Psychological Mechanisms of Mathematics Anxiety and Impact on Mathematical Problem-Solving Performance within a Blended Learning Ecosystem Utilizing a Learning Management System (LMS)

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Abstract: *This study investigates the psychological mechanisms of mathematics anxiety and its impact on mathematical problem-solving performance within a blended learning ecosystem supported by a Learning Management System (LMS). The primary aim of this research is to examine the relationship between mathematics anxiety and students' mathematical problem-solving abilities in technology-enhanced learning settings. The participants were 60 prospective elementary school teachers enrolled in a mathematics education course that used a blended learning model integrating face-to-face instruction and LMS-based activities. A mixed-methods design was employed to obtain both quantitative and qualitative insights. Quantitative data on mathematics anxiety and problem-solving performance were analyzed using correlational analysis and regression modeling to identify the strength and direction of the relationship between variables. Complementary qualitative data were collected through semi-structured interviews and learning-experience reflections to explore students' cognitive, emotional, and behavioral responses during blended learning, how particularly LMS-mediated tasks shaped their anxiety patterns and strategic approaches to problem solving. Research findings show that the influence of mathematics anxiety on learning performance or problem solving is indirect and influenced by psychological mechanisms and a more complex learning context. Thus, mathematics anxiety cannot be understood separately, but needs to be studied together with other cognitive, affective, and contextual factors.*

***Key Words**:* Mathematical Anxiety, Mathematical Problem-Solving, Blended Learning

Introduction

Mathematical problem-solving ability is a key 21st-century competency that demands the integration of logical reasoning, cognitive flexibility, and affective management throughout the thinking process. However, various studies show that students' mathematical problem-solving abilities are often hampered by non-cognitive factors, one of which is mathematics anxiety. Mathematics anxiety is understood as a negative emotional response in the form of tension, worry, and fear when faced with mathematical activities, which directly impacts decreased academic performance and a tendency to avoid mathematical tasks (Georges, Hoffmann, en Schiltz 2016); (Dowker, Sarkar, en Looi 2016). Over the past decade, consistent cross-cultural findings have shown that mathematics anxiety is not only negatively correlated with achievement but also affects the quality of problem-solving strategies used by students.

From a cognitive psychology perspective, math anxiety operates through specific psychological mechanisms that interfere with the problem-solving process. Attentional Control Theory and Processing Efficiency Theory explain that anxiety increases cognitive load through intrusive thoughts that deplete working memory capacity, particularly the executive and visuospatial components crucial for solving math problems (Eysenck 2016); (Carey en Stefaniak 2018). Recent research shows that individuals with high levels of math anxiety tend to have difficulty retaining information between steps in a problem-solving process, choose less efficient strategies, and give up more quickly when faced with non-routine problems (Chang en Beilock 2012); (Ei en Oo 2023); (Hasan en Juniati 2025a); (Hasan en Juniati 2025b). This confirms that the impact of math anxiety is mechanistic, not simply emotional.

Along with the digital transformation of education, the mathematics learning ecosystem has also undergone significant changes through the implementation of blended learning, which combines face-to-face and online learning based on a Learning Management System (LMS). LMSs provide various features such as digital modules, discussion forums, adaptive quizzes, automated feedback, and learning activity tracking, which have the potential to impact students' learning experiences cognitively and affectively (Technol et al. 2021); (Meeter 2021). Recent studies have shown that blended learning can increase learning flexibility and student independence, but at the same time, it can also give rise to new forms of anxiety, particularly when demands on self-regulation and information processing increase (Technol et al. 2021). In the context of mathematics, the time pressure of online quizzes, the lack of social cues, and text-based interactions can amplify anxiety responses in vulnerable students.

Research over the past decade has shown a shift in focus from simply measuring the relationship between math anxiety and achievement to understanding the underlying psychological mechanisms. Recent meta-analyses and systematic reviews emphasize the important roles of working memory, attentional control, and emotion regulation as key mediators of the relationship between math anxiety and performance (Barroso et al. 2020); (Ge et al. 2024). On the other hand, research on digital learning and LMSs has focused more on aspects of instructional design, learning engagement, and general learning outcomes, without deeply integrating psychological variables (Zamecnik, Kovanovi, en Liu 2022). Thus, a significant research gap remains regarding how the psychological mechanisms of math anxiety operate specifically within LMS-based blended learning ecosystems.

