

**Achievement Emotions and Academic Achievement: Reciprocal Relations and the
Moderating Influence of Academic Buoyancy**

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Journal of Educational Psychology, in press

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We have no known conflict of interest to disclose. Our work was funded by a grant from the Bowland Trust. We thank Emma Rainbird for her assistance with data collection.

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Abstract

Control-value theory proposes that achievement emotions impact achievement, and that achievement outcomes (i.e., success and failure) reciprocally influence the development of achievement emotions. Academic buoyancy is an adaptive response to minor academic adversity, and might, therefore, offer protection from achievement being undermined by negative achievement emotions. At present, however, there is little empirical evidence for these hypothesized relations. In this study we examined reciprocal relations between three achievement emotions (enjoyment, boredom, and anxiety) and test performance in the context of mathematics, and whether academic buoyancy moderated relations between these emotions and test performance. Data were collected from 1,242 primary school students (mean age = 9.3 years) over four waves within one school year. Achievement emotions (T₁ and T₃) and test performance (T₂ and T₄) were measured alternately. Academic buoyancy was measured at T₃. A structural equation model showed negative relations of anxiety to subsequent test performance, and negative relations of test performance to subsequent anxiety. Test performance also predicted enjoyment and boredom, but not vice versa. A latent-interaction structural equation model showed buoyancy moderated relations between anxiety and test performance. Test performance was highest when anxiety was low and buoyancy high. Practitioners should consider using interventions to reduce anxiety and downstream effects on achievement.

Keywords: control-value theory, achievement emotions, academic achievement, anxiety, buoyancy

Educational Impact and Implications Statement

In classroom settings, multiple emotions such as enjoyment, boredom, and anxiety may occur. Among these emotions, anxiety is especially important for students' achievement in mathematics according to this study with elementary school children. Reducing anxiety would be beneficial for students' achievement, for example through fostering their adaptive responses to failure and increasing perceptions of control. The findings also suggest that developing academic buoyancy can benefit the achievement of students with mild forms of anxiety.

Achievement Emotions and Academic Achievement: Reciprocal Relations and the Moderating Influence of Academic Buoyancy

Mathematics learning in elementary or primary school is generally considered to be of critical importance to the person and for society at large. Functional numeracy skills are vitally important in adult personal and work life (e.g., managing personal finances), and failure to master basic mathematics skills is associated with subsequent unemployment and lower earning potential (e.g., Hanushek & Woessmann, 2008). Furthermore, economic national competitiveness requires a highly skilled science, technology, engineering, and mathematics (STEM) workforce (Kärkkäinen & Vincent-Lancrin, 2013). Unfortunately, many students fail to learn these fundamental numeracy skills. For example, in the United States, 19% of children were judged to show below basic mathematics skills at the end of Grade 4 in 2019 (National Center for Educational Statistics, 2019). Similarly, 21% of children left primary school in England at the age of 11 years in 2019 without reaching the expected minimum standard in mathematics (Department for Education, 2019).

Achievement emotions have been found to be critically important for students' academic achievement (e.g., Loderer et al., 2018; Tze et al., 2016; von der Embse et al., 2018). However, few studies have been conducted that take into consideration the combined influence of multiple achievement emotions. Furthermore, the impact of possible protective factors has been neglected. The present longitudinal study with Year 5 elementary school children targets these deficits by examining joint relations between three emotions that students commonly experience in the classroom, namely enjoyment, boredom, and anxiety, and their performance in mathematics. In addition, we investigated whether an asset-driven psychological attribute, namely academic buoyancy, is influential in protecting students' mathematics test performance from the detrimental influences of boredom and anxiety.

Achievement Emotions

Concept of Achievement Emotions

Achievement emotions were defined by Pekrun (2017) as "...emotions that relate to achievement activities (e.g., participating in a competition) or achievement outcomes (e.g., success and failure)" (p. 252). Achievement emotions are multifaceted, containing affective, cognitive, physiological, and motivational components, and are distinct from moods which are of lower intensity, longer lasting, and often with no specific referent (Linnenbrink, 2006; Pekrun, 2006). Achievement emotions can be experienced in a variety of achievement-oriented settings including the classroom, tests and exams, and homework. In the present study we focused on three classroom-related emotions: Enjoyment, boredom, and anxiety. These emotions can be differentiated by valence and physiological activation. Enjoyment is a positive activating emotion, boredom is a negative deactivating emotion, and anxiety is a negative activating emotion.

Relations between Achievement Emotions and Academic Achievement: Control-Value Theory

CVT (Pekrun, 2006, 2018, in press; Pekrun & Perry, 2014; Pekrun et al., 2002, 2019) is a theoretical framework that incorporates the antecedents and outcomes of achievement emotions. Appraisals of value (how and why an achievement activity or outcome is important) and control (expectancy for future, and attributions of past success and failure) are considered as proximal antecedents of achievement emotions. Achievement emotions are thought to influence cognitive and motivational processes that, in turn, underpin performance and academic achievement. According to CVT, not only will achievement emotions influence performance and achievement, but performance and achievement outcomes can also influence achievement emotions in a cycle of reciprocal causation.

Enjoyment. In CVT, enjoyment is theorized to enhance academic achievement through promoting interest and intrinsic motivation, maintaining cognitive resources, focusing

attention on the task at hand, and supporting use of flexible and deep learning strategies as well as self-regulation of learning. These different motivational and cognitive mechanisms can interact. For example, the influence of positive affect on cognition and attention might differ according to the degree of motivational intensity (Gable & Harmon-Jones, 2010). When positive affect is combined with less intense approach motivation (e.g., in contentment), cognition and attention can be broadened, but when combined with high-intensity approach motivation (e.g., in enjoyment), cognition and attention can be narrowed to focus on the most salient task details in order to facilitate goal pursuit. As such, enjoyment should be especially conducive to academic learning. Furthermore, effects on achievement may also depend on interactions of these mechanisms with task demands. Specifically, effects on achievement mediated by different styles of processing may depend on the match between processing style and type of task (see, e.g., Fiedler & Beier, 2014). For example, as proposed in CVT, anxiety can facilitate rigid rehearsal of learning materials, whereas enjoyment can enhance more creative ways of studying, implying that these two emotions can promote different kinds of task performance. Given the interplay between mediating mechanisms and their interactions with type of task, the effects of emotions on students' learning may be complex. However, for resulting academic achievement, it is reasonable to expect that greater enjoyment typically results in greater achievement. In turn, academic success would, all things being equal, strengthen control and positive value appraisals resulting in greater enjoyment (a positive reciprocal cycle; for supporting evidence, see Pekrun et al., 2017).

Boredom. In CVT boredom is theorized to impair performance and achievement by undermining interest and intrinsic motivation, reducing cognitive resources, and promoting superficial learning. Types of boredom characterized by very low arousal (indifferent and apathetic) may be more damaging for learning than those (e.g., searching and reactant) characterized by an active search for less boring alternatives (Goetz & Hall, 2014). Students

in English Year 5 primary school mathematics lessons do not have the option to choose alternative (and potentially less boring) activities. It is likely that the more damaging types of boredom (indifferent and apathetic) would be experienced. Lower performance and success would, all things being equal, weaken value appraisals, resulting in greater boredom (a positive reciprocal cycle).

Anxiety. In CVT anxiety is theorized to have dual effects on performance and achievement. Interest and intrinsic motivation can be undermined and working memory processes and executive functions disrupted (also see Derakshan & Eysenck, 2011; Eysenck et al., 2007). However, anxiety can also facilitate more rigid information processing, such as simple rehearsal, and can increase motivation to invest effort to avoid failure. Rigid information processing is unlikely to benefit students on the mathematics test used in the present study as the items required not only the recall of previously learnt mathematical reasoning but the application of that reasoning to a novel question. While increased effort will likely reduce the negative effects of anxiety, the overall effects of anxiety on academic achievement are negative in the vast majority of students; a recent meta-analysis of 238 studies showed a mean correlation of $r = -.24$ between test anxiety and achievement (von der Embse et al., 2018). Lower performance and success would, all things being equal, weaken control and negative value appraisals resulting in greater anxiety (a positive reciprocal cycle).

Empirical Studies of Relations between Achievement Emotions and Academic Achievement

When considered in isolation, enjoyment shows positive, and boredom and anxiety show negative, relations with academic achievement (for meta-analyses see Loderer et al., 2018; von der Embse et al., 2018; Tze et al. 2016). Few studies have modeled enjoyment, boredom, and anxiety together, however, to account for the concurrent relations between these three emotions and their unique contributions to predicting achievement. Three notable

exceptions have included enjoyment, boredom, and anxiety, together in single analytic models. In secondary school students, Ahmed et al. (2013) found unique statistically significant relations with mathematics achievement for enjoyment (positively), and boredom and anxiety (negatively). However, Raccanello et al. (2019; elementary school students) and Putwain et al. (2020; primary school students) found that only enjoyment and anxiety, but not boredom, remained statistically significant unique predictors of subsequent mathematics achievement.

A few studies that have included enjoyment, boredom, or anxiety, alongside other emotions not included in the present study, further underscore how the predictive value of discrete emotions can differ when considered together with other emotions. When considered alongside pride, enjoyment positively and anxiety negatively predicted mathematics achievement in undergraduates (Villavicencio, & Bernardo, 2016). Neither enjoyment nor boredom or anxiety were significantly related to the mathematics achievement of elementary school students when considered alongside surprise, curiosity, confusion, and frustration (Muis et al., 2015). Another study of elementary school students that included the same achievement and epistemic emotions found that boredom negatively predicted mathematics achievement, mediated by lower use of cognitive learning strategies (DiLeo et al., 2019).

Achievement emotions are often moderately to highly intercorrelated (e.g., $r_s = -.62$ to $.82$ in Pekrun et al., 2011) due to the shared appraisal antecedents (Pekrun, 2006). The co-linearity between emotions reduces the predictive power for each discrete emotion; only those with stronger relations to performance and achievement, or that have relatively weaker co-linearity with other emotions, will remain statistically significant predictors. The practical corollary in classroom settings is that when achievement emotions co-occur, not all may exert effects of the same strength on performance and achievement; some emotions may be more practically significant for performance than others. Therefore, it is vital for empirical work to

combine achievement emotions to competitively identify the most robust predictors of performance and achievement.

