A Discriminant Model of Performance in Mathematics among College Students in a State University in the Philippines

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ABSTRACT

This study aimed to develop a discriminant model to classify the performance of students in Mathematics in the Modern World (MMW) at Pangasinan State University – Asingan Campus based on demographic and support factors. Using a quantitative descriptive-predictive design, data were collected from 154 students enrolled in MMW during the 2024-2025 academic year. Cluster analysis categorized students into high (61%) and low (39%) achievers based on their final grades. While students reported uniformly high levels of individual, motivational, and social support, these factors did not significantly differentiate performance groups. Discriminant analysis revealed that a student's specific academic program was the most critical predictor. Compared to the baseline course (BSBA MM 1), being an "Education student" was the strongest positive predictor of high achievement, and enrollment in "BIT AT 1" also showed a marginal positive influence. In contrast, demographic variables (age, sex, senior high school strand, parental education) and the measured support factors demonstrated negligible discriminatory power. The resulting model provides a tool for early identification of students at potential academic risk and underscores that program-specific factors outweigh broad demographic and perceived support in predicting mathematics performance. Recommendations include tailoring mathematics instruction to the contexts of non-Education programs and conducting qualitative research to explore the underlying reasons for the pronounced advantage held by Education students.

Keywords: Cluster analysis, higher education, mathematics performance, predictive analysis, support factors

INTRODUCTION

Mathematics has long been regarded as the universal language of logic and deductive reasoning, providing a framework for understanding the natural world. Its principles form the cornerstone of critical thinking and problem-solving. In recognition of its crucial role in contemporary life, higher education institutions in the Philippines have introduced courses like Mathematics in the Modern World (MMW), which seek to explain the subject by anchoring it in real-world contexts (Richard & Pacadaljen, 2021). Despite its relevance, many students continue to demonstrate varied levels of performance, suggesting that deeper factors both demographic and support factors affect their learning outcomes.

In the Philippines, mathematics consistently emerges as one of the most challenging subjects for learners, as reflected in both national and international assessment outcomes. Results from the Program for International Student Assessment (PISA) 2018 revealed that Filipino students ranked near the bottom among participating countries in mathematical literacy, demonstrating difficulties in interpreting, applying, and reasoning with mathematical information in real-world contexts (Organization for Economic Co-operation and Development, 2019). This poor performance indicates systemic issues in mathematical understanding and problem-solving skills. Complementing these findings, national analyses and reviews conducted by the Department of Education further show that Filipino learners have persistently struggled in large-scale assessments such as the Trends in International Mathematics and Science Study (TIMSS) and the National Achievement Test (NAT). These assessments point to ongoing challenges not only in computation but also in higher-order thinking, conceptual understanding, and the application of mathematical concepts across grade levels (Department of Education, 2023). Together, these results underscore gaps in mathematics instruction, learning progression, and curriculum effectiveness, highlighting the urgent need for targeted interventions to improve students' comprehension, reasoning abilities, and overall mathematics performance.

Several factors contribute to these outcomes. Disparities in resources and instructional quality, differences in teaching styles, and variations in students' prior mathematical preparation led to uneven performance across schools and regions, affecting students' ability to master and apply mathematical concepts effectively (Bernardo et al., 2022). Furthermore, Bernardo et al. noted that socioeconomic conditions, access to technology, and parental educational background significantly influence students' engagement and confidence in learning mathematics. This is closely linked to parental involvement, as the support parents provide in their children's mathematical learning has been shown to affect performance and attitudes toward the subject (Hyde et al., 2006). These realities underscore the need for research that examines how student-related and contextual factors shape mathematical performance at the tertiary level particularly in general education courses like MMW.

Students' mathematical achievement is often shaped by their demographic profiles. Sex, for example, has been shown to relate to mathematics outcomes not because of innate ability differences, but due to variations in self-efficacy, interest, motivation, and socialization experiences that shape how learners engage with mathematical tasks (Palomares-Ruiz and García-Perales, 2020). College and course affiliation determine students' exposure to mathematical concepts and problem-solving practices, while parental involvement and parents' educational background have been shown to influence students' academic performance, engagement, and access to learning support (Cinadre et al., 2023). Furthermore, a student's chosen Senior High School strand significantly influences their mathematical proficiency. This is clearly illustrated by the findings of Cerbito (2020), which show that students in the STEM strand reached an advanced level of mathematics proficiency, surpassing the performance of students in ABM, HUMSS, Maritime, and TVL tracks. Age likewise contributes to differences in maturity and learning mathematics (Ünal, 2019).

Despite these findings, a research gap persists in the Philippines regarding how these demographic characteristics collectively distinguish between high and low achievers in mathematics. While international research has explored demographic correlates of mathematical performance (Hathella and Priyanath, 2021), few local studies have developed predictive models using statistical techniques such as discriminant analysis to classify student performance based on combined demographic factors.

