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Multiple Regression Modelling for Mathematics Performance: Best Model Selections

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Abstract

Initiating mastery of mathematics in primary school is pivotal for successful learning at higher levels. Multiple regression analysis stands as a cornerstone in statistical methods for modelling mathematical achievement. However, despite its prevalence, earlier studies often neglect to disclose the essential assumptions requisite for effective multiple regression modelling. Moreover, the impact of variable selection methods on model generation and subsequent identification of the optimal model remains insufficiently explored. Considering these gaps, this study was undertaken to identify significant factors influencing students' mathematics achievement while ensuring adherence to multiple regression analysis assumptions. Utilizing demographic data, the number of books, home educational resources, student attitudes, and mathematics anxiety as independent variables, two models were derived: Model 1 incorporated all variables without domains, while Model 2 included domain-specific variables and adhered to multiple regression assumptions. The findings revealed that the Model 2 is the best model since it has highest R^2, adjusted R^2, lowest standard error of estimation, lower values in 8 selection criteria which also fulfilled assumptions of multiple regression analysis. In conclusion, key determinants of mathematics achievement were identified as the number of books (101-200), student confidence, and mathematics learning anxiety. The constructed model elucidated 27.6% of the variance in mathematics achievement. This study underscores the importance of meeting regression test assumptions for modelling accuracy and provides actionable insights for schools to design interventions aimed at enhancing mathematics achievement among fifth-year students and the broader elementary school population.

Keywords: Mathematics Achievement, Multiple Regression, Mathematics Anxiety, Attitudes towards Mathematics

Introduction

The field of research consistently prioritizes the study of mathematics achievement due to its crucial role in education and everyday human life (Barroso et al., 2021; Jansen et al., 2013;

OECD, 1999). Mathematics is an important skill not only for academic success, but also for improving functional efficiency in everyday life (Carey et al., 2017). Efforts to boost participation in high-mathematics-demanding fields like science, technology, engineering, and mathematics (STEM) have emerged as a global agenda (Ejiwale, 2013; Timms et al., 2018). Despite this importance, research indicates a decline in mathematics achievement among students in most countries in TIMSS and PISA (Barroso et al., 2021; Kastberg et al., 2015; Wijsman et al., 2016). Despite the availability of more effective learning methods, some students still perform poorly in mathematics. Therefore, it is necessary to study the factors that influence their performance (Kushwaha, 2014).

Reports from TIMSS and PISA, frequently referenced by various stakeholders, are considered limited due to the narrow range of variables they cover (Gamazo et al., 2016). This limitation creates opportunities for more in-depth exploration, such as uncovering relationships between variables and drawing conclusions not addressed by international assessment reports (Gamazo & Martínez-Abad, 2020).

To model mathematics achievement, the factors considered must be relevant to the study population. Researchers recommend selecting factors based on theoretical frameworks and existing empirical evidence (Hair et al., 2010, 2018). Guidelines from the National Science Education standards in the United States recommend that educational research should include factors grounded in theory or existing empirical evidence. This ensures that the study's results can contribute to the development, modification, and evaluation of interventions by stakeholders. Additionally, the selected factors should be malleable, meaning they can be influenced or changed, such as children's behaviors, technology, educational programs, policies, and practices (National Science Foundation, 2013). This is to ensure that the research conducted has a direct impact on the field of education.

Previous studies have shown that attitudes, beliefs, and emotions significantly impact students' engagement with mathematics and its application in real-world contexts (Lap, 2021; OECD, 2015). One of the most widely used statistical methods for modeling mathematical achievement is multiple regression analysis. Geesa et al (2019) employed multiple analysis methods to model mathematics achievement using data from TIMSS 2015 in Turkey, South Korea, and the United States. However, the study did not report on the assumptions of the multiple regression tests, such as the normality of data distribution. This results in uncertainty regarding the accuracy of the research findings. A simulation study by Orcan (2020) shows that there is a difference in findings if the normality of the data distribution is met and not met using parametric tests and non-parametric tests.

Model selection is used to overcome three aspects, namely interpretation, computing time and overfitting (Fox, 2016). The interpretation aspect pertains to the ease of understanding the model and gaining a clear overview of how the data is generated. Model selection addresses the issue of having too many potential variables by reducing the number of variables in the final model. This reduction in model dimensions lowers the computational cost compared to a model that considers all possible variables. Additionally, model selection helps prevent a decrease in predictive power caused by high variance, also known as overfitting (Wheatcroft, 2020).

