Examining the Relationship between Math Anxiety, Effort, and Learning Outcomes Using Latent Class Analysis

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Abstract

Math anxiety has been found to negatively correlate with math achievement, affecting students' choices to take fewer math classes and avoid math educational opportunities. Educational technology tools can ameliorate some of the negative effects of math anxiety. We examined students' math anxiety, effort in an educational technology platform, and their relationship with students' math achievement. Multilevel latent class analysis was used to identify student profiles of math anxiety. Regression analysis was used to examine how students of different profiles interacted with MathSpring, an adaptive intelligent tutor that provides affective supports to students during math problem-solving. The student's math achievement was measured by a standardized test. Our analysis indicated heterogeneity in math anxiety, and students could fall into one of three groups: *Highly Anxious*, *Performance Anxious*, and *Calm*. *Highly Anxious* students tended to give up more often when solving questions in MathSpring and had the lowest math achievement outcomes. For these students, using hints to solve problems in MathSpring was significantly associated with increased math outcomes. These findings have implications for the field's understanding of how students of different math anxiety profiles can demonstrate varying efforts in math educational technology platforms, and different math learning outcomes.

CCS Concepts

• **Applied computing** → Education; E-learning.

Keywords

math learning, math anxiety, social-emotional learning, latent class analysis

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1 INTRODUCTION

Mathematical anxiety, defined as a feeling of tension, panic, helplessness, paralysis, and mental disorganization that arises during math problem solving [1] [2] [3], is a pressing issue for middle school students. Troublingly, math anxiety negatively correlates with math achievement [4]. The importance of understanding math anxiety is even more crucial after the COVID-19 pandemic; students' math anxiety reached high levels, resulting in decreased motivation for math learning [5] [6]. Education technology tools developed to provide emotional support to students have been found to alleviate issues related to math anxiety [7] [8]. However, students with math anxiety may interact with educational technology in different, potentially unproductive ways, which might in turn impact their math achievement.

In this study, we took a person-centered approach to uncover math anxiety profiles within a sample of middle school students recruited as part of a large-scale randomized control trial (RCT) and examined the characteristics of their math anxiety profiles. We analyzed how students with different anxiety profiles interacted with a web-based intelligent math tutor MathSpring, the intervention studied in the RCT, that provides affective support during math problem solving. In particular, we examined the effort that students put in when learning with the tutor (as detected by MathSpring's effort-based algorithm; [9]), such as skipping a problem or giving up on a problem without solving it, and potential differences in their learning outcomes. The research questions (RQs) guiding this study were:

- What are students' math anxiety profiles and how are they characterized?
- How do students with different math anxiety profiles interact with MathSpring as measured by their effort?
- To what extent do learning outcomes differ for students with different math anxiety profiles?
- Does students' effort in MathSpring mediate the relationship between anxiety and learning?

This study helps to interpret findings from the RCT by identifying whether and how students' anxiety profiles and engagement with the tutor influence the observed outcomes in the treatment classrooms, ultimately enhancing our understanding of the intervention's effectiveness across diverse learner groups. The study also aims to shed lights on how individual differences shape responses to the interventions and in particular, how education technology platforms can be utilized to better support students with math anxiety.

2 BACKGROUND

2.1 Math Anxiety and Achievement

Math anxiety is concerning among middle school students because it negatively correlates with math achievement [4]. A meta-analysis found a statistically significant negative correlation between math anxiety and math achievement, which held for subgroups such as grade level, math ability level, and math assessment [4]. Another meta-analysis [10] found a similar relation among primary and secondary students.

Besides math anxiety's effect on math achievement, math anxiety can affect students' class choices; students may take fewer math classes and avoid math educational opportunities [11] [12]. This behavior exacerbates the cycle by lowering exposure, practice, and competency in math, which can then increase anxiety and decrease mathematical achievement further [13]. Math achievement and math anxiety correlate with educational and career outcomes [14], such as influencing high school and college career interests and degrees [15] [16]. Characterizing students' math anxiety and examining the ways in which math anxiety affects problem solving and math learning outcomes is of critical importance.

2.2 Education Technology and Math Anxiety

Educational technology platforms may relieve math anxiety by providing students with emotional support. Digital technologies used in instruction have been found to improve students' understanding of math and increase positive feelings, thereby decreasing math anxiety [8]; if used properly, technology-based approaches could help reduce math anxiety [17]. In particular, math intelligent tutoring systems have the potential of lowering anxiety by walking students through personalized learning plans and gently guiding them to learn from their mistakes [18]. The effect of educational technology on reducing anxiety may be more prominent for students with high levels of anxiety [19]. Similarly, a math edtech program that featured an animated agent who guided algebra lessons with instructional support and anxiety-treating messages concluded that high-anxiety students would benefit the most from the anxiety messages [7].