A relevant approach to bridging this gap is the integration of a cognitive-affective psychology framework with digital learning analytics. LMSs provide learning traces, such as work time, repetition frequency, error patterns, and discussion participation, that can be used to identify behavioral indicators of anxiety-induced cognitive impairment (Gaševi et al. 2016); (Tempelaar, Rienties, en Nguyen 2021). By linking these data with measures of math anxiety and problem-solving performance, research can uncover more comprehensive pathways of influence, such as how anxiety triggers avoidance strategies, slows decision-making, or reduces persistence in solving complex problems in blended learning environments.

The significance of this research lies in its theoretical and practical contributions. Theoretically, this research broadens the understanding of mathematics anxiety by placing it within the context of modern technology-mediated learning, while strengthening the mechanistic model linking affective, cognitive, and problem-solving performance. Practically, the research findings can form the basis for developing LMS-based mathematics learning designs that are more sensitive to students' psychological states, such as providing adaptive feedback, adjusting the level of difficulty, and supporting emotional regulation in online environments. Thus, this research is expected to provide a strategic contribution to improving the quality of mathematics learning in the increasingly dominant blended learning ecosystem in the digital era

The introduction section must contain (in sequence) a general background, a previous literature study (state-of-the-art) as a basis for the statement of scientific novelty of the article, a statement of scientific novelty of science, and a research problem or hypothesis. At the end of the introduction, the purpose of the article should be clearly written. In the scientific article format, it is not permissible to review the literature as in the research report, but it is manifested in the form of a previous study review (state-of-the-art) to demonstrate the scientific novelty of the article.

Method

This study used a quantitative explanatory approach with a correlational-causal design to examine the psychological mechanisms of mathematics anxiety and its impact on mathematics problem-solving performance in a blended learning ecosystem based on a Learning Management System (LMS). This approach was chosen because it allows for testing direct and indirect (mediation) relationships between affective and cognitive variables and learning performance in an authentic digital learning context. The study was conducted in mathematics learning that combines face-to-face meetings and structured online activities through an institutional LMS.

The sample selection technique used cluster random sampling with classes as cluster units to minimize disruption to the learning process. The research sample involved secondary or first-year students taking mathematics courses in a blended learning format. The sample size was determined based on statistical power analysis for the mediation model, thus ensuring adequate parameter estimation and generalizability of the findings. The sample in this study consisted of 60 student teacher candidates.

The research instruments included: (1) a validated Mathematics Anxiety Scale (Abbreviated Math Anxiety Scale or Mathematics Anxiety Rating Scale), to measure the affective dimension; (2) a non-routine problem-solving test that measures planning, strategy execution, and solution accuracy; and (3) indicators of cognitive mechanisms represented by measures of mathematics anxiety or cognitive behavior from LMS data, such as response time, frequency of answer revision, and error patterns. In addition, LMS log data was used to capture student learning interactions during online activities.

Data collection was conducted through a combination of online surveys, performance tests, and LMS activity log extraction during one learning cycle. Data analysis used linear regression to examine the direct and indirect effects of math anxiety on problem-solving performance through psychological mechanisms. Descriptive analysis and statistical prerequisite tests were conducted first, while additional analysis based on learning analytics was used to support the interpretation of cognitive mechanisms in the context of blended learning.

Results and Discussion

Based on the regression statistics obtained, an analysis of the strength and quality of the regression model used in this study revealed a Multiple R value of 0.120, indicating a very weak relationship between the independent and dependent variables. This indicates that changes in the predictor variables only have a weak correlation with changes in the predicted variable. In other words, the independent variables are not yet able to adequately explain the variation in the dependent variable linearly.

Table 1. Regression Test Results

Regression Statistics	
Multiple R	0.120277061
R Square	0.014466571
Adjusted R Square	-0.002525384
Standard Error	20.59125995
Observations	60

An R-square value of 0.014 indicates that the regression model can only explain approximately 1.4% of the variation in the dependent variable, while approximately 98.6% of the remaining variation is influenced by other factors not included in the model. This very small percentage contribution indicates that the independent variables used in the model have low predictive power for the dependent variable. This condition is a strong signal that the phenomenon being studied is complex and likely influenced by many other variables, including cognitive, affective, and contextual.

Furthermore, a negative Adjusted R Square value (-0.0025) indicates that the regression model used is no better than the model without predictors (the mean model). Negative adjusted R square values often occur when the number of predictors is disproportionate to the sample size or when the predictors used are statistically irrelevant.

