Understanding the Impact of Test Anxiety on Study Behavior

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Abstract

Test anxiety, widely documented in undergraduate STEM education, is typically framed as an impediment to learning. However, whether test anxiety also reflects students' awareness of their preparation and can prompt adaptive changes in study behavior remains underexplored. Prior work has relied on cross-sectional designs that cannot fully capture whether students adjust their behavior in response to anxiety experiences over time. In this paper, we examine both concurrent and temporal relationships between test anxiety and study behavior in the course Numerical Methods at the University of Illinois Urbana-Champaign, using data from 248 students across six biweekly quizzes delivered through the platform PrairieLearn. We quantify study behavior through metrics capturing the breadth, success, and timing of practice quiz engagement, and use ordinary least squares regression and lagged mixed-effects models to assess these relationships. Results show that students who engage more effectively with practice materials report lower test anxiety. Furthermore, experiencing higher test anxiety on one quiz predicts broader practice coverage, better practice performance, earlier preparation, and less cramming when studying for the next quiz. These findings suggest that test anxiety can function as actionable feedback by prompting students to adjust their preparation strategies.

1 Introduction

Test anxiety is a common experience in undergraduate STEM education, affecting nearly one-half of undergraduate students [1]. Understanding how students navigate test anxiety, particularly in how they prepare for assessments, has important implications for supporting student success and well-being.

A key question is whether test anxiety is solely a problem that impairs student learning, or whether it also reflects students' awareness of their preparation and can motivate adaptive changes in study behavior. If students respond to experiencing anxiety by adjusting their study strategies, it would suggest that anxiety serves as a metacognitive monitoring function. Conversely, if anxiety leads to counterproductive patterns like cramming or avoidance, this would indicate a need for intervention. Existing research has largely examined concurrent relationships between anxiety and study behaviors, leaving open the question of whether students adapt over time in response to their anxiety experiences [2, 3].

We investigate this question by examining both concurrent and temporal relationships between test anxiety and study behaviors in an undergraduate engineering course. Specifically, we address the following two research questions:

RQ1: How do study behaviors relate to reported test anxiety?

RQ2: How does test anxiety influence subsequent study behavior?

The first question establishes whether different patterns of behavior are associated with varying levels of experienced anxiety. The second question addresses the critical gap in existing research by examining whether students modify their preparation strategies following experiences of anxiety on prior assessments. Together, these questions provide insight into whether test anxiety triggers adaptive self-regulatory responses, informing how educators might better support students in managing both their anxiety and their learning.

2 Related Works

Test anxiety encompasses both physiological reactions during assessments and the mental preoccupation with potential failure and its consequences [4]. This phenomenon is widespread in higher education, with approximately 18-50% of students experiencing some form of test anxiety and 7-25% experiencing very high levels [1]. National surveys indicate that anxiety is one of the two most common impediments to academic performance, reported by 29% of undergraduate students [5]. Test anxiety is particularly prevalent in engineering education, where it has been shown to negatively correlate with academic performance [6, 7]. The cognitive mechanisms underlying these performance effects include interference with working memory, reduced concentration, and difficulties in organizing and retrieving information during both studying and testing [6, 1].

While the relationship between test anxiety and academic performance has been well-documented, the directionality and nature of this relationship appears complex. Some research suggests anxiety can have both facilitating and debilitating effects on achievement [6], and recent work in engineering contexts has found that students with higher anxiety sometimes achieve higher grades, though they still experience problematic levels of stress [4]. Recent studies comparing different testing modalities, such as Computer-Based Testing Facilities versus bring-your-own-device setups, have found no significant differences in test anxiety or performance between these environments, though implementation details such as exam timing within asynchronous timing windows can significantly impact outcomes [8, 9].

Researchers have increasingly examined the role of study behaviors in the relationship between test anxiety and academic performance. Early work established that highly test-anxious students differ from their low-anxious peers in both performance outcomes and study behaviors, where high-anxious students report poorer study skills yet spend more hours studying, suggesting a compensatory effect [2]. This relationship appears to be bidirectional, with ineffective study habits and time management correlating with increased anxiety [5], while some students harness anxiety to motivate greater study effort through strategies like “defensive pessimism” [10]. However, recent work examining whether study behaviors moderate the anxiety-performance relationship have yielded mixed results, with some studies finding that test preparation strategies do not significantly buffer anxiety’s negative effects on achievements [3].