The research suggests the educational technology in general can help students with math anxiety. However, this study examines the effects of an educational technology program specifically designed to support students' affect and approaches towards math, MathSpring. This platform might be particularly well-suited to improve math anxious students' behaviors and learning outcomes. Additionally, research on the impact of educational technology on student math anxiety has often considered math anxiety as a uniform construct across students, without considering that there may be heterogeneity in students' math anxiety.

2.3 Person-centered Approaches in Understanding Math Anxiety

This study uses a person-centered analysis approach, which identifies and describes groups of individuals who share characteristics based on the assumption that the population is heterogeneous [20], in contrast with variable-centered approaches such as linear regression, which assumes that the relations between variables apply to every individual [21]. Person-centered approaches include finite mixture models such as latent class analysis, latent profile analysis, and latent transition analysis. These methods express the population distribution as a finite mixture of some unknown groups within the population that differ from one another quantitatively [21] and provide multiple sets of parameters per group [22] [23] [24].

Studies using person-centered approaches to understand math anxiety have highlighted the need to understand heterogeneity in students. A study using latent profile analysis on math anxiety profiles and math motivation [25] found eight distinct profiles characterized by various combinations of dimensions of math anxiety and math motivation, revealing the complexity in the math-specific emotion-motivation relation. The study found that students with the highest math achievement reported modest exam math anxiety and high math motivation, whereas the most engaged students were characterized by a combination of high exam math achievement and high math motivation [25].

Person-centered approaches in math anxiety also examined how protective factors, such as self-concept and resilience, were differently related to the risk of math anxiety [26]. Researchers found that self-concept was lower in students who were classified as high anxiety risk. They also examined test anxiety, a form of academic anxiety that is a "psychological, physical, or behavioral reaction to worry cognitions regarding potential failure in achievement/school assessment situations" [27]. This group may not appear to have high or low anxiety but could worry about situations under which they feel pressure in math.

In sum, research has found that math anxiety is related to poorer academic outcomes, which may impact the ways that students interact with educational technology platforms that could ultimately support their outcomes and in turn decrease their math anxiety. In addition, math anxiety has been also found to have conflicting or non-linear relationships with achievement. This highlights the need to understand student math anxiety profiles and characteristics, their behavior when solving math problems, and investigate how these factors relate to students' math achievement.

2.4 The Learning Platform and its Theoretical Foundation

The study was part of an RCT on the MathSpring learning platform. MathSpring is an intelligent tutoring system developed by University of Massachusetts, Amherst and Worcester Polytechnic Institute. It is a supplemental program that provides students with personalized math problems to solve, and tracks and responds to student affect [28]. MathSpring provides students with guidance using hints, worked examples, and videos. A self-reflection page helps students set goals and track their progress through the program. Teachers can view effort data (Figure 1) for the class and for

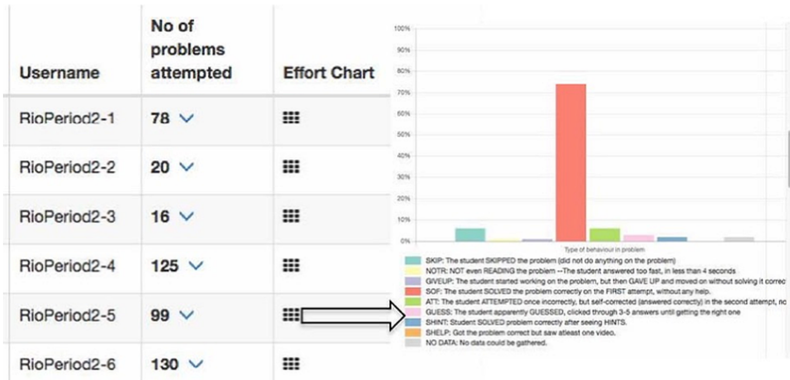

Figure 1: MathSpring's analytic data dashboard view for teachers with data on students' effort

Figure 2: The "learning companions" in MathSpring show a range of emotion and growth mindset messages

individual students, use the data to inform discussions, and adjust their math instruction.

MathSpring's computational models detect students' engagement and emotions and offers supports accordingly via a learning companion avatar who shows sympathy through facial expressions, supportive comments, and growth mindset messages (see Figure 2; [9]). Empathic responses from a teacher or graphic character might be able to promote positive affective experiences when students do not themselves feel positive about a learning experience [29] [30] [31]. Thus, a computer persona in an education technology program such as MathSpring could alleviate students' feeling of anxiety during math problem solving.

In addition, an effort-based tutoring algorithm analyzes students' in-system actions to produce indicators of students' effort, including whether students skip or do not read problems, use hints, or solve on their first attempt [32]. This learning analytics data provides insight into the effort that students exert when solving problems in MathSpring and can be used to help us understand how this platform can support student learning.