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Therefore, this study aims to identify the factors contributing to mathematics achievement through multiple regression modeling, focusing on various student-related aspects. The study emphasizes testing and reporting regression assumptions, applying model selection methods, and interpreting the selected model. Given the complexity of the factors influencing mathematics achievement, it is crucial to break them down into sub-variables and examine how each sub-variable relates to mathematics achievement (Brezavšček et al., 2020). This study aims to evaluate the contribution and strength of each domain within the identified factors on mathematics achievement.

Materials and Methods

In this study, five factors are considered: respondents' demographics, the number of books, the number of learning supports, mathematics anxiety, and students' attitudes toward mathematics. The number of books and learning supports at home were measured using the TIMSS 2019 questionnaire. (Mullis et al., 2020). ATMI simple version Lim & Chapman (2013) as a tool to measure students' attitudes towards Mathematics. While the Modified Abbreviated Mathematics Anxiety Scale (mAMAS) questionnaire Carey et al (2017) was used to measure mathematics anxiety. Mathematics achievement variables are obtained through Final Academic Session Examination 2022 (FASE). The mathematics questions in FASE 2022 are obtained through the Instrument Collection and Installation Application (ICIA) system.

In this study, the selected population consists of year five students in Semporna, Sabah. A total of 267 students, aged around 11 and from diverse family backgrounds, participated in the study conducted from August to December 2022. According to the sample size table by Krejcie & Morgan (1970), a sample size of approximately 214 students was used.

Multiple Regression

Multiple regression is a method used to identify changes in two or more predictor variables that contribute to changes in the response variable (Fox, 2016; Harrell, 2015; Keith, 2015). In general, the formula that is often used to obtain the multiple regression equation is as follows;

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_k X_{ki} \dots \epsilon_i \qquad i = 1, \dots, n \tag{1}$$

Where;

Y_i = Dependent variable

X_1, X_2 dan X_k = Independent variables up to k

ϵ_i = Stochastic disturbance term

β_0 = Intercept of a straight line

$\beta_2, \beta_2, \beta_k$ = Partial regression coefficient

The formula for obtaining numerical coefficients is as follows;

$$\beta = \frac{\sum XY - \frac{(\sum X)(\sum Y)}{n}}{\sum X^2 - \frac{(\sum X)^2}{n}} \tag{2}$$

While the formula to obtain the shortcut value β_0 is as follows;

$$\beta_0 = \frac{\sum Y - \beta_0 \sum X}{n} \tag{3}$$

In linear regression, the least squares estimation method is used to find the best value of the straight line. This method is used to calculate the slope and intercept as a representation of the line that provides the best fit of the data and minimizes the total squared difference (mean) between the data points predicted on the line and the actual observed points (Randolph & Myers, 2013). The difference between the predicted data point and the actual point represents the error between what was predicted and what was obtained. The difference is known as residual which allows us to construct $e_i = Y_i - \widehat{Y}_i$. The best model from among candidate models is the one that yields the smaller e_i but greater R-squared adjusted values.

Multiple Regression Assumptions

Meeting the assumptions of multiple regression is necessary to ensure that the results achieved represent the sample and achieve the best results. The method to ensure that the study meets the basic assumptions of multiple regression analysis involves two steps. First, the dependent variable and the independent variable are tested individually. Second, the overall relationship is tested after the model is estimated (Fox, 2016; Hair et al., 2018; Tabachnick & Fidell, 2013)

The three assumptions in the first step are linear relationship, homogeneity of variance and normality of data distribution (Copeland, 1997; Field, 2018; Warner, 2013). After the model is fitted, several terms must be checked. The Durbin-Watson test was used to check for the presence of autocorrelation. A value approaching two and not exceeding three Mayers (2013); Field (2018) is said to reject the existence of autocorrelation.

Referring to the value of Cook's distance is one of the methods for identifying the outliers. The value of Cook's distance < 1 indicates that there is no need to delete cases because the outlier's value does not significantly affect the regression analysis (Pituch & Stevens, 2016). To investigate multicollinearity problems, both variance inflation factor (VIF) and tolerance are used. The tolerance value closest to one is better, while the VIF value is less than 10, indicating no multicollinearity problem between the variables (Keith, 2015).

