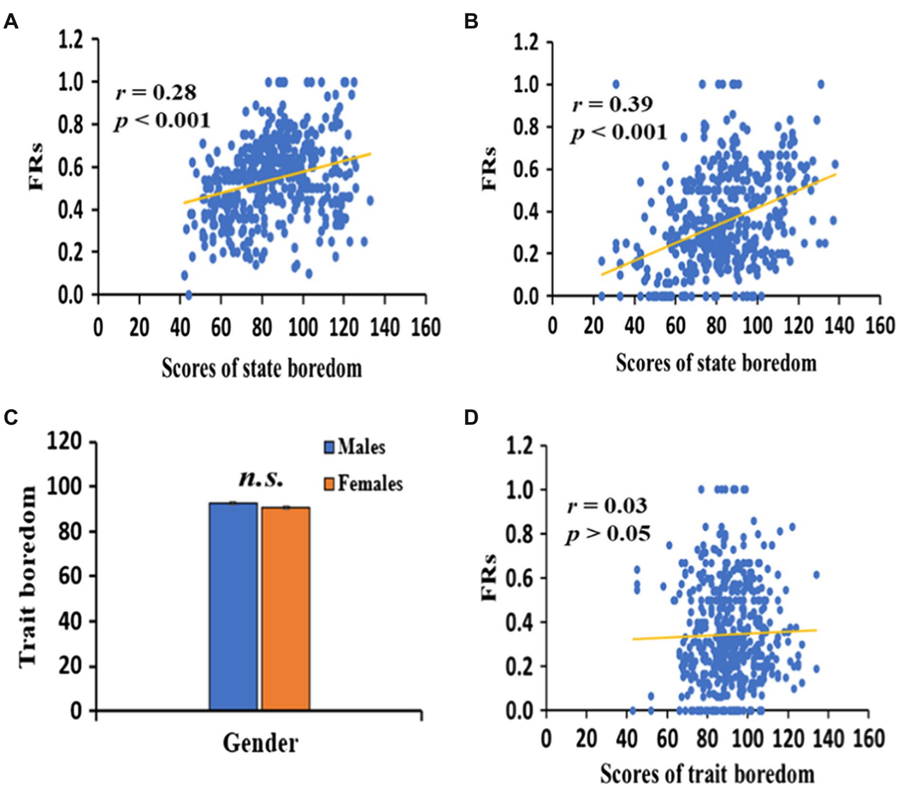

FIGURE 3 | Correlation between FRs and scores of state boredom in Experiment 1 **(A)** and Experiment 2 **(B)**. Gender difference for scores of trait boredom **(C)** and correlation between FRs and scores of trait boredom **(D)** in Experiment 1. n.s. means no significance.

both Experiment 1 ($r = 0.28$, $p < 0.001$, see **Figure 3A**) and Experiment 2 ($r = 0.39$, $p < 0.001$, see **Figure 3B**), suggesting that high level of state boredom was associated with worse lexicon learning. The stepwise regression was performed to determine what factors in state boredom could be regarded as predictors of FRs. The FRs were used as the dependent variable, and the five dimensions constituting the MSBS were used as the predictor variables. As shown in **Table 3**, two of the five factors—inattention and low arousal—exerted positive predictive effects on the FRs (Experiment 1: $\beta = 0.281$, $p < 0.001$; $\beta = 0.237$, $p < 0.001$; Experiment 2: $\beta = 0.225$, $p < 0.001$; $\beta = 0.210$, $p < 0.001$, respectively), the contribution rates reached 16.1 and 4.2%, respectively, in Experiment 1, and 10.0 and 3.6%, respectively in Experiment 2. The results of Experiment 2 replicated that of Experiment 1, showing that inattention and low arousal of state boredom were reliably predictive of novel lexicon learning.

In contrast to state boredom, no correlations were observed between trait boredom and FRs ($r = 0.03$, $p > 0.05$ in Experiment 1, see **Figure 3D**), suggesting no significant effects of trait boredom on novel lexicon learning. Taken together, these results suggest that state and trait boredom had different relationships with lexicon learning.

Gender Effects on Novel Lexicon Learning

We conducted a hierarchical multiple regression analysis to determine the extent to which gender and state and trait boredom could be viewed as predictors of FRs in Experiment 1. **Table 4** summarizes the results. Gender was a significant predictor of FRs ($p < 0.001$) and explained about 2.3% of the variance of FRs. When state and trait boredom were included, the model explained about 9.5% of the variance of FRs. State boredom ($p < 0.001$) and gender ($p < 0.05$) were significant predictors of FRs in this model, while trait boredom was not a significant predictor of FRs ($p > 0.05$).