Reciprocal Relations between Achievement Emotions and Academic Achievement

Studies testing reciprocal relations between achievement emotions and achievement are largely lacking, with three notable exceptions. Over ten waves of measurement reciprocal relations were shown between boredom and test performance (β s -.10 to -.23) in undergraduate students taking an introductory psychology course (Pekrun et al., 2014). Over five waves of measurement, Pekrun et al. (2017) showed reciprocal relations with mathematics achievement for enjoyment (β s .11 to .13), boredom (β s -.06 to -.09), and anxiety (β s -.07 to -.14) in secondary school students. Only one study (Putwain, Becker, et al., 2018; primary school students) has modelled reciprocal effects for more than a single emotion (enjoyment and boredom) simultaneously. Over four waves, reciprocal relations were shown between enjoyment and achievement (β s .12 to .30), and boredom and achievement (β s -.07 to -.36); enjoyment and boredom were shown to have unique effects. No studies thus far have included more than two emotions simultaneously in a single analytic model. In the present study we address this limitation of the literature.

Academic Buoyancy

What is it, and how does it differ from Cognate Constructs?

Academic buoyancy is the ability to respond adaptively to the everyday challenges, setbacks, and pressures experienced by students during their studies (Martin & Marsh, 2009). Examples are periods of poor performance; dips in confidence, motivation, and engagement; receiving negative feedback from teachers; and the demands of tests and assessments. Academic buoyancy can be contrasted with academic resilience which refers to adaptive responses to major adversities such as chronic underachievement and failure, school truancy and refusal, and clinical levels of anxiety or depression (Martin & Marsh, 2009). In short,

academic buoyancy is the ability to ‘bounce back’ from minor adversities whereas academic resilience is the ability to ‘bounce back’ from major adversities.

Fong and Kim (2019) showed that academic buoyancy was distinct from other cognate constructs, including grit (i.e., persistency of effort and consistency of interest; Duckworth et al., 2007) and future time perspective (i.e., the perceived connection between present activities and future goals; Lens & Seginer, 2015), in a sample of undergraduate students. Items for academic buoyancy loaded separately from those of grit and future time perspective in factor analysis, and correlations between academic buoyancy and the other two constructs were small ($r_s < .27$).

An unresolved question in the literature is the extent to which some level of exposure to adversity is necessary for persons to build adaptive responses (e.g., Brooks, 2006; Compas, 2004). The types of adversities that academic buoyancy is theorized to protect against are those experienced during routine schooling by the majority of students (Martin & Marsh, 2009). Indeed the very utility of the academic buoyancy construct is founded on this point; unlike resilience it has relevance to the majority of students. Evidence has shown that children in primary or elementary school can experience and overcome difficulties in reading, writing, and numeracy (e.g., Holmes & Dowker, 2013; O’Connor et al., 2015), may receive negative feedback from teachers (Hattie & Timperley, 2007), negatively compare themselves to higher achieving classmates (Marsh, 2007), and be exposed to the pressures of testing (e.g., von der Embse & Witmer, 2014). These are the types of everyday academic adversities that buoyancy is theorized to protect against, and they are adequately captured by the academic buoyancy scale (Martin & Marsh, 2008).

Relations with Achievement

Although academic buoyancy shows positive relations with adaptive beliefs, affect, and behaviors in primary and secondary school students (e.g., Martin et al., 2010, 2013;

Hirvonen, Yli-Kivistö, et al., 2019; Hirvonen, Putwain, et al. 2019; Putwain et al., 2012, 2015) relations between academic buoyancy and achievement are equivocal. Putwain et al. (2016) showed that domain general academic buoyancy positively predicted performance in aggregated scores for English, science and mathematics secondary school exit examinations ($\beta = .16$), after controlling for concurrent relations with test anxiety. Martin (2014) showed that greater academic buoyancy predicted higher achievement ($\beta = .07$) on standardized secondary school numeracy and literacy tests, after controlling for socio-demographical variables and 'big-five' personality traits.

However, other studies have shown that buoyancy did not always predict achievement when included in more complex models with multiple predictors. In studies of secondary school students that have included control, academic buoyancy did not predict academic achievement on standardized school numeracy and literacy tests (Collie et al., 2015) or secondary school exit examinations in English, mathematics, and science (Putwain & Aveyard, 2018). In the aforementioned study by Fong and Kim (2019), academic buoyancy was not significantly related with self-reported GPA in undergraduates after controlling for grit and future time perspective.

While the bivariate correlations in these studies (Collie et al., 2015; Fong & Kim, 2019; Putwain & Aveyard, 2018) were positive ($r_s = .10$ to $.15$), in the presence of related variables the predictive value of academic buoyancy was reduced. This reduction of direct effects may be due to the effects of buoyancy being mediated by other variables (e.g., buoyancy bolstering perceived control, and control influencing performance in the studies by Collie et al., 2015, and Putwain & Aveyard, 2018). Alternatively, the reason may be construct overlap reducing the individual predictive power of buoyancy when combined with, for instance, the perseverance component of grit. Furthermore, reduced direct effects do not rule out the possibility that buoyancy interacts with other variables, especially those that pose

academic adversity (such as low perceived control). It is also possible that small or statistically non-significant relations between academic buoyancy and achievement also arise from using domain-general measures of academic buoyancy and achievement or mismatching domain-general measures of academic buoyancy with domain-specific measures of achievement (see Swann et al., 2007).

Only two studies have used domain-specific measures of academic buoyancy to examine relations with achievement. Yun et al. (2018) showed that academic buoyancy in second language (L2) acquisition predicted end-of-course L2 exam scores ($\beta = .31$) after controlling for prior achievement in a sample of undergraduate students. Colmar et al. (2019), however, found only small relations between academic buoyancy for mathematics and mathematics test performance ($r = .10$), and between academic buoyancy for reading and reading test performance ($r = .09$), in primary school students. Yun et al.'s (2018) findings suggest there is some merit in the idea that relations between academic buoyancy and achievement are stronger when analyzed in a domain-specific fashion. Accordingly, in the present study we adopted a domain-specific approach.

The Buffering Effect of Academic Buoyancy for Adaptive Educational Outcomes

Academic buoyancy is linked to adaptive responses to adversity, including strengthened positive and reduced negative emotions. In addition, it is plausible that academic buoyancy would not only lessen the intensity of emotions such as anxiety and boredom but also reduce their educational detrimental impact. Low levels of academic buoyancy would be expected to have little impact on the negative relations between boredom and anxiety, on the one hand, and achievement, on the other. As buoyancy increases, it would be expected to buffer against the detrimental impact of boredom and anxiety such that the negative relation would be weakened. An interaction between academic buoyancy and boredom or anxiety would therefore be expected. At low boredom or anxiety, there would be

little difference in the achievement of low and high academically buoyant students. As boredom and anxiety increase, however, high academically buoyant students will show higher achievement than their low academically buoyant counterparts.

Few studies have examined the possible moderating role of academic buoyancy. Putwain et al. (2016) showed that the negative relation between test anxiety and task-focused coping was reduced in academically buoyant secondary school students. Symes et al. (2015) found that the negative relation between teachers' use of failure-avoidance messages prior to a forthcoming high-stakes exam, on the one hand, and the appraisal of that exam as threatening, on the other, was reduced in academically buoyant secondary school students. Finally, Martin and Marsh (2019) found a marginally significant effect ($\beta = -.13, p = .10$) of the interaction between academic buoyancy and academic adversity on subsequent academic adversity in a sample of secondary school students. The positive relation between prior and later academic adversity, a year apart, was weaker at higher academic buoyancy in keeping with its theorized adaptive nature.

No studies have examined how academic buoyancy buffers the effects of performance impairing negative classroom emotions, such as boredom and anxiety. In the present study we address this gap in the literature. As low enjoyment is not typically considered as academically adverse, we would not expect enjoyment to interact with academic buoyancy but keep this as an exploratory question.

Aims and Hypotheses

Given the age of the participants in our study, namely students in Year 5 in their penultimate year of primary education (Year 5) aged 9-10 years, we chose to measure classroom emotions specifically. In England, where the study was based, students take standardized National Curriculum Tests (NCTs) in reading (two papers) and mathematics (two papers) at the end of Year 2, aged 6-7 years (Key Stage 1 NCTs), and in English (three

papers) and mathematics (three papers) at the end of primary schooling, Year 6, aged 10-11 years (Key Stage 2 NCTs). Key Stage 1 NCTs are administered informally and marked by teachers whereas Key Stage 2 NCTs are administered formally and marked by an external agency.

Students in Year 5, therefore, have fewer experiences of formal testing than in other countries (notably the United States) and have less homework (or self-study) than students in secondary or higher education. To capture the typical affective learning experiences of English students at this age it is preferable to focus on classroom experiences. We focused on enjoyment, boredom, and anxiety partly as they are three of the most commonly experienced achievement emotions (see Pekrun et al., 2002a). Furthermore, the only instrument presently available for measuring achievement emotions in elementary/ primary school children (Lichtenfeld et al., 2012) contains scales for these three emotions. When combined with the need to limit the number of items required by participating schools, and use high-quality age-appropriate instruments, we took the pragmatic decision to focus on enjoyment, boredom, and anxiety.

The aim of the study was twofold. First, we examined reciprocal relations between achievement emotions and achievement, with multiple emotions entered simultaneously in the same analytical model. More specifically, we aimed to test a model of reciprocal relations between three classroom achievement emotions (enjoyment, boredom, and anxiety) and test performance in a sample of Year 5 primary school students (aged 9-10 years) in the domain of mathematics, over four waves. We alternated the assessment of emotions and test performance over waves as sequential models are suited to test reciprocal relations (Little et al., 2007; Pekrun et al., 2014; Rosel & Plewis, 2008). Thus the first novel contribution of this study was to examine enjoyment, boredom, and anxiety, simultaneously using a four-wave design in a sample of primary school students. Despite the (often) greater ethical and

logistical challenges involved, in order to ensure a robust and generalizable evidence base for CVT it is critical that empirical work uses samples of pre-secondary students as well as those in secondary and higher education. The present study contributes to the paucity of empirical studies to use samples of younger students in pre-secondary education. Second, we examined whether academic buoyancy moderated relations between achievement emotions and test performance. The second novel contribution of our study was, therefore, to test if academic buoyancy could protect achievement from emotions like boredom and anxiety. Like with achievement emotions, to ensure a robust evidence base for the buoyancy construct, it is essential for empirical work to use younger students in primary (or elementary) schooling as well as older students in secondary or university education. Only one study to date (Colmar et al., 2019) has examined academic buoyancy in primary school students. The present study, therefore, makes a noteworthy contribution to the understanding of academic buoyancy by also using a sample of students in primary education.