3 METHODS

Data for this study was from a cluster RCT conducted in the state of Massachusetts of the United States that examined MathSpring's efficacy in supporting students' math achievement and attitudes towards math. The study was approved by WestEd's Institutional Review Board (IRB). There were three cohorts of teachers who participated who participated in the study (Cohort 1: 2020-2021, Cohort 2: 2021-2022, Cohort 3: 2022-2023). Teachers were randomly assigned to the treatment group (using MathSpring with their students for at least 20 minutes every other week) or the control group (continue business-as-usual math instruction). At the beginning of the school year, teachers distributed electronic opt-out forms to parents of students. Data of opt-out students were excluded from the analysis.

Students completed pre-surveys in the fall to index their math anxiety (RQ1). They then solved problems in MathSpring topics that have been selected and assigned by their math teachers during the course of the school year, which generated effort data (used in RQ2). In the spring, students took the state standardized math test, used as the outcome measure in RQ3 and RQ4. At end of each academic year, districts provided student background data and prior years' standardized math test scores (used as covariates in RQ3 and RQ4).

3.1 Student Sample

There were 53 5th and 6th grade math teachers (30 treatment, 23 control) and their 2,003 students in three cohorts (2020-2021, 2021-2022, and 2022-2023). Teachers and students were from 38 schools

Table 1: Student effort designations and descriptions

Effort designation	Description
SKIP	The student SKIPPED the problem by moving onto the next problem or leaving practice mode without making any attempts on the problem.
SOF	The student SOLVED the problem correctly on the FIRST attempt, without clicking on any hints or demos.
GIVEUP	The student started working on the problem and made attempts to answer the question, but then GAVE UP and moved on without solving it correctly.
SHINT	Student SOLVED problem correctly after seeing at least one HINT.

id.history	time.problem.start	time.problem.end	effort	sec.first. attempt	sec.first. hint	sec.solve	num. mistakes	num. hints	num. attempts	solution. seen	example. seen	num. hints. solve	solved
252985	2020-12-02T16:21:59Z	2020-12-02T16:26:17Z	SOF	246.696	-1	246.696	0	0	1	0	0	0	1
366976	2022-11-16T18:52:18Z	2022-11-16T18:52:23Z	SKIP	-1	-1	-1	0	0	0	0	0	0	0
347495	2022-10-21T13:31:41Z	2022-10-21T13:32:00Z	GIVEUP	-1	-1	-1	0	0	0	0	1	0	0
462456	2023-05-15T07:59:49Z	2023-05-15T08:00:33Z	SHINT	17.68	21.621	41.114	1	3	2	0	0	3	1

Figure 3: Sample data showing student effort in MathSpring

with diverse backgrounds, including low-performing schools and schools with students of lower socio-economic status. Students were 69% White, 7% Black or African American, 8% Hispanic, 6% Asian. 49.5% of students were female and 50.5% were male. 40% of students received either free or reduced-price lunch, the Transitional Aid to Need Families benefit, or were eligible for food stamps. We used the full sample of students from both treatment and control groups (N = 2,003) to uncover the math anxiety profiles in students (RQ1). Subsequent analyses examining students' levels of effort during interaction with the MathSpring platform and how interacting with it related to student learning outcomes (RQs 2-4) were conducted with the students in the treatment condition only (N = 984).

3.2 Measures

3.2.1 Math Anxiety. Students' mathematics anxiety was measured using a validated five-item survey scale from the PISA 2012 Student Questionnaire [33] (see Table 2). Students completed the scale in the fall before treatment students began implementing MathSpring. The scale has high reliability (a = 0.88, [34]; a = 0.88 based on data from this study). Response categories ranged from "Strongly agree" to "Strongly disagree." We dichotomized the items ("Strongly agree" and "Agree" = 1, "Strongly disagree" and "Disagree" = 0) to reduce the number of parameters in the analyses.

3.2.2 Student effort in MathSpring. As students work through problems in MathSpring, the system assigns an effort designation for each problem viewed or attempted. The effort designation is assigned based on actions taken by the students in MathSpring (e.g., attempts, time, hints; see Figure 3 for a small sample of the problem-level data with effort designation in column 4). Effort variables that were theoretically motivated to relate to math anxiety were selected for the analysis: *SKIP*, *SOF*, *GIVEUP*, and *SHINT* (see Table 1).

To analyze student effort in MathSpring, we calculated a percentage for each effort designation at the student level across all problems the student has seen. The effort percentage shows what percentage of the total practice problems viewed by a student that were assigned each effort designation. For example, a *SKIP* percentage of 0.20 indicates that a student skipped 20% of all the practice problems they viewed.

3.2.3 Learning outcome: state standardized math test scores. Students' math learning outcome was measured using the Massachusetts state standardized math assessment – the Massachusetts Comprehensive Assessment System (MCAS) scaled scores. MCAS was administered to all eligible students in Massachusetts in May. Questions on the MCAS are aligned with the learning standards from the 2017 Massachusetts Curriculum Framework for Mathematics [34]. MCAS scaled scores were used in analyses (range: 440 – 560). Because MCAS scores are not vertically scaled, i.e., a 5th grade student's score cannot be compared to a 6th grade student's score, we standardized the scores of the fifth- and sixth-grade students in the study to z-scores by grade using the statewide mean and standard deviations for the respective grades (Table 2). Students' fourth grade MCAS scaled scores were used as a measure of student's prior math achievement as a covariate in the analytic models.