Selection Techniques

This study employs three selection techniques: stepwise, forward addition, and backward elimination. The stepwise method allows researchers to test the contribution of each independent variable in the regression model by sequentially adding variables based on their significance. The variable with the largest contribution is added first, followed by others based on their incremental contribution to the model.

Forward addition and backward elimination are trial-and-error processes aimed at finding the best regression estimates. The forward addition technique is similar to the stepwise procedure, starting with one independent variable and adding others incrementally. In contrast, the backward elimination method begins with all independent variables included in the model, and then sequentially removes those that do not contribute significantly.

Model Selection Criteria
Several criteria have been developed over the years to help researchers choose the best or a better model. Adjusted R-squared is often used to help identify the best model because, unlike R^2, it penalizes the addition of unhelpful predictors. When adjusted R-squared is used as a criterion, the model with the largest adjusted R-squared is considered the best. The adjusted R-squared is also useful in comparing models between different data sets because it will compensate for the different sample sizes (Hair et al., 2018). The standard error of estimate (SEE) or root mean square error (MSE) is also often used. Because it is based on error, the best model has the smallest SEE when SEE is used. In this study, there are eight selection criteria that were used to choose the best model. The following are among the criteria for selecting the best model. The model with the lowest value will be selected as the best model (Jubok et. al., 2018).

Table 1
Eight selection criteria

No.	Selection Criteria	Formula
1.	Akaike Information Criterion (AIC)	(4) $AIC = \left(\frac{SSE}{n}\right)e^{\frac{2(k+1)}{n}}$
2.	Finite Prediction Error (FPE)	(5) $FPE = \left(\frac{SSE}{n}\right)\frac{n+k+1}{n-(k+1)}$
3.	Generalized Cross Validation (GVC)	(6) $GVC = \left(\frac{SSE}{n}\right)\left(1-\frac{k+1}{n}\right)^{-2}$
4.	Hannan and Quinn (HQ)	(7) $HQ = \left(\frac{SSE}{n}\right)(\ln n)^{\frac{2(k+1)}{n}}$
5.	RICE	(8) $RICE = \left(\frac{SSE}{n}\right)\left(1-\frac{2(k+1)}{n}\right)^{-1}$
6.	SCHWARZ	(9) $SCHWARZ = \left(\frac{SSE}{n}\right)(n)^{\frac{(k+1)}{n}}$
7.	SQMASQ	(10) $SGMASQ = \left(\frac{SSE}{n}\right)\left(1-\frac{k+1}{n}\right)^{-1}$
8.	SHIBATA	$SHIBATA = \left(\frac{SSE}{n}\right)\frac{n+2(k+1)}{n}$ (11)

Results and Discussion
There are three types of models tested. First, Model 1 contains all study variables without domains. Second, Model 2 contains all the variables and domains that have met the assumptions of the multiple regression analysis. Table 2 shows the variables used in the multiple regression analysis of Model 1 and Model 2.

Table 2
Model 1 and Model 2 potential factors

Model 1		**Model 2**	
Y	Mathematics achievement	Y	Mathematics achievement
x_1	Family income	x_1	Family income
	<RM 1179 (Reference)		<RM 1179 (Reference)
$x_{1(<1179)}$	>RM 1179	$x_{1(<1179)}$	>RM 1179
x_2	Number of books	x_2	Number of books
$x_{2\,(0-10)}$	0-10 (Reference)	$x_{2\,(0-10)}$	0-10 (Reference)
$x_{2\,(11-25)}$	11-25	$x_{2\,(11-25)}$	11-25
$x_{2\,(25-100)}$	25-100	$x_{2\,(25-100)}$	25-100
$x_{2\,(101-200)}$	101-200	$x_{2\,(101-200)}$	101-200
x_3	Number of learning supports	x_3	Number of learning supports
x_{3l}	Low	x_{3l}	Low
x_{3m}	Moderate	x_{3m}	Moderate
x_{3h}	High	x_{3h}	High
x_4	Mathematics anxiety	x_{4a}	Mathematics anxiety (evaluation)
x_5	Students' attitudes	x_{4b}	Mathematics anxiety (learning)
		x_{5a}	Students' attitude (motivation)
		x_{5b}	Students' attitude (confidence)
		x_{5c}	Students' attitude (value)

For variables that did not meet the normality assumption, transformations were applied, considering the importance of data normality in multiple regression analysis. These transformed variables were then incorporated into Model 2. The transformed variables are the mathematics learning anxiety domain (X_{4b}) and the student appreciation (X_{5c}). Table 3 shows the transformation method carried out.