The mediation model was further used to explore whether gender, directly or indirectly (through state boredom), affected FRs in both Experiments 1 and 2. The analysis confirmed that gender effect on learning was mediated by state boredom in both experiments (see **Figures 4A,B**). A bootstrap resampling analysis of the effect size showed that the confidence interval of 95% for gender to influence FRs through state boredom was [−0.03, −0.01] in Experiment 1, and [−0.03, −0.01] in Experiment 2. To explore which dimension of state boredom mediates the relationship between gender and learning outcomes, we also performed a mediation analysis on the dimensions of state boredom. The results indicated that gender effect on novel lexicon learning was mediated *via* inattention in both Experiment 1 and Experiment 2 (confidence intervals were [−0.04, −0.01] and [−0.03, −0.01], respectively, see **Figures 4C,D**). These results suggested that the inattention dimension of state boredom partially mediated the relationships between gender and novel lexicon learning.

DISCUSSION

In the present study, two independent experiments with a large sample of over 1,000 college students were conducted to explore the relationships between gender-related differences in boredom and lexicon learning. This study provides converging evidence supporting the advantage of female over male

TABLE 3 | Stepwise regression analysis of the use of state boredom and FR.

Dependent variable	Independent variable	R	R^2	ΔR^2	F	β	B	t
Experiment 1								
FRs	Inattention	0.401	0.161	0.161	100.445	0.281	0.015	6.240***
	Low arousal	0.450	0.203	0.042	27.714	0.237	0.013	5.264***
Experiment 2								
FRs	Inattention	0.316	0.100	0.100	58.325	0.225	0.010	4.977***
	Low arousal	0.369	0.136	0.036	21.721	0.210	0.009	4.661***

****p < 0.001.*

TABLE 4 | Hierarchical multiple regression analysis of gender, state and trait boredom as predictors of FR.

Variable	R	$R2$	$\Delta R2$	F	β	B	t
Step 1	0.153	0.023		12.623			
Gender					−0.153	−0.069	−3.553***
Step 2	0.309	0.095	0.072	20.745			
Gender					−0.107	−0.049	−2.535*
State boredom					0.272	0.003	6.434***
Trait boredom					−0.01	0	−0.247

**p < 0.05; ***p < 0.001.*
Gender: 1 = male, 2 = female.

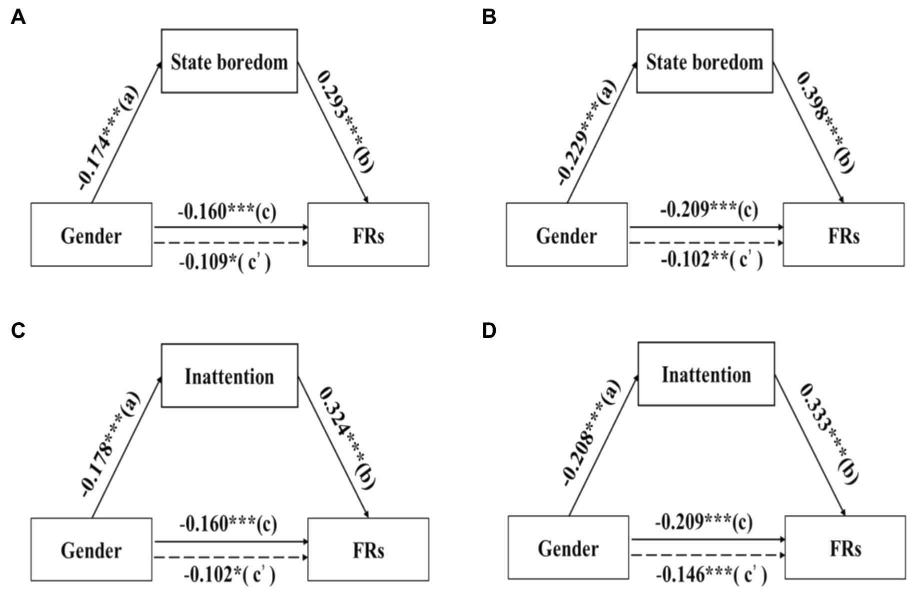

FIGURE 4 | Gender effect on forgetting rates (FRs) was mediated by state boredom in Experiment 1 **(A)** and Experiment 2 **(B)**. Gender effect on forgetting rates (FRs) was mediated by inattention in Experiment 1 **(C)** and Experiment 2 **(D)**. $^*p < 0.05$, $^{**}p < 0.01$ and $^{***}p < 0.001$.

participants in state boredom as well as in novel lexicon learning performance. Moreover, we found that only state boredom, not trait boredom, showed significant effects on lexicon learning, and the differences in state boredom partially explained the differences in lexicon learning outcomes between females and males. These findings suggest that lower-level state boredom in female learners contributes to better language-learning ability in college students.