Succinctly stated, we tested the following hypotheses (see Figure 1):

Hypothesis 1. Enjoyment and academic buoyancy are positively related, and boredom and anxiety are negatively related, to subsequent test performance.

Hypothesis 2. Test performance is positively related to subsequent enjoyment and negatively related to subsequent boredom and anxiety.

Hypothesis 3. Academic buoyancy attenuates the negative relations between boredom and subsequent test performance, and between anxiety and subsequent test performance

Method

Participants and Procedure

Data were collected over four waves; self-report data at T₁ and T₃ and mathematics test performance at T₂ and T₄ (see Figure 1). All data were collected in the participants' classrooms at school by the regular classroom teacher following a standardized script. The

survey items and mathematics tests were hosted online and prompted students where they had missed an answer. This was to minimize missing data arising from participants inadvertently missing an item. T₁ and T₂ data were collected in December 2018, and T₃ and T₄ data in June 2019. Mathematics tests were scheduled for approximately one week after the surveys. The project was approved by an institutional research ethics committee (19/EHC/01) at the first author's university. Written consent was provided by the head teacher of each participating school and the parent or carer of each participating student. Individual verbal assent for each participant was sought at each wave of data collection. The script required teachers to check the voluntary participation of each student, verbally, and provide an alternative activity if the students declined to participate. Students were informed that all survey and test responses would remain anonymous and not be seen by teachers or parents. These points were also explained on the online survey and mathematics tests. Although timed, the classroom setting and anonymity of results would characterize these tests as being low-stakes.

At Time 1, data were collected from 1,242 students (633 male, 609 female; mean age = 9.3 years, $SD = .49$) from 24 English primary schools (45 different classrooms). The ethnic backgrounds of participants were Asian = 246 (19.8%), black = 58 (4.7%), white = 876 (70.5%), Chinese = 11 (0.9%), other = 22 (1.8%), and mixed heritage = 29 (2.3). Data could not be collected for the socio-economic backgrounds of individual students due to private data protection reasons. However, the schools were located in two of twelve nationally designated 'opportunity' areas characterized by relatively high levels of deprivation (Department for Education, 2017).

There was attrition at subsequent waves of data collection (T₂ $n = 979$, T₃ $n = 863$, and T₄ $n = 734$) resulting from participants either being absent from school at the time of data collection or from choosing not to participate. To assess potential bias in missing data we conducted an omnibus test for missing completely at random (MCAR; Little's test, Little,

1988). This was followed by a series of *t*-tests comparing mean values of T₁ and T₃ age and emotions, and T₂ and T₄ mathematics test performance, as well as logistic regressions for T₁ and T₃ frequencies of gender, for participants with complete versus incomplete data. Little's test was statistically significant ($p < .001$) indicating that MCAR could not be assumed.

Participants who scored lower on the T₂ mathematics test were less likely to participate at T₃, $t(977) = 4.87, p < .001$, and T₄, $t(734) = 6.58, p < .001$. All other differences were not statistically significant ($ps > .05$). Since missing data could be accounted for by T₂ mathematics test performance, they were treated as missing at random (MAR) and handled using full-information-maximum-likelihood (FIML) estimation. FIML has been found to result in trustworthy, unbiased estimates for MAR when the variable causing missingness is included in the model (Nicholson, Deboeck, & Howard, 2017), even in the case of a high amount of missing values (Enders, 2010), and to be an adequate method to manage missing data in longitudinal studies (Jeličić, Phelps, & Lerner, 2009).

Measures

Emotions

Achievement emotions were measured at T₁ and T₃, using the 12 items from the *Achievement Emotions Questionnaire-Elementary School* classroom emotions scales (AEQ-ES; Lichtenfeld et al., 2012). These scales measure three achievement emotions (enjoyment, boredom, and anxiety) experienced in classroom settings with four items each (e.g., 'I look forward to maths lessons' for enjoyment; 'I find maths lessons so boring I would rather do something else' for boredom; 'When I think about maths lessons, I get nervous' for anxiety). All items were mathematics-specific and adapted to use parlance typical for the English context (e.g., 'class' changed to 'lesson'). Participants responded to items on a 5-point scale (1 = *not at all*, 5 = *very much*). Internal consistency coefficients for the present study were excellent (Table 1).

Buoyancy

Academic buoyancy was measured at T₃ using the *Academic Buoyancy Scale* (ABS; Martin & Marsh, 2008). The ABS comprises of four items that were adapted to be mathematics-specific and the example included in the one item simplified to make appropriate to the age of the target sample ('I'm good at dealing with setbacks in maths at school, e.g., getting a question wrong'). Participants responded to these items on a five-point scale (1 = *not at all*, 5 = *very much*). The internal consistency of the scale in the present study was excellent (Table 1).

Performance

Mathematics test performance was measured at T₂ and T₄ using items pooled from the 2016, 2017, and 2018 Key Stage 2 National Curriculum Test (NCT) reasoning papers (Standards and Testing Agency, 2016a, 2016b, 2017a, 2017b, 2018a, 2018b). NCTs are tests taken by English schoolchildren at the end of primary schooling (Year 6) covering the curriculum taught from Years 3 to 6 (Key Stage 2; age 7 to 11 years). There are three mathematics NCTs: one 30-minute arithmetic paper and two 40-minute reasoning papers scheduled over two days using a paper and pencil format. Each paper consisted of a series of closed-response questions worth between one and three marks each that used constructive and substantive styles of reasoning (Bohn-Gettler, 2009; Forgas, 2008). Questions required convergent analytical thinking (reasoning with one correct solution) rather than divergent and more creative thinking. The maximum score was 40 for the arithmetic paper and 35 for each of the reasoning papers (the exact number of questions differs in each paper depending on the number of marks allocated to each question)¹.

¹ Papers and mark schemes can be found at <https://www.gov.uk/government/collections/national-curriculum-assessments-practice-materials>.

All schools in England follow a prescribed national curriculum which at Key Stage 2 covers arithmetic, measurement, geometry, fractions and statistics, ratio and proportion, and simple algebra (Department for Education, 2013). As participants in the present study were in Year 5, we did not include arithmetic questions (typically taught in Years 3 and 4) as these are easier and may have resulted in a ceiling effect. We asked two primary school mathematics teachers unrelated to this study to select all those items from the 2016, 2017, and 2018 reasoning papers that would be appropriate for a Year 5 student (questions on measurement, geometry, fractions and statistics, were included). The resulting pool of items was subsequently confirmed as being appropriate for Year 5 students by two mathematics learning specialists unconnected to the present study.

Items were randomly selected from this pool to create two tests. Each test was timed for 40 minutes (to correspond to that of a NCT reasoning paper) and contained one- and two-point questions worth twenty marks in total (the first test comprised of 17 questions and the second test 18 questions). Responses required students to either provide a numerical value, or choose one or more answers from a list or menu of options. Unlike NCTs, marks were awarded for a correct answer only and no marks were awarded for correct reasoning when an incorrect answer was given. An exemplar item is: “A box contains 2.6kg of washing powder. Jack used 65grams of powder per wash. He uses all of the powder. How many washes did Jack do?” Participants were not provided with feedback on their test score. The internal consistency for the two tests was excellent (Table 1).

Demographic variables

We controlled for self-reported gender (0 = male, 1 = female) and age in the analysis.

Data Analysis

A latent variable modeling approach was adapted using *Mplus* v.8 (Muthén & Muthén, 2017). Confirmatory factor analysis (CFA) was employed to check the properties of

measurement models, check for measurement invariance, and estimate latent bivariate correlations. Structural equation modeling (SEM) was used to estimate reciprocal relations between emotions and achievement, and a latent interaction structural equation model (LI-SEM) was used to estimate the moderating effects of academic buoyancy on the relations between emotions and achievement. The ‘type = complex’ command was used to adjust standard errors for the clustering of data. Using single-level modeling and adjusting standard errors is recommended to account for nestedness when relations between variables at higher levels are not the target of investigation (Wu & Kwok, 2012).

All latent models were estimated using maximum-likelihood with robust standard errors (MLR) and evaluated using the following model fit indices: Root mean error of approximation (RMSEA), standardized root mean residual (SRMR), confirmatory fit index (CFI), and Tucker-Lewis index (TLI). A good model fit is indicated by RMSEA $<.05$, SRMR $<.06$, and CFI and TLI $>.95$ (Hu & Bentler, 1999). Caution must be used, however, when applying guidance derived from simulations studies to more complex studies, such as ours, using naturalistic data (Heene et al., 2011; Lance et al., 2006).

Results

Descriptive Statistics

Participants reported relatively high levels of enjoyment and academic buoyancy and low levels of boredom and anxiety (see Table 1). T1 enjoyment showed a slightly negative and T1 boredom a slightly positive skew (hence the decision to use the MLR estimator). The internal consistency of self-report measures (Cronbach’s α s and McDonalds’ ω s $\geq .79$) and mathematics tests (α s $\geq .79$ and ω s $\geq .81$) was good, and items loaded substantively on their target factors (λ s $\geq .64$) in CFA (see Table 1). Intraclass correlation coefficients (ICC1 or ρ_1) showed that the proportion of variance attributable to the school level was relatively small for

the classroom achievement emotions and academic buoyancy (approximately 3 – 7%) and somewhat larger for the mathematics test performance (approximately 12 – 14%).

Latent Bivariate Correlations

To estimate latent bivariate correlations, a measurement model was built that included achievement emotions (4 items each for enjoyment, boredom, and anxiety at T₁ and T₃), academic buoyancy (4 items at T₃), and mathematics test performance at T₂ and T₄. The corresponding indicators for classroom achievement emotions at T₁ and T₃ were allowed to correlate. Mathematics test performance was treated as a single-item latent variable with $\sigma_\epsilon = .1$ in line with estimates derived from previous empirical studies (Hoy et al., 2006; Watkins et al., 2007). Gender (0 = male, 1 = female) and age were added as covariates and treated as manifest variables.