Beyond demographic influences, students' performance is also affected by individual, motivational, and social support factors. Individual factors, including study habits, mathematical self-efficacy, and anxiety, directly impacting persistence and confidence in problem-solving (Bandura, 1997; Usher et. al, 2009). Motivational factors, such as interest, perceived usefulness of mathematics, and goal orientation, influence students' engagement in learning (Deci & Ryan, 2000). Meanwhile, according to Martinot et al. (2022), peers and teachers are the best sources of social support for students, as this support not only promotes positive learning experiences but also enhances their engagement in school activities, contributing to greater motivation, reduced anxiety, and overall academic well-being. However, another research gap exists: while many studies address these aspects independently, few integrate them into a single quantitative model capable of classifying mathematical performance levels. This gap is particularly evident in local research, where such multivariate approaches remain underexplored.

Within this national context, the Pangasinan State University (PSU) serves as an ideal site for investigating the combined influence of demographic and support factors on mathematics performance. As a public higher education institution catering to students from diverse socioeconomic and academic backgrounds, PSU reflects the broader challenges of Philippine mathematics education. Understanding the predictors of success and difficulty in mathematics can guide the development of evidence-based interventions, enhance instructional quality, and strengthen the university's commitment to inclusive and transformative education.

This research aligns with the United Nations Sustainable Development Goals (SDGs), particularly SDG 4: Quality Education, which calls for inclusive and equitable education and the promotion of lifelong learning opportunities, and SDG 8: Decent Work and Economic Growth, which emphasizes the need for relevant skills in mathematics, science, and technology. By developing a discriminant model that identifies key determinants of student performance, this study contributes to both educational quality and the broader goal of human capital development in the Philippines.

Hence, this study aims to develop a discriminant model that explains and classifies the performance of students in Mathematics in the Modern World (MMW) in 1st semester and 2nd semester of school year 2024-2025 based on their demographic and support factors. Specifically, this study aims to:

1. Describe the demographic profile of students who took mathematics in school year 2024-2025 in terms of sex, college, course, highest educational attainment of parents, strand in senior high school, and age;

2. Analyze and classify students' performance in mathematics into high and low achievers through cluster analysis;

3. Determine the level of individual, motivational, and social support factors towards learning mathematics; and

4. Develop a discriminant mathematical model that best explains and classifies the students' performance.

Ultimately, this research seeks to bridge the gap between demographic and psychosocial factors influencing mathematics achievement, offering a comprehensive model that classifies and predicts student performance. By doing so, it supports efforts to improve mathematics education in the Philippines, ensuring that learners not only understand mathematics but also appreciate its role in the modern world.

Conceptual Framework

This study is anchored on the idea that students' performance in mathematics is influenced by a combination of demographic characteristics and psychosocial factors. The framework is built on Bandura's (1997) Social Cognitive Theory, which posits that learning outcomes are shaped by the interaction of personal, behavioral, and environmental influences. Additionally, Deci and Ryan's and Deci's (2000) Self-Determination Theory supports the inclusion of motivational variables, asserting that students' engagement and achievement are strengthened when intrinsic motivation and external support coexist.

Within this theoretical lens, the present study assumes that students' demographic profiles (sex, college, course, age, strand, and parents' educational attainment) and learning-related factors (individual, motivational, and social support) collectively affect and classify their academic performance in mathematics. Using cluster analysis and discriminant analysis, these variables are statistically examined to identify patterns and predictors of high and low achievement levels.

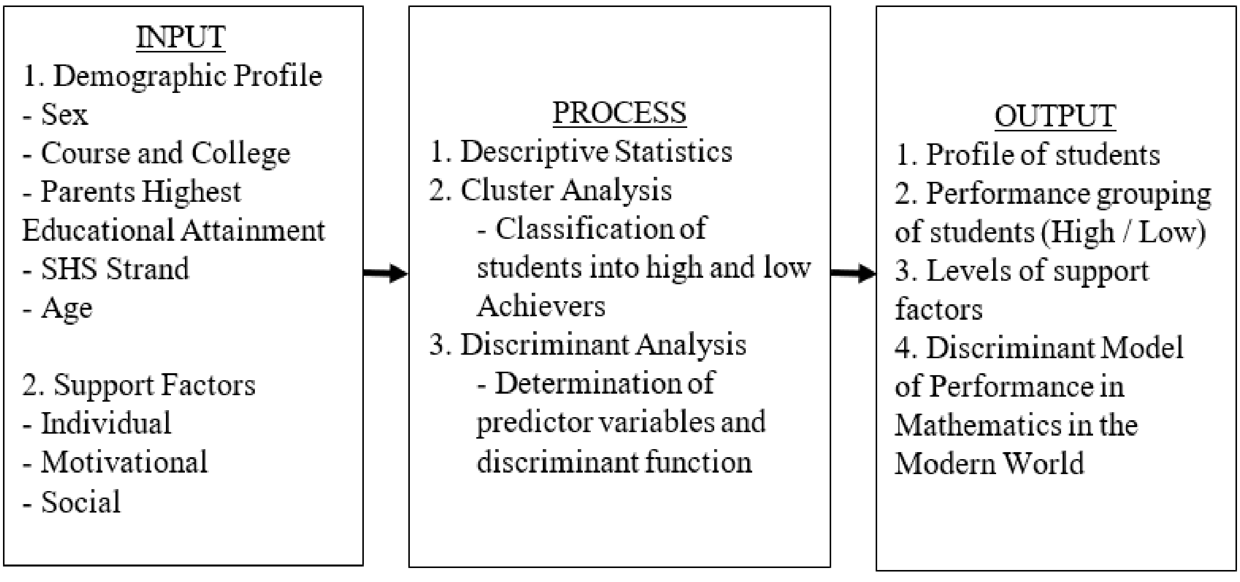

Figure 1. The Research Paradigm

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The research paradigm illustrates how the variables of the study interact to explain students' performance in mathematics. The inputs include the students' demographic profile which are sex, college, course, highest educational attainment of parents, strand in senior high school, and age, and their support factors, namely individual, motivational, and social support factors. These inputs serve as the bases for identifying patterns and determinants of students' achievement in mathematics.