Gender Difference in Lexicon Learning

Concerning the novel lexicon learning results, females achieved significantly lower FRs than males. The results were in line with previous findings that females are quite often better in areas involving memorization (Van et al., 2015) and learning strategies (Shukri et al., 2009). The biological viewpoint suggests that gender difference depends on cognitive ability and learning style derived from fundamental physiological differences, such as differences in brain development and higher-level cortical functions (Keefe, 1982). According to the lateralization effect on language, less lateralization for language functions in females could (at least partially) explain why they outperform males in many language skills (Ruigrok et al., 2014). The Gender Role Theory also posits that prevalent gender stereotypes are culturally shared expectations that females and males should learn the appropriate behaviors and attitudes from the sociocultural environment they grow up in (Eagly and Karau, 2002). Consistent with this proposition, females did better than males because females may be more inclined to have the advantage over male learners in learning motivation (Sylvén and Thompson, 2015; Iwaniec, 2019), which subsumes a range of constructs such as positive attitudes and interest (Deci and Ryan, 1985). Consequently, female learners could use a broader range of learning strategies such as cognitive, meta-cognitive, and cognitive refinement strategies than male learners (Gu, 2002). In addition, females' higher self-regulation (Tseng et al., 2006) and/or more effort investment (Okuniewski, 2014) could contribute to better learning performance. Taken together, the findings that gender impacted novel lexicon learning fit well with the Gender Role Theory (Eagly and Karau, 2002).

Gender Difference in State Boredom

Our results also indicated that males had higher state boredom than females, which is in line with many previous studies showing that females experienced lower state boredom than males (e.g., Liu et al., 2013; Mehdi, 2021). Males tend to have greater needs for various stimuli, be more active and more risk-seeking, and have greater motivation to seek novel sensations and experiences than females (Mikulas and Vodanovich, 1993; Daschmann et al., 2011; Vodanovich et al., 2011; Burbano et al., 2020). In contrast, females tend to pay more attention to psychological and emotional control and have more strategic competence in coping with experiences of boredom than males (Hogan et al., 2010). However, we did not find significant differences in trait boredom between males and females, suggesting that males and females may have similar structures of trait boredom as stable personality attributes.

Negative Impacts of State Boredom on Lexicon Learning

We found positive correlations between state boredom scores and the word forgetting rates in both experiments, indicating that higher levels of state boredom are associated with the worse lexicon learning outcome. These results aligned with previous research showing that boredom was related to poor academic achievement (Ahmed et al., 2013; Jaradat, 2015; Suárez-Pellicioni et al., 2016) and more attention deficit (Pekrun et al., 2010; Eastwood et al., 2012; Hunter and Eastwood, 2016; Westgate, 2020). The Control-Value Theory of achievement emotions posits that boredom may result from a lack of control or perceived value in academic tasks (Pekrun, 2006). Therefore, the learners with a high level of boredom may consider the novel lexicon learning as being of little importance or value and perceive control over it as particularly low or high. The aversive state of boredom might trigger their desire to escape the boring situation and at the same time their inability to engage in the learning task.

The findings suggest that state boredom might be characterized in terms of inattention to influence lexicon learning. This helps to explain the relationship between inattention as a dimension of state boredom and learning achievement measures. The interpretation is dependent on the assumption of the CVT, although the adequate measures of control and value appraisals, as the two proximal determinants of achievement emotions when state boredom occurs, are absent in the present research. Further investigations are needed to examine this account: how control and value appraisals contribute to the individual differences in state boredom, respectively. Another possible explanation can be found in the Meaning and Attentional Components model (Westgate and Wilson, 2018), which specifies that the production of boredom was often related to a lack of not only attention but also meaning. Individuals have difficulty concentrating on the current task and are unable to perceive the meaning or importance of a task when state boredom occurs. The fact that state boredom had a significantly negative effect on novel lexicon learning may imply that the learners immersed in high state boredom viewed the issue of novel lexicon learning as less meaningful. Thus, it may contribute to the lack of learning motivation and disengagement from the task at hand, resulting in attention deficit and low arousal in learners. Presumably, repetition of vocabulary memorization made it difficult for the learners to sustain attention and perceive the value of learning. As a result, their academic performance was poor (Malkovsky et al., 2012). Therefore, attention deficit, to some extent, may present novel lexicon learning as meaningless or lack of value, and hence, impacts the performance of lexicon learning. Interestingly, the current study found that state boredom but not trait boredom had significant negative effects on novel lexicon learning. A possible explanation is that different cognitive impairments could be associated with a different type of boredom (Malkovsky et al., 2012). The possible accounts might be different cognitive impairments that could be associated with a particular type of boredom (Malkovsky et al., 2012). However, our current findings cannot ascertain whether this discrepancy was due to the differences between state and trait boredom on neural basis. Future research is needed to elucidate whether state boredom and trait boredom are sufficiently distinct to be treated as separate entities in the brain. In addition, it is unknown whether learning achievements might have influenced learners' emotions about language learning. Emotions affect learners' achievement, while experiences of learning outcomes can in turn influence learners' emotions (Pekrun et al., 2017). This is especially true for the dynamic state of boredom, because determining this fact would require a longitudinal study of the reciprocal causation between boredom and L2 or FLL. This might be an interesting question to expand the present research in the future.

