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Exploring the Predictive Relationship between Students' Math Anxiety and their Mathematical Performance

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ABSTRACT

Math anxiety is widely recognized as a significant factor influencing students' mathematical performance. This study investigates whether students' final course grades can be predicted based on their math anxiety levels measured at the beginning of the semester. Using both ordinal logistic regression and simple linear regression models, we quantified the predictive relationship between math anxiety and academic performance. To ensure the reliability of our findings, we evaluated *model performance through cross-validation techniques. Results revealed a strong inverse relationship between math anxiety and final grades, indicating that higher levels of math anxiety are generally associated with lower academic performance. However, our analysis also demonstrates that math anxiety alone is not sufficient to achieve robust grade predictions using these regression models. These findings emphasize the need to consider additional factors influencing student outcomes alongside math anxiety.*

Keywords: Educational Psychology, Math Anxiety, Mathematical Performance, Regression Analysis

INTRODUCTION

Recent research in math education has increasingly focused on exploring math anxiety and its effects on mathematical performance across all educational stages. Psychologist Ashcraft (2002) explains math anxiety as a feeling of uneasiness that hinders the ability to tackle math-related tasks. The psychological origin of math anxiety is related to self-compassion (Leppma & Darrah, 2024) and belief in math myths, such as that math is a difficult subject or that it requires inborn skill (Luo et al., 2024). Mathematical performance is the ability to successfully address tasks requiring various mathematical skills. Mathematical competence can be critical for personal fulfillment and career success (Namkung et al., 2019) and is related to people's "satisfaction with life, health, income, employability, and longevity" (Lipnevich et al., 2016).

In this study, we investigate the performance of a simple linear regression model and an ordinal logistic regression model in predicting the mathematical performance of collegiate students based on their mathematical anxiety alone.

LITERATURE REVIEW

Math anxiety is negatively correlated with math performance (Barroso et al., 2021; Namkung et al., 2019; Hembree, 1990). These adverse effects have been observed in matriculated students (Zakaria & Nordin, 2008), undergraduate students (Legg & Locker, 2009), children (Wu et al., 2012), adults (Ma, 1999), males (Andrews & Brown, 2015), and females (Beilock et al., 2010). Studies have used statistical inferencing tools such as t-tests (Cates & Rhymer, 2003), ANOVA (Tsui & Mazzocco, 2007), regression analysis (Tsui & Mazzocco, 2007; Legg & Locker, 2009), chi-square analysis (Tsui & Mazzocco, 2007), controlled or Pearson correlational analysis (Wu et al., 2012; Karimi & Venkatesan, 2009; Ashcraft & Moore, 2009), structural equation modeling (Krinzinger et al., 2009), and factor analysis (Lee, 2009). However, these studies are limited in their ability to establish a negative relationship between math anxiety and math performance and not a predictive relationship. Research is needed to identify a possible model to predict math performance from math anxiety.

Studies have been conducted on the predictability of mathematical performance based on various factors, such as voluntary or assigned enrollment in developmental math classes (Lane & Saxon, 2024); high school GPA, faculty status, and major of the student (Andrews & Tolman, 2021); motivational and emotional factors (Minano & Castejon, 2011); enjoyment of mathematical tasks (García et al., 2016); and cognitive, motivational, and emotional variables (Abín et al., 2020). The objective of these studies has been to aid teachers and educational institutions in forming intervention strategies and policies to improve student learning, prevent early class withdrawals, and make other related decisions. Thus, various predictors of math performance have been studied, and the usefulness of such predictions has been established. However, studies exploring math anxiety as an exact predictor of math performance are yet to be performed.

