Emotion Regulation and Motivation Modulate the Associations Between Math Anxiety, Attention, and Math Performance

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ZW designed the study. TL, ZW, MQ, MW, AC, and the entire BSID lab collected and processed the data. ZW conducted the analyses. ZW and TL drafted the manuscript. All authors reviewed the manuscripts, provided constructive feedback, and approved the submitted version of the manuscript.

Research Highlights

- Trait and state level emotion regulation and motivation were examined as moderators in the association between math anxiety (MA), attention, and performance during a math task.
- The use of reappraisal as an emotion regulation strategy mitigated attentional interference and performance deficits among students with high MA.
- A physiological pattern of high state motivation mitigated avoidance of math problems, but did not reduce performance deficits among students with high MA.
- Neither the physiological correlate of emotion regulation nor trait level motivation moderated the association between MA and attention during math problem-solving.

Abstract

Although math anxiety (MA) and math performance are generally negatively correlated (Barroso et al., 2021), several studies reported variability in the strength of this association (Lyons & Beilock, 2012a; Tsui & Mazzocco, 2006; Wang et al., 2015). The present study investigated emotion regulation and motivation as potential mechanisms underlying this heterogeneity, particularly with regard to the attention patterns underlying successful math performance. A sample of 207 elementary and middle school students completed a math problem-solving task, during which their attention was measured using eye-tracking. Students' trait level and state level emotion regulation and motivation were assessed using self-reports and physiological measures, respectively. Our findings revealed that the use of reappraisal as an emotion regulation strategy mitigated attentional interference during math problem-solving, which in turn attenuated performance deficits among students with high MA. In addition, students with high MA exhibited more avoidance of the math problems only if their physiological pattern indicated low state motivation. These findings highlight the importance of enhancing both reappraisal and motivation as potential intervention targets to combat math deficits among students with high MA.

Keywords: math anxiety, emotion regulation, motivation, eye-tracking, psychophysiology

Educational Impact and Implications Statement

Although students with high math anxiety often have poorer math performance than their peers with low math anxiety, the current study found that not all students with high math anxiety experience the same challenges. For students who struggle to adaptively regulate their emotions, math anxiety was associated with difficulties staying focused on math problems, but this challenge was not observed among students with good emotion regulation skills. For students with low motivation, math anxiety was associated with avoidance of math problems. However, this avoidance pattern was not observed among students with high motivation. These findings suggest that helping students improve their emotion regulation skills and foster their motivation could potentially be effective strategies for reducing the impact of math anxiety on math learning and performance.

Emotion Regulation and Motivation Modulate the Associations Between Math Anxiety, Attention, and Math Performance

Math anxiety (MA), a negative academic emotion, involves students experiencing fear and worry when anticipating or actively participating in math-related activities (Hembree, 1990). MA is highly prevalent with an estimated 20% of students experiencing constant high levels of MA and an additional 15% experiencing high MA at some point in their secondary school years (Wang et al., 2020). According to several recent meta-analyses, MA is modestly to moderately negatively correlated with math achievement and motivation across all educational stages, highlighting the negative implications of MA in math learning (Barroso et al., 2021; Li et al., 2021; Namkung et al., 2019).

Despite this general negative outlook for highly math anxious students in their math learning outcomes, several studies have reported cases of exceptions in which students with high MA demonstrate resilience against poor math performance (Lyons & Beilock, 2012a; Tsui & Mazzocco, 2006; Wang et al., 2015). These studies highlight the possibility that various regulatory mechanisms may be employed by some students that enable them to achieve independence between their high MA and their math performance. It is critical to identify effective regulatory mechanisms utilized by these students, as such efforts will provide promising intervention targets to promote positive math learning outcomes among students highly anxious in math. The present study aims to investigate the potential roles of several regulatory mechanisms (i.e., emotion regulation and motivation) in modulating the association between MA and elementary and middle-school students' performance in a math task.

Mechanisms for the Association Between MA and Math Performance

Students with high MA, in general, tend to underperform in math tasks (Barroso et al., 2021; Namkung et al., 2019). Several mechanisms have been put forth to explain this negative association between MA and math performance (Carey et al., 2016; Lau et al., 2024; Ramirez et al., 2018). The first is reduced competency theory, which considers MA as an outcome of poor math performance. This theory argues that students with a history of underperformance in math develop negative perceptions of their math competency, which causes fear and worry in subsequent math situations (Maloney, 2016). The second is processing efficiency theory, which considers MA as a cause of poor math performance. This theory argues that students with high MA have overwhelming worrying thoughts, which occupy cognitive resources (e.g., attention) required for math problem-solving and consequently leads to a temporary performance drop (Ashcraft & Kirk, 2001; Beilock & Carr, 2005). The third is math avoidance theory, which suggests that the negative emotional climate surrounding math learning experienced by students with high MA causes avoidance behaviors in math-related activities, thereby holding students back from learning and practicing math (Lau et al., 2024). Similar to processing efficiency theory, math avoidance theory also considers MA as an antecedent of poor math performance. However, while math avoidance theory suggests that MA leads to deficits in math skills and knowledge, processing efficiency theory argues that MA is only tied to temporary performance drop, not deficits in knowledge. These three accounts are not mutually exclusive. Rather, they complement each other and suggest the possibility of a reciprocal link between MA and math achievement (Carey et al., 2016).

Empirical evidence supports both math avoidance theory and processing efficiency theory by demonstrating both avoidance behaviors and temporary cognitive interference among students with high MA. Specifically, there are important differences among students with different levels of MA in their long-term choices, everyday learning behaviors, and strategies in the moment of problem-solving. Students with higher MA are more likely to avoid math elective courses and college majors and careers that are math-intensive (Ahmed, 2018; Hembree, 1990; LeFevre et al., 1992) compared to their less anxious peers. In addition, students with higher MA are less attentive or engaged in everyday math class and afterschool math learning settings (Quintero et al., 2022; Song et al., 2023). In the moment of problem-solving, individuals with higher MA tend to prefer easier over harder problems (Choe et al., 2019) and are less likely to engage in effortful learning strategies (Jenifer et al., 2022). Additionally, individuals with higher MA are less reflective in their thinking and are less likely to enjoy cognitively demanding tasks (Maloney & Retanal, 2020; Morsanyi et al., 2014). Together, these findings suggest that students with high MA may generally *lack motivation* to engage in math learning and problem-solving despite potential long-term and short-term rewards associated with such math activities (e.g., high paying jobs in STEM, experimentally manipulated monetary rewards; Lau et al., 2024).

In addition, students with high MA also demonstrate patterns of cognitive interference during problem-solving. Several studies have reported that individuals with higher MA were more easily distracted by irrelevant information during cognitive tasks (Hopko et al., 1998; Suárez-Pellicioni et al., 2015). A recent study provides direct evidence for such attentional interference among students with high MA in a math task. This study found that students with higher MA distributed more attention to external distractors (e.g., timer) during math problem-solving, and such stimulus-driven task-irrelevant attention pattern predicted less accurate performance among these students than students with lower MA (Li et al., 2023). These findings are in line with Attention Control Theory (ACT; Eysenck et al., 2007), which argues that high anxiety impairs goal-driven attention by inducing an attentional bias to distractors, which occupies the cognitive resources required for processing task-relevant information. As such, students with high MA may *struggle to regulate their negative emotion* to focus on the problems at hand.

Acknowledging that there are alternative accounts for the negative association between MA and math performance (e.g., reduced competency theory; Carey et al., 2016; Ramirez et al., 2018), the current study focuses on math avoidance theory and processing efficiency theory and explores factors that may modulate the avoidance pattern and attentional interference experienced by students with high MA.

Heterogeneity in the Association Between MA and Math Performance

Although the negative relation between MA and math performance is well established in the general student population, several studies have found groups of students whose math performance was less or not impaired by high MA (e.g., Lyons & Beilock, 2012a; Tsui & Mazzocco, 2006; Wang et al., 2015). In a study of mathematically gifted 6th graders, the performance of students high in MA were found to be comparable to or even better than the performance of those with low MA, especially in timed math tasks (Tsui & Mazzocco, 2006), suggesting the potential facilitative role of MA among mathematically gifted students. These findings reveal the heterogeneity in the association between MA and math performance among students and highlight the importance of investigating the nature of this heterogeneity. Why are some students exempt from the negative achievement consequences associated with MA?

Two studies have provided insights into possible processes that may critically modulate performance differences among students with high MA. In two independent samples of middle school and undergraduate students, Wang and colleagues found that the negative linear association between MA and math performance was only observed among students who reported low math motivation (Wang et al., 2015). Among students who reported high math motivation, a moderate level of MA was associated with optimal math performance (Wang et al., 2015). These findings suggest that math motivation may be a critical factor that distinguishes students who exhibit a negative association between MA and math performance from those whose performance is not associated with MA.

Similarly, in a neuroimaging study of a sample of undergraduate students, Lyons and Beilock (2012a) revealed that the degree of math performance deficit among students with high MA was predicted by neural activities in the inferior frontoparietal regions, right caudate nucleus, and left hippocampus. Activities in these brain regions are thought to attenuate MA-induced performance deficits by way of supporting the regulation of negative emotion in anticipation of an unpleasant experience as well as an approach-oriented motivational response to the math task (Lyons & Beilock, 2012a). This study suggests that in addition to motivation, regulation of negative emotions may constitute another pivotal mechanism for cultivating performance resilience among students with high MA.

Two recent studies provide additional support for the use of emotion regulation strategies to modulate MA experiences or to promote math performance among undergraduate students (Daker et al., 2023; Pizzie & Kraemer, 2021). One study found that although elevated physiological arousal was generally associated with lower math performance, this negative association was reduced among students who used cognitive reappraisal during the math task, regardless of their MA levels (Pizzie & Kraemer, 2021). The other study examined the role of a physiological marker associated with the effectiveness of central nervous system emotion regulation – high frequency heart rate variability (hfHRV) – in modulating students' state MA (Draker et al., 2023). Among students with high trait MA, those with higher levels of hfHRV experienced less MA in the moment of problem-solving. However, hfHRV did not modulate the overall association between trait MA and math performance in this study (Draker et al., 2023). Additionally, some interventions are designed to promote effective regulation of MA by implementing therapy, relaxation, reappraisal exercises, and expressive writing (Sidney et al., 2025). These interventions are generally found to be effective at reducing MA, although their effects on improving math performance are less robust (Balt et al., 2022; Petronzi et al., 2021; Sammallahti, et al., 2023).

Gaps in the Current Literature

While the aforementioned studies have offered initial insights into two potential regulatory mechanisms for mitigating math performance deficits among students with high MA, several important gaps remain to be addressed. First, it is unclear whether these mechanisms are effective in regulating MA among younger students, particularly those in elementary school and early middle school.

Second, previous studies have investigated emotion regulation and motivation as moderators in the association between MA and math performance. However, these regulatory mechanisms do not directly operate on performance; rather, they are hypothesized to modulate the cognitive and behavioral responses in math learning and problem-solving. For example, emotion regulation was hypothesized to modulate the negative emotional experiences, which helps to mitigate their interference with goal-driven attention (Daker et al., 2023; Lyon & Beilock, 2012; Pizzie & Kraemer, 2021). In addition, motivation was hypothesized to modulate avoidance tendencies, which helps to encourage approach-oriented problem-solving (Lyon & Beilock, 2012; Wang et al., 2015; Wang et al., 2018). Given that these hypothesized moderations were not directly tested in past work, the present study aimed to bridge this important gap by examining how emotion regulation and motivation moderate the association between MA and avoidance as well as the association between MA and attentional interference.