The standard error value of 20.59 indicates the average magnitude of the model's prediction error. The larger this value, the lower the model's accuracy in predicting the actual value of the dependent variable. In the context of educational or psychological research, a relatively large standard error value indicates high individual response variability, which is not accommodated by a simple regression model.

Overall, the results of this analysis indicate that the regression model still has significant limitations. These findings underscore the need to develop more comprehensive models, for example by adding mediator or moderator variables, using a multivariate approach, or considering other psychological and contextual factors to substantially improve the model's predictive ability.

Table 2. ANOVA

	df	SS	MS	F	Significance F
Regression	1	360.9841154	360.9841154	0.851377658	0.359985482
Residual	58	24591.99922	423.9999865		
Total	59	24952.98333			

On the regression model used, an evaluation of the overall significance of the model in explaining the variation of the dependent variable can be carried out. The regression Sum of Squares (SS) value of 360.98 indicates the magnitude of variation that can be explained by the regression model, while the residual SS of 24,591.99 represents variation that cannot be explained by the model and originates from errors or other factors outside the predictor variables. This comparison indicates that the portion of variation explained by the model is relatively very small compared to the remaining variation in the data.

Furthermore, the F-Significance value of 0.36, which is much greater than the conventional significance limit ($\alpha = 0.05$), indicates that the regression model is statistically insignificant. This means that the predictor variables used simultaneously do not have a significant effect on the dependent variable. Therefore, the null hypothesis that the regression coefficient is equal to zero cannot be rejected.

These results indicate that the relationship between the independent and dependent variables in this regression model is still weak and not strong enough to explain the phenomena that occur. In the context of educational or psychological research, this condition reflects the complexity of learning behavior, which is influenced by many other factors, such as cognitive, affective, motivational, and learning environment variables, which are not yet accommodated in the model. Therefore, the development of a more comprehensive model is needed, either by adding other predictor variables, considering mediation or moderation effects, or using a more complex analytical approach such as multivariate regression or structural equation modeling, so that the relationships between variables can be explained more accurately and meaningfully.

Table 3. Intercept Values

	Coefficients	S. Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	74.143353	13.090223	5.6640248	4.8453	47.94042	100.3462
Anxiety	0.3001697	0.3253162	0.9227012	0.3599	0.951360	0.3510

Based on the regression coefficient estimation results obtained, the influence of the Anxiety variable on the dependent variable in this research model can be analyzed. The intercept value of 74.14 indicates the average predicted value of the dependent variable when the anxiety variable is at zero. This intercept is statistically significant, as indicated by the t value = 5.66 and p-value = 4.85×10^{-7}, which is much smaller than the 0.05 significance level. The 95% confidence interval for the intercept ranges from 47.94 to 100.35, which does not cross zero, thus confirming that the model constants are estimated stably and meaningfully.