The process involves a sequence of statistical procedures. First, descriptive statistics summarize the demographic and support factors of students. Then, cluster analysis classifies the students into high and low achievers based on their final grades in Mathematics in the Modern World. Finally, discriminant analysis determines which demographic and support factors best explain and predict the students' performance classification, leading to the development of a discriminant mathematical model.

The outputs of the study include the description of students' profiles, the classification of achievers, the determination of support factor levels, and the discriminant model that explains their performance in mathematics.

METHODOLOGY

Research Design

This study employed a quantitative research design, specifically using descriptive, cluster analysis, and predictive approaches. It aimed to describe the demographic profile and support factors of students enrolled in Mathematics in the Modern World (MMW), classify them into performance groups into high and low, and develop a discriminant model that predicts their achievement. The descriptive method was used to summarize the demographic profile and support factors of the respondents, while cluster analysis and discriminant analysis were employed to identify patterns and relationships among variables that influence students' performance in mathematics.

Research Environment

This study was conducted at Pangasinan State University - Asingan Campus. The campus is one of the nine campuses of the Pangasinan State University (PSU). It is located in Barangay San Vicente, Asingan, Pangasinan.

PSU serves a large number of students, mostly from Pangasinan and nearby provinces. PSU - Asingan Campus offers a variety of undergraduate programs. These include courses in Teacher Education, Business Administration, and Industrial Technology. The campus is known for its commitment to providing quality education. It has a "Culture of Excellence" and focuses on teaching, research, and community service. PSU - Asingan Campus provides a rich and varied environment for this research. The diversity of its students will help in understanding how different demographic and support factors come together to affect success in a foundational course like Mathematics in the Modern World.

Research Respondents

The respondents of the study were students of Pangasinan State University – Asingan Campus who were officially enrolled in the Mathematics in the Modern World (GE7) course during the first and second semesters of the school year 2024–2025. These students came from various colleges and courses across the university. They were chosen using purposive sampling, since only those who had completed the course and received final grades in MMW were qualified to participate in the study.

Research Instrument

The main instrument used in this study was a structured questionnaire composed of two parts. The first part gathered the students' demographic profile including sex, college, course, highest educational attainment of parents, strand in senior high school, and age. The second part measured the individual, motivational, and social support factors toward learning mathematics, respectively. The items were adapted on the study of Hufana and

Gurat (2023) with a Cronbach's alpha of 72.5% which is an acceptable level of reliability. The responses were measured using a four-point Likert scale, where 4 means very agree, 3 means agree, 2 means disagree and 1 means very disagree.

Data Gathering Procedure

Before the conduct of the study, a formal request letter was sent to the Campus Executive Director of Pangasinan State University–Asingan Campus to seek permission to conduct the research and gather data from students who took Mathematics in the Modern World (MMW) during the school year 2024–2025. Upon approval, the researcher proceeded to the Registrar's Office to obtain the official final grades of the students, which served as the basis for classifying them into high and low achievers.

After securing the necessary data and permissions, the researcher distributed the survey questionnaire to the students through a Google Form. The online survey included items on the respondents' demographic profile and their levels of individual, motivational, and social support factors toward learning mathematics. The purpose of the study was clearly explained at the beginning of the form, and respondents were assured that their responses would be treated with strict confidentiality.

The collected data from both the Registrar's records and the online survey responses were consolidated, checked for completeness, and encoded for statistical analysis. These datasets served as the basis for conducting cluster and discriminant analyses to determine the factors that explain and predict students' performance in mathematics.

Treatment of the Data

The collected data were analyzed using appropriate descriptive and inferential statistical tools with the aid of SPSS software. Descriptive Statistics such as frequency, percentage, mean, and standard deviation were used to describe the respondents' demographic profile and their levels of individual, motivational, and social support factors. The mean was interpreted as very low (1.00-1.49); low (1.50-2.49), high (2.50-3.49), and very high (3.50-4.00). Cluster Analysis was used to classify students into high achievers and low achievers based on their final grades in MMW. Discriminant Analysis was employed to predict the performance groups and to establish the discriminant mathematical model that explains students' achievement in mathematcs. Classification accuracy and Wilks' Lambda were used to evaluate the reliability and significance of the discriminant function.

Ethical Considerations

The study ensured that all research activities followed to ethical standards. Participation was voluntary, and informed consent was obtained from all respondents. Their identities and academic records were kept strictly confidential, and data were used solely for academic purposes. The researcher ensured that the results would be reported objectively and that no part of the study would cause harm or disadvantage to any participant.