The Mediating Role of State Boredom

Our results indicated that state boredom partially mediated the interaction between gender and novel lexicon learning. A potential explanation of the mediating role of state boredom reason in lexicon learning may be related to attention, which is influenced by the perceived meaning of a goal or a task. Specifically, weakened attention and mild negative emotions induced by boredom affect the learning process (Pekrun, 2006). When individuals are in a state of boredom, their attentiveness is vulnerable. A lack of attention could drive negative emotions. When attention is not fully engaged, activities would be negatively treated, resulting in poor academic grades or achievement (Hunter and Eastwood, 2016).

Higher-level state boredom has been linked to more inattention and poor achievement based on the boredom mechanism. It is reflected in the findings that males showed significantly higher state boredom and poorer learning effects as compared to females. These findings are in line with the Control-Value Theory of boredom (Pekrun, 2006). The basic structures and causal mechanisms of emotions follow general nomothetic principles. In contrast, the contents, frequency, and intensity of emotions can differ due to different cultures and genders. Regarding gender differences, females' and males' emotions should be structurally equivalent as emotions depend on control and value appraisals in both female and male students. To some extent that the perceived control and academic values may differ between female and male students, leading to different emotional experiences. Thus, it is reasonable to expect that state boredom mediates the relationship between gender and novel lexicon learning. Notably, this study has demonstrated that the association between gender and novel lexicon learning is partially mediated by state boredom. Integrating further factors affecting beneficial learning could therefore be important for future studies on this topic. It may be important to examine the relationship between gender and learning achievements by including further individual variables.

Practical Implications

The findings of this study have important implications for language educators and learners. Boredom is frequently associated with inattention and may be a marker of the emotional status that signals a lack of task value and meaning (Pekrun et al., 2010; Van Tilburg and Igou, 2012). If learning tasks are situationally monotonous and meaningless, learners will feel dissatisfied and disengage from the learning activities (Eastwood et al., 2012). As suggested by the Control-Value Theory, learners' emotions can be positively influenced by cultivating their ability to perceive and control over academic activities and outcomes, as well as shaping their evaluation of the value of these activities and outcomes (Pekrun, 2006). This shows that students' boredom experience in the learning context could be potentially attenuated by increasing their sense of control over the task. Students' boredom may also be attenuated by the enhanced positive feeling of academic values from instruction on task difficulty or importance. Feedback from teachers may play another important role by directing effort to strategies rather than avoidance (Fritea and Fritea, 2013). Cumulative feedback of failures would undermine students' sense of control and meaning, thus contributing to negative outcomes such as attention deficit. To the extent that this assumption is true, efforts should be made to offer students more opportunities to learn rather than assessing their insufficient attainment.

Findings from this study demonstrate that males had a greater state of boredom and achieved less academic success in novel lexicon learning than females. But this does not mean that males cannot be as effective learners as females. Males tend to adopt cognitive avoidance more than females, who prefer to employ behavioral avoidance to avoid exhausting situations (Mehdi, 2021). Therefore, it may be a good strategy to encourage male students to focus on the utility value of what they are learning to enhance their motivation and minimize boredom during learning (Nett et al., 2010; Tulis and Fulmer, 2013; Coelho et al., 2018). In contrast, female students may be encouraged to use more behavioral avoidance strategies, such as chatting with peers, during the learning task to avoid exhausting situations (Eren and Coskun, 2016). Such gender-specific education strategies may help to reduce students' boredom in the process of language learning and narrow the gap in language acquisition (Zimmerman, 2014).

Limitations

The present study had the advantage of enrolling a large sample of over 1,000 healthy and young college students and replicating the main findings in two independent experiments. However, several important limitations should be noted. First, although our findings are in line with the Control-Value Theory which indicates that control and value appraisals play roles in the situation and for the development of boredom, control and value appraisals were not assessed and investigated in this study. Future studies are needed to include the measures of control and value appraisals to further understand their roles in gender differences in boredom and language learning. Second, all participants in this study were young Chinese college students with narrow age ranges; thus it remains unclear whether the present results can be generalized to other age groups such as younger students from primary and secondary schools as well as older learners from the community. Future studies are necessary to replicate the findings in different age populations. Third, since the value appraisals and emotions may differ across countries and cultures (Pekrun, 2006), future research on boredom and learning should be promoted in other countries and cultures. Finally, future studies are needed to use psychophysiological and neuroimaging technologies such as EEG and functional magnetic resonance imaging (fMRI) to determine the neural mechanisms underlying gender differences in boredom and language learning.