3.3 Analysis Approaches

3.3.1 RQ1: Multilevel Latent Class Analysis: Model specification. To understand and characterize students' anxiety profiles (RQ1), a multilevel latent class analysis (MLCA; [35] [36] [37]) was used to identify possible anxiety profiles. This method is appropriate to be used for latent class analysis (LCA) with nested or hierarchical data. In a one-level LCA, where $P(Y_i = s)$ is the probability of subject i's response to K observed items with a response pattern s, is a function of 1) the probability of the subject being in a given latent class, and 2) the probability of the subject selecting a particular

Table 2: Descriptive statistics for measures and the outcome variable in the study (N = 2,003)

Variable	Mean	Std Dev.	Min.	Max.
Pre-test scores: MCAS 4th Grade Scaled Scores (converted to Z scores)	-0.10	0.98	-2.27	2.00
Anxiety Variables*				
I often worry that it will be difficult for me in mathematics classes.	0.53	-	-	-
I get very tense when I have to do mathematics homework.	0.37	-	-	-
I get very nervous doing mathematics problems.	0.34	-	-	-
I feel helpless when doing a mathematics problem.	0.22	-	-	-
I worry that I will get poor grades in mathematics.	0.54	-	-	-
Effort Variables**				
SKIP	0.16	0.11	0	0.69
SOF	0.39	0.18	0	1.00
GIVEUP	0.09	0.09	0	1.00
SHINT	0.05	0.08	0	0.55
Outcomes Variable				
MCAS Math Scaled Scores (converted to Z scores)	0.2	0.91	-2.37	2.97

Note: *Proportions for item = 1; **For students in the treatment condition only (N = 803)

response to an item, condition on their latent class membership. The model can be expressed as:

$$P\left(Y_i = s\right) = \sum_{c=1}^{L} P\left(C_i = c\right) P(Y_i = s \mid C_i = c) \tag{1}$$

where Y_i is subject $i's$ response pattern to K indicators and s is a vector of a specific response pattern for K items. The conditional response probabilities (CRP) is shown as $P(Y_i = s \mid C_i = c)$, indicating the probability of the subject selecting a particular response to an item, condition on their latent class membership and the latent class probability, is shown as $P(C_i = c)$ where C_i is the latent variable and c is the latent class membership where $c = 1, 2, \ldots L$.

In the MLCA, group-specific parameters are introduced, allowing the CRP and latent class probabilities to vary from group to group. In addition, random components are included to "capture the variations in each group's latent class probabilities and conditional response probabilities" [38]. The model includes an index j denoting level 2 classes:

$$P\left(Y_{ij} = s\right) = \sum_{c=1}^{L} P\left(C_{ij} = c\right) P(Y_{ij} = s \mid C_{ij} = c) \tag{2}$$

Latent class enumeration Step 1: Explore number of one-level LCA classes. Because the number of latent classes for math anxiety within the study sample is unknown, we used an exploratory approach to determine the number of classes using students' responses to the math anxiety survey in a one-level latent class analysis (LCA). The five items for math anxiety were first used in a level 1 LCA model. We started the exploration process by fitting a level-1 LCA model with only one latent class ($K = 1$), and then iteratively increasing the parameter K to 2, 3, ... to increase the number of latent classes specified in the LCA model, until the models are not identified or not well identified, i.e., when the models failed to replicate the highest log likelihood despite increasing the number of random starts in the model.

The selection of the final model is based on evaluating 1) relative fit using indices such as the Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), sample size adjusted BIC (saBIC), 2) absolute fit indices that compare model estimated frequencies to actual frequencies [23], and 3) classification diagnostics based on model posterior probabilities where class separation and homogeneity are evaluated. Convergence rates for the models across different start values, the replication rate of the best maximum log likelihood value, and the size of the smallest class were used to evaluate the models [39]. Finally, we looked for models with identified latent classes that are interpretable based on research on math anxiety.

Latent class enumeration Step 2: Use findings from one-level LCA to find the best MLCA model. To identify the best MLCA model, we used the best model from the Level-1 LCA and tested neighboring classes (one additional class) in the MLCA [40]. We ran parametric and non-parametric MLCA models to determine if we could retain the number of classes in the MLCA [40]. Fit statistics between the MLCA models were compared to select the model with the best fit. After selecting the best model, students' most likely class membership was assigned using maximum posterior probabilities.