Despite this growing body of research, a critical limitation remains in that nearly all studies examining the relationship between test anxiety and study behaviors have employed cross-sectional designs, measuring anxiety and study behaviors at the same time point [2, 3]. This design cannot address whether students adapt their study behaviors in response to experiencing anxiety on prior assessments. Self-regulated learning theory suggests that students should monitor and adjust their metacognitive strategies accordingly [11], yet empirical evidence of such adaptive responses to test anxiety remains lacking. The present study addresses this gap by examining both the concurrent relationship between study behaviors and test anxiety (RQ1) and the temporal relationship in which experiencing test anxiety on one assessment could influence study behaviors for subsequent assessments (RQ2). By employing a within-subjects design that tracks individual students across multiple assessments, this study can capture adaptive changes in study behavior that cross-sectional designs cannot detect.

3 Methods

3.1 Course Context

The research team obtained IRB approval before proceeding with the study. This study was conducted in the course *Numerical Methods* at the University of Illinois Urbana-Champaign, taken generally by second- and third-year computer science or math students. The course was offered in two parallel sections: in-person and online. Both sections covered identical content and maintained the same assessment structure, with student grades determined by performance on prelecture activities, homework assignments, weekly group activities, five extended machine projects, six bi-weekly quizzes, and a comprehensive final exam.

The two sections differed only in the mechanism for earning group activity participation credit. In-person students earned participation points through synchronous class attendance, while online students submitted group collaboration reflection surveys to document their engagement. All other grading policies, assignment weightings, and course requirements were identical across sections.

All assignments were delivered online through the PrairieLearn platform, which enables the use of randomization, question variants, instant feedback, and autograding [12].

3.1.1 Quiz Structure

Each of the six bi-weekly quizzes consisted of two sections: (1) multiple-choice and short-answer questions, and (2) coding questions.

Each unique question is identified by a Question ID (QID). For any given QID, PrairieLearn generates multiple question variants, which are parameterized versions of a QID with randomized numerical values that preserve the underlying concept while providing different surface features. For example, a QID asking students to convert a floating-point number from binary to decimal may generate question variants with different floating-point numbers each time, while remaining of similar length and difficulty. Each quiz was comprised of multiple slots, where each slot was linked to a pool of QIDs covering specific course topics. When a student took a quiz, the system drew QIDs from each slot's pool and generated a specific question variant for that student's assessment.

All quiz problems were auto-graded, providing students with immediate feedback on their submissions. Students received their score for each individual question as well as their overall assessment score in real time. The quiz configuration supported multiple attempts with different grading policies. Multiple-choice and short-answer questions allowed 2-3 additional attempts with diminishing credit: each successive attempt after the first was worth progressively less toward the final score for that question. In contrast, coding questions permitted unlimited attempts without penalty, allowing students to iteratively debug and refine their solutions while maintaining full credit potential.

3.1.2 Practice Quizzes

Beginning the week prior to each quiz, students had access to practice quizzes designed to mirror the structure and content of the actual assessments. Each practice quiz consisted of two sections matching the format of the actual quiz, with a short question section and a coding section.

The multiple-choice and short-answer practice questions used nearly the same slot structure and QID pools as the actual quizzes. When students generated a practice quiz instance, each slot drew QIDs from its pool and generated a question variant for that student. This design allowed students to encounter the same question types (QIDs) they would see on the actual quiz while practicing with varied parameters, supporting both familiarity with question formats and adaptability to parameter variations.

The coding questions followed a different approach: practice quiz coding slots drew from different QID pools than the corresponding slots in the actual quiz to preserve assessment of problem interpretation rather than solution recall. A key learning goal for these questions was the ability to read a word problem grounded in a real application of numerical methods, translate it into a mathematical formulation, and then implement a solution in code. Once students have seen and solved a specific problem context, this interpretive step can no longer be meaningfully assessed, even with parameter randomization. Accordingly, practice coding QID pools differed from those on the actual quiz while maintaining similar difficulty levels and problem structures, providing students with realistic expectations for the assessment.

Students could generate unlimited practice quiz instances throughout the week preceding each quiz. Each newly generated instance provided a fresh selection of QIDs from each slot's pool and generated new question variants for all questions, enabling iterative practice across the available content.

3.1.3 Quiz Modality

All quizzes were administered in one of two proctored computer-based testing environments: Computer-Based Testing Facilities (CBTF) or Bring-Your-Own-Device (BYOD) settings.

- *Computer-Based Testing Facilities.* CBTFs are institutional proctoring services that provide secure, controlled testing environments with standardized institutional computers. Students schedule individual appointment times within designated testing windows, allowing flexible scheduling while maintaining exam security through locked-down systems and continuous proctoring [13].