RESULTS AND DISCUSSION

Section 1. Demographic Profile of Students

Table 1. Demographic Profile of the Students

Demographic Profile	Number of Students	Percent
Course		
BIT FSM 1	31	20.13
BIT AT 1	27	17.53

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BIT ET 1	16	10.39
BSBA MM 1	35	22.73
BSBA FM 1	31	20.13
BSEd English 1	8	5.19
BSEd Science 1	3	1.95
BSEd Math 1	3	1.95
TOTAL	154	100
Age		
17 years old	1	00.65
18 years old	54	35.06
19 years old	64	41.56
20 years old	23	14.94
21 years old	6	03.90
22 years old	3	01.95
23 years old	1	00.65
27 years old	1	00.65
29 years old	1	00.65
TOTAL	154	100
Sex		
Male	61	39.61
Female	93	60.39
TOTAL	154	100
College		
College of Education	14	9.09
College of Technology and Business	140	90.91
TOTAL	154	100
Senior High School Strand		
STEM	14	9.09

HUMSS	47	30.52
ABM	32	20.78
GAS	37	24.03
TVL	24	15.58
TOTAL	154	100
Father's Highest Educational Attainment		
Kindergarten	1	0.64
Elementary	22	14.28
High School	90	58.44
College	40	25.97
Masters	1	0.64
TOTAL	154	100
Mother's Highest Educational Attainment		
Kindergarten	1	0.64
Elementary	13	8.44
High School	104	67.53
College	35	22.72
Masters	1	0.64
TOTAL	154	100

Table 1 illustrate the demographic profile of the 154 students who participated in this research. Majority of the students are from the College of Technology and Business, which is 90.91% of the sample, with the College of Education representing a smaller portion at 9.09%. Within these colleges, the students are distributed across various degree programs, with BSBA MM 1 (22.73%), BIT FSM 1 (20.13%), and BSBA FM 1 (20.13%) being the most represented.

In terms of age, most of the students, with 91.56% of participants falling between 18 and 20 years old. The median age appears to be 19 years old, which is the largest single group at 41.56%. The sample is mostly female, with females making up 60.39% of respondents compared to 39.61% male. Regarding their academic background, the students come from a range of senior high school strands, with HUMSS (30.52%), GAS (24.03%), and ABM (20.78%) being the most common, followed by TVL (15.58%) and STEM (9.09%).

A majority of both fathers (58.44%) and mothers (67.53%) have a high school education as their highest level of attainment. College-level education is held by 25.97% of fathers and 22.72% of mothers, while very few parents have attained a master's degree (0.64% for both) or only an elementary/kindergarten education.

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Section 2. Performance of Students in Mathematics using Cluster Analysis

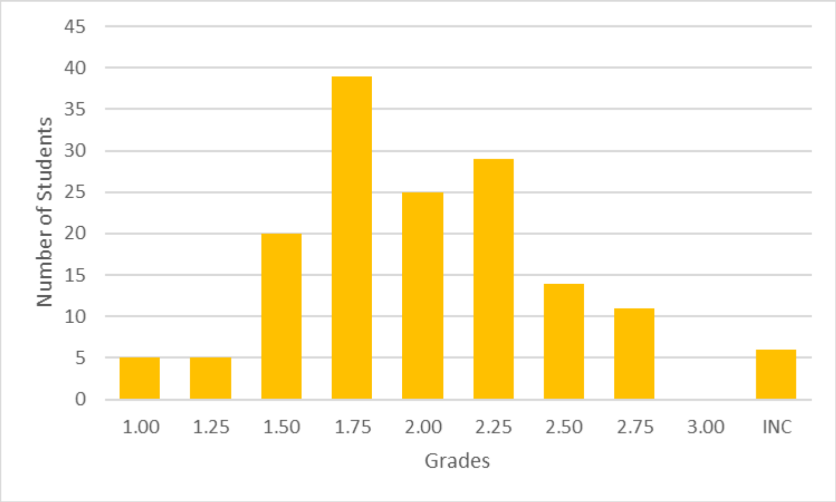

Figure 2. Performance of Students Respondents in Mathematics

Figure 2 illustrates the distribution of final grades of the respondents in matehamtics for the 1st and 2nd semesters of school year 2024-2025. The figure shows that student performance is heavily concentrated in the satisfactory range, with the highest number of students (39) achieving a grade of 1.75. This is closely followed by grades 2.25 (29 students) and 2.00 (25 students). There are five students who earned a 1.25 and the five who earned the highest mark of 1.00. Additionally, the figure reveals a significant number of students who faced academic challenges, with 14 students receiving 2.50 and 11 students with 2.75. While no respondent received a final grade of 3.00, the presence of an "incomplete" (INC) mark points to issues with course completion for 6 student respondents.