The CFA showed a good fit to the data, $\chi^2(298) = 589.30, p < .001$, RMSEA = .026, SRMR = .028, CFI = .982, and TLI = .977, and so we proceeded to inspect correlation coefficients (see Table 2). Enjoyment and buoyancy were positively, and boredom and anxiety negatively, correlated with mathematics test performance. Female students reported lower enjoyment, higher anxiety and boredom, lower buoyancy, and lower mathematics test performance. Older students reported lower enjoyment and higher boredom, and they showed higher mathematics test performance.

The intercorrelations between T₁ emotions ($r_s = -.68$ to $.64$) and T₃ emotions and academic buoyancy ($r_s = -.78$ to $.62$) indicate the possibility of multicollinearity in subsequent analyses that model constructs simultaneously. T₄ mathematics test performance was regressed onto T₁ and T₃ classroom emotions, and T₂ mathematics test performance, and T₂ mathematics test performance regression into on T₁ and T₃ classroom emotions, in SPSS. Tolerance statistics were $> .33$ and variance inflation factors < 3.00 , suggesting that multicollinearity would not unduly bias parameter estimates.

Measurement Invariance

A prerequisite for the modelling of longitudinal relations is temporal measurement invariance (Widaman et al., 2010). Accordingly, we tested a series of models for classroom achievement emotions that included successively strict constraints (Meredith, 1993). The configural model specified the measurement model at T₁ and T₃ and included correlations between the corresponding indicators at the two time points. The metric invariance model constrained factor loadings of items to be equal, the scalar invariance model additionally constrained intercepts of items to be equal, and the strict invariance model additionally constrained item residual variances of items to be equal. Tests of measurement invariance are reported in Table 3. A decline in model fit of $\Delta\text{RMSEA} > .015$ or $\Delta\text{CFI}/\text{TLI} > .01$, from one model to the next, indicates non-invariance (Chen, 2007; Cheung & Rensvold, 2002). All classroom achievement emotions showed strict measurement invariance, and so we proceeded to examine longitudinal relations.

Structural Equation Modelling of Reciprocal Effects

A SEM was used to test the fully forward reciprocal relations model (RRM) shown in Figure 1. This model was tested competitively (see Table 4) against three alternative models: A baseline model where all directional paths were constrained to zero, a unidirectional model where paths from classroom achievement emotions to test performance were freely estimated but those from test performance to achievement emotions were constrained to zero, and a unidirectional model where paths from test performance to achievement emotions were freely estimated but those from achievement emotions to test performance were constrained to zero. All models included age and gender as covariates. The RRM showed a good fit to the data that was superior to all other models (Table 4). Furthermore, the RRM showed a significantly better fit than the other models using the Satorra–Bentler scaled χ^2 difference test (TRd; Bryant & Satorra, 2012) and an improved relative fit on the Akaike Information Criterion

(AIC). Lower AIC values are indicative of a better model fit and $\Delta AIC > 10$ indicates a substantive change in model fit (Hix-Small et al., 2004). The RRM (Figure 2) was accepted as the better fitting model. Standardized path coefficients and standard errors are reported in Table 5 and were interpreted as $\beta s \leq .09$ indicating small effects, .10 to .24 moderate effects, and $>.25$ large effects (Keith, 2006).

Relations from T₁ Emotions to T₂ Test Performance

T₁ anxiety negatively predicted T₂ mathematics test performance. T₁ enjoyment and T₁ boredom were not significantly related to T₂ performance.

Relations from T₂ Test Performance to T₃ Emotions

T₂ mathematics test performance positively predicted T₃ enjoyment over and above the auto-lagged relation with prior T₁ enjoyment and the cross-lagged relations with prior T₁ boredom and T₁ anxiety. T₂ mathematics test performance negatively predicted T₃ boredom over and above the auto-lagged relation with prior T₁ boredom and the cross-lagged relations with prior T₁ enjoyment and T₁ anxiety. T₂ mathematics test performance also negatively predicted T₃ anxiety over and above the auto-lagged relation with prior T₁ anxiety and the cross-lagged relations with prior T₁ enjoyment, and T₁ boredom.

Relations from T₃ Emotions to T₄ Test Performance

T₃ anxiety negatively predicted T₄ mathematics test performance over and above the auto-lagged relation with prior T₂ performance. T₃ enjoyment, T₃ boredom, T₁ enjoyment, T₁ boredom, and T₁ anxiety were not significantly related to T₄ test performance.

Relations with Covariates

Gender showed a significantly negative relation with T₁ enjoyment and significantly positive relations with T₁ boredom and anxiety. Age was significantly negatively related to T₁ enjoyment and positive related to T₁ boredom.

Moderating Effects of Academic Buoyancy in the Relation between Emotions and Test Performance

Interactions for Academic Buoyancy \times Enjoyment, Academic Buoyancy \times Boredom, and Academic Buoyancy \times Anxiety, were estimated in a single model using the latent moderated structural equation modeling (LMS) approach (Klein & Moosbrugger, 2000) implemented in *Mplus* v.8 (Muthén & Muthén, 2017). Absolute model fit indices are not provided in the LMS approach. However, it is possible to establish whether a model including an interaction term offers a better fit to the data using relative fit indices (Maslowsky et al., 2015): Akaike Information Criterion (AIC), sample-size adjusted Bayesian information criterion (aBIC), the log likelihood ratio test, and the change in the proportion of variance (ΔR^2) explained in the outcome variable (i.e., T₄ mathematics test performance).

A better model fit is indicated by smaller AIC and aBIC values (Hix-Small et al. 2004) and a larger R^2 in explaining the variance of the outcome. A statistically significant log likelihood ratio test (D) would indicate a worse fit for the more parsimonious model (i.e., the model without the interaction term). Due to the computational power required for the LMS approach 5,000 Monte Carlo Integration points were used.

Age and gender were included as covariates. As we were predicting T₄ test performance, autoregressive relations with T₂ test performance were also controlled for. Because T₃ emotions were predictor variables in these analyses, there would have been no benefit to including T₁ emotions in the models. Hence, to keep the models as parsimonious as possible, T₁ emotions were not included. In the log likelihood ratio test the three additional parameters, one per interaction term, equate to three degrees of freedom.

A model without an interaction term showed a good fit to the data: $\chi^2(146) = 422.44$, $p < .001$, RMSEA = .036, SRMR = .031, CFI = .971, and TLI = .962. However, the model

including three interaction terms (Academic Buoyancy \times Enjoyment, Academic Buoyancy \times Boredom, and Academic Buoyancy \times Anxiety) showed an improved fit ($\Delta\text{AIC} = -4.31$, $\Delta\text{aBIC} = -3.97$) and explained a greater proportion of variance in T_4 test performance ($\Delta R^2 = .01$). Furthermore, a statistically significant likelihood ratio test, $D(3) = 22.26$, $p < .001$, indicated a worse fit for the model without the three interaction terms. Structural coefficients are shown in Table 6. A statistically significant interaction was shown for Academic Buoyancy \times Anxiety, but not Academic Buoyancy \times Enjoyment or Academic Buoyancy \times Boredom.

To probe the Academic Buoyancy \times Anxiety interaction simple slopes were estimated at $\pm 1\text{SD}$ buoyancy (Figure 3a; please note that the *Mplus* software estimates simple slopes as unstandardized regression coefficients only). At $+1\text{SD}$ buoyancy a negative relation was shown between anxiety and performance ($B = -3.91$, $SE = 1.27$). This relation was weaker at mean buoyancy ($B = -1.38$, $SE = .34$) and at -1SD buoyancy became non-significant ($B = 1.16$, $SE = 1.25$). To facilitate interpretation of the interaction, we also plotted relations between academic buoyancy and test performance at $\pm 1\text{SD}$ anxiety (see Figure 3b). At $+1\text{SD}$ anxiety, a negative relation was shown between academic buoyancy and test performance ($B = -2.80$, $SE = 1.38$). This relation was not significant at mean anxiety ($B = -.01$, $SE = .21$) and became positive at -1SD anxiety ($B = 2.20$, $SE = 1.33$). The findings suggest that performance benefited from lower anxiety combined with higher buoyancy. At higher levels of anxiety the performance-enhancing influence of buoyancy declined.

Discussion

Using a longitudinal design with four alternating waves of data collection, we investigated the relations between three classroom achievement emotions (enjoyment, boredom, and anxiety) and test performance in the context of mathematics at primary school. Supporting Hypothesis 1, anxiety negatively predicted subsequent mathematics test scores

after controlling for gender, age, concurrent classroom achievement emotions, and autoregressive relations with prior achievement. Enjoyment and boredom, however, were not significantly related to subsequent test scores. In line with Hypothesis 2, test scores positively predicted subsequent enjoyment and negatively predicted boredom and anxiety after controlling for prior emotions and the covariates. Thus, a positive feedback loop over time was shown between anxiety and test scores; higher anxiety was related to subsequent lower test scores, and lower test scores, in turn, to higher subsequent anxiety. Overall, this pattern of findings suggests that when multiple achievement emotions are considered simultaneously, anxiety exerts a stronger effect on performance than enjoyment and boredom. It is notable that despite low mathematics test scores at T₂, there was sufficient variance with which to model relations with previous and subsequent classroom emotions.

We also investigated whether academic buoyancy moderated relations between negative emotions that are detrimental to learning (boredom and anxiety) and protected test scores from these emotions. The model including interaction terms showed a superior fit relative to a model not including interactions and a significant effect was shown for the Academic Buoyancy \times Emotion interaction. In partial support of Hypothesis 3, test performance was highest when anxiety was low and buoyancy high. With higher anxiety, the benefit for performance shown for high academic buoyancy diminished.

Relations between Achievement Emotions and Academic Achievement

CVT proposes reciprocal relations between achievement emotions and indicators of achievement, such as test scores, as measured in the present study. Emotions exert cognitive-motivational effects that influence learning and performance, and learning and performance, in turn, reinforce the control-value appraisals that underpin emotions (Pekrun, 2006, 2017; Pekrun & Perry, 2014). Previous studies have shown how achievement emotions relate to subsequent mathematics achievement in primary/ elementary, secondary, and undergraduate

students (e.g., Ahmed et al., 2013; Raccanello et al., 2019; Villavicencio, & Bernardo, 2016) but far fewer have examined how emotions and mathematics achievement are reciprocally related over time (Pekrun et al., 2014, for an undergraduate psychology course, Pekrun et al., 2014, for secondary school students, and Putwain, Becker, et al., 2018, for primary school students).