3.3.2 RQ2 – RQ4: Hierarchical Linear Models. To address RQ2, RQ3, and RQ4, we ran two-level hierarchical linear models (students nested within teachers). To understand how students with different math anxiety profiles interacted with MathSpring differently at different levels of effort (RQ2), we ran four models, one for each effort variable as the outcome and with the anxiety classes as the

Table 3: Model fit indices for LCA and MLCA Models (N = 1,794)

Model	Number of Level 1 Classes				
	1	2	3	4	5
		Model 1 Traditional LCA			
No. of free parameters	5	11	17	23	29
Log-likelihood	-5685.826	-4637.282	-4537.386	-4529.274	-4527.023
BIC	11409.113	9356.978	9202.139	9230.869	9271.320
p-value LMR-LRT	<.001	<.001	.087	.366	NA
Entropy	1	0.789	0.707	0.66	0.701
		Model 2: Parametric			
No. of free parameters	-	-	29	29	-
Log-likelihood	-	-	-4515.401	-4494.433	-
BIC	-	-	9180.645	9206.14	-
Entropy	-	-	0.711	0.673	-
		Model 3: Non-parametric			
2 level-2 classes					
No. of free parameters	-	-	33	44	-
Log-likelihood	-	-	-4504.956	-4494.139	-
BIC	-	-	9257.155	9317.934	-
Entropy	-	-	0.812	0.776	-
		Model 4: Non-parametric			
3 level-2 classes					
No. of free parameters	-	-	49	65	-
Log-likelihood	-	-	-4479.852	-4465.062	-
BIC	-	-	9326.821	9417.118	-
Entropy	-	-	0.841	0.776	-

predictor. Post-hoc Tukey tests were used if the main effect was significant.

To understand the extent to which learning outcomes differed for students with different math anxiety profiles (RQ3), we ran a model with score on the MCAS as the outcome, math anxiety classes as a predictor, and controlled for MCAS pre-test scores and student demographics (gender and race) using the form:

$$StudentLevel : Y_{ij} = \beta_{0\mathrm{j}} + \beta_{1\mathrm{j}} X_{ij} + \varepsilon_{ij} \tag{3}$$

$$TeacherLevel : \beta_{0\mathrm{j}} = \gamma_{00} + \mu_{0j} \tag{4}$$

where $\mathrm{Y_{ij}}$ = the outcome for the ith student in the jth teacher's classroom and $\mathrm{X_{ij}}$ are the student-level predictors. The teacher level consists of the random intercept γ_{00} and the residual error terms at the student and teacher level are respectively modelled by $\varepsilon_{\mathrm{ij}}$ and $\mu_{0\mathrm{j}}$.

Lastly, to understand how student effort in MathSpring mediates the relationship between student anxiety and learning outcomes (RQ4), we added an interaction term (effort by anxiety profiles) to the model used for RQ3 to examine how math anxiety classes interacted with the effort exerted in MathSpring on MCAS scores. There were four models for RQ4, one for each effort variable.

4 RESULTS AND FINDINGS

4.1 RQ1: Math anxiety profiles

After a series of LCA and MLCA analyses, we were able to identify three classes of student math anxiety, *Highly Anxious, Performance Anxious*, and *Calm.* To do so, we first fit a series of one-level latent class models ranging from one to five classes and found that the three-class model had the lowest (best) CAIC, BIC, SaBIC, and AWE values and the Lo-Mendel-Rubin likelihood ratio test (Adjusted LMR-LRT) had a non-significant p-value (see Table A for more information). The average posterior class probabilities (avePP) for the three-class model were 0.90, 0.83, 0.80, suggesting that the given model does a good job of classifying individuals into their most likely class. This indicated that the three-class one-level model was the best model. Therefore, we proceeded to run the MLCA with three- and four-class models (Model 2, Table 3; [40]). There was a small improvement in the BIC when compared to the one-level LCA model (Model 1). The entropy was very similar for the three-class model but increased very slightly by 0.01 for the four-class model. Comparisons between these models suggested that the three-class model (Model 2) is preferred with a lower BIC.

Next, the nonparametric approach was utilized for the three- and four-class Level-1 LCA models (Table 3). The BIC for the non-parametric models with two and three Level-2 classes (Models 3 and 4) had a slightly worse fit compared to the parametric three-class model (Model 2). Although the entropy values for the non-parametric MLCA models were higher, entropy should not be used as a model selection statistic [41]. Therefore, the parametric three-class model (Model 2) was selected as the final model. This is a 3-class LCA of students nested within teachers.

