Structural Equation Modelling of Students' Difficulties in General Mathematics

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ABSTRACT

In the modern era of K-12 education, experts in the field of education have extensive experience in addressing challenges related to student learning, particularly in mathematics. To investigate these issues further, a study on Structural Equation Modelling of Students' Difficulties in General Mathematics was conducted. The research employed a quantitative, descriptive-correlational design and involved 390 Grade 11 students from Banga National High School. A researcher-made questionnaire was utilized to assess the difficulties students face in General Mathematics.The findings reveal that demographic factors (e.g., socio-economic background and prior academic experience) significantly and strongly influence the challenges students face in mathematics ($\beta = 0.694$, $p < 0.001$), highlighting the importance of targeted interventions for different demographic groups. The relationship between the learning environment and student engagement was found to be moderate, with the learning environment showing a significant positive effect on student engagement ($\beta = 0.383$, $p < 0.001$), but it did not significantly impact the challenges students face in mathematics. On the other hand, student engagement had a marginally significant effect on the difficulties students experience, with a weak relationship ($\beta = 0.041$, $p > 0.05$), indicating that engagement alone is insufficient to address these challenges.The structural equation modeling revealed that the predictors accounted for 51.2% of the variance in students' difficulties and 17.1% of the variance in student engagement, underscoring the need for comprehensive approaches.These findings suggest that targeted interventions aimed at improving study habits, enhancing parental involvement, and fostering a more supportive learning environment are crucial in reducing student difficulties in General Mathematics. While improving student engagement is important, focusing on addressing demographic challenges should be prioritized. The study provides a solid framework for designing academic support strategies tailored to the needs of Grade 11 students at Banga National High School, ultimately improving their academic success in mathematics.

Keyword- Structural Equation Model, Students' Difficulties, General Mathematics, Banga National High School, Grade 11 Students.

INTRODUCTION

Mathematics is a foundational subject essential for developing critical thinking and problem-solving skills, yet many students across the globe, including the Philippines, continue to struggle with mastering general mathematics. International assessments such as TIMSS and PISA reveal a persistent gap between expected and actual student performance, highlighting a widespread issue that affects learners at all educational levels.

In the Philippines, these challenges are particularly evident, with students consistently underperforming in mathematics compared to their international peers. This situation is further exacerbated by limited educational resources, inadequate teacher training, and students' lack of motivation and effective study habits, particularly in schools such as Banga National High School.

This study utilizes Structural Equation Modeling (SEM) to analyze the complex factors contributing to the mathematics difficulties of Grade 11 students, focusing on variables such as demographic profile, student engagement, and learning behaviors. By examining these interrelated factors, the study seeks to provide a deeper understanding of the root causes of students' struggles and to inform the development of context-specific interventions.

The findings aim to support educators and policymakers in creating targeted strategies that enhance mathematics instruction, foster greater student engagement, and ultimately improve academic performance in general mathematics.

METHODOLOGY

Research Design

This study employing descriptive-correlational research design investigated to formulate Structural Equation Model (SEM) of Students' Difficulties in General Mathematics. The research design of the study will be used descriptive-correlational. According to Shinija (2024) descriptive designs are used to observe, record, and describe a phenomenon as it occurs naturally, without any manipulation or control. The descriptive design was used on this study to gather and interpret data based on the extent of predicators in student performance in mathematics and students' performance in General Mathematics subject in first quarter grading period of school year 2024-2025. The correlational design was used to examine the relationships between two or more variables within a single group and is a type of non-experimental design that investigates the connection between multiple variables. (Devi et al., 2023). The correlational design was used to interpret the relationship between the predicators of students' difficulties and student performance in the first quarter of General Mathematics.

Locale of the Study

The study was conducted at the Banga National High, Senior High School Department. Banga National High School is a public secondary school, the first public school established in the municipality of Banga where the researcher employed. The school is located in Brgy. Benitez, Banga, South Cotabato, Philippines. The school covers the junior high school and and senior high school department offers also ABM, HUMSS, STEM, Electrical Installation and Maintenance (EIM),EPAS, Furniture Making, Beauty Care, Cookery, Information and Communication Technology (ICT), Automotive, Driving and Agricrop Production.

The said locations are identified since it has enough and rich data that created an acceptable and valid result since based on the recent Regional Science and Technology Fair 2024, the said schools qualify to the regional level competition on different researches. Those researches showcased the skills, knowledge and expertise of the STEM students in terms of Science, Mathematics and Innovations researches. The two schools have a high expectancy of producing competitive students in the field of science, technology, engineering and mathematics field.