Table 3
Transformation methods

	$Z_{skewness}$	Transformation method	$Z_{tskewness}$	$Z_{tkurtosis}$
X_{4bT}	3.7895	$\log_{10} X_{4b}$	-0.7757	-1.6097
X_{5cT}	-4.6434	(Highest score – raw score + 1) and $\sqrt{X_{5ci}}$	0.5331	0.2881

The transformation carried out is log 10 for the mathematics learning anxiety domain. For the student appreciation domain, score reflection and the square root of the raw score were utilized due to the negatively skewed distribution of the data (Tabachnick & Fidell, 2013). Following these transformations, it can be inferred that the skewness and kurtosis z-values for each transformed variable ultimately satisfied the assumption of normal data distribution (z<3.29). Figure 1 depicts the p-p plot post-transformation.

Original Variables	Transformed Variables

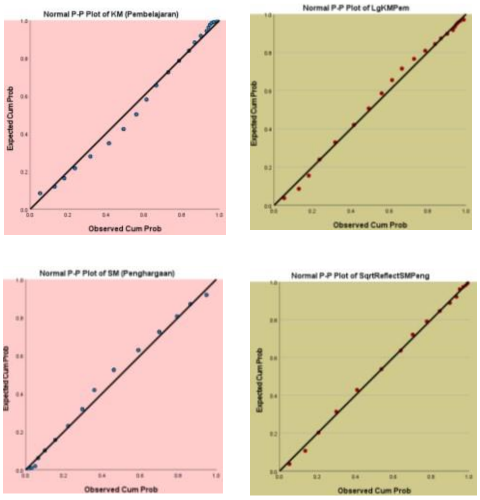

Figure 1. Normality Distributions of the Original Variables and the Transformed Variables

The Best Model Selection

To select a regression model for mathematics achievement in this study, a comparison of all multiple regression models was performed. Table 4 and Table 5 summarize the result of the analysis. In model 1, forward and stepwise demonstrated that the number of books $\left(x_{2\,(101-200)}\right)$, mathematics anxiety (x_4), family income $\left(x_{1\,(>1179)}\right)$ and students' attitudes were the significant factors. Conversely, enter[F] and backward methods revealed that the number of books $\left(x_{2\,(101-200)}\right)$, number of learning support (x_{3m}, x_{3h}), mathematics anxiety (x_4), and students' attitudes (x_5) were the significant factors that contributed to students' mathematics achievement. Both constructed models are significant (p<0.05). However, enter[F] and backward methods showed improvement in the values of SSE and adjusted R^2 as compared to stepwise and forward methods.

In the context where two variables in Model 2 were transformed, all these four selection techniques produced similar findings, suggesting that mathematics anxiety (learning) after log transformation (x_{4bT}), number of books $\left(x_{2\,(101-200)}\right)$, and students' attitude (confidence) (x_{5b}) as the significant factors. The constructed model is significant (p<0.05).

Table 4
F-Table with Adjusted R^2

Model		***SS***	***df***	***MS***	F	p	R^2	R^2_{adj}	**Standard Error**
Model 1									
Enter[a] Method	Regression	34115.840	8	4264.480	9.654	<0.001	0.274	0.245	21.017
	Residual	90555.600	205	441.735					
	Total	124671.439	213						
Stepwise, Forward Method	Regression	32401.454	4	8100.363	18.348	<0.001	0.260	0.246	21.012
	Residual	92269.985	209	441.483					
	Total	124671.439	213						
Enter[F], Backward Method	Regression	33404.513	5	6680.903	15.226	<0.001	0.268	0.250	20.947
	Residual	91266.926	208	438.783					
	Total	124671.439	213						
	Residual	88839.061	210	423.043					
	Total	124671.439	213						
Model 2									
Enter[a] Method	Regression	39590.114	11	3599.101	8.545	<0.001	0.318	0.280	20.523
	Residual	85081.325	202	421.195					
	Total	124671.439	213						
Backward Method	Regression	38084.220	5	7616.844	18.297	<0.001	0.305	0.289	20.403
	Residual	86587.220	208	416.285					
	Total	124671.439	213						
Enter[F], Backward[F]	Regression	35737.686	3	11912.562	28.129	<0.001	0.287	0.276	20.579

, Stepwise, Forward Method	Residual	88933.753	210	423.494				
	Total	124671.439	213					

***a- Initial model (models contain non-significant variables), F – Finalized model (non-significant variables in the model have been deleted)*

Table 5 shows the regression coefficients with tolerance and VIF values. All the VIF and tolerance values were within the acceptable range. Therefore, no multicollinearity problem was detected in this study.