Finally, alternative operationalizations of emotion regulation and motivation are needed to provide more robust evidence as to whether these processes mitigate performance deficits among students with high MA. The Lyons & Beilock (2012a) study investigated neural activities in anticipation of, and during, math problem-solving. However, there is a lack of one-to-one correspondence between neural activation and a specific strategy or mental process, which leaves room for interpretation of the meaning of these neural activities. The Wang et al. (2015) study used self-report to measure math motivation. Although this study provides additional evidence supporting the moderating role of motivation in the association between MA and math performance, the self-report scale used in this study measured trait level motivation, making it unclear the degree to which these findings generalize to state level motivation in the moment of math problem-solving. Additionally, the motivation measure used by Wang et al (2015) consisted of a mixture of items that tapped into intrinsic motivation, extrinsic motivation, and attention regulation. As such, additional work that allows for the separation of the effects of these various aspects of motivation is critically needed. The Daker et al (2023) study measured emotion regulation at both the trait level using a self-report questionnaire and the state level using a physiological correlate (i.e., hfHRV). However, neither avoidance nor attentional interference was investigated as the mediating mechanism in the association between MA and math performance in this study. Given that these are the only studies that provide evidence supporting the beneficial roles of emotion regulation and motivation in math performance among students with high MA, additional work in this area using alternative measures of emotion regulation and motivation is needed to strengthen the evidence base.

Operationalization of Emotion Regulation and Motivation

Emotion regulation refers to the dynamic processes in which individuals coordinate, evaluate, and express their emotional experiences and reactions to accommodate various situational demands (Gross, 1998). Cognitive reappraisal (reappraisal for short hereafter) is the most widely studied emotion regulation strategy (Gross, 2015). According to the process model of emotion regulation, reappraisal involves modifying one's emotions by way of reinterpreting the meaning of an emotion-eliciting situation (Gross, 2015). This strategy is generally adaptive in individuals' socioemotional, cognitive, and academic adjustments. For example, reappraisal is an overall effective strategy to downregulate negative emotions (Buhle et al., 2014; Gross, 2015; Webb et al., 2012). In achievement settings, students who are better able to reappraise their anxiety and stress responses show lower test anxiety and state MA, more engagement in learning, and higher performance on cognitive and achievement tests (Brady et al., 2018; Daches Cohen et al., 2021; Jamieson et al., 2013; Jamieson et al., 2016; Megreya & Al-Emadi, 2024; Strain & D'Mello, 2015). Importantly, compared to other emotion regulation strategies such as suppression (i.e., efforts to inhibit the expression of emotions), the use of reappraisal in negative emotion eliciting situations occupies less cognitive resources and is associated with less threat-related attentional interference (Jamieson et al, 2012; Kim et al, 2016; Zhu et al., 2021). In conjunction with results from Lyons & Beilock (2012a), these findings suggest that reappraisal may be a viable candidate moderator that modulates the degree of impact MA has on attentional interference during math problem-solving.

Math motivation refers to the reasons that drive students to strive to perform well in math (Middleton & Spanias, 1999). According to the Self-Determination Theory (Ryan & Deci, 2000), there is a spectrum of motivation, ranging from intrinsic motivation to extrinsic motivation to amotivation. We focus on two adaptive forms of motivation, namely intrinsic motivation and autonomous forms of extrinsic motivation (extrinsic motivation for short hereafter). Intrinsic motivation refers to involvement in activities for their inherent enjoyment and interests (Ryan & Deci, 2000). Extrinsic motivation refers to involvement in activities that an individual identifies with or values (Ryan & Deci, 2000). Empirically, both intrinsic and extrinsic motivations are consistently positively associated with overall academic achievement as well as achievement in math (Hossein Sabzevari, 2024; Howard et al., 2021; Kriegbaum et al., 2018). Importantly, students with higher intrinsic and extrinsic motivations are academically more engaged, more resilient during academic challenges, and are less likely to avoid learning (Howard et al., 2021; Jiang et al., 2018; Wu & Fan, 2017), which contribute to explaining their higher academic performance (Buzzai et al., 2021; Froiland & Worrell, 2016; Hofverberg et al., 2022; Jang et al., 2012). Within the math domain, a previous study reported that middle and high school students who reported a combination of high MA and high math motivation demonstrated the highest level of effort in afterschool math learning among all students (Wang et al., 2018). This finding points to the possibility that a high level of math motivation may foster an approach-oriented learning strategy that mitigates the MA-induced avoidance pattern. As such, it is possible that both intrinsic and extrinsic motivation may mitigate performance deficits among students with high MA by modulating avoidance during math problem-solving.

In terms of the operationalization of emotion regulation and motivation, both constructs are most commonly measured using self-reports (Fulmer & Frijters, 2009; Willner et al., 2022). Self-reported questionnaires are easy to administer, and when well designed, are highly internally consistent and specific in construct definition (Fulmer & Frijters, 2009). This type of measure provides the most direct insight into students' conscious, subjective emotional and motivational experiences, and are ideal measures of trait level attributes. In contrast, physiological signals that reflect underlying psychological processes offer a valuable means of examining how emotion regulation and motivation fluctuate moment to moment at a state level, as they are continuous, objective, and non-interruptive. Toward this end, there is a rich psychophysiological literature that investigates central and peripheral physiological changes associated with various emotional and motivational states during laboratory tasks (Albinet et al., 2024; Balzarotti et al., 2017; Beauchaine, 2015; Kelsey, 2012; Porges, 2007; Smith et al., 2020; Thayer & Lane, 2000). Relevant to the current discussion are two cardiac parameters, hfHRV and initial systolic time interval (i.e., RZ). As discussed below, these two autonomic measures effectively complement self-report questionnaires, as they are theoretically and empirically tied to emotion regulation and motivation processes that unfold throughout the course of a task. As such, they are respectively used as physiological correlates of state emotion regulation and motivation in the present study.

hfHRV refers to the variation in the time interval between heartbeats corresponding to the respiratory cycle and measures the influence of the parasympathetic nervous system on heart rate through the vagus nerve (Berntson et al., 1997; Porges, 2007). The vagus nerve functions as a brake to inhibit firing of pacemaker cells in the sinoatrial node, thus supporting resting states that conserve energy and enhance growth and restoration (Porges, 2007; Thayer & Lane, 2009). Rapid vagal withdrawal occurs in response to environmental demands (e.g., stress) to increase metabolic output needed to deal with mental and physical challenges (Porges, 2007). The withdrawal versus engagement of vagal control is regulated by the central autonomic network that functions to control visceromotor, neuroendocrine, and behavioral responses critical for emotion regulation and goal-directed behaviors (Thayer et al., 2012). As such, hfHRV is argued to provide a peripheral index of the integration of the brain mechanisms that underlie effective emotion regulation (Beauchaine, 2015; Thayer et al., 2012). Numerous studies report that emotion regulation effort, especially reappraisal, evokes increases in hfHRV (Butler et al., 2006; Segerstrom & Nes, 2007; Smith et al., 2020; Thayer et al., 2012). Finally, increases in hfHRV in emotion regulation tasks are correlated with concurrent increases in neural activities in brain areas critical for emotion regulation (e.g., medial prefrontal cortex; Lane et al., 2009). These findings point to hfHRV increases as a physiological correlate of state emotion regulation efforts, such as reappraisal (Beauchaine, 2015; Thayer & Lane, 2000).

Research on mental effort emphasizes indicators of sympathetic activity on the heart, because increased cardiac sympathetic activation is required for effective mobilization of energy and resources that are needed by the mind and body to engage in active coping with situational demands (Bandler et al., 2000). RZ, refers to the time interval between the heart's peak electrical activity and its peak mechanical activity (Meijer et al., 2008). Decreases in RZ indicate increases in sympathetic cardiac activation, which can be induced by incentive tasks or tasks that require one to "do their best" (Silvia et al., 2014; Silvia et al., 2021). In addition, RZ behaves similarly to pre-ejection period (PEP; Silvia et al, 2021), which is the most used measure of sympathetic contractility in mental effort research. Numerous studies have shown that decreases in PEP (i.e., increased cardiac contractility) primarily correlate with approach-oriented motivation and effortful coping strategies in challenging situations (Albinet et al., 2024; Brenner et al., 2005; Kelsey, 2012; Mazeres et al., 2021; Richter, 2012). More drastic decreases in PEP are observed in more difficult task conditions that require more mental effort as well as in more rewarding conditions that are more motivating (Albinet et al., 2024; Kelsey, 2012; Richter, 2012). In addition, several recent studies reported that individuals with higher achievement motivation show more pronounced decreases in PEP during arithmetic and other cognitive tasks, particularly when tasks are challenging (Mazeres et al., 2019; Mazeres et al., 2021). Overall, the literature converges to show that PEP is a valid physiological correlate of mental effort mobilization that indicates the degree of state motivation and engagement during cognitive tasks (Albinet et al., 2024; Kelsey, 2012). Given that RZ behaves similarly as PEP, but is psychometrically more reliable than PEP (Meijer et al., 2008; Silvia et al., 2021; van Eijnatten et al., 2014), RZ has emerged as an indicator of sympathetically mediated mental effort during cognitive tasks in more recent studies (Framorando et al., 2021; Silvia et al., 2021).

The Present Study

The present study aims to investigate the roles of emotion regulation and motivation in the heterogeneous association between MA, attentional pattern, and performance outcomes in a math problem-solving task. The study is designed to address the three primary gaps in this literature as reviewed above. First, it is unclear whether these mechanisms are effective in regulating the impact of MA among younger students, particularly among elementary and middle school students. The present study included a sample of 3rd to 7th graders.

Second, although previous studies elucidate emotion regulation and motivation as potential moderators in the association between MA and math performance (Lyons & Beilock, 2012a; Wang et al., 2015), it is unclear whether these regulatory mechanisms mitigate math performance deficits by modulating the attentional interference and avoidance tendencies among students with high MA. The present study aimed to bridge this important gap by utilizing eye-tracking measures in a math problem-solving task that allows for the differentiation between attentional interference and avoidance during problem-solving. Additionally, these eye-tracking measures allow for an investigation of the cognitive and behavioral processes in the moment of problem solving beyond the traditional operationalization of avoidance as course/career choices (Lau et al., 2024).

In this math problem-solving task, students verify the accuracy of a series of arithmetic equations (e.g., 33 – 3 = 30) within a designated time limit. Each equation is presented along with either a task-relevant distractor (a rotating countdown clock) or task-irrelevant distractor (a rotating star). Our previous work has shown that students with higher MA allocated more overt attention to both types of distractors, indicating that the distractors induced attentional interference during math problem-solving among students with high MA (Li et al., 2023). Two eye-tracking measures were chosen in the present study to capture overt attention indicative of attentional interference and avoidance: fixation count and run count[1]. Fixation count in an area of interest (e.g., an equation or a distractor) is the total number of fixations on that area, which is a measure of the overall level of overt attention allocated to that area. Run count in an area refers to the number of times gaze enters that area from other areas. Therefore, a higher fixation count and a higher run count in the distractor area both capture a higher level of attentional interference during problem-solving. A higher fixation count in the equation area can indicate less avoidance (i.e., one does not avoid looking at the equation)[2]. However, a viable alternative interpretation of a higher fixation count in the equation area is less efficient problem-solving (i.e., one needs more time to process the task information). Given that math problem-solving efficiency is dependent on math abilities, the impact of problem-solving efficiency on fixation count in the equation area can be minimized by controlling for students' math achievement levels in the analysis. Overall,

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[1] We also analyzed dwell time (i.e., cumulative duration of fixations) in both the distractor and equation areas. Results are the same as the those obtained using fixation count.