CONCLUSION

To our knowledge, this is the first study to investigate the contribution of boredom to the gender-related difference in lexicon learning. Findings from two independent experiments with large samples of female and male students consistently demonstrated greater state boredom in male than female participants, which was associated with worse lexicon learning (forgetting more words during the test). Moreover, state boredom but not trait boredom, partially explained the performance difference between male and female participants in the novel lexicon learning task. This study provides new evidence supporting the negative impacts of state boredom on lexicon learning and suggests that better lexicon learning ability in female learners may be partly accounted for by the reduced level of state boredom during learning.

DATA AVAILABILITY STATEMENT

The datasets used and analyzed in the current study are available from the corresponding author on reasonable request.

AUTHOR CONTRIBUTIONS

HR, HW, and YX contributed to the ideas of research and design of research methods. HR, HW, and HS contributed to the collection of data and empirical analysis. XZ, TM, HS, SX, and YH participated in developing a research design and interpreting the analysis. All authors contributed to the article and approved the submitted version.

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REFERENCES

Ahmed, W., van der Werf, G., Kuyper, H., and Minnaert, A. (2013). Emotions, self-regulated learning, and achievement in mathematics: A growth curve analysis. *J. Educ. Psychol.* 105, 150–161. doi: 10.1037/a0030160

Aldosari, D. A., Alsultan, M., and Unviversity, K. S. (2017). The influence of early bilingual education (English) on the first language (Arabic) literacy skills in the second grade of elementary school: Saudi arabia. *J. Educ. Pract.* 8, 135–142. doi: 10.1371/journal.pone.0187993

Anusic, I., Lucas, R. E., and Donnellan, M. B. (2016). The validity of the day reconstruction method in the German socio-economic panel study. *Soc. Indic. Res.* 1, 213–232. doi: 10.1007/s11205-015-1172-6

Bryła-Cruz, A. (2021). The gender factor in the perception of English segments by non-native speakers. *Stud. Sec. Lang. Learn. Teach.* 11, 103–131. doi: 10.14746/ssllt.2021.11.1.5

Burbano, V., Padilla, N., and Meier, S. (2020). Gender differences in preferences for meaning at work. IZA Discussion paper no. 13053, Available at: https://ssrn.com/abstract=3562843

Chan, C. S., Van Tilburg, W. A., Igou, E. R., Poon, C., Tam, K. Y., Wong, V. U., et al. (2018). Situational meaninglessness and state boredom: cross-sectional and experience-sampling findings. *Motiv. Emot.* 42, 555–565. doi: 10.1007/s11031-018-9693-3

Chee, K. H., Pino, N. W., and Smith, W. L. (2005). Gender differences in the academic ethic and academic achievement. *Coll. Stud. J.* 39, 604–619.

Coelho, D., Andrade, A. I., and Portugal, G. (2018). The 'awakening to languages' approach at preschool: developing children' s communicative competence. *Lang. Aware.* 27, 197–221. doi: 10.1080/09658416.2018.1486407

Daschmann, E. C., Goetz, T., and Stupnisky, R. H. (2011). Testing the predictors of boredom at school: development and validation of the precursors to boredom scales: antecedents to boredom scales. *Br. J. Educ. Psychol.* 81, 421–440. doi: 10.1348/000709910X526038

de Lima Xavier, L., Hanekamp, S., and Simonyan, K. (2019). Sexual dimorphism within brain regions controlling speech production. *Front. Neurosci.* 13, 1–7. doi: 10.3389/fnins.2019.00795

Deci, E. L., and Ryan, R. M. (1985). *Intrinsic Motivation and Self-Determination in human Behavior*. New York: Plenum.

Eagly, A. H., and Karau, S. J. (2002). Role congruity theory of prejudice toward female leaders. *Psychol. Rev.* 109, 573–598. doi: 10.1037/0033-295X.109.3.573

Eastwood, J. D., Frischen, A., Fenske, M. J., and Smilek, D. (2012). The unengaged mind: defining boredom in terms of attention. *Perspect. Psychol. Sci.* 7, 482–495. doi: 10.1177/1745691612456044

Eren, A., and Coskun, H. (2016). Students' level of boredom, boredom coping strategies, epistemic curiosity, and graded performance. *J. Educ. Res.* 109, 574–588. doi: 10.1080/00220671.2014.999364

Fahlman, S. A., Mercer, K. B., Gaskovski, P., Eastwood, A. E., and Eastwood, J. D. (2009). Does a lack of life meaning cause boredom? Results from psychometric, longitudinal, and experimental analyses. *J. Soc. Clin. Psychol.* 28, 307–340. doi: 10.1521/jscp.2009.28.3.307

Farmer, R., and Sundberg, N. D. (1986). Boredom proneness—the development and correlates of a new scale. *J. Pers. Assess.* 50, 4–17. doi: 10.1207/s15327752jpa5001_2

Frenzel, A. C., Pekrun, R., and Goetz, T. (2007). Perceived learning environments and students' emotional experiences: A multilevel analysis of mathematics classrooms. *Learn. Instr.* 17, 478–493. doi: 10.1016/j.learninstruc.2007.09.001

Fritea, I., and Fritea, R. (2013). Can motivational regulation counteract the effects of boredom on academic achievement? *Procedia Soc. Behav. Sci.* 78, 135–139. doi: 10.1016/j.sbspro.2013.04.266

Gass, S., and Varonis, E. (1986). "Sex differences in non-native speaker interactions," in *Talking to learn: Conversation in second Language Acquisition*. ed. R. Day (Newbury House: Rowley, MA), 327–351.