In this context, our study explores math anxiety as another factor for predicting math performance. Such predictions can help implement successful intervention strategies for students at all educational levels. However, collegiate students enrolled in an intermediate algebra course--usually the class after a developmental algebra course and before a precalculus course--form a special demography. Intermediate algebra is taken by college students with the most majors in the U.S. According to Gonzalez-DeHass et al. (2024), this class usually determines students' attitudes toward math and their decision to include it in their education. Additionally, students may be required to pass such math classes to qualify for advanced courses or to graduate (Ayele et al., 2022). Therefore, intervention strategies are crucial for these students to foster their success in math classes and motivate them to enroll in additional math courses. It can help mathematics educators devise suitable teaching techniques, such as differentiated instruction (Bal, 2016), to help students reduce their math anxiety and improve their performance. Students themselves can use the prediction to understand their math anxiety and its impact on their mathematical performance so that they can take measures to reduce stress and minimize the negative impact. Finally, these predictions may help university advisors guide their students in choosing classes and appropriate learning resources. Given the significance of intermediate algebra students in math education, we chose this population for our study.

We measured math anxiety via the Abbreviated Math Anxiety Rating Scale (sMARS) (Alexander & Martray, 1989) via a Qualtrics survey and math performance according to the final course grade. We modeled the relationship via simple linear regression and ordinal logistic regression. The linear regression used numerical scores, and the ordinal logistic regression used letter grades. The prediction capacity of both models was evaluated via a 10-fold cross-validation technique. For the ordinal logistic regression, the classification accuracy of the overall model and for each grade level were individually determined along with the model's no information rate and kappa coefficient. For the simple linear regression model, the root mean square error (RMSE), R^2, and mean absolute error (MAE) were calculated. The cross-validation was repeated 10 times, and the metrics were averaged.

To measure math anxiety, we used a psychometric tool such as sMARS instead of other forms of measurements such as physiological measurements (Salvia et al., 2013) and behavioral measurements (Ashcraft & Faust, 1994), as these other metrics are subjective (Cipora et al., 2019). Our choice of sMARS over other psychometric tools, such as the Math Anxiety Rating Scale (Richardson & Suinn, 1972), the Abbreviated Math Anxiety Scale (Hopko et al., 2003), and the Fennema-Sherman Mathematics Anxiety Scale (Fennema & Sherman, 1976), is due to its open access. The final grade was used as the indicator of math performance, as it is a common metric among students, advisors, and officials. We emphasize that we do not emphasize grades as the best performance indicator but only use them because of their easy availability and multiple applications.

The choice of a simple linear regression model and an ordinal logistic regression model for prediction was based on their ability to provide interpretable results that can be corroborated with literature along with the required prediction. The models we used can be validated by assessing whether they indicate a well-established negative correlation between math anxiety and mathematical performance. The appropriateness of the ordinal logistic regression model also comes from the fact that letter grades are usually expressed in letters with a clear hierarchy. Other nonparametric regression methods, such as nearest neighbor models and neural networks, do not provide interpretable relationships for validation. Additionally, handling the hierarchy of grades in nonparametric models is complicated, whereas it is trivial in ordinal logistic regression.

In this regard, our study is unique in exploring the predictive relationship between math anxiety and mathematical performance under the following conditions: math anxiety is measured by sMARS, the subjects are college students enrolled in an intermediate algebra class, the final course grade measures mathematical performance, and the predictive models used are simple linear regression and ordinal logistic regression. This is a brief report of our first study. Preparations for an extensive study using similar conditions and addressing the limitations of this study are underway at three different U.S. universities.

METHOD

In this quantitative method, ordinal logistic regression and a simple linear regression model were used to investigate the relationship between math anxiety and final math grades. This study was conducted at a medium-sized midwestern university in the USA. We measured the math anxiety of undergraduates enrolled in intermediate algebra classes in the first two weeks of a semester via the sMARS via a Qualtrics survey. The sMARS is a Likert-type scale and has 25 questions. The respondents indicate their level of math-induced anxiety from ‘Not at all’ to ‘Very much’ on a 5-point scale in twenty-five situations, such as “Studying for a math test” and “Taking the math section of a college entrance exam.” The internal reliability of the scale is 0.96, the test-retest reliability is 0.90, and the validity of the test is 0.92 (Alexander & Martray, 1989). The sMARS is traditionally scored from one to five, where one corresponds to the ‘Not at all’ option and indicates no anxiety, whereas five corresponds to the ‘Very much’ option and indicates high anxiety.