[2] We did not examine run count in the equation area because it does not distinguish attentional interference from avoidance. A run count in the equation area measures the number of times gaze is returned to the equation area from the distractor and other undefined areas. Although a higher run count in the equation area can indicate less avoidance, it also indicates the extent to which continuous attention to the equation is disrupted by repeated visits to task-irrelevant areas.

these eye-tracking measures allow for inferences of avoidance and attentional interference during math problem-solving. We investigated their associations with students' MA as well as the degree to which emotion regulation and motivation mitigate these associations.

Finally, alternative operationalizations of emotion regulation and motivation are needed to build a stronger evidence base. In the present study, we operationalized emotion regulation and motivation in two different ways. We first measured trait level reappraisal and motivation using self-reported questionnaires. In addition, we measured hfHRV and RZ during the math task to respectively gauge state level emotion regulation and motivation employed during math problem-solving.

In summary, the present study investigated trait level and physiological correlates of state level emotion regulation and motivation as moderators in the associations between MA, attention distribution patterns, and performance outcomes in a math problem-solving task in a sample of 3rd to 7th graders. Based on the literature reviewed above, we provide the following hypotheses:

1. Both trait and state level emotion regulation measures would moderate the association between MA and attentional interference (i.e., fixation count and run count in the distractor area). Specifically, higher MA would be more strongly associated with more attentional interference (i.e., higher fixation count and higher run count in the distractor area) at lower levels of emotion regulation.
2. Both trait and state level motivation measures would moderate the association between MA and attention patterns indicative of avoidance (i.e., fixation count in the equation area). Specifically, higher MA would be more strongly associated with more avoidance (i.e., lower fixation count in the equation area) at lower levels of motivation.

3. There would be a stronger negative association between MA and math performance, mediated by a stronger attentional interference (i.e., higher fixation count and higher run count in the distractor area), at lower levels of trait and state level emotion regulation.
4. There would be a stronger negative association between MA and math performance, mediated by a stronger avoidance pattern (i.e., lower fixation count in the equation area), at lower levels of trait and state motivation.

Method

Participants

Two hundred and seven students (51% female) and one of their parents (81% female) were recruited from a west Texas community to participate in the initial wave of a longitudinal study. Students were 8 to 13 years old (M = 10.71; SD = 0.99) and were between 3rd and 7th grade (9% 3rd grade, 37% 4th grade, 33% 5th grade, and 20% 6th grade, and 1% 7th grade). The composition of student race was: 77% White, 8% Black, 7% Asian, 1% Native American or Alaska Native, and 6% multiracial. In addition, 38% of the students were Hispanic. In terms of parents' education levels, 10% received high school diploma or below, 54% received some college education or graduated from college, and 36% received graduate level training or completed graduate school. Regarding family annual income, 23% families had an annual income below $40,000, 49% families between $40,000 to $100,000, 25% families between $100,000 and $200,000, and 1% families above $200,000.

Procedures

Each family visited the lab to complete an initial 3-hour assessment. Consent and assent procedures were completed first. Next, each student completed a series of computerized tasks, which included the Problem Verification Task (PVT) and several executive function tasks. Only

PVT was used in the current analyses. During PVT, students' physiological activities were monitored using electrocardiography (ECG) and impedance cardiography (ICG). Their eye movements were also recorded. Prior to the computerized tasks, each student was instructed to relax and sit comfortably. They were then played a five-minute calming video of aurora when their baseline ECG and ICG were collected. After the computerized tasks, each student completed a series of standardized reading and math tests. Finally, they completed a series of surveys that included measures of their MA, math motivation, emotion regulation, and general anxiety. Each parent also completed several tasks. First, they completed the standardized reading and math tests. They then filled out a series of surveys regarding their child's learning activities, their own educational beliefs and practices, and their home environment. Finally, parents completed a series of computerized tasks. Most parent data were not used in the present study, except for their reported demographic information. The study procedure was approved by the Institution Review Board of Texas Tech University and Texas A&M University.

Measures

Math Anxiety

Students' MA was self-reported using the Mathematics Anxiety Scale for Children (Chiu & Henry, 1990), which contains 22 items. Students rated how anxious they felt in various math-related situations, such as when they take a math test, learn new math materials, and solve math problems. Each item was rated on a 4-point scale (1 = *Not nervous* to 4 = *Very very nervous*). A scale score was created by taking an average of all the item scores, with a higher score representing a higher level of MA. This scale had a Cronbach's alpha of .92.

Emotion Regulation

Students' emotion regulation was self-reported using the Emotion Regulation Questionnaire for Children and Adolescents (Gullone & Taffe, 2012). There are 10 items on this scale, with each item depicting a strategy that people may use to regulate their emotions. Among these, six items described reappraisal strategies. Students rated the degree to which they use each strategy on a 5-point scale (1 = *strongly disagree* to 5 = *strongly agree*). Sample items are "I control my feelings about things by changing the ways I think about them". A reappraisal subscale score was created by taking an average of the six item scores, with a higher score indicating more use of reappraisal strategies. The internal consistency reliability was acceptable, with Cronbach's alpha being .77.

Math Motivation

Students self-reported their math motivation using a modified version of the Fennema-Sherman Mathematics Attitude Scales (Fennema & Sherman, 1976). Four items were used to measure extrinsic motivation: "I study math because I know how useful it is", "Knowing math will help me earn a living", "Math is a worthwhile and necessary subject", and "I will use math in many ways as an adult". Four items were used to measure intrinsic motivation: "Math is enjoyable and stimulating to me", "I enjoy reading about math", "I like math", and "I am interested in the things I learned in math". Students provided their responses on a 5-point scale (1 = *strongly disagree* to 5 = *strongly agree*). An extrinsic motivation scale score and an intrinsic motivation scale score were calculated by taking an average of their respective item scores, with higher scores indicating higher extrinsic and intrinsic motivation, respectively. Cronbach's alpha was .77 for extrinsic motivation and .90 for intrinsic motivation.

PVT Efficiency

Students completed a series of mental arithmetic problems in PVT (Figure 1; adapted from Murphy & Mazzocco, 2008). They were given 10 seconds (s) to indicate, by pressing a key, whether each equation (e.g., 33 – 3 = 10) was correct or incorrect. They were instructed to provide their responses as accurately and as quickly as possible. A total of 2 practice and 132 test arithmetic problems were presented in two blocks, which included addition and subtraction problems (up to three-digit integers) as well as multiplication and division problems (up to two-digit integers). The task took 10 – 20 minutes to complete, depending on each student's speed. In one block, each equation was presented along with a circular countdown timer that indicated the amount of time left for each problem at a given moment. In the other block, each equation was presented along with a rotating star that was irrelevant to the task. According to ACT, anxiety does not directly affect how accurately one performs, but it decreases the efficiency required to reach the same level of accuracy as those who are not anxious (Eysenck et al., 2007). As such, each student's efficiency score was used as the indicator of performance in this study, which was calculated using the overall task accuracy (i.e., percent of correctly solved items) divided by average reaction time[3]. This performance indicator captures both the speed and accuracy aspects of performance and takes into consideration speed-accuracy trade-off.

Eye-Tracking During PVT

The PVT stimuli were presented on a 24-inch monitor with a resolution of 1920 by 1080 pixels. Font sizes for the stimuli were: Cambria Math 65 for the equation, 172.8 by 140.4 pixels for the timer, and 192 by 162 pixels for the rotating star. The distractor was placed either above or below the equation, with the exact position being randomized across trials. A central fixation

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[3] Analyses were done separately for the two blocks and results remain consistent across blocks. As such, we reported results from the two blocks combined.

point in font Consolas 45 was presented for 500 or 800ms to recenter gaze attention between trials.

During PVT, students' eye movement were recorded using an EyeLink 1000 Plus eye tracker (SR Research, 2016). Eye movements were sampled at 1000 Hz in a remote mode. Students' eyes were aligned with the top quarter of the monitor and distanced from the monitor by approximately 106 to 111 cm. Prior to the task, a 13-point calibration and validation procedure were carried out to align the output against the spatial position on the monitor. The acceptable spatial error was set at 0.5° of visual angle or below for the average error and 1° of visual angle or below for the maximum error. Each student's right eye was tracked by default. However, when there were technical issues tracking the right eye, the left eye was tracked instead (n = 29).

Data Viewer (SR Research, 2016) was used to process the eye movement data. We created two interest areas (IAs) for each trial, one for the equation and one for the distractor. The sizes of the IA for the equation varied across trials as a function of the length of the equation. Each IA was tight against each equation. The IAs for the distractors were of the same sizes as the distractors. We investigated three eye movement behaviors. The first is fixation count, or the total number of fixations, in the distractor IA. The second is fixation count in the equation IA. The third is run count in the distractor IA, which is defined as the number of times gaze entered the distractor IA from the equation IA. A summary score was created for each eye movement behavior by taking an average of the corresponding scores across all 132 trials.

Physiological Correlates of Emotion Regulation and Motivation: ECG and ICG During PVT

ECG and ICG data were collected during baseline and PVT using the Mindware Bionex ECG and ICG modules and the BioLab Acquisition Software v3.0 (MindWare Technologies

LTD, 2011a). ECG was measured by placing three electrodes on the thorax using modified lead II alignment (Sterm et al., 2001). ICG was collected by placing four electrodes, one on the jugular notch, one below the sternum, one on the lower back, and one on the back of the neck (Sherwood et al., 1990). Signals were sampled at 1000Hz.

The Heart Rate Variability Analysis Software (MindWare Technologies LTD, 2011b) and Kubios (Tarvainen et al., 2021) were used to derive the hfHRV scores. ECG signals were processed to remove or correct artifacts in accordance with the MindWare Heart Rate Variability Training Guide (MindWare Technologie LTD, n.d.a). Interbeat intervals (IBIs; distance between two consecutive R-spikes) were derived from ECG and then analyzed with autoregressive modeling to obtain the spectral power in the 0.20 to 0.50 Hz high-frequency band (Shader et al., 2018; Wallis et al., 2005). The actual respiration rate ranged from 0.21Hz to 0.40Hz during baseline, and from 0.25Hz to 0.44Hz during PVT. hfHRV was derived for the baseline and each block of PVT. An average PVT hfHRV was calculated by taking an average of the scores from each block. In addition, heart rate (HR) during baseline was obtained and included in the analyses as a covariate.

The RZ interval was obtained using the Impedance Cardiography Analysis Software (MindWare Technologies LTD, 2011c). Processing of the ICG data was in accordance with the MindWare Impedance Cardiography Training Guide (MindWare Technologie LTD, n.d.b). RZ interval was measured by the time in milliseconds between the R and Z points on the ECG and ICG waves. Ensemble averages were formed for the entire baseline and for each block of PVT. An average PVT RZ was calculated by taking an average of the scores from each block.

Covariates

Student Sex. Student sex was coded such that 1 = *male* and 2 = *female*.

Student Grade. Students self-reported their grade level, which ranged from 3^{rd} to 7^{th} grade.

General anxiety. Students reported their general anxiety using six items from the Spence Children's Anxiety Scale (Spence, 1997). Students rated how often they experienced various anxious feelings on a 4-point scale (1 = *Never* to 4 = *Always*). A sample item is "When I have a problem, I feel shaky". A scale score was created by taking an average of the item scores, with higher scores indicating more general anxiety. This scale has a Cronbach's alpha of .82.