- *Bring-Your-Own-Device.* In the BYOD modality, students bring their personal computers or devices to a designated classroom and complete assessments synchronously under the supervision of course staff. All students taking a quiz via BYOD complete it together during the same time period [14].

To systematically vary testing environments while maintaining equivalence across students, each student was randomly assigned to one of three staggered rotation groups. Within each rotation, students took every third quiz via BYOD and all other quizzes via CBTF. This design resulted in each student completing two quizzes in the BYOD environment and four quizzes in the CBTF environment over the semester.

The scheduling structure differed by modality. For CBTF quizzes, students individually scheduled appointments within a three-day testing window. For BYOD quizzes, all students assigned to that modality for that particular quiz completed the assessment synchronously during a scheduled class period during the fourth day of the testing window. This scheduling approach follows the design used in prior work comparing testing modalities [15], ensuring equivalent conditions across modalities.

Students from both course delivery formats (in-person and online sections) were distributed across all three rotation groups. Consequently, all students, regardless of their course section, experienced both testing modalities during the semester.

3.2 Study Behavior Metrics

We quantify study behavior in practice quizzes using behavioral metrics defined by [16]. Specifically, we refer to the following definitions:

1. **Fraction attempted.** This is the fraction of all possible practice quiz QIDs a student attempted, regardless of whether they answered the problems correctly or not, measuring the breadth of student's practice quiz studying.

2. **Average proportion attempted per instance.** This is the average proportion of questions available in a practice quiz instance that the student attempts. While some students may prefer to attempt most or all questions in each generated practice quiz instance, others may choose to pick certain problems they have trouble with and generate new instances to work on those problems repeatedly.

3. **Fraction attempted that were correct.** This is the fraction of attempted QIDs that the student got correct at some point during their practice quiz studying. Given that students may have received multiple variants of the same QID over different practice quizzes, a QID is counted in this metric if the student solved it correctly at any point, even if they solved it incorrectly later.

4. **Average proportion correct per instance.** This is the proportion of attempted questions per practice quiz instance that the student gets correct, averaged over all the practice quizzes they attempt for the given quiz. If a student does not attempt a question variant in a generated practice quiz, that question is not counted in this metric.

5. **Cramming rate.** This metric is operationalized as the proportion of practice quiz question variant submissions happening in the 24 hours before the student takes the actual quiz.
6. **Early-start rate.** In contrast to cramming, early-start is the proportion of practice quiz question variant submissions happening greater than 48 hours before the student takes the actual quiz.

We further separate these metrics into three groups. Metrics 1 and 2 measure *study amount*, metrics 3 and 4 measure *study success*, and metrics 5 and 6 measure *study timings*.

3.3 Post-Quiz Anxiety Survey

After each quiz, students had the option to complete a survey measuring their test anxiety, adapted from The Revised Test Anxiety Online Short Form [17], a validated instrument to measure state anxiety. The survey consisted of nine items and assessed both the cognitive and physiological dimensions of test anxiety experienced during the assessment. Students responded to each item using a 5-point Likert scale ranging from "Completely disagree" (1) to "Completely agree" (5). State anxiety scores for each student on each quiz were calculated by averaging their responses across all nine items. The full survey is shown in Table 1.

Table 1: Post-Quiz Anxiety Survey Items

Item	Question
1	I seemed to defeat myself while taking this test.
2	During this test I found myself thinking about the consequences of failing.
3	I started feeling very uneasy just before seeing my scores for questions.
4	During this test I felt very tense.
5	I got a headache during this test.
6	While taking this test, I often thought about how difficult it was.
7	I was anxious about this test.
8	I found myself trembling before or during this test.
9	I had difficulty breathing while taking this test.

Note: All items used a 5-point Likert scale: Completely disagree (1), Disagree (2), Neutral (3), Agree (4), Completely agree (5).

3.4 Data Collection

We ran our study in the Fall 2023 semester. Student consent was collected through a pre-course survey administered by the research team. This pre-course survey also measured trait anxiety using nine items parallel to those in the post-quiz survey (Section 3.3), asking students to indicate their level of agreement with statements about exams in general (e.g., "I am anxious about exams") on a 4-point scale: Almost never (1), Sometimes (2), Often (3), and Almost always (4). Trait anxiety scores were calculated by averaging responses across all nine items.