Table 5
Coefficients Table with Tolerance and VIF Values

Model	**Variable**	***B***	***Std. Error***	***β***	***t***	***p***	**Tol.**	**VIF**
Model 1								
Enter Method[a]	Constant	41.011	11.494		3.568	<0.001		
	$x_{1\,(>1179)}$	4.638	4.546	0.090	1.020	0.309	0.454	2.204
	$x_{2\,(11-25)}$	-2.052	4.574	-0.033	-0.449	0.654	0.637	1.570
	$x_{2\,(25-100)}$	0.936	6.904	0.010	0.136	0.892	0.664	1.505
	$x_{2\,(101-200)}$	19.194	6.122	0.242	3.135	0.002	0.597	1.675
	x_{3m}	6.236	3.629	0.119	1.718	0.087	0.741	1.349
	x_{3h}	7.899	5.309	0.105	1.488	0.138	0.710	1.409
	x_4	-0.571	0.199	-0.204	-2.866	0.005	0.696	1.437
	x_5	0.324	0.164	0.141	1.979	0.049	0.702	1.425
Stepwise, Forward Method	Constant	42.052	11.414		3.684	<0.001		
	$x_{2\,(101-200)}$	21.353	5.149	0.269	4.147	<0.001	0.844	1.185
	x_4	-0.586	0.199	-0.210	-2.951	0.004	0.701	1.426
	$x_{1\,(>1179)}$	7.241	3.401	0.141	2.129	0.034	0.810	1.234
	x_5	0.339	0.163	0.147	2.087	0.038	0.712	1.405
Enter[F], Backward Method	Constant	41.886	11.380		3.680	<.001		
	$x_{2\,(101-200)}$	21.561	4.989	0.271	4.321	<.001	0.893	1.120
	x_{3m}	7.382	3.327	0.141	2.219	0.028	0.876	1.141
	x_{3h}	9.683	4.862	0.129	1.992	0.048	0.841	1.189
	x_4	-0.595	0.197	-0.213	-3.026	0.003	0.711	1.407
	x_5	0.326	0.163	0.142	2.004	0.046	0.706	1.417
Model 2								
Enter Method[a]	Constant	49.200	14.225		3.459	<0.001		
	$x_{1\,(>1179)}$	2.551	4.477	0.050	0.570	0.569	0.446	2.242
	$x_{2\,(11-25)}$	0.343	4.519	0.006	0.076	0.940	0.622	1.607
	$x_{2\,(25-100)}$	1.410	6.816	0.015	0.207	0.836	0.650	1.539
	$x_{2\,(101-200)}$	21.132	6.001	0.266	3.521	<0.001	0.593	1.688
	x_{3m}	5.239	3.564	0.100	1.470	0.143	0.733	1.365
	x_{3h}	7.415	5.227	0.099	1.418	0.158	0.698	1.432

	x_{4a}	0.286	0.449	0.053	0.638	0.524	0.495	2.019
	x_{4bT}	-33.785	10.618	-0.266	-3.182	0.002	0.484	2.065
	x_{5a}	0.270	0.457	0.048	0.590	0.556	0.515	1.943
	x_{5b}	0.914	0.309	0.208	2.957	0.003	0.684	1.462
	x_{5cT}	3.043	2.100	0.097	1.449	0.149	0.748	1.336
Backward Method[a]	Constant	59.469	10.939		5.436	<.001		
	$x_{2\ (101-200)}$	21.588	4.863	0.272	4.439	<.001	0.892	1.121
	x_{3m}	6.548	3.249	0.125	2.016	0.045	0.872	1.147
	x_{3h}	8.607	4.744	0.115	1.814	0.071	0.838	1.194
	x_{4bT}	-29.670	8.046	-0.233	-3.688	<.001	0.834	1.200
	X_{5b}	0.937	0.277	0.213	3.377	<.001	0.839	1.191
Enter[F], Backward[F], Stepwise, Forward Method	Constant	64.394	10.831		5.945	<0.001		
	X_{5b}	0.985	0.279	0.224	3.531	<0.001	0.844	1.184
	$x_{2\ (101-200)}$	25.066	4.673	0.315	5.364	<0.001	0.982	1.018
	x_{4bT}	-32.604	8.004	-0.256	-4.074	<0.001	0.857	1.167

***a- Initial model (models contain non-significant variables), F – Finalized model (non-significant variables in the model have been deleted)*

Table 6 shows the eight selection criteria. Model 2, by using enter, backward, stepwise, and forward methods is the best model since it has lower values in most criteria and higher R^2_{adj} than others after deleting non-significant factors and transforming variables to meet the assumption.