The sampling process was voluntary response sampling. We discussed the study with instructors of different intermediate algebra course class sections. The instructors shared a link of the electronic version of the sMARS with the students. The survey was not mandatory for students, and one student could take it only once. A consent question to grant access to students’ final grades was included in the survey to adhere to the Family Educational Rights and Privacy Act (FERPA). The final letter grades of the students who consented to the use of their grades were collected at the end of the semester. Any information from students under 18 years of age was excluded.

A total of 103 responses were received for the survey. Only 83 responses were completed, 57 of which provided consent for using their grade. Three of those 57 responses had written “yes” instead of their names, preventing the collection of their final grades. Four students dropped out of class. Therefore, their data were removed from the analysis. Overall, 50 observations were used. The instructors gave us only the final letter grades and no numerical grades for reasons unknown. However, we needed numerical grades, as we also wanted to use linear regression. To overcome this problem, we used the average of the numerical grade range shown in Table 1 to convert the letter grades into numerical grades.

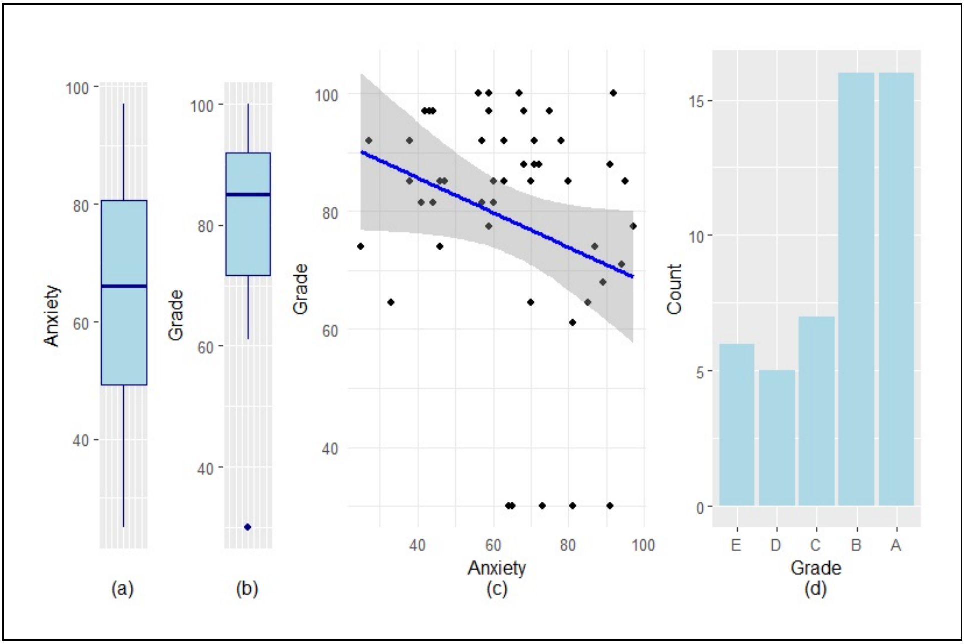
Table 1: **Grading Scale**

A+	A	A-	B+	B	B-	C+	C	C-	D+	D	D-	E
100	95-99	90-94	87-89	84-86	80-83	77-79	73-76	70-72	67-69	63-66	60-62	≤59

Note. The table presents the grading scale used in this study.

Preliminary Data Exploration: As shown in Figure 1(a), the anxiety scores ranged from a minimum of 25 to a maximum of 97. This minimum of 25 is the lowest possible score on the sMARS scale, corresponding to any student with no math anxiety. The median (66) and mean (65.14) values were similar, suggesting a symmetric distribution of anxiety. Similarly, the numerical grades ranged from a minimum of 30, corresponding to students with the lowest possible grade, “E,” to 100, the highest possible grade. The median (85) was greater than the mean (78.27), suggesting a left-skewed distribution. The Pearson correlation coefficient between math anxiety and numerical grade was -0.27, indicating a near-moderate inverse correlation. Figure 1(d) shows that the number of students scoring grades "A" and "B" was the same but was more than twice the frequency of other letter grades.