Through PrairieLearn, the research team additionally collected detailed practice and quiz logs for each quiz, enabling a detailed view into student interaction with the given practice quizzes and actual quizzes. After each quiz, a member of the research team sent out the post-quiz survey described in Section 3.3 for students to reflect on their feelings before, after, and during their quiz. Overall, data was collected and analyzed from 248 consented students over six quizzes.

3.5 Analysis

To address our research questions, we conducted two complementary sets of regression analyses: cross-sectional analyses examining concurrent relationships between study behavior and anxiety (RQ1), and lagged temporal analyses examining how anxiety influences subsequent study behavior (RQ2). Statistical significance was assessed at $\alpha = 0.05$.

Values for state anxiety per student were calculated by converting each Likert item on the surveys to a numeric equivalent (Completely disagree = 1, Disagree = 2, Neutral = 3, Agree = 4, Completely agree = 5) and averaging the values per quiz.

3.5.1 RQ1

To examine how study behaviors relate to reported test anxiety on the same quiz, we estimated three ordinary least squares regression models, one for each category of study behavior: study amount, study success, and study timing. Each model followed the same specification:

$$\text{StateAnxiety}_{i,j} = \alpha + \sum_{k \in K} \beta_k \cdot \text{StudyMetric}_{i,j,k} + \beta_{\text{trait}} \cdot \text{TraitAnxiety}_i + \epsilon_{i,j} \tag{1}$$

where $\text{StateAnxiety}_{i,j}$ represents the average reported state anxiety after quiz j for student i, $\text{StudyMetric}_{i,j,k}$ represents the value of study behavior metric k for student i after quiz j, and TraitAnxiety_i represents the baseline trait anxiety measured pre-course for student i. The set K varies by model:

- **Study amount model:** $K = \{\text{fraction attempted, average attempted per instance}\}$
- **Study success model:** $K = \{\text{fraction correct, average correct per instance}\}$
- **Study timing model:** $K = \{\text{cramming rate, early-start rate}\}$

All study behavior metrics are expressed in proportions ranging from 0 to 1 to ensure comparable scales across predictors. Each metric is calculated as a ratio; for example, fraction attempted is the number of unique QIDs divided by total available QIDs, while cramming rate is the number of submissions in the 24 hours before the quiz divided by total submissions. This approach allows us to assess the independent contribution of each metric within its conceptual category while controlling for the other.

We included trait anxiety as a control variable in all models to account for stable individual differences in anxiety disposition, allowing us to isolate the relationship between situational study behaviors and state-level anxiety responses.

3.5.2 RQ2

To examine how anxiety experienced on one quiz influences study behavior for the next quiz, we estimated lagged regression models that preserve the temporal sequence of quizzes. These models allow us to test whether students' emotional experiences on one assessment predict behavioral changes in their preparation for subsequent assessments. The general form of these models was:

$$\text{StudyMetric}_{i,j} = \alpha + \beta_1 \cdot \text{StateAnxiety}_{i,j-1} + \beta_2 \cdot \text{Modality}_{i,j} + \beta_{\text{trait}} \cdot \text{TraitAnxiety}_i + \epsilon_{i,j} \quad (2)$$

where $\text{StudyMetric}_{i,j}$ represents one of the six study behavior metrics (defined in Section 3.2) for student i preparing for quiz j, $\text{StateAnxiety}_{i,j-1}$ represents the state anxiety reported after the previous quiz, and $\text{Modality}_{i,j}$ is a binary indicator of whether student i took quiz j in the Computer-Based Testing Facility ($\text{Modality}_{i,j} = 1$) versus in the classroom with Bring-Your-Own-Device ($\text{Modality}_{i,j} = 0$).

We estimated six separate mixed-effect linear models, one for each study behavior metric, to examine how prior anxiety influences different dimensions of preparation. To account for the nested structure of observations within students (multiple quizzes per student), we included student-specific intercepts to account for baseline individual differences in study behavior. This approach accounts for within-student correlation across quiz observations while maintaining interpretability of fixed effects.

4 Results

4.1 RQ1

To highlight differences associated with extreme levels of state anxiety, we focus on the top and bottom quartiles of the state anxiety distribution. For each student–quiz observation, state anxiety scores were classified as "low" if they fell in the bottom quartile of all state anxiety scores and as "high" if they fell in the top quartile. Figure 1 presents a comparison of study behavior metrics between observations classified as having low state anxiety (bottom 25%) and high state anxiety (top 25%).