Table 6
Measures of Eight-Selection Criteria

Model	***SSE***	***p***	***AIC***	***FPE***	***GVC***	***HQ***	***RICE***	***SCH.***	***SGM.***	***SHI.***
Model 1										
Enter Method[a]	90555.600	8	460.2894	1255.8252	461.1279	487.3869	462.0184	530.2853	441.7346	458.7497
Stepwise, Forward Method	92269.985	4	451.7944	1229.4781	452.0450	466.3827	452.3038	488.7599	441.4832	451.3162
Enter[F], Backward Method	91266.926	5	451.0790	1228.1448	451.4405	468.6132	451.8165	495.7222	438.7833	450.3958
Model 2										
Enter[a] Method	85081.325	11	444.7607	1217.0665	446.2161	480.0099	447.7964	537.1528	421.1947	442.1643
Backward Method	86587.220	5	427.9500	1165.1718	428.2929	444.5851	428.6496	470.3041	416.2847	427.3018

Enter[F], Backward [F], Stepwise, Forward Method	**88933.753**	**3**	**431.4080**	**1173.5237**	**431.5606**	**442.5165**	**431.7172**	**459.4222**	**423.4941**	**431.1139**

***a- Initial model (models contain non-significant variables), F – Finalized model (non-significant variables in the model have been deleted)*

Model Evaluation
The Durbin-Watson test results indicate no presence of autocorrelation in the data, with a value of 1.8688, which is close to the ideal range of two and does not exceed three. This suggests that the assumption of independence from other variables can be met. Subsequently, checks for multicollinearity and outliers were conducted. Examination of Cook's distance values in Table 7 revealed no instances exceeding the threshold of 1, indicating no outliers significantly impacting the regression analysis. Similarly, analysis of Centered Leverage Values showed consistent findings, with a maximum value of 0.0802, well below the threshold of 2. Hence, there is no evidence of influential sample data issues.

Table 7
Model Evaluation

Model 2	Durbin-Watson value		1.8688
	Minimum	Maksimum	N
Mahalanobis Distance	0.1228	17.0780	214
Cook's Distance	0.0000	0.0388	214
Centered Leverage Value	0.0058	0.0802	214

Conclusions
The constructed multiple regression model contributed 27.6% of the explanation of the mathematics achievement variance (F=28.129, p<0.05). Model 2 was selected as the best regression model in this study based on the highest R^2, adjusted R^2, the lowest standard error of estimation, lower values in 8 selection criteria, which also fulfilled assumptions of multiple regression analysis. All the selection techniques (enter, backward, forward, and stepwise) produced similar findings after the deletion of non-significant factors.

In the constructed regression model, only the domains of mathematics anxiety, student confidence, and the number of books at home demonstrate significant effects on mathematics achievement. Multiple regression analysis highlights the number of books at home as having the most substantial impact in the model (0.315), with a significant p-value below 0.05. Additionally, mathematics anxiety (-0.256) and student confidence (0.224) also make significant contributions.

Both anxiety and attitude are influential factors in primary school students' mathematics learning. Lower levels of anxiety often coincide with increased confidence in mathematics learning. Additionally, previous studies, such as Haciomeroglu (2017), have highlighted a notable relationship between anxiety and attitude towards mathematics. While the correlation between these components may not be exceptionally strong, they nonetheless hold significant importance in the learning process of mathematics.

The findings of this study indicate that the learning mathematics anxiety domain provides a more significant explanation for the variance in mathematics achievement compared to the evaluation domain. This finding aligns with the results of a study by Megreya et al. (2023) that emphasizes the significance of mathematics anxiety ($p<0.05$). Notably, for male students, mathematics evaluation anxiety emerges as the most influential factor ($p<0.05$), followed by learning mathematics anxiety, though the latter is not deemed statistically significant. Both subdomains in this study demonstrate a consistent pattern, wherein learning mathematics anxiety is found to explain the variance more effectively in mathematics achievement compared to evaluation anxiety.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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