Math achievement. Students' math achievement was assessed using the Mathematics Cluster, including the Applied Problem and Calculation subtests, from the Woodcock-Johnson IV Tests of Achievement (Schrank et al., 2014). For the Applied Problem subtest, students listened to each problem, identified the appropriate math procedures, and performed the calculations to solve each applied math word problem. For the Calculation subtest, students solved a series of increasingly difficult arithmetic, geometric, trigonometric, logarithmic, and calculus problems. There was a total of 56 items for the Applied Problem subtest and 57 items for the Calculation subtest. Each student may see a different number of items depending on their individual basal and ceiling. The internal consistency reliability was .86 and .89 for Applied Problem and Calculation, respectively. The cluster W score was used in the analysis, with a higher score indicating higher math achievement.

Statistical Analysis

Data cleaning and descriptive statistics were done in IBM SPSS v29.0 (IBM Corp, 2023). Moderation analyses and moderated mediation analyses were conducted in Mplus v8.11 (Muthén & Muthén, 1998–2017).

Figure 2a presents the model that investigated the effects of the interactions between MA and trait measures of emotion regulation (i.e., reappraisal) and motivation (i.e., intrinsic motivation and extrinsic motivation) on the three indicators of the attention distribution patterns during PVT (Model 1). Students' sex, grade, general anxiety, and math achievement were included in this model as covariates. General anxiety was included as a covariate to ensure that any effect of MA is attributable to anxiety specific to the math domain, not to general anxiety. In addition, differences in students' math abilities may impact their attention distribution pattern during PVT. For example, students with higher math abilities may be more efficient and spend less time fixating on the equation IA. Therefore, students' math achievement was included as a covariate in the model to control for its potential impact on attention distribution.

Figure 2b presents the model that investigated the effects of the interactions between MA and physiological correlates of emotion regulation and motivation (i.e., PVT hfHRV and PVT RZ) on the three indicators of the attention distribution pattern during PVT (Model 2). To conceptualize physiological changes associated with emotion regulation and motivation during PVT, we investigated hfHRV and RZ during PVT as predictors while controlling for tonic hfHRV and RZ during baseline. As such, in addition to the covariates included in Model 1, baseline HR, baseline hfHRV, and baseline RZ were also included as covariates in Model 2. In both Model 1 and Model 2, parameters were estimated using the maximum likelihood estimator with robust standard errors.

Results from Model 1 and Model 2 were used to inform the construction of the moderated mediation models. The primary goal of the moderated mediation models was to investigate the strength of MA's indirect effect on PVT efficiency that was mediated by attentional interference and avoidance at different levels of trait and state emotion regulation and motivation. As such, a predictor would only be retained in these moderated mediation models if they had significant main or interaction effects in Models 1 and 2. Parameters in the moderated mediation models were estimated using the maximum likelihood estimator. The corresponding standard error and 95% bias-corrected bootstrap confidence interval for each parameter estimate were obtained from 5,000 bootstrapping draws.

Data cleaning showed that 18 participants did not have eye movement data, and 11 participants did not have physiology data due to technical issues during data collection. An addition of three participants did not have valid eye movement data as their attention to the equation IA was minimal during PVT (i.e., defined as students who did not look at the equation IA at all in more than 20% of the trials). Finally, one student did not complete the standardized math achievement tests, and 5 students did not complete at least one of the surveys used in the present analyses. Missing data analyses suggested that the missing pattern was not associated with student sex, grade level, or MA. Students with higher math achievement had less missingness ($\beta = -0.27$, $p < .001$). Descriptive analyses were conducted using all available data for each variable. Full information maximum likelihood (FIML) was used to handle missing data in the correlation analyses, moderation models, and moderated mediation models. As students' math achievement was included in the model as a covariate, potential bias generated by missingness associated with students' math achievement was accounted for using FIML. The final effective sample sizes for Model 1 and Model 2 were respectively 182 and 175. The final effective sample sizes were respectively 201 and 187 for the trait level and state level moderated mediation models.

Transparency and Openness

We reported all manipulations and measures relevant to the present study, as well as criteria for data exclusions. De-identified data and analysis scripts are available on OSF (Wang, 2025). The present analyses were not pre-registered.

Results

Descriptive statistics for and correlations between the main study variables are respectively shown in Table 1 and Table 2. On average, students reported a modest level of MA and general anxiety, a moderate level of extrinsic and intrinsic motivation, as well as a moderate level of use of reappraisal. During PVT, students distributed more attention to the equation area than to the distractor area, as indicated by a higher fixation count in the equation IA than the distractor IA. The mean hfHRV and RZ were both slightly lower during PVT than the baseline, which indicated cardiac parasympathetic suppression and sympathetic activation from baseline to PVT. Finally, all variables were widely distributed across their respective scales.

Results from the two models investigating the interactions between MA and emotion regulation and between MA and motivation on attention distribution during PVT are presented in Tables 3 and 4. These models were saturated for which the model fit cannot be estimated. The model that investigated the interactions between MA and trait level emotion regulation and motivation (Model 1; Table 3) included four covariates, students' grade, sex, math achievement, and general anxiety. After controlling for the effects of the covariates, the main effects of MA, reappraisal, intrinsic motivation, and extrinsic motivation were not significant. In terms of the interaction effects, MA did not interact with intrinsic or extrinsic motivation to predict attention. MA interacted with reappraisal to predict fixation count and run count in the distractor IA.

To further interpret these interaction effects, post-hoc analyses were conducted to investigate the effects of MA at different levels of reappraisal (i.e., very low = -2sd below the mean, low = -1sd below the mean, moderate = the mean, high = 1sd above the mean, and very high = 2sd above the mean). These results are presented in Figure 3. First, MA did not predict fixation count in the distractor IA at moderate or high levels of reappraisal. At low and very low levels of appraisal, higher MA predicted more fixations in the distractor IA. Similarly, higher MA predicted more runs to the distractor IA at very low levels of reappraisal. At high levels of reappraisal, higher MA was associated with fewer runs to the distractor IA. These findings revealed that the association between MA and attentional interference (i.e., heightened attention to the distractor) was only observed among students who reported low levels of reappraisal.

The model that investigated the interaction between MA and physiological correlates of emotion regulation and motivation (Model 2; Table 4) included seven covariates, students' grade, sex, math achievement, general anxiety, baseline HR, baseline hfHRV, and baseline RZ. After controlling for the effects of the covariates, none of the main effects of MA, PVT hfHRV, or PVT RZ were significant. In terms of the interactions, PVT hfHRV did not interact with MA to predict attention. MA interacted with PVT RZ to predict fixation count in the equation IA.

To further interpret this interaction effect, post-hoc analyses were conducted to investigate the effects of MA at different levels of PVT RZ (i.e., very low = -2sd below the mean, low = -1sd below the mean, moderate = the mean, high = 1sd above the mean, and very high = 2sd above the mean; Figure 3). At low levels of PVT RZ, students with higher MA had more fixations in the equation IA. In contrast, at high levels of PVT RZ, students with higher MA had fewer fixations in the equation IA. These findings indicated that for students who exhibited a physiological pattern of high motivation (i.e., low PVT RZ), higher MA was associated with less avoidance of the equation IA, as indicated by their heightened attention to the equation IA. In contrast, for students who exhibited a physiological pattern of low motivation (i.e., high PVT RZ), higher MA was associated with more avoidance of the equation IA.

Next, three moderated mediation models (Models 3, 4, and 5) were conducted to further investigate whether the different attention patterns at different levels of reappraisal and PVT RZ contributed to explaining the heterogeneous association between MA and math performance. Model 3 tested whether reappraisal moderated the indirect effect of MA on PVT efficiency via fixation count in the distractor IA (Figure 4a). Model 4 tested whether reappraisal moderated the indirect effect of MA on PVT efficiency via run count in the distractor IA (Figure 4b). Model 5 tested whether PVT RZ moderated the indirect effect of MA on PVT efficiency via fixation count in the equation IA (Figure 4c). Covariates for the trait level models (Models 4 and 5) included students' grade, sex, math achievement, and general anxiety. Additional covariates for the state level model (Model 6) included baseline HR and baseline RZ. Models 3 and 4 were saturated for which the model fit cannot be estimated. Model 5 did not converge initially. Inspection of the model resulted in the removal of the predictive path from math achievement to fixation count in the equation IA. The removal of this path did not affect estimates of the other paths in the model, as math achievement did not emerge as a significant predictor of fixation count in the equation IA in Models 1 or 2. The removal of this path resulted in 1 degree of freedom for Model 5, which fit the data well, χ^2 (*df*) = 0.15 (1), *p* = 0.70. Results for Models 3 – 5 are shown in Table 5.

Controlling for the effects of all the covariates, MA did not directly or indirectly predict PVT efficiency in any of the three models. In addition, MA did not interact with reappraisal or PVT RZ to directly predict PVT efficiency. However, MA interacted with both reappraisal and

PVT RZ to indirectly predict PVT efficiency in all three models. To further investigate these moderated mediation effects, post-hoc analyses were conducted to examine the indirect effect of MA on PVT efficiency at different levels of reappraisal and PVT RZ (Figures 5, 6, and 7).

Post-hoc results for Model 3 (Figure 5) indicated that higher MA predicted lower PVT efficiency via predicting higher fixation count in the distractor IA, but this indirect effect was observed only at low levels of reappraisal. At high levels of reappraisal, MA did not directly or indirectly predict PVT efficiency. Post-hoc analyses for Model 4 (Figure 6) indicated that higher MA predicted lower PVT efficiency via higher run count in the distractor IA, but this negative indirect effect was observed only at very low levels of reappraisal. Interestingly, at high levels of reappraisal, higher MA predicted higher PVT efficiency via predicting lower run count in the distractor IA. Finally, post-hoc results from Model 5 (Figure 7) indicated that MA did not directly or indirectly predict PVT efficiency via fixation count in the equation IA at high or low levels of PVT RZ. The model that tested the indirect effect of MA at very high and very low levels of PVT RZ did not converge. Together, these findings suggest that the use of reappraisal as an emotion regulation strategy contributed to explaining the heterogeneous association between MA and PVT performance, primarily because students with high MA who used reappraisal demonstrated less attentional interference during problem-solving.

Discussion

The present study investigated the roles of emotion regulation and motivation in modulating attentional interference and avoidance as possible mechanisms underlying the heterogenous association between MA and math performance reported in previous studies (Lyons & Beilock, 2012a; Tsui & Mazzocco, 2006; Wang et al., 2015). Before discussing the specific findings, it is important to highlight several methodological strengths of the current study, which address significant gaps in the current literature. First, the current study fills a developmental gap in the literature by utilizing a sample of 3rd to 7th grade students. Second, we investigated attentional processes during problem-solving, in addition to examining math performance as the outcome variable. This approach provides deeper insights into the cognitive mechanisms that may distinguish students whose performance remains unaffected from those whose performance is negatively impacted by MA. Finally, both emotion regulation and motivation were operationalized at the trait level using self-reported surveys and at the state level using physiological indicators. Although the various operationalizations did not converge to yield consistent findings, they provided nuanced insights into the complex interplay among the state and trait level emotional, motivational, and cognitive processes that contribute to the diverse performance patterns among students with high MA.

The Interaction Between MA and Emotion Regulation

We first hypothesized that emotion regulation would moderate the association between MA and attentional interference, such that better emotion regulation would mitigate the association between MA and attentional interference. In addition, we hypothesized that better emotion regulation would attenuate the association between MA and math performance via mitigating attentional interference. Both hypotheses were partially supported.