A question of conceptual and applied importance is whether achievement emotions exert unique effects when considered simultaneously. Notably, only one study thus far examined reciprocal relations with mathematics achievement for more than a single emotion in tandem; Putwain, Becker, et al. (2018) examined enjoyment and boredom simultaneously and found that unique reciprocal effects for both of these emotions. The findings of the present study offer novel insights into the question of unique reciprocal effects by considering three classroom emotions (enjoyment, boredom, and anxiety) simultaneously in a single analytic model. When the variance shared between emotions measured concurrently was controlled for in this way, reciprocal relations with mathematics achievement were only shown for anxiety. Although mathematics test performance predicted subsequent enjoyment and boredom (in the expected direction), enjoyment and boredom were not significantly related to subsequent test performance.

Thus, when these three emotions are pitted competitively against each other, anxiety exerts the strongest predictive power for achievement. It is important to clarify that we do not argue against the presence of reciprocal relations between enjoyment and achievement, and between boredom and achievement. Rather, the findings suggest that anxiety emerges as the most significant (statistically and practically) of the three emotions when they are modeled together. Analytically speaking, this is a combined result of anxiety being related more strongly to test performance than enjoyment or boredom and of the intercorrelations between

enjoyment, boredom, and anxiety. The result is that insufficient unique variance remained in enjoyment and boredom to predict test performance.

Theoretically speaking, the implication is that the cognitive-motivational mechanisms affected by anxiety, specifically interference with working memory capacity and function (Derakshan & Eysenck, 2011; Eysenck et al. 2007), may exert a stronger influence on performance than the cognitive-motivational mechanisms affected by enjoyment and boredom, such as interest, intrinsic motivation, and depth of learning (Fredrickson, 2001; Fredrickson & Branigan, 2005). Practically speaking, when multiple emotions are considered simultaneously in achievement settings, or when the presence of unpleasant emotions is associated with the absence of pleasant emotions, it may be more important to focus on reducing anxiety in the first instance than to attempt to reduce boredom and foster enjoyment.

In summary, we found support for our second hypothesis, that test performance would be positively related to subsequent enjoyment and negatively related to subsequent boredom and anxiety. There was, however, only mixed support for our first hypothesis, that enjoyment would be positively, and boredom and anxiety negatively, related to subsequent test performance. Our findings build on the body of evidence to show that anxiety is detrimental for mathematics achievement and that it is not just an outcome or epiphenomenon of prior performance, but can predict lower achievement beyond the influence of prior performance.

A minor, but nonetheless intriguing, point is that T_1 enjoyment was a stronger predictor of T_3 boredom than T_1 boredom. We suspect that this finding is due to students' enjoyment being more stable over time as compared with boredom (see the autoregressive effects for the two emotions from T_1 to T_3 , .59 and .24, respectively; Table 5). The high stability of enjoyment may have made it possible for enjoyment to more continuously influence students' subsequent boredom. The exact reason why enjoyment was more than stable than boredom is unclear, but could be related to the differential role of perceived

control as an antecedent of the two emotions. Perceived control will result in greater enjoyment and will also lead to lower boredom in most cases, but can alternatively induce higher boredom due to a lack of challenge (e.g., Pekrun, 2006, 2018; Pekrun & Perry, 2014), thus explaining lower stability of boredom.”

It could be questioned whether findings from the present study would generalize to non-testing situations typically encountered by students during classroom learning. There is evidence that domain-specific emotions related to learning (e.g., in math, science, and L2 learning) can influence classroom achievement (for reviews see Horwitz, 2001; Maloney, 2016; Sinatra et al., 2016). For emotions related to classroom activities specifically, class-related anxiety has been shown to relate negatively to both class grades and test scores in mathematics ($r_s = -.21$ to $-.32$; Lichtenfeld et al., 2012; Peixoto et al., 2016; Putwain et al., 2020; Racanello et al., 2019; for L2 class-related anxiety, see Shao et al., 2020). In the study by Lichtenfeld et al. (2012), the magnitude of correlations between classroom-related anxiety and two different measures of math achievement (class grades vs. test scores) did not differ ($z = -.40$ and $.43$ for 2nd and 3rd grade samples, respectively; $p_s > .05$). Overall, these findings would suggest the results of the present study for relations between class-related emotions, notably anxiety, and test scores would be applicable to classroom achievement, such as grades based on classroom activities, as well.

The Moderating Effect of Academic Buoyancy

Academic buoyancy is the capacity to respond effectively to minor academic adversities (Martin & Marsh, 2009). Studies have shown that higher domain general academic buoyancy is related to adaptive educational outcomes in secondary school students (e.g., Malmberg et al., 2013; Martin et al., 2013) including higher positive, and lower negative, achievement emotions in primary and secondary school students (e.g., Hirvonen et al., 2019; Martin et al., 2010; Putwain et al., 2012). Studies linking domain general academic

buoyancy to aggregated achievement in mathematics and reading have shown equivocal results, however, with some reporting statistically significant relations but others not (e.g., Collie et al., 2015; Martin, 2014). We reasoned this may be partly an artifact of reduced predictive power arising from lack of domain specificity and used a mathematics-specific measure of academic buoyancy in the present study (also ensuring matching specificity with domain-specific achievement emotions).

Conceptually, higher levels of buoyancy could moderate (i.e., buffer) the impact of academic adversities on subsequent outcomes (e.g., Martin & Marsh, 2019; Putwain et al., 2016; Symes et al., 2015). Accordingly, we theorized that higher levels of buoyancy could protect test performance from boredom and anxiety. The model including the interaction terms between academic buoyancy and emotions showed a superior fit to the model not including these interactions and a statistically significant interaction between Academic Buoyancy and Anxiety. Interactions between Academic Buoyancy and Enjoyment, and between Academic Buoyancy and Boredom, were not statistically significant.

The pattern of the observed interaction partially supported our third hypothesis. Rather than protecting test performance at *higher* levels of anxiety, higher academic buoyancy amplified test performance at *lower* levels of anxiety. With higher anxiety, the differential benefit to performance offered by higher academic buoyancy diminished. This finding suggests that academic buoyancy did not protect test performance against the adverse effects of high classroom anxiety. Furthermore, there is the intriguing finding that high buoyancy may even be detrimental for performance when anxiety is also high. We offer three considerations to explain this pattern of effects.

First, buoyancy may not have protected performance because anxiety was too adverse. Although academic anxiety is often considered a minor form of adversity in comparison to clinical anxiety (Martin, 2013a), it is known that high levels of academic

anxiety overlap with clinical anxiety (e.g., Herzer et al., 2014; Warren et al., 1996; see also Pekrun & Loderer, in press). It may be that the higher levels of anxiety measured in the present study constituted more of a major than a minor adversity to students, in which case buoyancy may not have been a sufficiently strong factor to offer protection. Classroom anxieties may have been furthered by the subject material; mathematics learning and reasoning is, for many students, a source of anxiety (e.g., Maloney, 2016). Martin (2013a) and Martin and Marsh (2008, 2009) argue that resilience, rather than buoyancy, is required to respond to chronic or stronger academic adversities.

Second, an alternative interpretation would be that buoyancy did not protect against performance because the classroom measure of anxiety underestimated the level of anxiety experienced during the test. Although the mathematics test used in the present study was characterized as low-stakes, it is possible that a greater degree of anxiety was experienced during the test than was typically experienced during classroom learning. In this respect the classroom measure may have reported anxiety as not being sufficiently adverse for academic buoyancy to effectively offer protection. To investigate this possibility, future research could include a measure of test-related emotions occurring during test taking. Furthermore, measures of engagement and learning during mathematics lessons (e.g., on-task behaviors, cognitive strategies used, and tasks completed) may have been more sensitive to the protection offered by buoyancy against classroom learning anxiety, than test performance.

Third, it is known that children can over-estimate their abilities (see Muenks et al., 2018; Salles et al., 2016). It is possible that participants may have over-estimated their academic buoyancy and believed they had a greater capacity to bounce back than was actually the case. This may account for the diminishing protection offered by academic buoyancy as anxiety increased; there was less buoyant than was reported. This over-estimation could also account for why very high (+2SD) academic buoyancy became

detrimental to performance. If participants anticipated they would be highly able to effectively respond to difficulties encountered during the test but experienced the opposite, they could be highly de-motivated, reduce effort, or even give up completely. This is somewhat akin to ‘choking’ when the pressure from performing mathematics tasks becomes exaggerated by concerns about one’s performance overloading working memory (e.g., Beilock et al., 2004).

Fourth, a curious finding reported by Martin and Marsh (2019) was that academic buoyancy exerted a greater protective role for academic adversities reported 12 months later than with current academic adversities. This finding is in line with the view that some exposure to adversity is necessary in order for persons to build adaptive responses. It is therefore possible that the benefits of buoyancy play out, or accumulate, over time rather than contemporaneously. If this were the case, then we would have been unlikely to observe a protective effect on a test taken one week after measurements of self-reported anxiety and academic buoyancy. In this respect academic buoyancy can be considered as a malleable trait, a lasting attribute that can develop over time and that is responsive to intervention (Martin, 2013b). Beneficial effects would occur downstream at a later point in time. We conclude the theoretical proposition that academic buoyancy can protect subsequent outcomes from minor adversity may be valid despite having been confirmed only partially in the present study.

Although we focused on mathematics in the present study, as we wanted to adopt a domain-specific approach, other studies on buoyancy have considered English and reading in research with primary and secondary students (e.g., Colmar et al., 2015; Putwain & Aveyard, 2018). There are no theoretical reasons for academic buoyancy to differentially relate to achievement and adaptive beliefs, emotions, and behaviors, in varying academic subjects. While mathematics may be anxiety-provoking for some students, it is known that literacy

also presents a challenge for students, and reading motivation begins to decline at the end of elementary school (see Wigfield, 1997). These are adversities that buoyancy is theorized to protect against. However, we are mindful that some subjects do present unique challenges for students and it would be beneficial for academic buoyancy studies to broaden the repertoire of academic subjects considered.