As shown in Figure 1, several study behavior metrics differ modestly between observations with low and high state anxiety. Observations classified as high anxiety show a slightly higher fraction attempted and fraction correct, but lower average correctness per attempted instance. In contrast, early-start and cramming rates appear similar across anxiety groups. Overall, these descriptive comparisons suggest that differences associated with state anxiety are subtle and vary across dimensions of study behavior, motivating the regression analyses that follow.

To examine whether these descriptive patterns persist when considering the full distribution of anxiety levels, we estimated three regression models to examine the relationship between study behaviors and state anxiety for all observations, regardless of quartile, controlling for trait anxiety. Results are presented in Tables 2 - 4.

Study amount. The results for the study amount model are shown in Table 2. Consistent with prior research on stable anxiety dispositions [18], trait anxiety was a strong predictor of state anxiety ($\beta_{\text{trait}} = 0.529, p < 0.001$). Among the study amount metrics, the breadth of question coverage (fraction attempted) was not significantly associated with state anxiety ($\beta_1 = 0.161, p = 0.154$). However, the depth of engagement per practice session (average proportion attempted per instance) showed a significant negative relationship with state anxiety ($\beta_2 = -0.369, p = 0.007$).

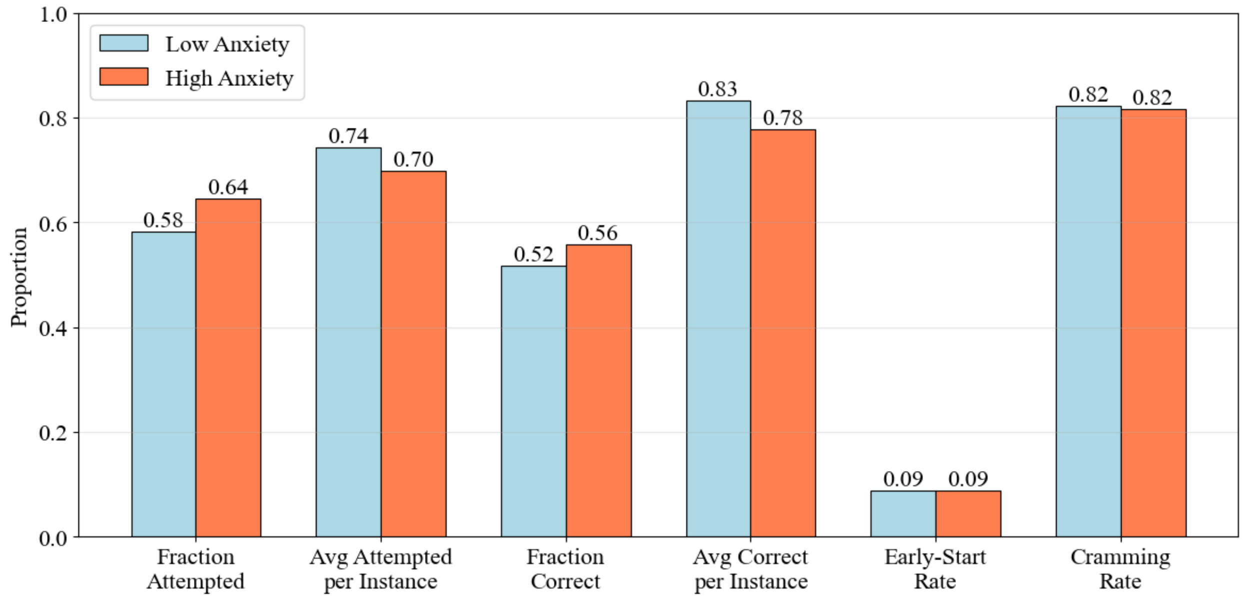

Figure 1: Study behavior metrics by anxiety level. Observations were classified as low anxiety (bottom 25%) or high anxiety (top 25%) based on state anxiety scores. Values show mean proportions.

Students who attempted a smaller proportion of available questions within each practice quiz instance reported higher anxiety on the corresponding quiz, suggesting that less complete practice sessions are associated with elevated anxiety.

Table 2: Regression results showing the impact of *Study Amount* metrics on state anxiety.

Coefficient	**Metric**	**Value**	**p-value**
β_1	Fraction attempted	0.161	0.154
β_2	Average proportion attempted per instance	-0.369	0.007^*
β_{trait}	Trait anxiety	0.529	$< 0.001^*$

* $p < 0.05$.