Gathercole, S. E., Willis, C., Emslie, H., and Baddeley, A. D. (1991). The influences of number of syllables and wordlikeness on children' s repetition of nonwords. *Appl. Psycholinguist.* 12, 349–367. doi: 10.1017/S0142716400009267

Gerritsen, C. J., Toplak, M. E., Sciaraffa, J., and Eastwood, J. (2014). I can't get no satisfaction: potential causes of boredom. *Conscious. Cogn.* 27, 27–41. doi: 10.1016/j.concog.2013.10.001

Główka, D. (2014). The impact of gender on attainment in learning English as a foreign language. *Stud. Sec. Lang. Learn. Teach.* 4, 617–635. doi: 10.14746/ssllt.2014.4.4.3

Goetz, T., and Hall, N. C. (2014). "Academic boredom," in *International Handbook of Emotions in Education* (United Kingdom: Routledge), 321–340.

Goldberg, Y. K., Eastwood, J. D., LaGuardia, J., and Danckert, J. (2011). Boredom: an emotional experience distinct from apathy, anhedonia, or depression. *J. Soc. Clin. Psychol.* 30, 647–666. doi: 10.1521/jscp.2011.30.6.647

Gu, Y. (2002). Gender, academic major, and vocabulary learning strategies of chinese EFL learners. *RELC J.* 33, 35–54. doi: 10.1177/003368820203300102

Hogan, M. J., Parker, J. D. A., Wiener, J., Watters, C., Wood, L. M., and Oke, A. (2010). Academic success in adolescence: relationships among verbal IQ, social support and emotional intelligence. *Aust. J. Psychol.* 62, 30–41. doi: 10.1080/00049530903312881

Huang, S. H., Li, D., and Zhang, W. (2010). The preliminary compilation of college students' boredom tendency questionnaire. *Psychol. Dev. Educ.* 26, 308–314.

Hunter, A., and Eastwood, J. D. (2016). Does state boredom cause failures of attention? Examining the relations between trait boredom, state boredom, and sustained attention. *Exp. Brain Res.* 236, 2483–2492. doi: 10.1007/s00221-016-4749-7

Iwaniec, J. (2019). Language learning motivation and gender: The case of Poland. *Int. J. Appl. Linguist.* 29, 130–143. doi: 10.1111/ijal.12251

Jaradat, A. (2015). Differences in boredom proneness according to gender and academic achievement. *Indian J. Health Wellbeing.* 6, 982–985.

Jiménez, R. M. (ed.) (2010). *Gender Perspectives on Vocabulary in Foreign and second Language*. Basingstoke: Palgrave MacMillan.

Ke, W., and Dong, Y. (2001). A study on the effect of context on L2 vocabulary direct learning. *Mod. For. Lang.* 4, 353–358. doi: 10.3969/j.issn.1003-6105.2001.04.003

Keefe, J. W. (1982). "Assessing student learning styles: An overview," in *Student learning styles and bmzn beliauior* (National Association of Secondary School Principals: Reston), 43–53.

Krashen, S. D. (1981). *Principles and Practice in Second Language Acquisition*. United Kingdom: Pergamon Press.

Kruk, M. (2019). Dynamicity of perceived willingness to communicate, motivation, boredom and anxiety in Second Life: the case of two advanced learners of English. *Comput. Assist. Lang. Learn.* 1–27. doi: 10.1080/09588221.2019.1677722

Kruk, M., and Zawodniak, J. (2020). A comparative study of the experience of boredom in the L2 and L3 classroom. *Eng. Teach. Learn.* 44, 417–437. doi: 10.1007/s42321-020-00056-0

Larson, R. W., and Richards, M. H. (1991). Boredom in the middle school years: blaming schools versus blaming students. *Am. J. Educ.* 99, 418–443. doi: 10.1086/443992

LePera, N. (2011). Relationships between boredom proneness, mindfulness, anxiety, depression, and substance use. *New Sch. Psychol. Bull.* 8, 15–25. doi: 10.1037/e741452011-003

Li, C. (2021). A control–value theory approach to boredom in English classes among university students in China. *Mod. Lang. J.* 105, 317–334. doi: 10.1111/modl.12693