Figure 1: Summary Statistics



Note. Box plots of anxiety (a) and grade (b). (c) is the scatter plot of anxiety vs. grade, and (d) is the bar diagram of grade levels.

RESULTS

Ordinal logistic regression: An ordinal logistic regression analysis was conducted to investigate the relationship between math anxiety and students' final semester letter grades in R. As different letter grades have a clear hierarchy, ordinal logistic regression is a suitable model. For an ordinal logistic regression, the log odds of being at or below a certain grade level 'k' can be modeled as:

$$\log\left(\frac{Pr(Grade > k)}{Pr(Grade \leq k)}\right) = \theta_k - (\beta \times Anxiety)$$

where θ_k are the intercepts for each grade level boundary and where β is the coefficient for anxiety. The estimates of these parameters, as obtained from R, are presented in Table 2.

The model was statistically significant, $\chi2(1) = 4.999$, $p = 0.02$, indicating that it fit the relationship well. Anxiety was a significant predictor of grade, β

=−0.030, SE = 0.014, Wald = 4.723, p =0.03. A negative β indicates that as anxiety increases, the log odds of being in a higher grade decrease. All the thresholds for the ordinal categories except B|A were significant, with p values less than 0.05. As such, the anxiety score can significantly influence grades transitioning among the levels "E," "D," and "C" than from "B" to "A."

The adherence to assumptions of independence of observations and ordinality of target levels can be argued qualitatively. The observations were independent, as we had only one observation from each student. The data also satisfy the assumption of the natural order of grades. For example, 'A' is higher than 'B'. Additionally, the 'distance' between different letter grades is not uniform. For example, a student starting with a numerical grade of zero has to score up to 59 to obtain an 'E' but only needs to score an additional 1 point to obtain a 'D' or 10 points to obtain a 'C'. For the assumption of proportional odds, the Brant test yielded an omnibus test statistic of 0.42 ($p = 0.94$) and a chi-square statistic of 0.42 ($p=0.94$) for predictor anxiety, indicating that the proportional odds assumption holds. All the assumptions for the ordinal logistic model were met.

Table 2: Ordinal logistic regression results with predictor letter grade

Variables	Coefficient	SE	Wald Statistic	p value
Anxiety	-0.030	0.014	4.723	0.030
E|D (k=1)	-4.092	1.086	14.195	0.000
D|C (k=2)	-3.336	1.038	10.324	0.001
C|B (k=3)	-2.590	0.991	6.821	0.009
B|A (k=4)	-1.150	0.928	1.537	0.215

Prediction Metrics. Prediction metrics were calculated at two scales: the overall model's classification accuracy and the classification accuracy for each grade level. A 10-fold cross-validation method, repeated 10 times, was used. The model accuracy estimated via the cross-validation method was 57.5% (accuracy=0.575). The no-information rate (NIR) was 0.32, which is the accuracy that can be achieved by always predicting the majority class. Therefore, the model classifies better than it does when it predicts the majority class. Moreover, the kappa value of 0.32 indicates fair agreement between the predicted and observed classifications beyond the possibility of agreement occurring by chance. Overall, the model's prediction metrics indicate that it performs moderately well in predicting grades using anxiety. For individual grade levels, the model had high accuracy for predicting grade "A" (accuracy = 1), whereas the accuracy for other grades was less than 0.2.

Simple linear regression: A simple linear regression model was used to examine the relationship between math anxiety as a predictor and grades as a response in R. For this model, the letter grades were converted into numerical grades using the average of the numerical grade range presented in Table 1. The choice of simple linear regression is based on the established negative correlation between math anxiety and math performance. The model proposed was

$Grade = \beta_0 + \beta_1 * Anxiety + \in$, where $\in$ represents the error.

The results of the regression obtained from R are shown in Table 3.