Study success. The study success model (Table 3) similarly revealed a strong effect of trait anxiety on state anxiety ($\beta_{\text{trait}} = 0.534, p < 0.001$). The overall fraction of attempted questions answered correctly (fraction correct) was not significantly related to state anxiety ($\beta_1 = -0.282, p = 0.166$). However, performance within individual practice sessions (average correct per instance) was significantly negatively associated with state anxiety ($\beta_2 = -0.364, p = 0.020$). Students who answered a higher proportion of questions correctly during their practice quiz attempts reported lower anxiety on the actual quiz, indicating that successful practice experiences may reduce test anxiety.

Study timings. The study timing model (Table 4) examined whether the timing of students' studying was associated with reported test anxiety. Neither cramming (studying within 24 hours of the quiz) nor early preparation (studying more than 48 hours before the quiz) significantly

Table 3: Regression results showing the impact of *Study Success* metrics on state anxiety.

Coefficient	**Metric**	**Value**	**p-value**
β_1	Fraction correct	-0.282	0.166
β_2	Average correct per instance	-0.364	0.020^*
β_{trait}	Trait anxiety	0.534	$< 0.001^*$

* $p < 0.05$.

predicted state anxiety ($\beta_1 = 0.018, p = 0.898$; $\beta_2 = 0.076, p = 0.684$). Trait anxiety, similar to the other two models, had a significant association with state anxiety ($\beta_{\text{trait}} = 0.572, p < 0.001$).

Table 4: Regression results showing the impact of *Study Timing* metrics on state anxiety.

Coefficient	**Metric**	**Value**	**p-value**
β_1	Cramming rate	0.018	0.898
β_2	Early-start rate	0.076	0.684
β_{trait}	Trait anxiety	0.572	$< 0.001^*$

* $p < 0.05$.

4.2 RQ2

To visualize the temporal relationship between anxiety and subsequent study behaviors, Figure 2 compares how students change their preparation after experiencing high anxiety. We identified student-quiz observations where state anxiety fell into the top 25% across all observations. For these high anxiety observations, the green bars show students' study behavior metrics for that quiz, while the purple bars show their study behavior metrics when preparing for the immediately subsequent quiz. This visualization focuses on descriptive changes in study behavior following high-anxiety quiz experiences.

Figure 2 shows modest but consistent shifts in several study behavior metrics following high-anxiety quiz experiences. After a high-anxiety quiz, students attempt a larger fraction of available practice questions and exhibit higher correctness on subsequent preparation, both in terms of overall fraction correct and average correctness per attempted instance. Average engagement per practice instance increases only slightly, while early-start and cramming rates remain largely unchanged. These patterns suggest that, following episodes of elevated anxiety, students may increase the thoroughness and effectiveness of their practice rather than substantially altering the timing of their studying.

To formally examine these relationships across all observations, regression results for RQ2 are shown in Table 5. For these models, study behavior metrics served as outcome variables, with prior state anxiety (β_1), testing modality (β_2), and trait anxiety (β_{trait}) as predictors (Equation 2).

Study amount and prior anxiety. Prior state anxiety significantly predicted greater engagement