Li, K., Peng, M. Y. P., Du, Z., Li, J., Yen, K. T., and Yu, T. (2020). Do specific pedagogies and problem-based teaching improve student employability? A cross-sectional survey of college students. *Front. Psychol.* 11:1872. doi: 10.3389/fpsyg.2020.01872

Liu, Y., Chen, J., Jiang, M., Xu, H., and Eastwood, J. D. (2013). The Chinese version of the multidimensional state boredom scale (MSBS): It' s applicability in Chinese college students. *Chin. J. Clin. Psych.* 21, 558–557. doi: 10.3760/cma.j.issn.1005-054X.2012.01.012

Lomas, T. (2017). A meditation on boredom: re-appraising its value through introspective phenomenology. *Qual. Res. Psychol.* 14, 1–22. doi: 10.1080/14780887.2016.1205695

Lynn, R., Fergusson, D., and Horwood, L. J. (2005). Sex differences on the WISC-R in New Zealand. *Personal. Individ. Differ.* 39, 103–114. doi: 10.1016/j.paid.2004.12.009

Malkovsky, E., Merrifield, C., Goldberg, Y., and Danckert, J. (2012). Exploring the relationship between boredom and sustained attention. *Exp. Brain Res.* 221, 59–67. doi: 10.1007/s00221-012-3147-z

Matthies, S., Philipsen, A., and Svaldi, J. (2012). Risky decision making in adults with adhd. *J. Behav. Ther. Exp. Psychiatry* 43, 938–946. doi: 10.1016/j.jbtep.2012.02.002

McLeod, C. R., and Vodanovich, S. J. (1991). The relationship between self-actualization and boredom proneness. *J. Soc. Behav. Pers.* 6, 137–146.

Mehdi, S. (2021). University students' multidimensional state boredom and strategies to cope with classroom boredom. Journal of. *Lang. Educ.* 7, 204–222. doi: 10.17323/jle.2021.12256

Miao, P., and Xie, X. (2019). State boredom: an emotion seeking change. *Acta Sci. Nat. Univ. Pekin.* 55:9. doi: 10.13209/j.0479-8023.2019.083

Mikulas, W. L., and Vodanovich, S. J. (1993). The essence of boredom. *Psychol. Rec.* 43, 3–12.

Nett, U. E., Goetz, T., and Daniels, L. M. (2010). What to do when feeling bored?: Students' strategies for coping with boredom. *Learn. Individ. Differ.* 20, 626–638. doi: 10.1016/j.lindif.2010.09.004

Ng, C. W. (2018). Gender difference in preferences for second language vocabulary learning strategies: A pilot study. *BAES* 1, 160–171. doi: 10.31559/baes2018.1.2.4

Okuniewski, J. E. (2014). Short communications. *Psychol. Lang. Commun.* 18, 75–78. doi: 10.2478/plc-2014-0006

Pawlak, M., Zawodniak, J., and Kruk, M. (2020). The neglected emotion of boredom in teaching English to advanced learners. *Int. J. Appl. Linguist.* 30, 497–509. doi: 10.1111/ijal.12302

Pekrun, R. (2006). The control–value theory of achievement emotions: assumptions, corollaries, and implications for educational research and practice. *Educ. Psychol. Rev.* 18, 315–341. doi: 10.1007/s10648-006-9029-9

Pekrun, R., Goetz, T., Daniels, L. M., Stupnisky, R. H., and Perry, R. P. (2010). Boredom in achievement settings: exploring control–value antecedents and performance outcomes of a neglected emotion. *J. Educ. Psychol.* 102, 531–549. doi: 10.1037/a0019243

Pekrun, R., Lichtenfeld, S., Marsh, H. W., Murayama, K., and Goetz, T. (2017). Achievement emotions and academic performance: longitudinal models of reciprocal effects. *Child Dev.* 88, 1653–1670. doi: 10.1111/cdev.12704

Putwain, D. W., Pekrun, R., Nicholson, L. J., Symes, W., Becker, S., and Marsh, H. W. (2018). Control-value appraisals, enjoyment, and boredom in mathematics: a longitudinal latent interaction analysis. *Am. Educ. Res. J.* 55, 1339–1368. doi: 10.3102/0002831218786689

Ruigrok, A. N. V., Salimi-Khorshidi, G., Lai, M. C., Baron-Cohen, S., Lombardo, M. V., Tait, R. J., et al. (2014). A meta-analysis of sex differences in human brain structure. *Neurosci. Biobehav. Rev.* 39, 34–50. doi: 10.1016/j.neubiorev.2013.12.004

Scheiber, C., Reynolds, M. R., Hajovsky, D. B., and Kaufman, A. S. (2015). Gender differences in achievement in a large, nationally representative sample of children and adolescents: gender and achievement. *Psychol. Sch.* 52, 335–348. doi: 10.1002/pits.21827

Seib, H. M., and Vodanovich, S. J. (1998). Cognitive correlates of boredom proneness: the role of private self consciousness and absorption. *Aust. J. Psychol.* 132, 642–652. doi: 10.1080/00223989809599295

Shukri, K., Teh, M., Embi, M. A., Mohd, N., and Mahamod, Z. (2009). A closer look at gender and Arabic language learning strategies use. *Eur. J. Soc. Sci.* 9.