The interaction between MA and the physiological correlate of state emotion regulation (i.e., PVT hfHRV) did not predict attention during PVT, which does not support our hypothesis. One possible explanation to the lack of support for our hypothesis is that the timing of hfHRV measurement may not have aligned with the moment when emotion regulation is the most effective. According to the process model of emotion regulation (Gross, 1998), reappraisal involves modifying the meaning of an emotion-eliciting situation, which typically occurs early in the emotion generative process before intense emotions are experienced. Thus, it is possible that state emotion regulation measured in anticipation of, rather than during, math tasks may emerge as a more effective moderator in the association between MA and math performance. Supporting this notion, previous research reported that individuals with high MA felt the most threatened and anxious in anticipation of an upcoming math task, rather than during the math task (Lyons & Beilock, 2012b). This finding highlights the importance for effective regulation of anxiety during the time leading up to the math task. Furthermore, brain regions associated with emotion regulation were found to become more active in anticipation of an upcoming math task among some individuals with high MA, and such activities were effective at mitigating their math performance deficits (Lyons & Beilock, 2012a). Therefore, future research would benefit from designs that allow for the measurement of state emotion regulation during the preparatory phase before a math task.

The interaction between MA and trait level reappraisal significantly predicted several attention measures, such that high MA was associated with attentional interference – characterized by greater focus on the distractor and more frequent shifts between the distractor and the equation – only among students who reported low levels of reappraisal. More importantly, MA only negatively predicted performance efficiency at lower levels of reappraisal, an effect attributable to attentional interference. Continuous and uninterrupted attention is essential for efficient mental arithmetic. Based on ACT (Eysenck et al., 2007), it has been suggested that students with high MA underperform relative to their counterparts with low MA partly due to attentional interference during problem-solving (Carey et al., 2016; Li et al., 2023; Remirez et al., 2018). This finding not only corroborates previous research on the beneficial roles of effective emotion regulation in breaking the MA – math performance link (Lyons &

Beilock, 2012a) but also underscores the effectiveness of reappraisal in helping students with high MA to avoid engaging with distracting stimuli during math problem-solving. This result aligns with the broader literature that reported positive effects of reappraisal on reducing threat-related attentional interference (Gross, 2015; Jamieson et al., 2016; Kim et al., 2016; Zhu et al., 2021).

Similar to the present investigation, a recent study examined the extent to which state MA accounted for the effect of trait MA on math performance, as well as the degree to which reappraisal and tonic hfHRV moderated these predictive effects (Daker et al., 2023). They found that tonic hfHRV, not trait level reappraisal, mitigated the MA experienced in the moment of math problem-solving among those with high trait MA. However, neither hfHRV nor reappraisal contributed to explaining the overall heterogeneous association between MA and math performance (Daker et al., 2023). The use of similar moderators but different mediators (attention pattern in our analysis vs. state MA in Daker's study) between these two studies provide several critical insights into the mechanisms underlying the heterogeneous MA – math performance association. First, both the emotional experience (i.e., state MA) and cognitive strategies (i.e., attentional pattern) during math problem-solving contribute to explaining why students with high MA underperform in math tasks. Second, reappraisal as an emotion regulation strategy does not mitigate performance deficits by alleviating negative emotions per se; rather, it does so by redirecting attention away from task-irrelevant information (e.g., distractor or perhaps negative thoughts). In contrast, physiological correlates of emotion regulation, such as hfHRV, may better capture processes that are responsible for the reduction of negative emotional experiences (i.e., state MA).

The Interaction Between MA and Motivation

We also hypothesized that both trait and state level motivation would moderate the association between MA and avoidance, such that MA would be more strongly positively associated with avoidance at lower levels of motivation. In addition, we hypothesized that higher motivation would mitigate the association between MA and math performance via mitigating avoidance of math problems. The former hypothesis was partially supported, while the latter hypothesis was not supported.

The interaction between trait level motivation (both internal and external) and MA did not predict attention during PVT, which did not support our hypothesis. Previous studies have consistently shown that students with higher levels of trait motivation are more engaged and less avoidant in learning (Howard et al., 2021; Jiang et al., 2018; Wu & Fan, 2017). Therefore, it is surprising that these trait level motivation measures did not moderate the avoidance patterns among students with high MA in the current study. One possible explanation is that these trait level motivations may not have been active during the math task in the lab setting. In other words, students with high math motivations may be driven by the practical value of learning important skills or by the enjoyment of a mastery learning experience in an authentic learning environment. These motivations may not have been sufficiently activated in the lab setting of this study, where the stakes of performance are low, and the tasks have little bearing on learning. Future research would benefit from experience sampling methods to better understand the degree of alignment between trait level and state level motivation during lab tasks (Moller et al., 2023).

Supporting our hypothesis, the interaction between MA and the physiological correlate of state motivation (i.e., PVT RZ) significantly predicted attention to the equation. Specifically, avoidance of the math problems – characterized by reduced focus on the equation – was associated with MA only among students with low state motivation (i.e., high PVT RZ). In contrast, among students with high state motivation, higher MA was associated with a less avoidant attention pattern – characterized by greater focus on the equation. These findings corroborate previous research demonstrating high levels of effort and cognitive engagement among individuals with physiological patterns of high state motivation (Albinet et al., 2024; Kelsey, 2012; Silvia et al., 2021).

However, the varying avoidance patterns observed among students with different levels of state motivation did not account for the association between MA and math performance. Perhaps the detrimental impact of avoidance on math performance in students with high MA is not evident in the short-term, as is tested in the current study, but instead may emerge gradually over time, as sustained avoidance of learning and practice can negatively impact knowledge and skill acquisition (Lau et al., 2024). The current operationalization of avoidance –as temporary disengagement from the math problems – may have been insufficient to capture these cumulative effects. This interpretation aligns with the existing literature suggesting that motivation enhances performance in students with high MA, in part by reducing their avoidance in everyday learning contexts (Wang et al., 2018). As such, future research on the role of avoidance in the MA – math performance association may benefit from examining patterns of long-term avoidance in everyday learning activities.

Limitations

Several limitations should be considered when interpreting the current findings. First, the present study was conducted in a lab setting, and the extent to which these results can be generalized to authentic learning environments requires further investigation. Future research would benefit from examining the roles of emotion regulation and math motivation among students with high MA in math classrooms during learning activities or tasks with greater realworld relevance. Second, although the eye-tracking method allows for inferences regarding the attention patterns during math problem-solving, future studies should examine the replicability of the current findings using more direct and subjective measures of cognitive strategies used by students. Similarly, the physiological correlates likely captured the implicit aspects of state emotion regulation and motivation. As such, more explicit state-level measures, such as experience sampling, should be incorporated to more comprehensively investigate the interplay among emotion, motivation, and cognition during math learning and problem solving. Finally, it is possible that the administration of math tests may have influenced subsequent report of MA particularly for those high in MA. Although it has been shown that the association between MA and math performance is similar regardless of the timing of the math test or anxiety measure (Conlon et al., 2021), future studies can randomize the order of MA and math achievement measures to test this possibility among children.

Implications and Conclusions

Our findings challenge the notion that MA is uniformly debilitating. Instead, they highlight emotion regulation and motivation as potential strategies that students may employ to combat the negative impacts of MA on math performance. Trait level emotion regulation, such as a habitual use of reappraisal, helps students with high MA resist distractions and attentional interference, which in turn reduce their performance deficits in math tasks. Although motivation did not improve performance efficiency among students with high MA, state level motivation affected how these students engaged with math problems by decreasing avoidance behaviors during problem-solving. It is possible that the beneficial effect of this motivational mechanism on math performance emerges over time through the day-to-day learning and practices (Wang et al., 2018). Therefore, educational practices that aim at enhancing both emotion regulation skills and math motivation are needed to improve math performance and long-term learning outcomes for students experiencing MA. Several existing programs could be leveraged to achieve this goal. For instance, some interventions designed to promote effective regulation of MA through therapy, relaxation, reappraisal exercises, and expressive writing are found effective at reducing MA (Balt et al., 2022; Petronzi et al., 2021; Sammallahti, et al., 2023). In addition, a variety of interventions have been shown to effectively promote both intrinsic and extrinsic motivation in students, such as using novel, surprising, and personalized learning materials, as well as incorporating activities that connect learning to students' personal interests and values (Harackiewicz et al., 2016; Rosenzweig et al., 2022). Future research should aim to integrate these interventions and test their combined effectiveness at fostering adaptive learning behaviors among students with MA.

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Table 1

Descriptive Statistics for the Main Study Variables

Variable	N	% missing	Mean	Std	Min	Median	Max
General anxiety	202	2%	2.10	0.68	1.00	2.00	4.00
Math anxiety	205	1%	1.92	0.54	1.00	1.82	3.64
Reappraisal	204	1%	3.43	0.81	1.00	3.50	5.00
Extrinsic motivation	205	1%	3.77	0.89	1.00	4.00	5.00
Intrinsic motivation	205	1%	3.22	1.21	1.00	3.50	5.00
Fixation count – distractor	186	10%	0.43	0.25	0.02	0.39	1.53
Fixation count – equation	186	10%	6.91	2.52	1.52	6.80	14.18
Run count – distractor	186	10%	.48	0.25	0.00	0.50	1.13
Baseline HR	205	1%	86.62	11.49	62.50	87.43	134.81
Baseline hfHRV	205	1%	1772.09	2192.47	16.03	1000.33	15445.05
PVT hfHRV	196	5%	1291.44	1782.12	17.35	751.75	15769.64
Baseline RZ	203	2%	92.44	21.72	34.00	93.00	153.00
PVT RZ	190	8%	91.98	20.56	37.30	92.61	154.40
PVT efficiency	203	2%	0.16	0.07	0.04	0.15	0.51
Math achievement	206	1%	501.69	17.11	452.00	502.00	553.00

Note. HR = heart rate; hfHRV = high frequency heart rate variability; RZ = the RZ interval.

Table 2

Correlations Between the Main Study Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. General anxiety	--													
2. Math anxiety	.43*	--												
3. Reappraisal	.03	.01	--											
4. Extrinsic motivation	-.20*	-.28*	.23*	--										
5. Intrinsic motivation	-.23*	-.41*	.18*	.54*	--									
6. Fix count – distractor	.10	.20*	-.03	-.05	-.07	--								
7. Fix count – equation	-.11	-.05	-.06	.08	.03	.24*	--							
8. Run count – distractor	.03	.02	.02	.04	.07	.60*	.49*	--						
9. Baseline HR	.03	.09	-.02	-.09	-.10	.06	-.08	.06	--					
10. Baseline hfHRV	-.05	-.15*	.01	.04	.12	.01	.02	-.05	-.56*	--				
11. PVT hfHRV	.02	-.10	-.04	.01	.13	.06	-.04	.00	-.49*	.87*	--			
12. Baseline RZ	.12	.06	-.06	-.05	.01	-.18*	-.05	-.12	-.26*	.13	.17*	--		
13. PVT RZ	.12	.06	-.10	-.10	-.02	-.16*	-.02	-.05	-.26*	.13	.15*	.86*	--	
14. PVT efficiency	-.11	-.18*	.11	.14*	.19*	-.36*	-.35*	-.27*	.06	-.08	-.04	.07	.06	--
15. Math achievement	-.22*	-.28*	-.02	.21*	.10	-.35*	.03	-.21*	-.03	-.05	-.05	.02	-.03	.54*

Note. Fix count = Fixation count; HR = heart rate; hfHRV = high frequency heart rate variability; RZ = the RZ interval * indicates statistical significance under Type I error rate of .05.