We examined item probability plots for the MLCA parametric three-class solution (Figure 4). The plot shows the probability of a student endorsing a particular item, i.e., agreeing with statements

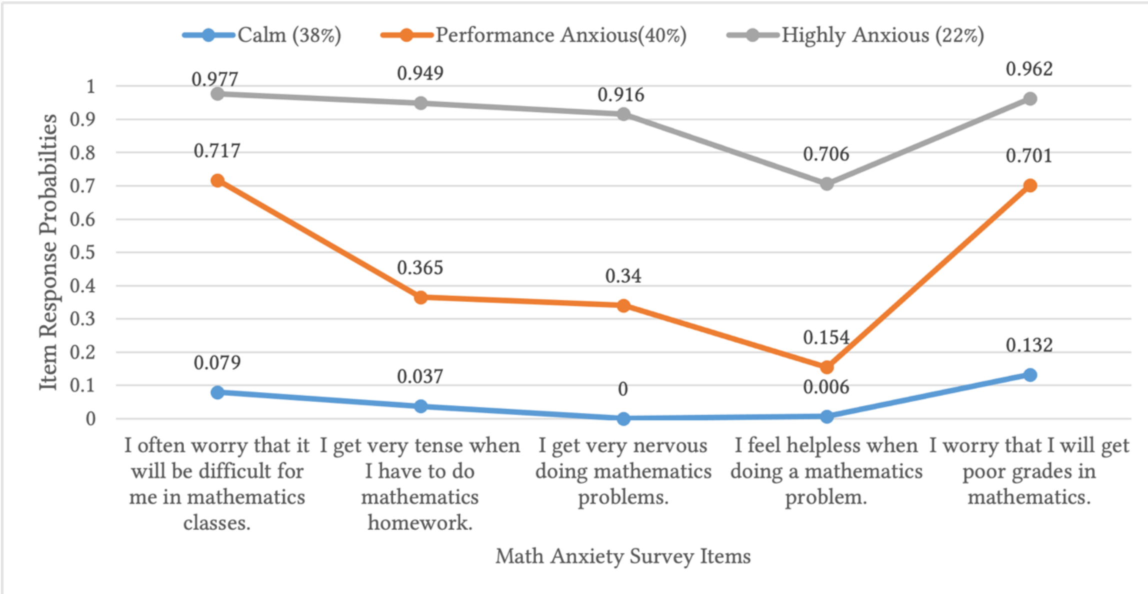

Figure 4: Item Probability Plot for the MLCA three-class solution (N = 1,794)

Table 4: Student pre-test math scores by math anxiety classes (N=1,669)

Math Anxiety Classes	Pre-test math scores*	SE
Calm	0.27	0.07
Highly Anxious	-0.59	0.08
Performance Anxious	-0.30	0.07

Note: *4th Grade MCAS Z-score range: -2.27 – 2.00

related to math anxiety. In the three-class solution, we named one class (22% of the sample) the *Highly Anxious* class, where students had the highest probabilities of endorsing all math anxiety indicators. Another class (40%) was named the *Performance Anxious* class. Students in this class had relatively low probabilities of endorsing three items pertaining to math anxiety but were characterized by having high probabilities of endorsing two items that related to math performance. Characteristics of this class are similar to the *Test Anxiety* class identified in prior research [26] [27]; students expressed worry for performing well in class and on assessments. The last class was the *Calm* class (38% of the sample) where students had a low probability of endorsing the indicators for math anxiety or performance, suggesting that they would be the least anxious about math.

The three classes of students differed significantly on their prior math knowledge as measured by 4th grade MCAS scores. Aligning with prior research [4] [10], we found that the students in the latent class who exhibited the highest levels of math anxiety (*Highly Anxious*) scored the lowest on the end-of-year math assessment and students in the latent class with the lowest math anxiety (*Calm*) scored the highest. Students who worried about their performance (*Performance Anxious*) did better than the *Highly Anxious* students, but not as well as the *Calm* students (Table 4).

RQ2: Math anxiety profiles and effort in MathSpring

We next analyzed how students with different anxiety profiles interacted with MathSpring. The results (Table 5) indicated that compared to the *Calm* or *Performance Anxious* classes, students in the *Highly Anxious* class on average had a significantly higher chance of skipping a question after seeing it (*SKIP*) (17% vs. 14% vs. 16%, $p < .05$). They tended to give up on solving a question (*GIVEUP*) more often compared to students in the *Calm* (diff = 0.05, $p < .001$) and *Performance Anxious* (0.02; $p = .031$) classes. Interestingly, we observed that students in the *Calm* class had a higher chance of solving a question on their first attempt (*SOF*) compared to both students in the *Highly Anxious* (45% vs. 31%, $p < .001$) and *Performance Anxious* (45% vs. 35%, $p < .001$) classes. They also skipped questions (*SKIP*) less often compared to the *Highly Anxious* class ($p = .003$) or the *Performance Anxious* class ($p = .025$). There were no significant differences between classes on solving problems with hints (*SHINT*). Overall, the results suggested that students of different math anxiety profiles demonstrate different ways interacting with the learning system. Students who are "calm" tend to show more desirable behaviors and put more effort when solving math problems in MathSpring.