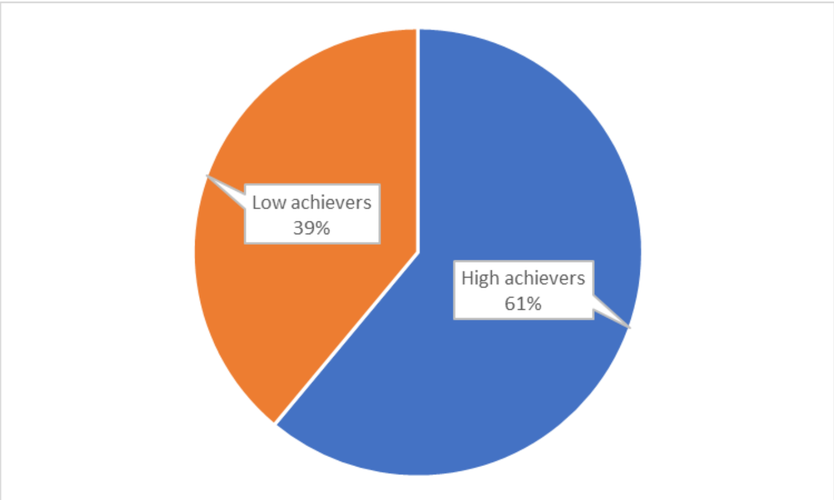

Figure 3. Performance of Students Respondents in Mathematics using Cluster Analysis

To categorize student performance into two groups, a cluster analysis was utilized. This statistical method grouped the student respondents into two distinct clusters based on their final grades in mathematics which are the high achievers and low achievers. The results of this grouping are presented in Figure 3. It was found that 61% (n = 94) of students were classified as high achievers, defined as those with grades ranging from 1.00 to 2.00. Moreover, 39% (n = 60) were classified as low achievers, a group comprising students with grades from 2.25 to 3.00, including those with an Incomplete (INC) mark. These two distinct groups will be used as the categories in a discriminant analysis to identify which demographic and support factors best predict membership in either the high or low achiever group.

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Section 3. Level of Individual, Motivational and Social Support Factors

Table 2. Mean, Standard Deviation and Qualitative Description of the Level of Individual, Motivational and Social Support Factors of Student

	Statements	Mean	Standard Deviation	Qualitative Description
Individual	1. I think I am pretty good at math activities.	2.77	0.66	High
	2. I think I am doing my best in my math activities if I am interested in the lesson.	3.14	0.50	High
	3. Math activities are valuable and interesting to me.	2.90	0.58	High
	4. Math activities are easy to do for me when I focus on studying.	2.99	0.58	High
	Overall Level of Individual Factors	**2.95**	**0.60**	**High**
Motivational	5. I always do my best to accomplish my math activities because I want to have a better performance in the subject.	3.10	0.50	High
	6. I think I will perform better in math if I am motivated to do my activities.	3.11	0.51	High
	7. I think I will perform better in math if I find the subject important and related in my daily living.	3.08	0.54	High
	Overall Level of Motivational Factors	**3.10**	**0.51**	**High**
Social	8. I think I only do good in math activities if I have a peer or partner to learn with.	2.95	0.62	High
	9. I only do math activities if my teacher assisted me to do.	2.86	0.65	High
	10. I think I can do math activities better if I have someone in my family who can lend a hand.	2.93	0.55	High
	Overall Level of Social Factors	**2.91**	**0.61**	**High**

Table 2 presents the mean, standard deviation, and qualitative description of the students' perceived level of individual, motivational, and social support factors. The data indicates that students, on average, reported high levels of support across all three support factors. The overall level of individual factors received a mean of 2.95 (SD = 0.60), which falls under the high qualitative description. This suggests that students generally possess positive self-perceptions regarding their math abilities and find value in the activities. Similarly, the overall level of motivational factors was the highest among the three, with a mean of 3.10 (SD = 0.51), also described as high. This shows that students are strongly driven by a desire for better performance. Finally, the overall level of social factors was also high, with a mean of 2.91 (SD = 0.61), indicating that students perceive collaboration and assistance as significant contributors to their success.

The student respondents consistently reported high levels of individual confidence, internal motivation, and perceived social support. The low standard deviations across all categories suggest that the students' responses were generally in agreement and did not vary widely from the mean. These findings align with the understanding that a combination of positive self-belief (Asare et. al, 2025), motivation (Mula et. al, 2024), and a supportive learning environment (Niu et. al, 2021) are crucial components for achievement in Mathematics.

Section 4. Discriminant Model that Classifies Students' Performance in Mathematics

Prior to conducting the discriminant analysis, several data preprocessing steps were implemented. Categorical variables including course, sex, senior high school strand, and the highest educational attainment of the parents were transformed using dummy coding. To ensure analysis, certain categories with low frequencies were merged. Specifically, the small number of students in BSED English (8), BSED Science (3), and BSED Math (3) were consolidated into a single "Educ Students" variable, resulting in a total of 14 students in this category. Similarly, for parental education, the 'Kinder' and 'Elementary' categories were merged into one predictor, and the 'College' and 'Masters' categories were merged into another, due to minimal counts in the original 'Kinder' and 'Masters' groups.

In dummy coding, a baseline or reference category is required for each variable. The baseline was systematically selected based on the category with the highest frequency. Consequently, the baseline groups were established as follows: 'BSBA MM 1' for course, 'Female' for sex, 'HUMSS' for academic strand, and 'High School' for parental educational attainment. The 'college belonging' variable was excluded from the analysis because it was conceptually redundant with the 'Educ Students'.

For the constructs of individual, motivational, and social support, the analysis used a composite score representing the sum of the participants' selected levels of agreeableness for each factor. The variable for age was included in the analysis without any special transformation.