Despite a positive bivariate correlation between academic buoyancy and subsequent test performance, there was no first-order effect of academic buoyancy on performance after controlling for current relations with emotion, the interaction with emotion, and prior achievement. The prediction made in Hypothesis 1 that buoyancy would be positively related to achievement was not supported in these models. It is possible that emotions mediate relations between academic buoyancy and subsequent achievement (see Putwain et al., 2015). Although we could not formally test this hypothesis because academic buoyancy and achievement emotions were assessed simultaneously at T₃, this interpretation is supported by the strong relations between buoyancy and emotions (Table 1), combined with the relations between emotions and subsequent test performance. Hence, the relations with emotions may have reduced the direct predictive power of academic buoyancy. In this case, academic buoyancy would represent a relatively rare example of the same variable operating as both a mediator and a moderator (for a related example for self-efficacy as a mediator and moderator, see Dicke et al., 2014).

When considering findings, it is important to acknowledge that the mathematics tests used in the present study contained only closed response questions that required reproductive styles of reasoning. Some students may have employed the correct approach to solving a question but ultimately arrived at an incorrect answer. Including open questions, where students could receive marks for showing their reasoning, as well as their final answer could potentially show a different pattern of relations with classroom emotions and academic

buoyancy. Similarly, questions requiring creative and global processing that requires making new connections between concepts, which are potentially more challenging, could also relate differently to classroom emotions and academic buoyancy than questions requiring convergent analytical reasoning.

We would also like to briefly comment on the missing data in our study and how it was treated. Analyses suggested that the cause of the missing data were T2 mathematics test scores (and hence missing data were treated as MAR). The implication of MAR is that missingness was not completely random, but could be treated as random after T2 mathematics scores were controlled for (see Little & Rubin, 2002). This situation is typical of applied research where substantive study variables or socio-demographic correlates may influence decisions whether to continue participation or not (e.g., Lamers et al., 2012). Attrition may be higher for groups of participants characterized by vulnerability, low motivation, or where the study may pose emotional distress. In the present study, it would seem plausible that students who experienced the T2 mathematics test as more difficult (and hence performed worse) may have been less motivated to continue participating as this may have reminded them of their difficulties with mathematics.

When the cause of the missing data is ignored, there is a danger that model estimates may be biased. In the present study, the risk would be an under-representation of participants with lower mathematics scores. However, simulation studies have shown that when the cause of missing data is included in the algorithm used for handling missing data (FIML was used in the present study), disproportional participant attrition can be corrected for to yield unbiased estimates (e.g., Collins et al., 2001; Nicholson et al., 2017). We followed a strategy to identify the cause of the missing data (T2 mathematics scores) and included that variable in our analytic models. Hence, we are confident that parameter estimates are applicable to the entire sample despite reduced representation of participants with lower T2 test scores. Future

studies may follow a similar approach to test and report assumptions of MCAR and MAR more completely and openly.

Limitations and Directions for Future Research

Despite the novel theoretical contributions of this study, and the use of a relatively understudied age group in achievement emotion and academic buoyancy research, there are limitations that should be considered and can be used to suggest directions for subsequent studies. First, we were able to measure data across two alternate assessments of emotions and performance. Thus, we were able to test the predictive power of emotions on subsequent performance twice, but reciprocal predictive effects of test performance on subsequent emotions only once. Although this design is sufficient to test reciprocal relations (Little et al., 2007; Rosel & Plewis, 2008), additional alternating waves of emotions and achievement would allow for multiple assessments of reciprocal relations between emotions and achievement. The present design only permitted a single test for the moderating effect of academic buoyancy while controlling for previous achievement. Additional alternating waves of academic buoyancy (alongside emotions) and achievement would also allow for multiple tests of protective effects of buoyancy on relations between adverse emotions and achievement.

A related point is that there were unequal time intervals between assessments. T_1 and T_2 , and T_3 and T_4 , were spaced apart by one week. T_2 and T_3 , however, were spaced apart by approximately seven months. We were constrained by school administration to schedule data collection this way in order to minimize impact on routine teaching and learning. Thus, we cannot make direct comparisons of the size of paths from emotions to test performance (with the one week time interval) to the size of the paths from test performance to emotions (with the seven month time interval).

Second, we measured three classroom emotions (enjoyment, boredom, and anxiety). Although being the first study to model reciprocal relations in all three simultaneously, there are other achievement emotions likely to co-occur in classroom settings (e.g., hope and hopelessness). It would be useful to include additional emotions to address the question of which emotions are the most meaningful predictors of achievement, when considered together. We were somewhat limited in that the only validated measure of achievement emotions available for the age group of participants used in the present study (AEQ-ES; Lichtenfeld et al., 2012) measures enjoyment, boredom, and anxiety specifically. It would be a useful extension of this measure to include additional emotions.

Third, from a CVT perspective, emotions influence subsequent achievement through cognitive-motivational mechanisms, and achievement influences subsequent emotions through control-value appraisals. Although it is useful to first test for reciprocal relations solely between emotions and achievement, partly as these relations are meaningful in their own right, and partly as a precursor to investigating mediating processes, future studies should additionally include cognitive-motivational mechanisms and control-value appraisals. A study that combined tests of reciprocal effects in conjunction with the presumed mediating mechanisms would offer an even more robust test of CVT.

Fourth, we speculated two reasons for the inconsistent relations shown between academic buoyancy and achievement in the extant literature; low domain specificity or mismatch between measures of academic buoyancy and achievement, and the presence of additional variables that may either overlap with academic buoyancy (e.g., grit or future time perspective; Fong & Kim, 2019) or mediate relations between academic buoyancy and achievement (e.g., perceived control; Collie et al., 2015, and Putwain & Aveyard, 2018). The correlations between domain-specific academic buoyancy in mathematics and students' mathematics achievement found in the present study ($r_s = .23$ and $.25$) were stronger than

correlations between domain-general academic buoyancy and achievement in previous studies (e.g., $r_s = .13 - .17$; Martin, 2014; Putwain et al., 2016). This would lend credibility to the view that high domain specificity between academic buoyancy and achievement strengthens relations. Furthermore, in the LI-SEM, the first-order effects of academic buoyancy were negligible; this indicates a possible mediating role of emotions. However, from the present study we cannot establish whether domain-general variables that overlap with academic buoyancy, such as grit and future time perspective, would reduce the magnitude of relations between academic buoyancy and achievement when using domain-specific measures of academic buoyancy. Future studies should continue to explore how academic buoyancy (especially when considered as a domain-specific construct) can be differentiated from cognate constructs and how relations with achievement can be used to inform understanding of overlap between similar constructs.

Fifth, we did not account for learning disabilities (e.g., dysgraphia or dyscalculia) in the present study. It is likely that they would have been meaningful covariates and might explain variance in both predictors and outcomes. In order to collect accurate data for learning disabilities for children aged 9 to 10 years, it would be necessary to use official school records rather than to rely on participant self-report; not all students at this age may understand if they have been diagnosed with a learning disability or if they have, what that learning disability is. In order to keep data collection anonymous for ethical reasons, we were unable to match participant self-report data with school records. However, it would be desirable for future studies, where ethical protocols permit, to include information about learning disabilities.

Finally, our test of the moderating effect of buoyancy on the relations between academic adversity and subsequent outcomes was limited to test performance. There are other salient outcomes that academic buoyancy could protect from adversity, including

attendance, compliance with school behavioral policy, positive relationships with peers and staff, adaptive motivation (e.g., intrinsic motivation), and behavioral engagement (e.g., participation in lessons and extracurricular activities). Future research should consider such outcomes, and where possible use official school recorded data (e.g., attendance) to complement self-report data on these outcomes. It would also be useful to include measures of emotional self-regulation to establish whether the moderating influence of academic buoyancy is related to differential use of regulatory strategies.

Insights for Practice

In classroom settings, when emotions such as enjoyment, boredom, and anxiety may co-occur, anxiety emerges as the strongest (negative) emotional predictor of achievement according to the present findings. Attempts to reduce anxiety would therefore be beneficial in helping students' learning and performance. Typically interventions have focused on test anxiety (von der Embse et al., 2013), school phobia, and school refusal (Lauchlan, 2003). There are fewer interventions for classroom or learning anxiety, and these are focused on specific forms of anxiety such as math anxiety (Schaeffer et al., 2018) and statistics anxiety (Smith & Capuzzi, 2019). Math anxiety interventions are germane to the present study with the substantive focus on classroom emotions in mathematics (cognate, although not identical with math anxiety).

Math anxiety interventions have focused broadly on either building subject mastery, reducing negative appraisals of competence or physiological arousal, or the normalization of failure as part of learning (Ramirez et al., 2018). In CVT (Pekrun, 2016, 2017; Pekrun & Perry, 2014) and the integrated model of emotion regulation in achievement situations proposed by Harley et al. (2019), mastery, reappraisal, and failure-response beliefs correspond to ways of building perceived control or regulating emotion through cognitive change. These theoretically derived mechanisms of reducing anxiety are not solely the

province of psychologists and specialist interventions. There are practical ways in which instructors can incorporate mastery practice and adaptive responses to failure in both mathematics and other subjects through directing student attributions for success and failure (Perry et al., 2014) and creating a classroom culture whereby failure is defined as a normal part of the learning process (Murphy & Dweck, 2010).

Conclusion

When the relations between three classroom emotions (enjoyment, boredom, and anxiety) and test performance were modelled simultaneously over four waves of data collection, reciprocal relations were shown for anxiety (in terms of negative reciprocal relations). High test performance predicted higher enjoyment and lower boredom, but enjoyment and boredom were not significantly related to subsequent test performance. Thus, when the shared variance between these emotions is considered (as is likely to happen in classroom situations where discrete emotions may co-occur), anxiety emerged as the emotion that is more important for achievement. We also investigated whether academic buoyancy might protect performance against anxiety. We found that this was partially the case. Buoyancy protected performance at lower levels of anxiety, suggesting that buoyancy can help students coping at least with mild forms of negative emotion.