Table 5: Results of Hierarchical Linear Regression – Adjusted Means and Comparisons between Student Math Anxiety Classes and Effort in MathSpring

Effort	*Highly Anxious* (N = 174)		*Calm* (N = 318)		*Performance Anxious* (N = 253)		Comparisons	Difference	*p*
	Adjusted mean	*SE*	Adjusted mean	*SE*	Adjusted mean	*SE*			
SKIP	0.17	0.01	0.14	0.01	0.16	0.01	C vs. HA	-0.03	.003
							C vs. PA	-0.02	.025
							PA vs. HA	-0.01	1.000
SOF	0.31	0.02	0.45	0.02	0.35	0.02	C vs. HA	0.14	< .001
							C vs. PA	0.10	.007
							PA vs. HA	0.04	< .001
GIVEUP	0.12	0.01	0.08	0.01	0.10	0.01	C vs. HA	-0.05	< .001
							C vs. PA	-0.02	.015
							PA vs. HA	-0.02	.031
SHINT	0.06	0.01	0.05	0.01	0.06	0.01	C vs. HA	-	-
							C vs. PA	-	-
							PA vs. HA	-	-

Table 6: Results of Hierarchical Linear Regression – Adjusted Means, Standard Deviations and Comparisons between Math Anxiety Classes on MCAS outcomes, controlling for Pretest scores and Covariate (N = 614)

Math Anxiety Classes	Adjusted mean (SD)	N	Comparisons	Difference	*SE*	*p*
Calm (C)	0.84 (0.84)	262	C vs. PA	0.16	0.06	.001
Highly Anxious (HA)	0.44 (0.82)	134	C vs. HA	0.39	0.07	< .001
Performance Anxious (PA)	0.68 (0.78)	218	PA vs. HA	0.24	0.07	.028

Note: C = *Calm* class; HA = *Highly Anxious* Class; PA = *Performance Anxious* Class

4.2 RQ3: Math anxiety profiles and learning

Next, we analyzed whether students' math anxiety profiles related to their math learning outcomes. The analysis showed that students in the *Calm* class scored higher than the other two classes on the MCAS math assessment (Table 6). The post-hoc tests showed that students in the *Calm* class scored 0.39 points higher than the *Highly Anxious* class ($p < .001$) and 0.16 points higher than the *Performance Anxious* class ($p < .05$). In addition, the *Performance Anxious* class scored 0.24 points higher than the *Highly Anxious* class ($p < .001$). These findings are consistent with literature showing that students with high math anxiety tend to perform poorly [4] [10] compared with their peers with lower anxiety.

4.3 RQ4: Effort in MathSpring mediates the relationship between math anxiety profiles and learning

Last, we tested whether the relation between students' anxiety profiles and their math achievement was mediated by the effort they exerted when using MathSpring. The results indicated that students' use of hints was a key mediator. In the model, student anxiety classes and *SHINT* (solving problems after seeing hints) had a significant interaction effect (Table 7). However, student anxiety classes and *GIVEUP*, *SOF*, and *SKIP* did not have significant interaction effects on MCAS outcome scores.

Both the means of the slope for the *Performance Anxious* and *Calm* classes were significantly lower compared to the *Highly Anxious* class (b = -2.40, $p = .01$ and b = -3.28, $p < .001$ respectively), suggesting that solving problems with hints had a greater significant positive effect on MCAS scores for the *Highly Anxious* students compared to students in the other classes (Figure 5). In other words, using hints was more strongly related to math achievement for *Highly Anxious* students compared with *Calm* or *Performance Anxious* students.

However, students would only receive hints in MathSpring if they requested hints, which typically occurs when students had trouble solving the problem without support. Students in the *Calm* and *Performance Anxious* classes, who demonstrated higher math achievement, would not have requested hints if they answered the questions correctly. Thus, the significant contrasts could be due to a skewed distribution for *SHINT*. We re-ran the analysis with only the *Highly Anxious* group, using robust standard errors to account for the skewness in the data. Results indicated that for the *Highly Anxious* group, a 1% increase in using hints to solve problems in MathSpring is associated with a significant increase in MCAS scores of 0.02 standardized units ($p = .019$). Despite needing more hints than *Calm* or *Performance Anxious* students, *Highly*

Table 7: Results of Hierarchical Linear Regression Models with Interaction - Adjusted Means between Math Anxiety Classes on MCAS outcomes, controlling for Pretest scores and Covariate (N = 569)

Effort	*Highly Anxious* (N = 124) *Adj. Mean*	*Calm* (N = 250) *Adj. Mean*	*Performance Anxious* *Adj. Mean*
SKIP	0.27	0.63	0.52
SOF	0.25	0.57	0.53
GIVEUP	0.24	0.65	0.41
SHINT	0.26	0.63	0.51