Table 3

The Interactions Between Math Anxiety and Trait Level Emotion Regulation and Motivation Predict Attention Distribution During the Problem Verification Task (Model 1)

	Outcome		
	Fix count distractor	Fix count equation	Run count distractor
Effects of Covariates			
Grade	-0.12 (0.08) [-0.28, 0.04]	0.01 (0.09) [-0.17, 0.19]	-0.22 (0.08)* [-0.38, -0.07]
Sex (1 = *male*; 2 = *female*)	-0.19 (0.07)* [-0.31, -0.06]	0.21 (0.08) [-0.13, 0.17]	0.03 (0.07) [-0.11, 0.17]
Math achievement	-0.29 (0.07)* [-0.43, -0.15]	-0.03 (0.09) [-0.21, 0.14]	-0.13 (0.09) [-0.30, 0.04]
General anxiety	0.02 (0.07) [-0.12, 0.15]	-0.10 (0.08) [-0.26, 0.05]	0.03 (0.07) [-0.10, 0.17]
Main Effects			
Math anxiety	0.11 (0.09) [-0.06, 0.28]	-0.00 (0.09) [-0.18, 0.18]	-0.07 (0.09) [-0.24, 0.10]
Reappraisal	-0.03 (0.07) [-0.16, 0.11]	-0.05 (0.08) [-0.21, 0.11]	0.01 (0.07) [-0.12, 0.15]
Extrinsic motivation	0.09 (0.08) [-0.07, 0.25]	0.11 (0.10) [-0.09, 0.30]	0.08 (0.10) [-0.11, 0.27]
Intrinsic motivation	-0.06 (0.09) [-0.24, 0.11]	-0.05 (0.11) [-0.26, 0.17]	-0.01 (0.11) [-0.22, 0.20]
Interaction Effects			
MA x reappraisal	-0.16 (0.06)* [-0.27, -0.04]	-0.10 (0.07) [-0.25, 0.04]	-0.20 (0.06)* [-0.31, -0.09]
MA x extrinsic motivation	0.09 (0.10) [-0.11, 0.28]	-0.08 (0.08) [-0.23, 0.08]	0.02 (0.08) [-0.14, 0.18]
MA x intrinsic motivation	-0.01 (0.11) [-0.21, 0.20]	0.07 (0.08) [-0.09, 0.24]	-0.08 (0.09) [-0.26, 0.10]

Note. Numbers out of/in parentheses are standardized parameter estimates and standard errors. Numbers in brackets are 95% confidence intervals. * indicates significance under α of .05.

Table 4

The Interaction Between Math Anxiety and Physiological Correlates of Emotion Regulation and Motivation Predict Attention Distribution During the Problem Verification Task (Model 2)

	Outcome		
	Fix count distractor	Fix count equation	Run count distractor
Effects of Covariates			
Grade	-0.07 (0.08) [-0.22, 0.08]	0.03 (0.08) [-0.13, 0.19]	-0.19 (0.08)* [-0.35, -0.04]
Sex (1 = *male*; 2 = *female*)	-0.19 (0.07)* [-0.32, -0.05]	-0.01 (0.08) [-0.16, 0.14]	0.00 (0.08) [-0.15, 0.16]
Math achievement	-0.29 (0.08)* [-0.44, -0.13]	-0.05 (0.09) [-0.22, 0.11]	-0.12 (0.09) [-0.30, 0.06]
General anxiety	0.02 (0.08) [-0.14, 0.17]	-0.07 (0.08) [-0.22, 0.09]	0.04 (0.08) [-0.12, 0.19]
Baseline HR	-0.01 (0.08) [-0.16, 0.15]	-0.14 (0.10) [-0.33, 0.06]	-0.05 (0.09) [-0.22, 0.13]
Baseline hfHRV	-0.20 (.13) [-0.45, 0.06]	0.14 (0.19) [-0.23, 0.51]	-0.23 (0.17) [-0.56, 0.10]
Baseline RZ	-0.16 (.10) [-0.35, 0.03]	-0.16 (0.12) [-0.39, 0.07]	-0.28 (0.15) [-0.57, 0.01]
Main Effects			
Math anxiety	0.12 (0.10) [-0.08, 0.33]	-0.02 (0.08) [-0.16, 0.13]	-0.06 (0.08) [-0.23, 0.10]
PVT hfHRV	0.24 (0.15) [-0.06, 0.53]	-0.20 (0.17) [-0.54, 0.13]	0.14 (0.14) [-0.14, 0.42]
PVT RZ	-0.01 (0.11) [-0.23, 0.21]	0.10 (0.11) [-0.13, 0.32]	0.21 (0.13) [-0.05, 0.47]
Interaction Effects			
MA x PVT hfHRV	0.10 (0.10) [-0.11, 0.30]	0.08 (0.07) [-0.05, 0.22]	0.02 (0.08) [-0.13, 0.17]
MA x PVT RZ	-0.11 (0.08) [-0.26, 0.05]	-0.21 (0.07)* [-0.35, -0.07]	-0.12 (0.06) [-0.23, 0.01]

Note. HR = heart rate; hfHRV = high frequency heart rate variability; RZ = the RZ interval

Numbers out of/in parentheses are standardized parameter estimates and standard errors.

Numbers in brackets are 95% confidence intervals. * indicates significance under α of .05.

Table 5

Results from the Moderated Mediation Models

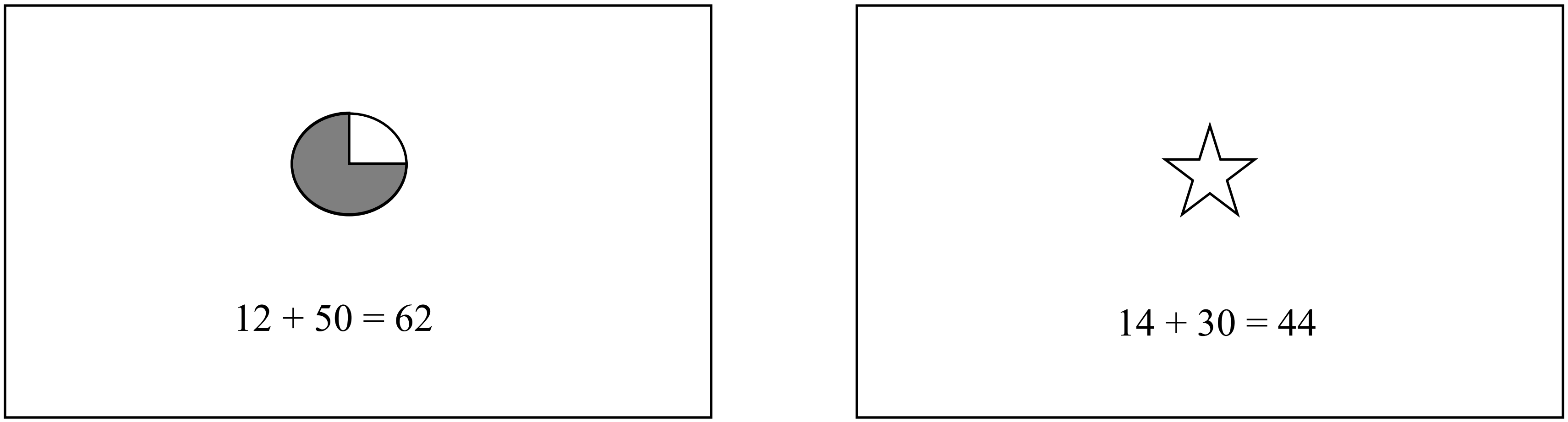
	Model 3 MA x Reappraisal (Mod) → Fixation Count in Distractor (Med) → PVT Efficiency (Out)	Model 4 MA x Reappraisal (Mod) → Run Count in Distractor (Med) → PVT Efficiency (Out)	Model 5 MA x PVT RZ (Mod) → Fixation Count in Equation (Med) → PVT Efficiency (Out)
Grade → Med	-0.12 (0.08) [-0.27, 0.04]	-0.23 (0.08)* [-0.39, -0.07]	0.02 (0.08) [-0.13, 0.17]
Sex → Med	-0.19 (0.07)* [-0.31, -0.05]	0.04 (0.07) [-0.10, 0.18]	0.003 (0.08) [-0.14, 0.15]
Math Achievement → Med	-0.28 (0.07)* [-0.41, -0.12]	-0.11 (0.09) [-0.29, 0.07]	--
General Anxiety → Med	0.01 (0.07) [-0.14, 0.15]	0.02 (0.07) [-0.12, 0.15]	-0.09 (0.08) [-0.24, 0.06]
Baseline HR → Med	--	--	-0.11 (0.09) [-0.27, 0.06]
Baseline RZ → Med	--	--	-0.20 (0.13) [-0.47, 0.06]
Grade → Out	-0.06 (0.07) [-0.18, 0.06]	-0.08 (0.07) [-0.20, 0.06]	-0.03 (0.07) [-0.15, 0.11]
Sex → Out	-0.06 (0.06) [-0.17, 0.03]	-0.01 (0.06) [-0.13, 0.10]	-0.04 (0.06) [-0.15, 0.07]
Math Achievement → Out	0.50 (0.09)* [0.32, 0.66]	0.54 (0.08)* [0.37, 0.68]	0.55 (0.08)* [0.38, 0.69]
General Anxiety → Out	0.02 (0.06) [-0.10, 0.13]	0.03 (0.06) [-0.10, 0.16]	-0.02 (0.07) [-0.16, 0.12]
Baseline HR → Out	--	--	0.09 (0.06) [-0.03, 0.22]
Baseline RZ → Out	--	--	0.01 (0.12) [-0.21, 0.26]
MA → Med	0.12 (0.08) [-0.04, 0.28]	-0.04 (0.07) [-0.18, 0.10]	0.01 (0.08) [-0.15, 0.17]
Mod → Med	-0.03 (0.07) [-0.16, 0.08]	0.04 (0.06) [-0.09, 0.16]	0.12 (0.13) [-0.14, 0.37]
MA x Mod → Med	-0.13 (0.06)*	-0.20 (0.06)*	-0.16 (0.07)*

	[-0.25, -0.004]	[-0.31, -0.09]	[-0.29, -0.02]
Med → Out	-0.21 (0.06)*	-0.20 (0.06)*	-0.34 (0.06)*
	[-0.33, -0.09]	[-0.32, -0.08]	[-0.44, -0.22]
MA → Out	-0.03 (0.08)	-0.07 (0.08)	-0.08 (0.08)
	[-0.18, 0.12]	[-0.22, 0.09]	[-0.22, 0.09]
Mod → Out	0.11 (0.06)	0.12 (0.06)*	0.13 (0.12)
	[-0.01, 0.23]	[0.002, 0.25]	[-0.12, 0.35]
MA x Mod → Out	-0.00 (0.08)	-0.02 (0.08)	0.06 (0.07)
	[-0.16, 0.15]	[-0.19, 0.14]	[-0.07, 0.19]
Indirect MA → Out	-0.03 (0.02)	0.01 (0.02)	-0.01 (0.03)
	[-0.07, 0.01]	[-0.02, 0.04]	[-0.06, 0.05]
Indirect Mod → Out	0.01 (0.02)	-0.01 (0.01)	-0.04 (0.04)
	[-0.02, 0.04]	[-0.04, 0.02]	[-0.13, 0.05]
Indirect MA x Mod → Out	0.03 (0.02)*	0.04 (0.02)*	0.05 (0.03)*
	[0.003, 0.06]	[0.01, 0.08]	[0.01, 0.11]

Note. Mod = moderator; Med = mediator; Out = outcome; HR = heart rate; hfHRV = high frequency heart rate variability; RZ = the RZ interval. Numbers out of/in parentheses are standardized parameter estimates and standard errors. Numbers in brackets are 95% bias-corrected bootstrap confidence intervals. * indicates significance under α of .05.