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Table 1*Descriptive Statistics and Item Factor Loadings*

	Mean	<i>SD</i>	α / ω	ρ_1	Skewness	Kurtosis	Factor loadings
T ₁ Enjoyment	16.24	4.48	.92 / .92	.07	-1.09	0.21	.84 - .90
T ₁ Boredom	7.87	4.38	.91 / .91	.04	1.12	0.16	.79 - .88
T ₁ Anxiety	8.30	4.38	.82 / .82	.03	0.99	0.17	.70 - .75
T ₃ Enjoyment	15.40	4.75	.93 / .93	.06	-0.86	-0.27	.84 - .96
T ₃ Boredom	7.78	4.38	.91 / .92	.04	0.94	-0.11	.86 - .89
T ₃ Anxiety	8.23	4.27	.82 / .83	.04	0.99	0.24	.79 - .90
T ₃ Buoyancy	15.58	3.85	.79 / .79	.03	-0.51	-0.28	.64 - .78
T ₂ Mathematics Test Performance	4.64	3.67	.79 / .81	.12	0.82	0.15	—
T ₄ Mathematics Test Performance	9.55	4.72	.85 / .85	.14	0.11	-0.73	—

Note. ω = McDonalds omega. ρ_1 = intraclass correlation coefficient (ICC1).

Table 2*Correlations between the Study Variables*

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. T ₁ Enjoyment	—	-.68**	-.36***	.60***	-.48***	-.24***	.44***	.14**	.13**	-.17***	-.07*
2. T ₁ Boredom	-.64***	—	.64***	-.40***	.45***	.28***	-.28***	-.18***	-.17***	.07*	.11***
3. T ₁ Anxiety	-.33***	.56***	—	-.24***	.25***	.51***	-.38***	-.32***	-.36***	.12**	.01
4. T ₃ Enjoyment	.57***	-.41***	-.27***	—	-.78***	-.40***	.62***	.18***	.16**	-.15***	-.01
5. T ₃ Boredom	-.48***	.56***	.27***	-.75***	—	.58***	-.43***	-.19***	-.19***	.11**	.05
6. T ₃ Anxiety	-.27***	.31***	.45***	-.38***	.53***	—	-.47***	-.34***	-.40***	.09*	.01
7. T ₃ Academic Buoyancy	.37***	-.26***	-.33***	.52***	-.28***	-.36***	—	.25***	.23***	-.10**	.02
8. T ₂ Test Performance	.15***	-.17***	-.29***	.21***	-.21***	-.32***	.22***	—	.67***	-.08*	.07
9. T ₄ Test Performance	.18***	-.19***	-.33***	.20***	-.21***	-.38***	.20***	.69***	—	-.06	.10**
10. Gender	-.16***	.05	.10**	-.16***	.11***	.09**	-.08**	-.08**	-.08*	—	—
11. Age	-.06*	.10***	.01	-.01	.03	.02	.01	.07*	.11**	—	—

Note. Latent bivariate correlations above the diagonal, manifest Pearson's correlations below the diagonal.

* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 3*Tests of Measurement Invariance for Classroom Achievement Emotions*

	χ^2 (df)	RMSEA	SRMR	CFI	TLI	Δ RMSEA	Δ CFI	Δ TLI
<i>Enjoyment</i>								
T ₁	3.16(2)	.022	.006	1.000	.999			
T ₃	3.47(2)	.026	.005	.999	.997			
Configural	17.89(15)	.011	.012	1.000	.999			
Metric Invariance	22.14(18)	.012	.020	.999	.999	+0.001	-0.001	<.001
Scalar Invariance	44.72(22)	.026	.037	.996	.995	+0.014	-0.003	-0.004
Residual Invariance	38.56(26)	.018	.034	.998	.998	-0.008	+0.002	+0.003
<i>Boredom</i>								
T ₁	1.42(2)	.000	.004	1.000	1.001			
T ₃	24.81(2)	.100	.020	.981	.944			
Configural	67.33(15)	.048	.023	.988	.977			
Metric Invariance	76.91(18)	.047	.027	.986	.978	-0.001	-0.002	-0.001
Scalar Invariance	85.82(22)	.044	.036	.985	.981	-0.003	-0.001	+0.003
Residual Invariance	88.38(26)	.040	.035	.985	.984	-0.004	<.001	+0.003
<i>Anxiety</i>								
T ₁	2.18(2)	.008	.007	1.000	1.000			
T ₃	8.95(2)	.055	.018	.990	.997			
Configural	40.78(15)	.034	.023	.988	.987			
Metric Invariance	42.26(18)	.030	.024	.989	.983	-0.004	+0.001	-0.004
Scalar Invariance	42.87(22)	.025	.025	.991	.988	-0.005	+0.002	+0.005
Residual Invariance	54.03(26)	.027	.030	.987	.986	+0.002	-0.004	-0.002

Note. χ^2 statistic for all models statistically significant at $p < .001$.

Table 4*Comparison of the Reciprocal Relations Model to the Baseline and Unidirectional Relations Models*

	χ^2 (df)	RMSEA	SRMR	CFI	TLI	AIC	Δ AIC	TRd(df)
Baseline Model	729.48 (315)***	.033	.082	.972	.967	76777.58	209.96	188.28 (18)***
Unidirectional Model A	609.64 (306)***	.028	.052	.980	.975	76647.67	80.05	79.89 (9)***
Unidirectional Model B	686.71 (312)***	.031	.070	.975	.969	76734.32	166.70	140.07 (15)***
Reciprocal Relations Model	526.24 (297)***	.025	.027	.985	.980	76567.62	—	—

Notes. (a) Unidirectional Model A: Relations of emotions to subsequent performance freely estimated, relations of performance to subsequent emotions constrained to zero. Unidirectional Model B: Relations of performance to subsequent emotions freely estimated, relations of emotions to subsequent performance constrained to zero. (b) χ^2 statistic for all models statistically significant at $p < .001$.

Table 5*Standardized Path Coefficients for the Fully-Forward Reciprocal Relations Model (Standard Errors in Parentheses)*

	T ₁ Enjoyment	T ₁ Boredom	T ₁ Anxiety	T ₂ Test Performance	T ₃ Enjoyment	T ₃ Boredom	T ₃ Anxiety	T ₄ Test Performance
T ₁ Enjoyment				.09 (.06)	.59 (.05)	-.31 (.07)	-.19 (.08)	.05 (.05)
T ₁ Boredom				-.11 (.07)	.04 (.06)	.24 (.07)	-.18 (.07)	.08 (.08)
T ₁ Anxiety				-.36 (.06)	-.03 (.05)	-.05 (.06)	.50 (.07)	-.13 (.08)
T ₂ Test Performance					.12 (.04)	-.14 (.03)	-.19 (.04)	.60 (.03)
T ₃ Enjoyment								-.05 (.06)
T ₃ Boredom								-.01 (.05)
T ₃ Anxiety								-.16 (.07)
Gender	-.17 (.03)	-.07 (.03)	.12 (.04)	-.05 (.03)	-.03 (.04)	.02 (.03)	-.01 (.03)	.01 (.04)
Age	-.07 (.03)	.11 (.03)	.01 (.04)	.06 (.04)	.02 (.03)	.01 (.03)	.03 (.04)	.05 (.04)

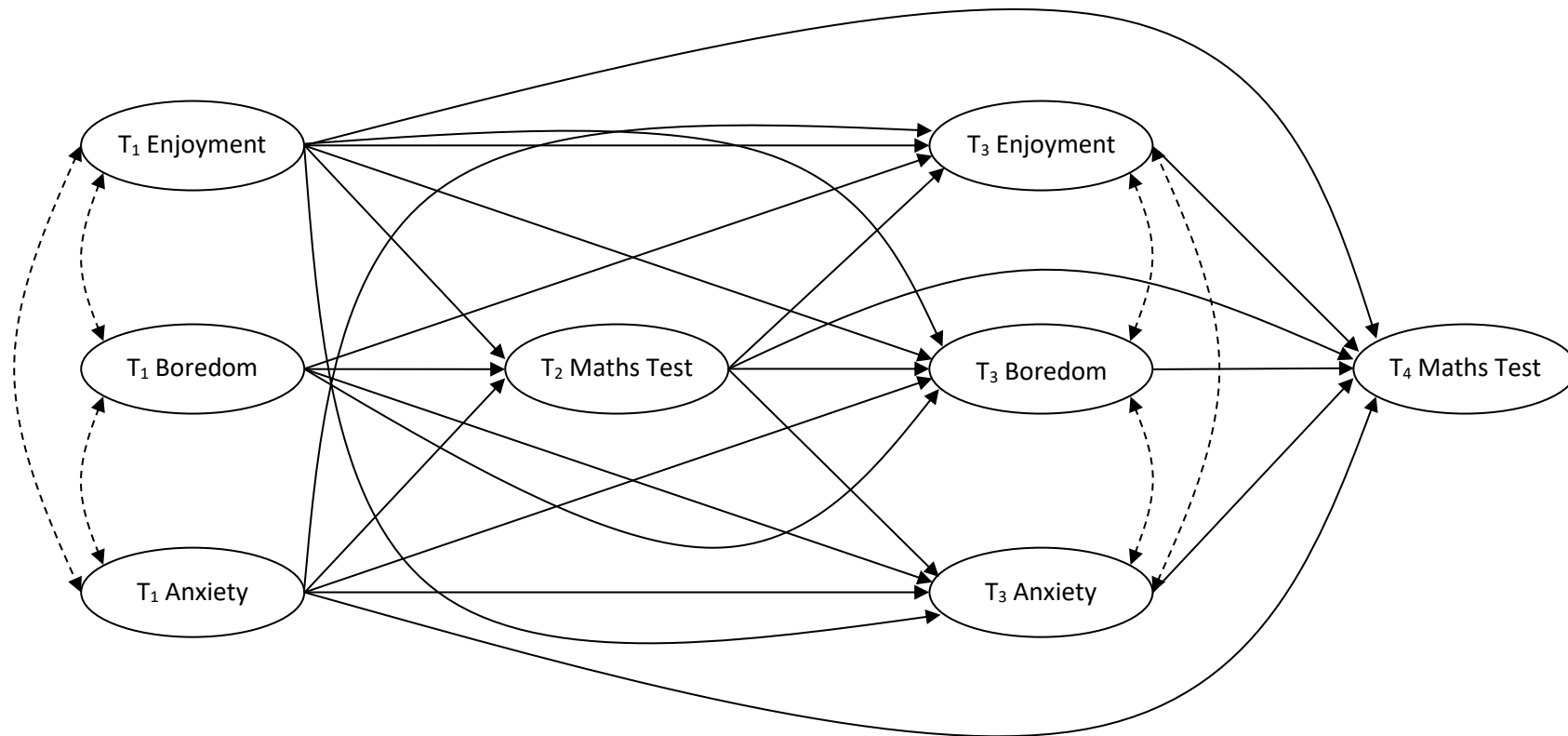
Table 6

Standardized Path Coefficients for the LI-SEM to Predict T₄ Test Performance from Interactions between Academic Buoyancy and Enjoyment, Boredom, and Anxiety (Standard Errors in Parentheses)