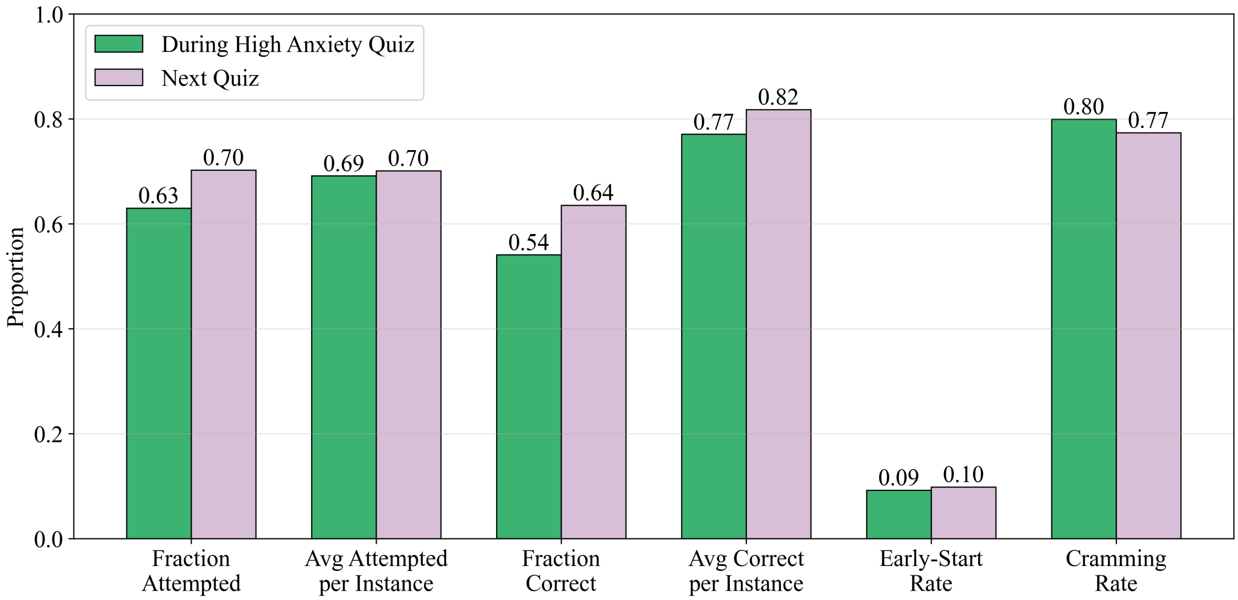

Figure 2: Study behavior during high anxiety quizzes (top 25%) versus the subsequent quiz. Values show mean proportions.

with practice materials. Students who experienced higher anxiety on one quiz attempted a larger proportion of available questions when preparing for the next quiz ($\beta_1 = 0.043, p < 0.001$). However, prior anxiety did not affect the depth of engagement within individual practice sessions, suggesting that anxiety influences the breadth rather than the intensity of practice attempts.

Study success and prior anxiety. Higher previous state anxiety also predicted better practice performance. Students reporting higher anxiety on one quiz achieved higher performance on practice materials for the subsequent quiz, both in terms of the overall proportion of questions answered correctly ($\beta_1 = 0.054, p < 0.001$) and performance within individual practice sessions ($\beta_1 = 0.024, p = 0.005$). This pattern suggests that anxiety prompts students to engage more carefully or thoroughly with practice quizzes.

Study timings and prior anxiety. The study timing models revealed significant behavioral shifts in response to prior anxiety. Students who experienced higher anxiety on one quiz began preparing earlier for the next quiz ($\beta_1 = 0.021, p = 0.038$) and engaged in less last-minute cramming ($\beta_1 = -0.028, p = 0.037$). Testing modality also influenced timing behavior, with students taking quizzes in the CBTF demonstrating lower early-start rates ($\beta_2 = -0.039, p = 0.003$) and higher cramming rates ($\beta_2 = 0.036, p = 0.018$) compared to those in BYOD settings .

Individual differences. Student-specific intercepts variance estimates ranged from 0.010 to 0.043 across models (standard deviation = 0.10 to 0.21), indicating heterogeneity between students in baseline study behaviors [19]. Between 37% and 56% of the variation in study behaviors was attributable to stable differences between students rather than changes within students across quizzes (intraclass correlation coefficients = 0.37 to 0.56 [20]). This suggests students have persistent individual tendencies in how they prepare for assessments. Additionally, trait anxiety showed no significant associations with any study behavior outcome (all $p > 0.05$), indicating that changes in preparation strategies are driven by situational anxiety experiences rather than predispositions.

Table 5: Lagged temporal regression analysis results. β_1 corresponds with state anxiety reported after the previous quiz and β_2 corresponds with modality.

Metric Measured	β_1	**p-value**	β_2	**p-value**	β_{trait}	**p-value**
Fraction attempted	0.043	$< 0.001^*$	0.009	0.461	0.007	0.608
Average proportion attempted per instance	0.005	0.580	-0.005	0.640	-0.014	0.242
Fraction correct	0.054	$< 0.001^*$	-0.000	0.978	0.000	0.978
Average correct per instance	0.024	0.005^*	-0.007	0.494	-0.020	0.067
Cramming rate	-0.034	0.008^*	0.036	0.018^*	0.010	0.614
Early-start rate	0.021	0.038^*	-0.039	0.003^*	-0.013	0.325

* $p < 0.05$.

5 Discussion

5.1 RQ1

The concurrent relationships between study behaviors and test anxiety reveal that test anxiety is tied to preparation quality rather than quantity. Students calibrated their anxiety to the quality of engagement within individual practice quizzes (with the average proportion attempted per instance and average correct per instance) rather than to overall breadth metrics. This pattern is meaningful given the structure of the practice quizzes: each practice instance was designed to mirror the actual quiz structure, providing an ecologically valid simulation of the upcoming assessment. The per-instance metrics therefore represent students' most diagnostic signal of readiness, offering them measurable evidence of how they may perform under assessment conditions. Students who engaged fully with practice instances and performed well received concrete evidence of their readiness, corresponding to lower anxiety levels.