Independents Together

Table 3. Summary of Discriminant Analysis for Predicting High and Low Academic Achievement

Variables	Unstandardized Coefficients	Structure Matrix Correlation	p-value
Educ Students	2.114	0.571	0.001
BSBA FM 1	-0.518	-0.294	0.094
BIT ET 1	-1.077	-0.306	0.081
BIT AT 1	1.113	0.341	0.052
BIT FSM 1	-0.173	-0.149	0.395
Age	0.060	0.002	0.990
Male	-0.267	0.131	0.454
College of Education	---	---	0.001
TVL	-0.211	-0.028	0.874
GAS	-0.150	-0.028	0.873
ABM	-0.625	-0.246	0.160
STEM	0.311	0.154	0.378

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Kinder-Elementary (Mother)	-0.260	-0.045	0.796
College-Masters (Mother)	-0.565	-0.137	0.432
Kinder-Elementary (Father)	-0.215	-0.077	0.658
College-Masters (Father)	0.833	0.329	0.061
Individual Support	-0.009	0.209	0.233
Motivational Support	0.402	0.180	0.304
Social Support	-0.220	-0.107	0.540
Constant	-2.735		

Table 3 summarizes the contribution of each predictor variable to the discriminant function through their unstandardized coefficients, structure matrix correlations, and corresponding p-values. The unstandardized coefficients indicate the direction and relative strength of each variable in predicting group membership, where higher positive values increase the likelihood of belonging to the target group and negative coefficients decrease it. Among all predictors, Educ Students has the largest positive coefficient (2.114) when compared baseline course ‘BSBA MM 1’, supported by a strong structure correlation (.571) and a significant p-value (0.001), confirming that students enrolled in Education programs contribute most strongly to group separation. Meanwhile, College-Masters (Father) shows a positive coefficient (0.833) when compared to baseline father’s educational assistance ‘High School’ graduate and moderate structure correlation (.329), although its p-value (0.061) indicates only marginal influence.

The structure matrix correlations support these results by showing the degree to which each variable is associated with the discriminant function, with larger absolute values denoting stronger loadings. Variables such as BIT AT (.341), BIT ET (–.306), and BSBA FM (–.294) show moderate correlations when compared baseline course ‘BSBA MM 1’ but lack statistical significance ($p > .05$), suggesting that although they relate somewhat to the discriminant function, their contributions are not strong enough to be meaningful. In contrast, demographic variables such as age and sex, as well as academic strands and parental educational attainment, show very small coefficients and low structure correlations, paired with non-significant p-values, indicating they do not substantially influence group classification. Support-related variables which are individual, motivational, and social also show weak coefficients and non-significant p-values, signifying limited discriminatory power.

Overall, consistent patterns across all three indicators namely coefficients, structure loadings, and p-values demonstrate that program affiliation, particularly being an education student, is the strongest determinant in distinguishing groups, while demographic characteristics, support systems, and parental education levels contribute minimally to the discriminant model.

Table 4. Wilks' Lambda and the Discriminant Function

Test of Function	Wilks' Lambda	Chi-square	df	p-value
1	0.822	28.033	18	0.062

Table 4 presents the Wilks’ Lambda test for the discriminant function. The obtained Wilks’ Lambda value of 0.822 suggests that the function has a moderate ability to distinguish among the groups, with lower values indicating better discrimination. The associated Chi-square value is 28.033 with 18 degrees of freedom, and a corresponding p-value of 0.062. Since the p-value is greater than the 0.05 level of significance, the discriminant function is not statistically significant, indicating that the combination of predictor variables does not reliably differentiate the groups. Although the function shows some discriminatory tendency, it is insufficient to conclude that meaningful separation of groups exists based on the variables included in the analysis.

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Table 5. Functions at Group Centroids

Cluster	Function
0	0.579
1	-0.369

The analysis of the functions at group centroids reveals a clear and effective separation between the two achievement groups. The high achievers' group (Cluster 1) is positioned at a positive centroid value of 0.579, while the low achievers' group (Cluster 0) is located at a negative centroid value of -0.369. The midpoint between these two centroids, calculated to be 0.105, serves as the critical boundary for classification. According to this model, a case with a discriminant score greater than 0.105 would be classified into the high-achieving cluster (Cluster 1), while a score lower than 0.105 would be assigned to the low-achieving cluster (Cluster 0). This clear demarcation further confirms the model's ability to distinguish between the two groups effectively.

Table 6. Classification Result

Cluster	Original Group Membership	Number of Correctly Classified	Percentage of Correctly Classified
0	60	36	68.83
1	94	70	

Table 6 presents the classification results of the model in assigning respondents to their respective clusters. Cluster 0 originally consisted of 60 individuals, of whom 38 were correctly classified. Meanwhile, Cluster 1 included 94 individuals, with 70 correctly classified. The discriminant model reflecting a correct classification rate of 68.83%. These results suggest that the model demonstrates a moderate level of accuracy in predicting group membership, correctly categorizing about two-thirds of the respondents across both clusters. Despite this acceptable performance, the presence of misclassified cases indicates that the model may benefit from further refinement or the inclusion of additional predictors to enhance its classification capability.