Predictor	T ₂ Test Performance	Enjoyment	Boredom	Anxiety	Academic Buoyancy	T ₄ Test Performance
Enjoyment (ENJ)						.04 (.06)
Boredom (BOR)						-.08 (.05)
Anxiety (ANX)						-.25 (.06)
Academic Buoyancy (B)						.01 (.04)
B × ENJ						-.05 (.06)
B × BOR						-.03 (.07)
B × ANX						-.10 (.04)
T ₂ Test Performance		.19 (.04)	-.19 (.04)	-.34 (.04)	.25 (.05)	.61 (.03)
Gender	-.06 (.05)	.21 (.07)	.08 (.09)	.06(.07)	.03 (.05)	.02 (.06)
Age	.06 (.04)	.06 (.09)	.10 (.08)	.02 (.06)	.01 (.07)	.10 (.07)

Figure 1

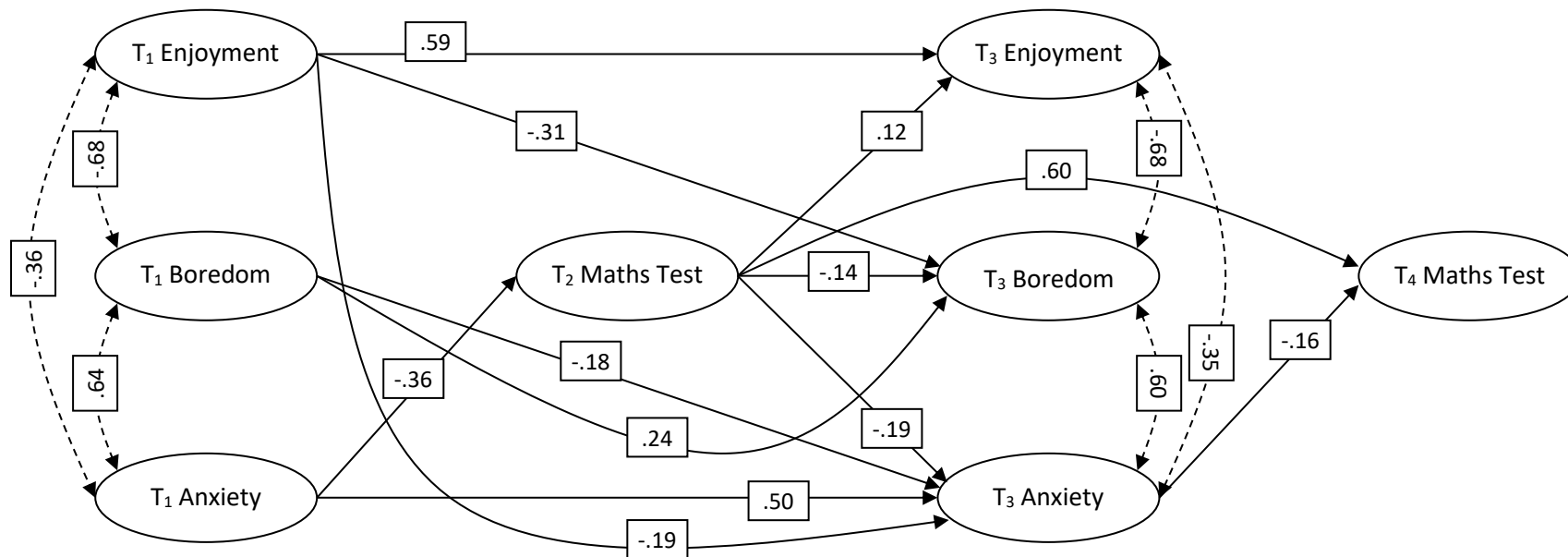
The Hypothesized Fully Forward Reciprocal Model Including Autoregressive, Cross-Lagged, and Concurrent Relations between Achievement Emotions and Mathematics Test Performance



Note. Paths for gender and age are not depicted.

Figure 2

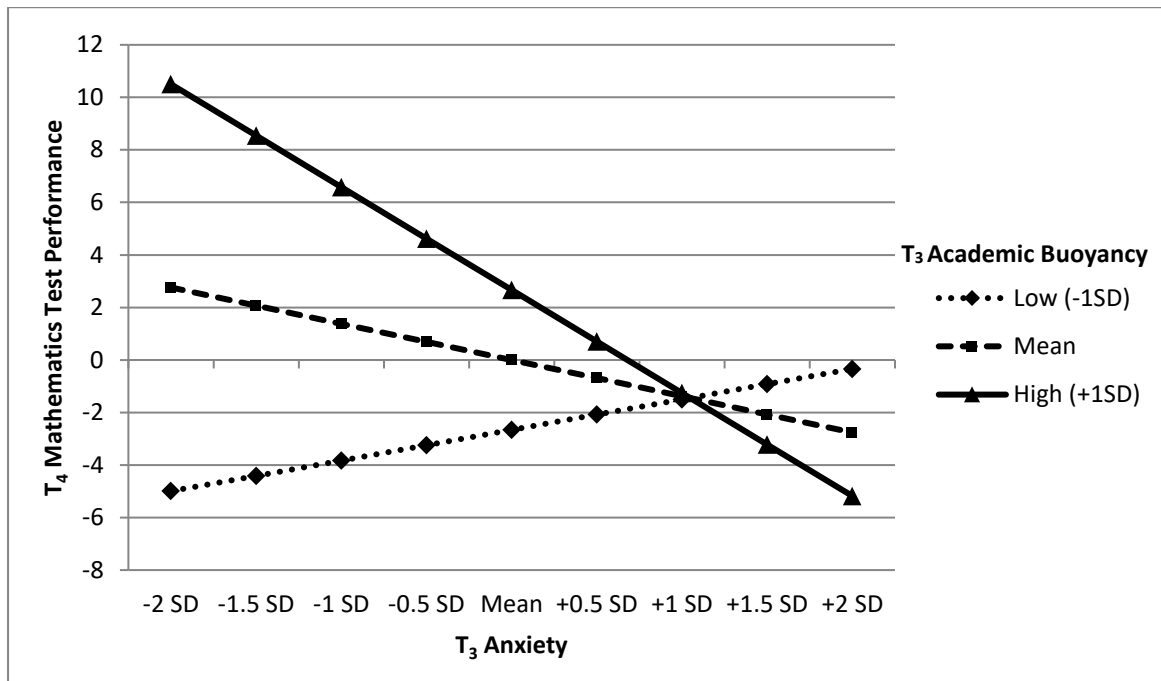
Significant Autoregressive, Cross-lagged, and Concurrent Relations Between Achievement Emotions and Test Performance



Note. Paths for gender and age are not depicted.

Figure 3a

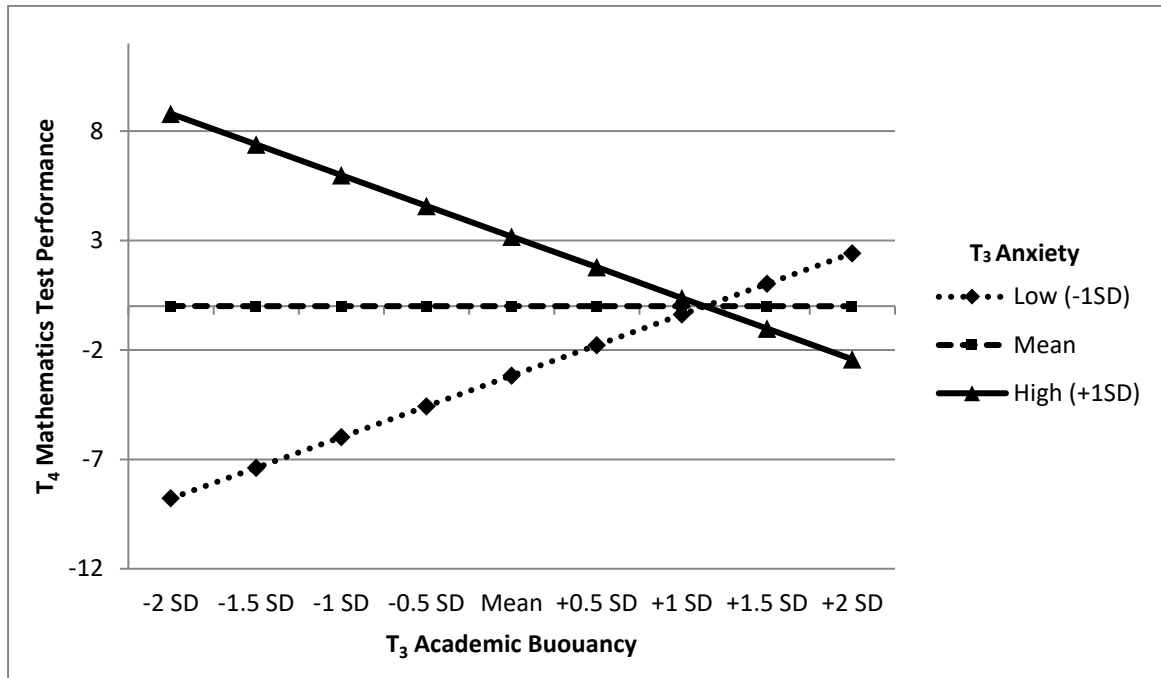
The Model-implied Effect of the T_3 Academic Buoyancy \times Anxiety interaction on T_4 Mathematics Test Performance



Note. Anxiety represented on the x axis and slopes plotted for $\pm 1SD$ academic buoyancy.

Figure 3b

The Model-implied Effect of the T_3 Academic Buoyancy \times Anxiety interaction on T_4 Mathematics Test Performance



Note. Academic represented on the x axis and slopes plotted for ± 1 SD anxiety.