Table 3: Linear Regression Results with Predictor Numerical Grade

Coefficients	Estimate	SE	95% CI		p value
			LL	UL	
Intercept	97.496	10.157	77.074	117.917	0.000
Anxiety	-0.295	0.150	-0.596	0.006	0.054

Note. CI = confidence interval; LL=lower limit; UL=upper limit.

A significant regression model (at the 0.05 significance level) was found ($F (1,48) = 3.89$, $p = 0.05$). R estimated the parameters as $\beta_0 = 97.496$ ($p < 0.05$) and $\beta_1 = -0.295$ ($p = 0.05$); hence, the model is as follows:

$$Grade = 97.496 + (-0.295) * Anxiety + \in.$$

The $\beta_0 = 97.496$ ($p < 0.05$) value is the expected value of grade when anxiety is minimal. This value is not only statistically significant ($p < 0.05$) but also consistent with common grading practices. The highest grade anyone can obtain is 100, and 97.496 is both close to 100 and smaller than 100. Similarly, $\beta_1 = -0.295$ ($p = 0.05$) indicates that the grade is expected to decrease by approximately 0.30 units for each one-unit increase in anxiety.

The assumptions of independence, normality, and homogeneity of variance of the residuals for the simple linear regression model were tested via standard statistical tests. The available sample failed to verify the normality assumption (Shapiro–Wilk $W = 0.86$, $p = 0.00$). However, the assumption of homoscedasticity (Breusch–Pagan $\chi^2 = 2.21$, $p = 0.14$) and independence was satisfied by the residuals (Durbin–Watson $D = 0.26$, $p = 0.00$).

Prediction Metrics. A 10-fold cross-validation was performed to check the model's predictive power on unseen data. The cross-validation was repeated 10 times, and the performance metrics were averaged. An RMSE of 19.09 suggested that, on average, the model's predictions deviated from the actual grades by approximately 19.09. Such a large deviation in grade makes the prediction less precise and less applicable. However, a relatively smaller MAE of 14.96 suggests that the deviation may be lower. As the RMSE is more highly affected by outliers than the MAE is, the difference suggests that some outliers exist in the data. Similarly, an R^2 of 0.29 indicates that the model explained only approximately 29% of the variance in grades using anxiety, suggesting that there are factors in addition to anxiety influencing grades. Overall, the model has some predictive power with moderate accuracy.

DISCUSSION AND CONCLUSIONS

The study's objective was to examine the predictive power of the ordinal logistic regression model and the linear regression model in predicting the final grades of students using math anxiety alone. Both models were found to be statistically significant ($\chi2(1) = 4.999$, $p = 0.02$, for ordinal logistic regression and $F(1,48) = 3.888$, $p = 0.05$ for simple linear regression). The ordinal logistic regression model had an average classification accuracy of 57.5%, and the linear regression models had an R^2 of 29%. These low values suggest that anxiety alone is not a good predictor of grade in the two models. A better prediction may be obtained by adding other variables, such as the age and gender of students, which are known to affect both math anxiety and math performance.

In addition to answering the research question, both simple linear regression and ordinal logistic regression revealed a negative relationship between math anxiety and mathematical performance ($\beta = -0.030$, SE = 0.013, Wald = 4.723, $p = 0.03$) for ordinal logistic regression and $\beta_1 = -0.295$, $p = 0.05$ for simple linear regression). This result corroborates the established inverse relationship between the two. This also adds credibility to sMARS as a tool to measure math anxiety and to final course grades, both letter and numeric, as a measure of math performance.

Similarly, the diagnostic tests suggest that ordinal logistic regression can be considered a better predictive model for this relationship than can simple linear regression. The data satisfied all three assumptions of ordinality, independence, and proportional odds of the ordinal logistic regression model. However, in the case of the linear regression model, the assumption of normality was not met, and only the assumptions of independence and homoscedasticity were satisfied.