These relationships are concurrent and do not establish causal direction. It is possible that higher anxiety leads students to engage thoroughly with practice materials, or conversely, that incomplete or unsuccessful practice experiences increase anxiety levels. Additionally, both anxiety and study behaviors could be jointly influenced by other factors such as perceived difficulty of the material or time constraints. Regardless of the causality, this finding supports a self-regulating learning perspective in which test anxiety serves as feedback about preparation adequacy. Students appeared to distinguish between breadth of exposure and readiness to perform, appropriately responding to signals most predictive of their likely quiz performance.

5.2 RQ2

The temporal relationships we observed suggest that test anxiety, despite its documented negative effects on performance, may also serve a constructive role in prompting students to recalibrate their preparation strategies. This aligns with the idea of defensive pessimism, where students harness anxiety to motivate productive effort [10]. Our data adds a demonstration that this adaptation is both systematic and multifaceted, as students make strategic adjustments to the breadth of coverage, practice effectiveness, and timing of their studying.

Test anxiety influenced which questions students practiced but not how they engaged with individual practice sessions. This suggests that students interpreted their test anxiety as a signal about insufficient content coverage rather than inadequate effort per session. Given that the practice quiz system allowed unlimited generation of new instances, anxious students could easily expand their exposure to different question types. Whether this strategy is optimal is an open question, but students clearly perceived breadth as a relevant dimension to adjust.

The fact that these behavioral changes were driven by state anxiety rather than trait anxiety is particularly noteworthy. Students with high trait anxiety were no more or less likely to engage in any particular study pattern. Instead, the behavioral shifts occurred in response to situational experiences of anxiety on specific assessments. This suggests that even students who are generally anxious can respond adaptively to their experience, reflecting a dynamic self-regulation in response to perceived unpreparedness.

Beyond test anxiety-driven adaptations, the testing environment itself influenced when students prepared. Students taking quizzes in the CBTF, where they could schedule flexibly within a multi-day window, showed more last-minute cramming and decreased early-start rates than students in the fixed-time BYOD setting. It is interesting that despite the lean towards procrastination with flexible deadlines, shifts towards earlier preparation and less cramming due to state anxiety occurred regardless of modality, suggesting that students' responses to their emotional experiences influenced timing behaviors beyond what the testing environment alone would predict.

6 Implications for Practice

Our findings offer a reframing of how to approach test anxiety. The temporal patterns we observed suggest that interventions might center on helping students recognize anxiety as actionable information and providing the infrastructure to act on it. Concretely, this means ensuring students have access to varied practice problems when anxiety signals the need for broader content coverage, providing feedback that identifies specific gaps in understanding to guide targeted remediation, and making these resources readily available in the period between assessments when students are adjusting their preparation strategies. Since students responded to anxiety by systematically expanding which topics they practiced, improving their practice performance, and adjusting when they studied, course designs that facilitate these specific adjustments, such as unlimited practice problem variants, immediate performance feedback on practice quizzes, and flexible but structured preparation timelines, may effectively support the adaptive self-regulation we observed.

7 Limitations and Future Directions

Several limitations suggest directions for future research. First, while we observed that anxiety prompts adaptive behavioral changes, we did not measure whether these adaptions actually improved subsequent quiz performance or reduced anxiety on later assessments. Future work should close this loop by examining whether the behavioral adjustments we documented translate to better learning and emotional outcomes for the students.

Second, our study focused on quiz-to-quiz changes within a single semester. Longer-term studies could investigate whether these adaptive patterns persist across courses or semesters, and whether students develop consistent self-regulatory strategies over time.

Finally, our analysis examined average effects across students. Individual students likely vary in how they respond to test anxiety, and some may engage in maladaptive rather than adaptive responses. Future research could identify distinct patterns of response and examine what factors predict whether a student responds productively to test anxiety.

8 Conclusion

Test anxiety is often viewed as an impediment to learning, but our findings suggest it can also serve as a constructive metacognitive function. We found that students calibrate their test anxiety to diagnostic indicators of preparation quality in realistic practice simulations. Importantly, when students experience test anxiety on one assessment, they systematically adjust their preparation for subsequent assessments by expanding content coverage, improving practice performance, and managing their time more effectively. These adaptations are driven by situational experiences rather than personality traits. We conclude that test anxiety may motivate strategic changes in study behavior rather than simply impairing learning.

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