The complete discriminant function with all independent variables is presented as follows:

$$y = -2.735 + 2.114x_1 - 0.518x_2 - 1.077x_3 + 1.113x_4 - 0.173x_5 + 0.06x_6 - 0.267x_7 - 0.211x_8 - 0.15x_9 - 0.625x_{10} + 0.311x_{11} - 0.26x_{12} - 0.565x_{13} - 0.215x_{14} + 0.833x_{15} - 0.009x_{16} + 0.402x_{17} - 0.22x_{18}$$

Legends: x_1: Educ Student

x_2: BSBA FM 1

x_3: BIT ET 1

x_4: BIT AT 1

x_5: BIT FSM 1

x_6: Age

x_7: Male

x_8: TVL

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x_9: GAS

x_{10}: ABM

x_{11}: STEM

x_{12}: Kinder and Elementary (Mother)

x_{13}: College and Masters (Mother)

x_{14}: Kinder and Elementary (Father)

x_{15}: College and Masters (Father)

x_{16}: Individual Support

x_{17}: Motivational Support

x_{18}: Social Support

Consider a student who is enrolled in BIT AT 1, is male, 22 years old, completed the TVL strand in senior high school, has a mother whose highest educational attainment is high school, and a father with a college degree. This student also has factor scores of 12 for Individual Support, 9 for Motivational Support, and 10 for Social Support.

The calculation for this student is performed by substituting the corresponding values (1 for 'Yes', 0 for 'No') for categorical variable into the function:

$$\begin{aligned} y = & -2.735 + 2.114(0) - 0.518*(0) - 1.077*(0) + 1.113*(1) - 0.173*(0) + 0.06*(22) \\ & - 0.267*(1) - 0.211*(1) - 0.15*(0) - 0.625*(0) + 0.311*(0) - 0.26*(0) \\ & - 0.565*(0) - 0.215*(0) + 0.833*(1) - 0.009*(12) + 0.402*(9) - 0.22*(10) \end{aligned}$$

$$y = 1.363$$

Since the resultant discriminant score (y = 1.363) is greater than the classification boundary of 0.105, this student is classified into Cluster 0, the high academic achievement group.

Stepwise Method

Table 7. Summary of Discriminant Analysis for Predicting High and Low Academic Achievement

Variables	Unstandardized Coefficients	Structure Matrix Correlation	p-value
Educ Students	3.228	0.778	0.001
BSBA FM 1	---	---	0.094
BIT ET 1	---	---	0.081
BIT AT 1	1.696	0.465	0.052
BIT FSM 1	---	---	0.395
Age	---	---	0.990

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Male	---	---	0.454
College of Education	---	---	0.001
TVL	---	---	0.874
GAS	---	---	0.873
ABM	---	---	0.160
STEM	---	---	0.378
Kinder-Elementary (Mother)	---	---	0.796
College-Masters (Mother)	---	---	0.432
Kinder-Elementary (Father)	---	---	0.658
College-Masters (Father)	---	---	0.061
Individual Support	---	---	0.233
Motivational Support	---	---	0.304
Social Support	---	---	0.540
Constant	-0.591		

Table 7 provides the summary of discriminant analysis for predicting high and low academic achievement using stepwise method. The stepwise discriminant analysis revealed a model with a limited number of variables that significantly contribute to predicting whether a student falls into a high or low academic achievement group. The most powerful predictor was the "Educ Students" variable, which possessed a strong, positive unstandardized coefficient (3.228) when compared baseline course ‘BSBA MM 1’ and a highly significant structure matrix correlation (0.778, p=0.001), indicating that students from an Education background were substantially more likely to be in the high-achieving group. "BIT AT 1" also entered the final function with a positive coefficient (1.696) when compared baseline course ‘BSBA MM 1’, though its correlation was moderate (0.326) and its significance was marginal (p=0.052). Other variables, such as "BSBA FM 1" and "BIT ET 1," showed moderate correlations but were not statistically significant enough to be strong, unique predictors in the model. The vast majority of variables, including age, gender, strand, parental education, and various forms of support, demonstrated very weak correlations and were not statistically significant, indicating they did not effectively discriminate between high and low achievers in this analysis.

Table 8. Wilks' Lambda and the Discriminant Function

Test of Function	Wilks' Lambda	Chi-square	df	p-value
1	0.895	16.678	2	<0.001

The model's overall significance is confirmed by Wilks' Lambda, a statistic that tests whether the discriminant function (the model that separates the groups) is effective as illustrated in Table 8. A Wilks' Lambda value of 0.895 indicates that approximately 89.5% of the variance in the discriminant scores is not explained by the differences between the high and low achievement groups. While this may seem high, the associated highly significant chi-square test ($\chi^2 = 16.678$, $p < 0.001$) confirms that the remaining 10.5% of the variance that the model does explain is statistically significant. This means that the combination of predictor variables in the model—primarily led by "Educ Students" and "BIT AT 1" successfully distinguishes between students with high and low academic achievement to a degree that is very unlikely to have occurred by chance. In essence, the model as a whole is a valid and significant predictor of group membership.