Figure 1

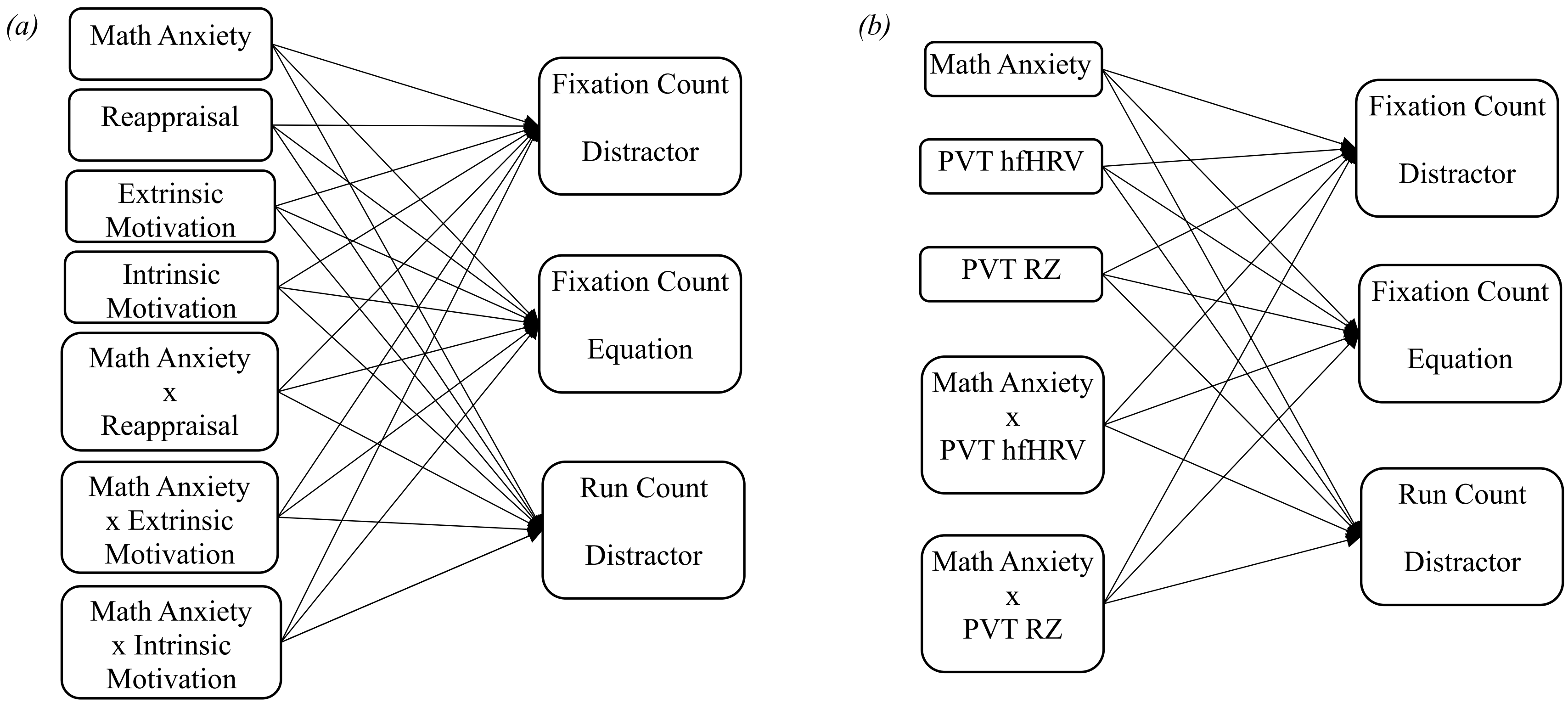
Illustration of the Problem Verification Task (PVT)



Note. In some trials, a timer appears along with the equation to indicate the amount of time left for the problem. In other trials, a rotating star irrelevant to the task appears along with the equation.

Figure 2

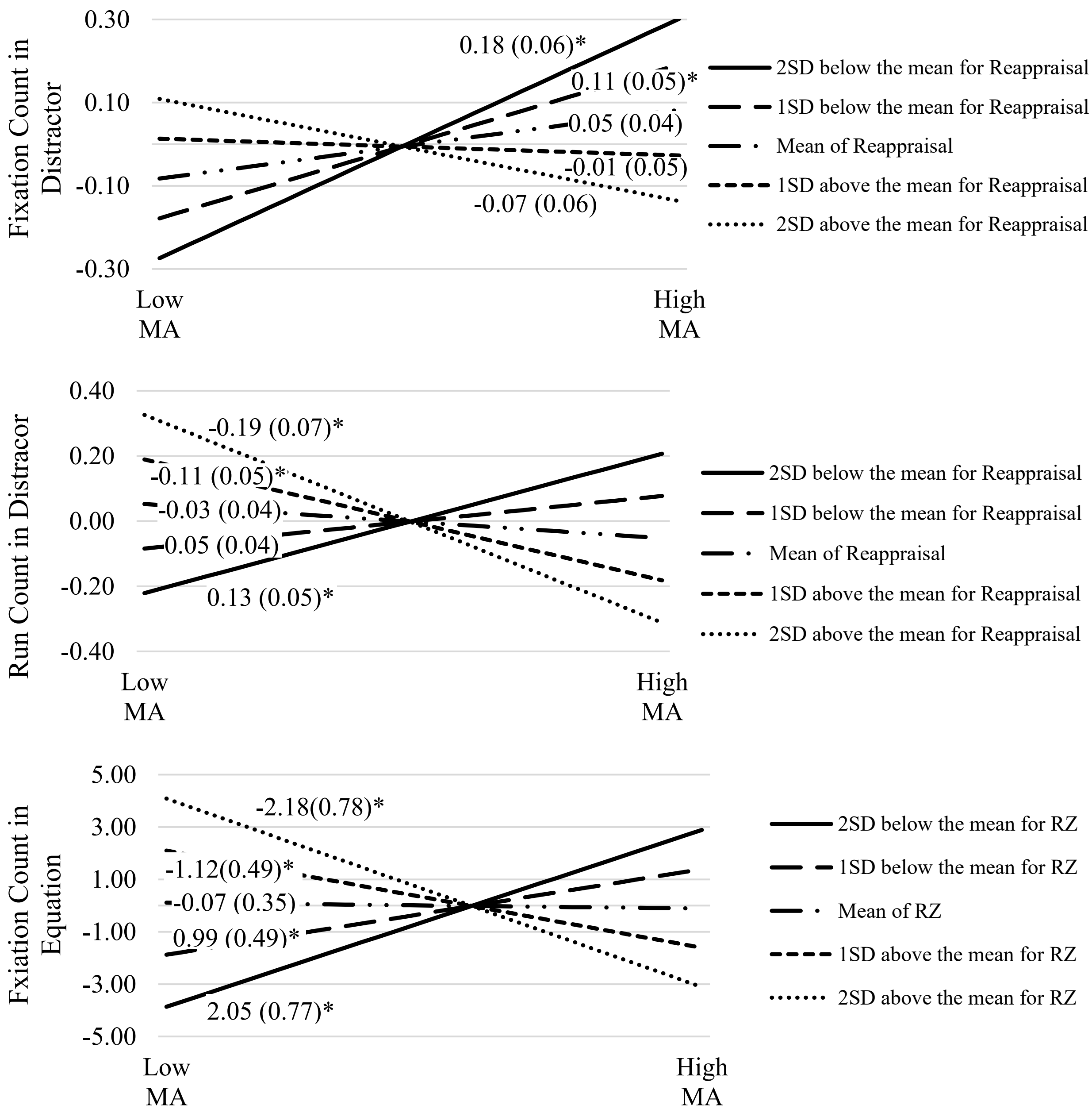
Math Anxiety Interacts with (a) Trait level Emotion Regulation and Motivation and (b) Physiological Correlates of Emotion Regulation and Motivation to Predict Attention Distribution During the Problem Verification Task



Note. Correlations between outcome variables and effects of covariates are not shown in the figure for simplicity of presentation. Covariates for the trait level model included sex, grade, general anxiety, and math achievement. Covariates for the state level model included sex, grade, general anxiety, math achievement, baseline HR, baseline hfHRV, and baseline RZ.

Figure 3

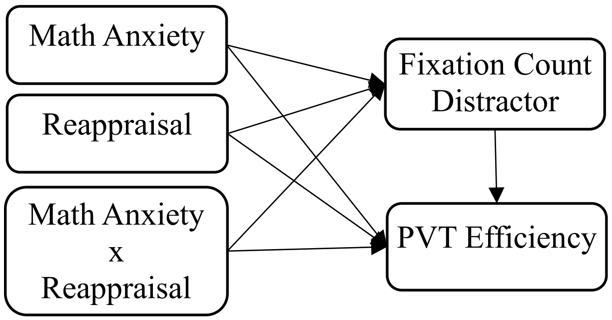
Posthoc Analyses: Effects of Math Anxiety on Attention Distribution at Different Levels of Reappraisal or PVT RZ



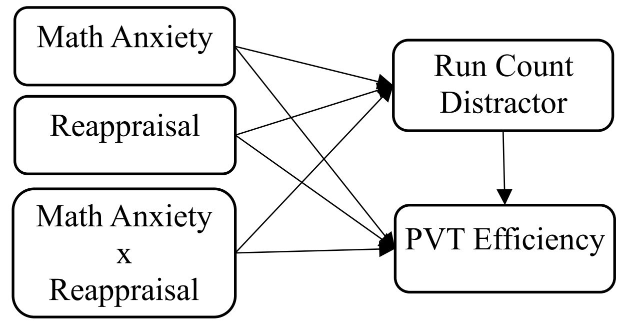
Note. Numbers out of/in parentheses are simple slopes and standard errors. * indicates significance under α of .05.

Figure 4

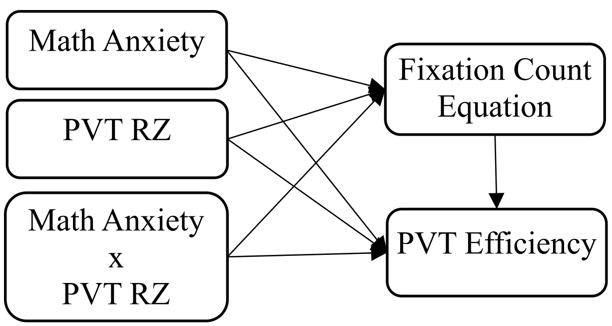
(a) The Interaction Between Math Anxiety and Reappraisal Predicts PVT Efficiency via Fixation Count in Distractor



(b) The Interaction Between Math Anxiety and Reappraisal Predicts PVT Efficiency via Run Count in Distractor



(c) The Interaction Between Math Anxiety and PVT RZ Predicts PVT Efficiency via Fixation Count in Equation.

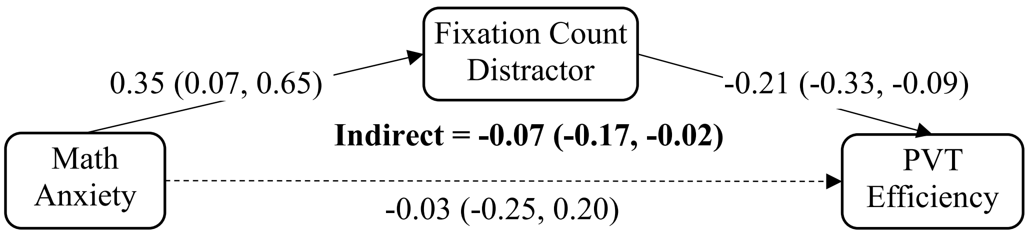


Note. Effects of covariates are not shown in the figure for simplicity of presentation. Covariates for the trait level models included sex, grade, general anxiety, and math achievement. Additional covariates for the state level model included baseline HR and baseline RZ.