Suárez-Pellicioni, M., Núñez-Peña, M. I., and Colomé, À. (2016). Math anxiety: a review of its cognitive consequences, psychophysiological correlates, and brain bases. *Cogn. Affect. Behav. Neurosci.* 16, 3–22. doi: 10.3758/s13415-015-0370-7

Sunderland, J. (2000). Issues of language and gender in second and foreign language education. *Lang. Teach.* 33, 203–223. doi: 10.1017/S0261444800015688

Syafrizal, S., and Putri, F. S. B. (2020). A linguistic politeness: an analysis of gender differences in speaking classroom. *Eng. Educ.* 5, 169–178. doi: 10.29407/jetar.v5i2.14436

Sylvén, L. K., and Thompson, A. S. (2015). Language learning motivation and CLIL: is there a connection? *JICB* 3, 28–50. doi: 10.1075/jicb.3.1.02syl

Tam, K. Y., Van Tilburg, W. A., and Chan, C. S. (2021). What is boredom proneness? A comparison of three characterizations. *J. Pers.* 89, 831–846. doi: 10.1111/jopy.12618

Tseng, W.-T., Dörnyei, Z., and Schmitt, N. (2006). A new approach to assessing strategic learning: the case of self-regulation in vocabulary acquisition. *Appl. Linguis.* 27, 78–102. doi: 10.1093/applin/ami046

Tulis, M., and Fulmer, S. M. (2013). Students' motivational and emotional experiences and their relationship to persistence during academic challenge in mathematics and reading. *Learn. Individ. Differ.* 27, 35–46. doi: 10.1016/j.lindif.2013.06.003

Van Tilburg, W. A. P., and Igou, E. R. (2012). On boredom: lack of challenge and meaning as distinct boredom experiences. *Motiv. Emot.* 36, 181–194. doi: 10.1007/s11031-011-9234-9

Van Tilburg, W. A., and Igou, E. R. (2017b). Can boredom help? Increased prosocial intentions in response to boredom. *Self Identity* 16, 82–96. doi: 10.1080/15298868.2016.1218925

Van, D., Van, H., Schepens, J. J., and Schiller, N. O. (2015). The gender gap in second language acquisition: gender differences in the acquisition of dutch among immigrants from 88 countries with 49 mother tongues. *PLoS One* 10:e0142056. doi: 10.1371/journal.pone.0142056

Vodanovich, S. J., and Kass, S. J. (1990). A factor analytic study of the boredom proneness scale. *J. Pers. Assess.* 55, 115–123. doi: 10.1207/s15327752jpa5501&2_11

Vodanovich, S. J., Kass, S. J., Andrasik, F., Gerber, W. D., Niederberger, U., and Breaux, C. (2011). Culture and gender differences in boredom proneness. *N. Am. J. Psychol.* 13, 221–230.

Vodanovich, S. J., Wallace, J. C., and Kass, S. J. (2005). A confirmatory approach to the factor structure of the boredom proneness scale: evidence for a two-factor short form. *J. Pers. Assess.* 85, 295–303. doi: 10.1207/s15327752jpa8503_05

Von Gemmingen, M. J., Sullivan, B. F., and Pomerantz, A. M. (2003). Investigating the relationships between boredom proneness, paranoia, and self-consciousness. *Personal. Individ. Differ.* 34, 907–919. doi: 10.1016/S0191-8869(01)00219-7

Watt, J. D., and Ewing, J. E. (1996). Toward the development and validation of a measure of sexual boredom. *J. Sex Res.* 33, 57–66. doi: 10.1080/00224499609551815

Watt, J. D., and Vodanovich, S. J. (1999). Boredom proneness and psychosocial development. *Aust. J. Psychol.* 133, 303–314. doi: 10.1080/00223989909599743

Westgate, E. C. (2020). Why boredom is interesting. *Curr. Dir. Psychol. Sci.* 29, 33–40. doi: 10.1177/0963721419884309

Westgate, E. C., and Wilson, T. D. (2018). Boring thoughts and bored minds: The MAC model of boredom and cognitive engagement. *Psychol. Rev.* 125, 689–713. doi: 10.1037/rev0000097

Zimmerman, C. B. (2014). "Teaching and learning vocabulary for second language learners," in *Teaching English as a Second or Foreign Language* (Boston: National Geographic Learning/Cengage), 288–302.

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