The main conclusion of this study is that math anxiety is a significant but not the sole predictor of math performance. As such, educators and school administrators should be mindful of the fact that interventions to reduce math anxiety, such as teaching strategies that reduce stress in math classrooms, promote a growth mindset, encourage relaxation exercises in math classes, and help all students with math anxiety, personalized learning strategies should be developed to address the unique needs of different student groups, as other variables, such as age and gender, have also been reported to affect math performance. For quantitative modelers and researchers of math anxiety and performance, a simple linear regression model and an ordinal logistic regression model using math anxiety alone as a predictor are not good predictive models. Accurate predictive models must incorporate other variables, such as age and gender.

A major limitation of this study is the specificity and size of the sample. The choice of collegiate-level students affects the generalizability of this study. However, we wanted to make this study more useful than a generalizable one; hence, the study focuses on this particular demography for the reasons mentioned in the introduction concerning the specialties of those students. The effect of small size was especially evident in the ordinal logistic regression, where each grade level lacked sufficient samples even after the '+' and '-' grade levels, such as 'B+' and 'B-', were merged into one single-letter grade, 'B.' The cross-validation method did not yield reliable grade-level classification accuracy. This limitation can be addressed by motivating more students to take the survey.

Another limitation of this study is the exclusion of factors such as age and gender, which have been shown to significantly affect math performance. The low value of R^2 also indicated that anxiety alone cannot capture all the variance in grade. This also limits the statistical models that could be used to explore predictive relationships. This limitation can be addressed by collecting additional demographic information on the students through the survey. Another study is currently being carried out using the additional demographic features of students and other predictive models, such as neural networks and decision trees. This will be communicated in the future.

Moreover, the Qualtrics survey to measure math anxiety was administered over the first two weeks of the semester. This could have affected the students' math anxiety, especially those who completed the survey later. Exposure to new instructors and course content may have influenced students' choice of answer in the survey. To minimize this effect, the survey should be the first thing administered in a class.

Furthermore, no steps were taken to minimize the bias induced by the voluntary response sampling procedure. This method usually oversamples subjects with strong opinions about the topic and undersamples disinterested subjects, biasing the inferences based on the sample (Greenberg & Weiner, 2014). One way of addressing this limitation is to convince more students to take the survey by explaining its usefulness.

Additionally, the final grade collection process can be more comprehensive. In this study, only final letter grades were collected, and the numerical grades were calculated by averaging. Moreover, some instructors awarded ‘A+’ as the highest grade, while some only awarded ‘A.’ As ‘A+’ was converted to 100 in this study, students who scored 100 but were in the class that was awarded ‘A’ as the highest grade had their grade converted to 97 incorrectly instead of 100. Hence, some information was lost in the conversion. A more systematic study in which all the instructors use the same letter grade conversion chart and provide both numerical and letter grades for the study can prevent this information loss.

Overall, the math anxiety of collegiate students in an intermediate algebra class was measured via sMARS in the first two weeks of class, and their final grade in the class at the end of the semester was regressed on the basis of the measured anxiety via simple linear regression (numerical form of the grade) and ordinal logistic regression (letter form of the grade). Both models indicated a significant inverse relationship between the two attributes. However, the low R^2 value and the low classification accuracy of the models suggest that math anxiety alone cannot make an acceptable prediction of math grades. Educational interventions should focus not only on reducing math anxiety but also on incorporating other demographic variables in intervention strategies to improve overall mathematical performance. The small sample size limited the study’s effectiveness. Nevertheless, this study provides some insight into the highly discussed effect of math anxiety on students' math performance.

IMPLICATIONS

The implication of this study is that math anxiety is a significant but not the sole predictor of math performance. As such, educators and school administrators should be mindful of the fact that interventions to reduce math anxiety, such as teaching strategies that reduce stress in math classrooms, promote a growth mindset, encourage relaxation exercises in math classes, and help all students with math anxiety, personalized learning strategies should be developed to address the unique needs of different student groups, as other variables, such as age and gender, have also been reported to affect math performance. For quantitative modelers and researchers of math anxiety and performance, a simple linear regression model and an ordinal logistic regression model using math anxiety alone as a predictor are not good predictive models. Accurate predictive models must incorporate other variables, such as age and gender.

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