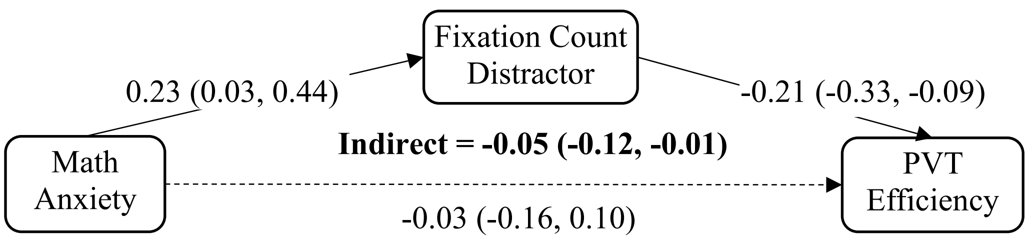
Figure 5

The Mediating Role of Fixation Count in Distractor by Levels of Reappraisal

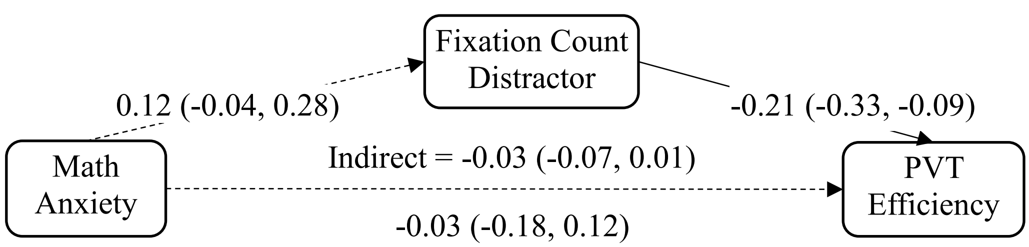
(a) At 2SD below the mean for reappraisal



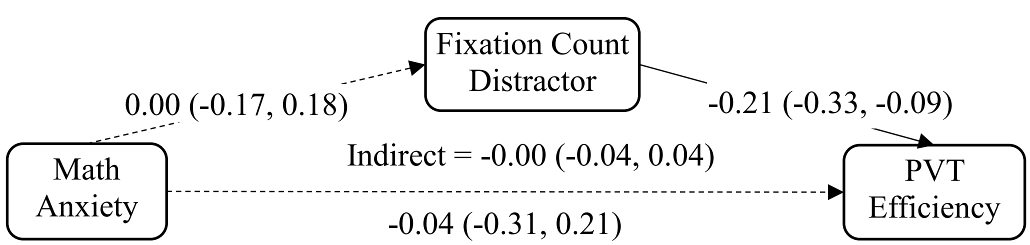
(b) At 1SD below the mean for reappraisal



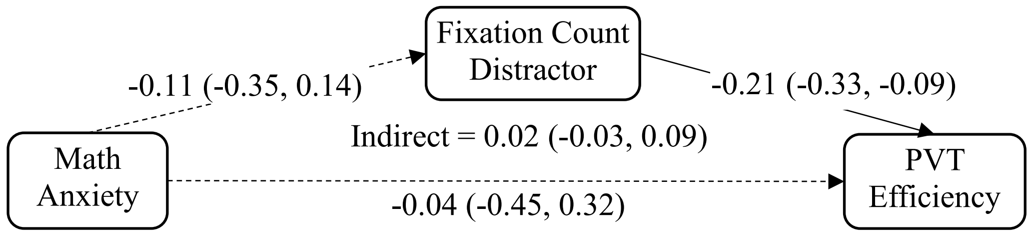
(c) At the mean of reappraisal



(d) At 1SD above the mean for reappraisal



(e) At 2SD above the mean for reappraisal

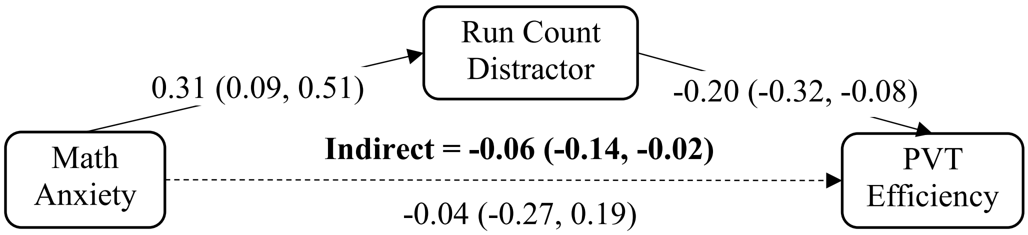


Note. Numbers shown are respectively standardized path estimates and their 95% bias-corrected bootstrap confidence intervals. Solid lines indicate significant effects and dashed lines indicate nonsignificant effects at α of .05. Significant indirect effects are in bold font.

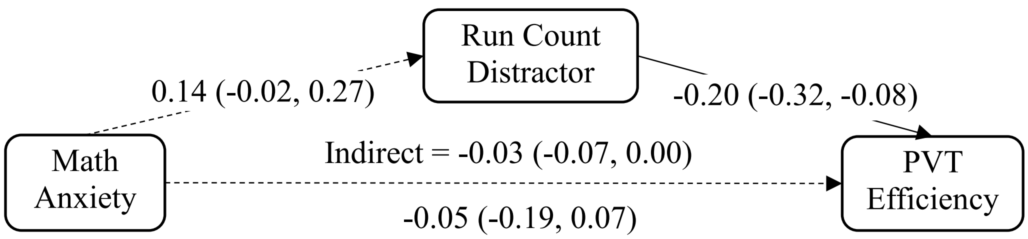
Figure 6

The Mediating Role of Run Count in Distractor by Levels of Reappraisal

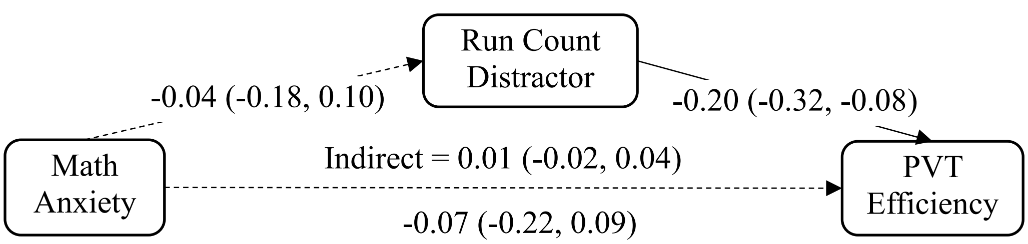
(a) At 2SD below the mean for reappraisal



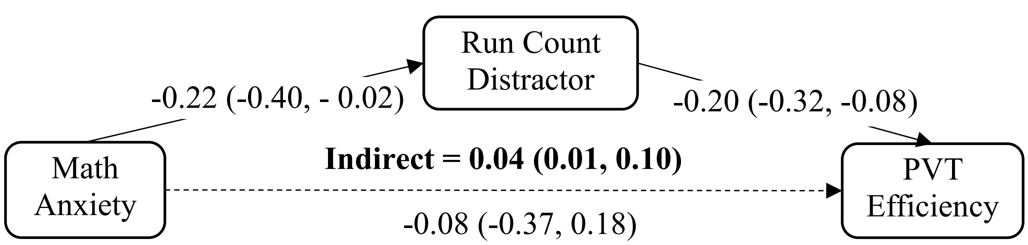
(b) At 1SD below the mean for reappraisal



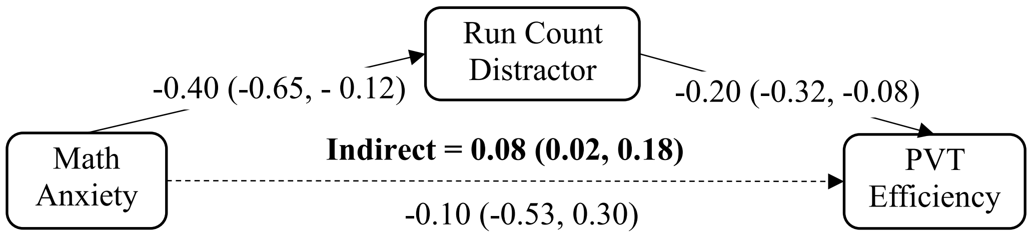
(c) At the mean of reappraisal



(d) At 1SD above the mean for reappraisal



(e) At 2SD above the mean for reappraisal

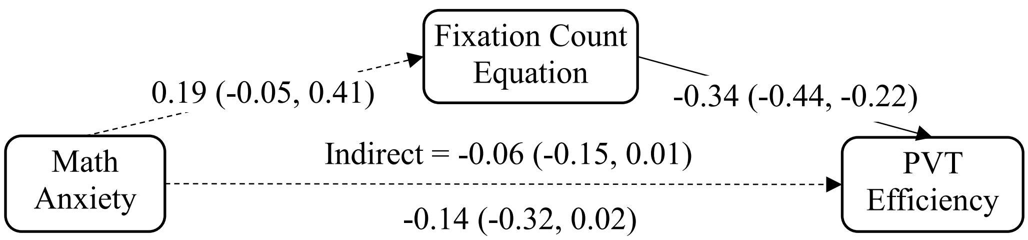


Note. Numbers shown are respectively standardized path estimates and their 95% bias-corrected bootstrap confidence intervals. Solid lines indicate significant effects and dashed lines indicate nonsignificant effects at α of .05. Significant indirect effects are in bold font.

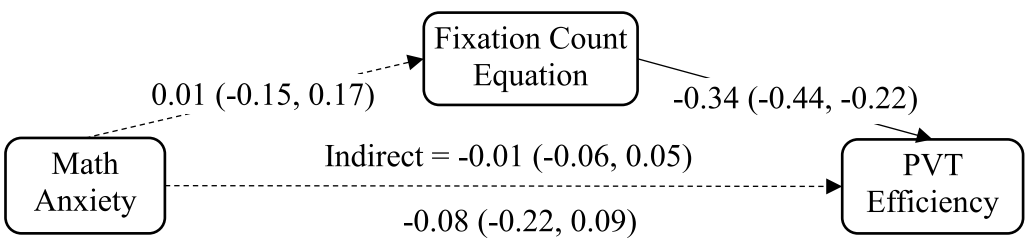
Figure 7

The Mediating Role of Fixation Count in Equation by Levels of PVT RZ

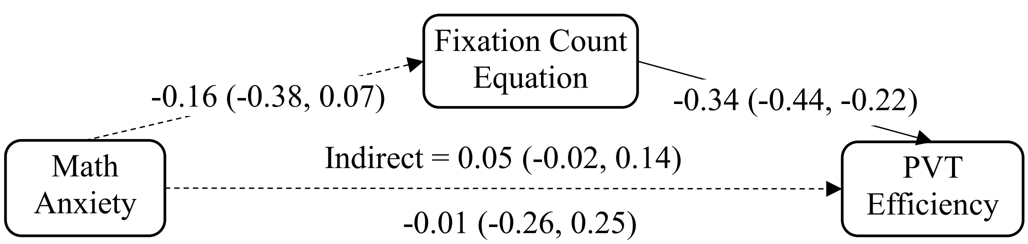
(a) At 1SD below the mean for PVT RZ



(b) At Mean of PVT RZ



(c) At 1SD above the mean for PVT RZ



Note. Numbers shown are respectively standardized path estimates and their 95% bias-corrected bootstrap confidence intervals. Solid lines indicate significant effects and dashed lines indicate nonsignificant effects at α of .05.