Table 9. Functions at Group Centroids

Cluster	Function
0	0.425
1	-0.271

Table 9 reveals the direction of the discriminant function's prediction. The group centroids, which are the mean discriminant scores for each cluster, show that Cluster 0 has a positive mean score (0.425) while Cluster 1 has a negative mean score (-0.271). The midpoint between these two clusters is 0.077, which serves as the classification boundary. A discriminant score greater than 0.077 leads to classification into Cluster 0, while a score lower than 0.077 leads to classification into Cluster 1. Recalling that the strongest predictor, "Educ Students," had a large positive coefficient, we can interpret that students with a higher score on the discriminant function—driven by such factors—are classified into Cluster 0. Therefore, it is concluded that Cluster 0 represents the group with High Academic Achievement, and Cluster 1 represents the group with Low Academic Achievement. This confirms that the model successfully separates the two groups, with high achievers scoring positively on the function and low achievers scoring negatively.

Table 10. Classification Result

Cluster	Original Group Membership	Number of Correctly Classified	Percentage of Correctly Classified
0	60	26	68.18
1	94	79	

Table 10 provides a measure of the model's practical accuracy in predicting student achievement. The discriminant function correctly classified 43.33% of the students in the high-achieving group (Cluster 0). However, its performance was not uniform across both groups. While it successfully categorized 79 out of 94 students in the low-achieving group (Cluster 1), its accuracy for the high-achieving group was lower, with only 26 out of 60 students correctly classified. This indicates that the model, built primarily on the strong predictor of being an Education student ("Educ Students"), is more effective at identifying the characteristics of low achievers. Consequently, it is better at predicting who will not be a high achiever than at correctly pinpointing all high achievers. Some high-achieving students likely possess attributes not fully captured by the final model, leading to their misclassification. Overall, this hit-rate confirms that the model has predictive power significantly better than random chance, but it also highlights a specific area where its predictive ability is weaker.

The final discriminant model, which includes all significant independent variables, is presented below:

$$y = -0.591 + 3.228x_1 + 1.696x_2$$

Legends: x_1: Educ Student

x_2: BIT AT 1

To illustrate the model's application, consider a student with the following profile: enrolled in BIT AT 1, male, 22 years old, from the TVL senior high school strand, with a mother whose highest education is high school and a father with a college degree. This student has factor scores of 12 for Individual Support, 9 for Motivational Support, and 10 for Social Support.

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The discriminant score for this student is calculated as follows:

$$y = -0.591 + 3.228(0) + 1.696 * (1)$$

$$y = 1.105$$

Since the resultant discriminant score (y = 1.105) is greater than the classification boundary of 0.077, this student is classified into Cluster 0, which represents the high academic achievement group.

CONCLUSIONS

Based on the analysis of data pertaining to student profiles, support factors, and academic performance in mathematics, the following conclusions are drawn:

1. The study participants are primarily first-year students (aged 18-20) from the College of Technology and Business, with a higher proportion of females. Their academic backgrounds are diverse, coming from various senior high school strands, and a majority have parents whose highest educational attainment is a high school diploma.

2. Student performance in Mathematics in the Modern World is categorized. While a majority (61%) are classified as high achievers, a significant minority (39%) are low achievers, with grades in the lower range or who did not complete the course (INC). This clear division creates two distinct groups suitable for further predictive analysis.

3. Students uniformly report high levels of perceived support across all three factors namely individual, motivational, and social. This indicates a generally positive and confident learning attitude among the respondents towards mathematics.

4. The student's specific academic program is the most critical factor in predicting their performance group. The discriminant model successfully identifies that being an "Education student" is the strongest predictor of high achievement, with "BIT AT 1" also having a positive influence. This program-specific effect is more significant than age, gender, academic strand, parental education, or any of the self-reported support factors.

RECOMMENDATIONS

Derived from the conclusions, the following recommendations are proposed to enhance student performance, refine instructional practices, and guide future research.

- For Curriculum Design and Instruction:

1. Given that academic program is a key differentiator, educators and curriculum developers should consider designing MMW modules and pedagogical approaches that are more closely aligned with the specific contexts and interests of different colleges, particularly for non-Education students in Technology and Business programs. Making the content more relevant to their fields could enhance engagement and performance.

2. The institution should implement early warning systems and targeted intervention programs, especially for students in programs not identified as positive predictors (programs other than Education and BIT AT). Supplemental instruction or tutorial sessions focused on MMW could be beneficial for these cohorts.

3. The developed discriminant functions can be used as a practical tool for early identification of students at potential risk of underperformance in MMW, allowing for proactive academic advising and support.

- For Future Research:

1. Future studies should explore variables beyond those measured here to explain the variance in achievement, particularly to identify the characteristics of high achievers. Potential factors could include prior mathematical knowledge, learning styles, specific teaching methodologies employed in the classroom, grit, or anxiety towards mathematics.

2. A qualitative follow-up study is highly recommended to deeply explore why Education students demonstrate a significant advantage in MMW. Interviews or focus group discussions could uncover the underlying reasons, such as specific learning strategies, motivation, or curriculum alignment, which are not captured by quantitative data.

3. Replicating this study with a larger and more balanced sample across all academic programs would help validate the discriminant model and improve the generalizability of the findings. A longitudinal study could also track how these predictors influence performance over time.

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