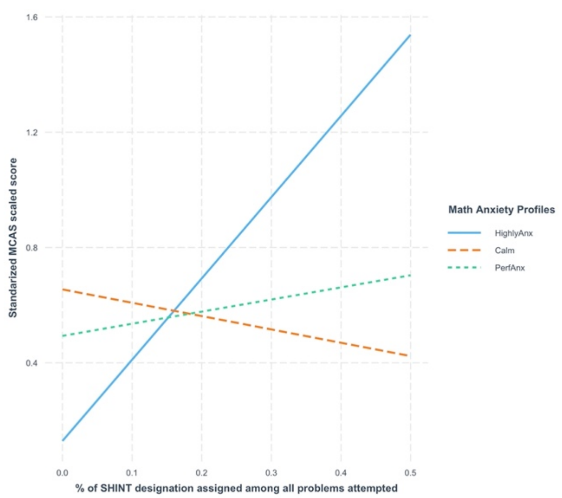

Figure 5: Plot for interaction effects between *SHINT* and Math Anxiety Classes on MCAS Math Outcomes

Anxious students who used more hints demonstrated significantly better math achievement.

5 DISCUSSION AND CONCLUSION

In this study, we examined different profiles of student math anxiety using MLCA, a person-centered approach, classifying students as *Highly Anxious*, *Performance Anxious*, or *Calm.* Adopting a person-centered approach in understanding profiles of student math anxiety has showed that there is heterogeneity in the way students exhibit math anxiety and engage with an educational technology platform. This study indicates that assuming that anxiety is linear in students fails to capture the complexity of their experiences. Using person-centered approaches to explore complex, multidimensional data from studies like this RCT add nuance and provide us with context to RCT impact findings.

While solving math problem in an online educational technology platform that was designed to support students' affect, highly anxious students skipped or gave up on questions more frequently, and students without math anxiety more often solved problems on their first attempt compared to the other groups. These results were consistent with prior research indicating that students with high math anxiety could exhibit avoidant behaviors when it came to math [42] and have lower math achievement scores [4]. Despite having the lowest math achievement scores among the three groups, students in the *Highly Anxious* group who used hints in MathSpring to solve problems had significantly better math achievement. These findings are in line with research on the ways that educational technology platforms can support students with anxiety, particularly those with high anxiety [7]. This suggests that MathSpring's affective supports could have encouraged *Highly Anxious* students to use hints, which could support math performance. This could lead to increased confidence in math and support emotions for *Highly Anxious* students. Future research could assess profiles of students *after* using MathSpring to understand if profiles shifted as a result of using the platform.

Despite the finding that the *Highly Anxious* group's use of hints was significantly associated with improvements in their MCAS outcomes, their scores did not surpass that of the other two groups. Further research could be conducted to understand whether extended use of edtech can support math learning for students with high math anxiety. In particular, longitudinal studies examining the long-term effects of edtech usage on math anxiety is a gap in the literature that could be addressed in future studies. Lastly, it is important to bear in mind that these findings are not causal — we do not know whether MathSpring's features helped encourage highly anxious students to use more hints, which improved their math outcomes, or whether there were other factors that led to students to use more hints in MathSpring, e.g., at the encouragement of the teacher.

The person-centered approach to understand different math anxiety profiles in students in this study contributes to the broader research on how education technology can support students with different math anxiety profiles. The relationship between math anxiety and achievement may be nonlinear and are often dependent upon other factors such as students' motivation [43]. Understanding how specific functions within an education technology platform can support students with different types of anxiety can help educational technology developers better understand and refine social emotional functions that can support students with different types of anxiety. For example, different motivation types may be needed — *Highly Anxious* students may need encouragement to keep trying or use a hint, despite getting a problem wrong. Developers could adopt strategies to encourage the use of hints to solve problems for *Highly Anxious* students by making clear that they would not be penalized for using hints. Similarly, students who are *Performance Anxious* may require more reassurance of their abilities to solve the problem, and more time in a problem in order to stay calm and focused. Although the learning companion in MathSpring offers these supports, they could be tailored to target students based on their anxiety profiles. Overall, this research has shed light on the heterogeneous math anxiety profiles in middle school students that differentially affected math achievement and effort in a math educational technology platform.

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A APPENDICES

A.1 Tables

Table A: A Model Fit Indices for Level 1 LCA (N = 1,794)

Model	LL	npar	Adj. X_LR^2 (df), *p*-value	CAIC	BIC	saBIC	AWE	Adj. LMR *p*-value	$B\hat{F}_{K,K+1}$
1-class	-5685.826	5	-	11414.113	11409.113	11393.228	11461.574	<.001	<.001
2-class	-4637.282	11	225.434 (20), <.001	9367.978	9356.978	9322.031	9472.392	<.001	<.001
3-class	-4537.386	17	25.643 (14), .029	9219.139	9202.140	9148.131	9380.507	.087	>10
4-class	-4529.274	23	9.419 (8), .308	9253.869	9230.869	9157.799	9472.189	.366	>10
5-class	-4527.023	29	4.917 (2), .086	9300.320	9271.320	9179.189	9575.594	-	-