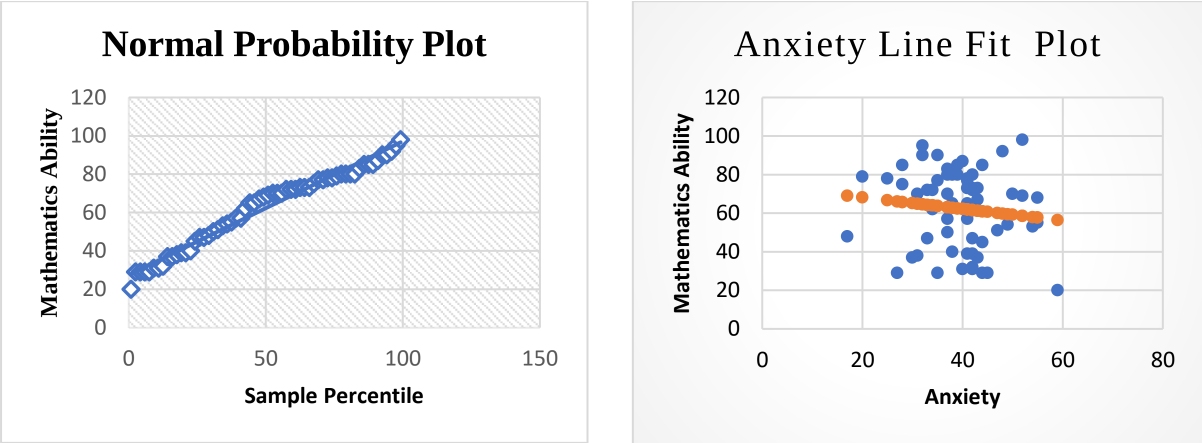

Figure 1. Normal Probability and Anxiety Line Fit Plot

Meanwhile, the regression coefficient for the Anxiety variable of –0.30 indicates a negative relationship between anxiety and the dependent variable. Substantively, this coefficient indicates that every one-unit increase in anxiety level is estimated to decrease the dependent variable score by 0.30 units, assuming other variables remain constant. However, the standard error value of 0.33 is relatively large compared to the coefficient value, which produces a t-statistic of –0.92. This small t-value indicates that the coefficient estimate still contains high uncertainty.

This is supported by a p-value of 0.36, well above the conventional significance limit ($\alpha = 0.05$). Thus, the effect of the anxiety variable on the dependent variable is not statistically significant, so the null hypothesis stating no effect of anxiety cannot be rejected. Furthermore, the 95% confidence interval for the anxiety coefficient ranges from –0.95 to 0.35, which crosses zero, indicating that the true effect could be negative, zero, or even positive.

Overall, these results indicate that although there is a tendency for a negative relationship between anxiety and the dependent variable, the empirical evidence obtained is not strong enough to conclude a significant effect. This finding indicates the need to include other variables or consider mediating and moderating mechanisms, such as cognitive capacity, learning strategies, or learning context, to more comprehensively understand the influence of anxiety.

The results of the study indicate that the regression model testing the effect of mathematics anxiety on the dependent variable (mathematical problem-solving performance) has very low explanatory power. The small Multiple R value and R Square of 1.4% indicate that mathematics anxiety, when treated as the sole predictor, is not able to adequately explain variations in performance. This finding is in line with the theoretical view that mathematics anxiety is not a single factor that directly determines learning outcomes, but rather operates through more complex and non-linear psychological mechanisms (Ashcraft en Krause 2007); (Dowker et al. 2016).

Theoretically, Processing Efficiency Theory and Attentional Control Theory explain that anxiety affects performance not by reducing basic competencies, but by disrupting the efficiency of cognitive processing through intrusive thoughts and decreased attentional control (Eysenck 2016). Therefore, the impact of math anxiety on problem solving is often indirect, mediated by variables such as working memory, emotion regulation, and cognitive strategies. The low R Square value and the insignificance of the regression model in this study strengthen the argument that the effect of anxiety cannot be optimally explained by a simple regression model without considering cognitive-affective mediators.

The ANOVA test results, which showed an F value <1 and a significance level of 0.36, confirmed that the simultaneous model was not significant. This finding is consistent with previous research findings that reported that the relationship between math anxiety and achievement tends to weaken when the learning context provides specific instructional or technological support (Carey en Stefaniak 2018). In LMS-based or blended learning contexts, features such as automated feedback, opportunities for repeated practice, and time flexibility can serve as buffers that reduce the direct impact of anxiety on performance.

The negative but insignificant regression coefficient for anxiety indicates a trend in the direction of the relationship, consistent with theory and previous research, but with a small effect size. This can be interpreted as meaning that math anxiety does have the potential to reduce performance, but this effect is highly dependent on individual conditions and the learning context. Emphasized that affective factors such as anxiety are strongly influenced by self-efficacy and previous success experiences, which are not measured in this model. Similarly, Cognitive Load theory (Sweller, Merriënboer, en Paas 2019) implies that cognitive load, well-managed through learning design, can mitigate the negative impact of anxiety.

Thus, this discussion confirms that the research findings do not indicate an unrelated relationship between math anxiety and performance, but rather indicate the limitations of analytical models that fail to comprehensively capture psychological mechanisms and learning contexts. Future research should develop models that incorporate mediating variables such as working memory, self-regulated learning, or learning engagement, and consider more complex analytical approaches such as structural equation modeling to gain a deeper and more theoretical understanding of the role of math anxiety in modern learning.

Conclusion

Based on the research results, it can be concluded that math anxiety, as a single predictor, has a very weak and insignificant relationship with the dependent variable studied. The regression model used was only able to explain a small portion of the data variation and was not statistically significant either overall or at the individual coefficient level. These findings indicate that the effect of math anxiety on learning performance or problem-solving is indirect and influenced by more complex psychological mechanisms and learning contexts. Therefore, math anxiety cannot be understood in isolation but needs to be studied in conjunction with other cognitive, affective, and contextual factors.

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