Respondents of the Study

The Grade 11 students from Banga National High School, which are enrolled on the first semester of the 2024-2025 academic year are respondents of the study. The Grade 11 students are qualified as respondents in the study on Structural Equation Modeling (SEM) of students' difficulties in General Mathematics because they are currently enrolled in the course and are actively experiencing the challenges associated with it. As students within this specific academic track, they may face distinct mathematical difficulties based on their curriculum and academic focus. Their input is essential for understanding the particular struggles they encounter in General Mathematics, which can then be analyzed using SEM to identify underlying factors and relationships influencing their difficulties. Additionally, these students represent the target population whose difficulties the study aims to explore and address.

Sampling Technique

This study employed a complete enumeration of all grades 11 students from the Banga National High School for the school year 2024-2025. Complete enumeration is applied in the study since it considers results in using a priori sample size for structural equation models with the given number of observed (17) variables and latent (4) variables in the model, the anticipated effect size (0.3), the desired probability (0.05), and statistical power levels (0.8) (Soper 2021). Based on the results of identifying the number of respondents 150 is the minimum sample size to detect effect, 148 was the minimum sample size for model structure, and the recommended minimum sample size is 150 respondents.

The three formulas: Error Function, Lower Bound Sample Size for a Structural Equation Model and Normal Distribution Cumulative Distribution Function (CDF) was used to calculate a priori sample sizes for structural equation model. Results identified the number of respondents a minimum sample size of 148 was required to detect an effect, while 150 was the minimum needed for the model structure. The recommended minimum sample size was 150 respondents. The Grade 11 students of Banga National High School – Senior High School

Research Instruments

Structural equation modeling of student's Mathematical Difficulties in Grade 11 General Mathematics will be conducted on the third quarter of the school year 2024-2025 of Grade 11 students of Banga National High School. As a result, the study required the researcher to use appropriate instruments to collect the necessary data.

The data collection process was started by gathering information on the demographic profile of the respondents. The students were asked to write their parents' highest level of education as well as their household income per month. Additionally, they will be asked about their study habits, including the average number of hours they spend studying each day. Students were asked to provide their General Weighted Average (GWA) in Mathematics 10 and their overall average in Grade 10 to offer insight into their previous academic performance. The statement on student engagement in mathematics includes exposure to technology, readiness and their study habits when learning mathematics. The statement in learning environment was address influencing students' study settings, teaching strategies, peer influence and parental support. And lastly, their performance in the first grading period of Grade 11 was explored to understand how their grades might affect their understanding of mathematical concepts through the least learned competencies and summative assessment.

Validity and Reliability Test of the Research Instrument

Reliability and validity are the two most crucial and essential aspects in assessing any measurement instrument or tool for quality research Mohajan (2017).

A researcher – made questionnaire was used as an instrument of the study. . Prior to the conduct of the study, thorough validation and reliability tests was secured on the instrument to guarantee its quality and accuracy. The researcher worked closely with the adviser, who will review the initial drafts of the questionnaire, offer guidance on its format and presentation, and verified that the indicators for the primary variables in the study are clearly defined.

The validation of the content by the validators was determined by calculating the agreement ratio (AR) using the following formula:

$$AR = \frac{n}{N} \times 100\%$$

where AR = Agreement Ratio

n = number of content validators

N = total number of content validators

Items from the questionnaire that received at least 60% approval from the content validators was included in the research instrument. Items that did not meet the required agreement percentage were either revised or removed. After revising all items, the updated research instrument, along with the validation tool developed by Good and Scates in 1972 and modified by Abullah (2020), was redistributed to the content validation panel for further feedback on the revisions. The validation criteria, rating scale, verbal description, and interpretation are outlined below.

Data Gathering Procedures

The researcher created a survey test questionnaire that was validated by the three professionals who evaluated it. Following the assessment, the researcher writes to the principal of Rizal3 National High School to ask for permission to carry out a pilot test and assess the questionnaire's reliability. Conducting a pilot study involved using the instrument in a trial run of the actual study procedures. This approach assesses not only the instrument's performance but also the feasibility of the research design, data collection methods, and analysis procedures. Well-organized and documented pilot tests can significantly enhance the validity, reliability, accuracy, and efficiency of the full-scale study Khanal and Chhetri (2024). The researcher calculated and analyzed the students' responses.

The researcher sent a letter to the Dean of the Graduate School, seeking permission to conduct the study with Grade 11 students at Banga National High School. Once the Dean approved the study, the researcher then wrote a permission letter to the Principal of the Senior High School Department at Banga National High School. The researcher also sent comparable letters to the Senior High School Academic Coordinator, General Mathematics teacher, and High School Registrar of the Senior High School Department.

On February 2024-2025 school year, the researcher administered the survey questionnaire to Grade 11 students. Before they began, the researcher provided clear instructions on how to complete the questionnaire to ensure the validity and integrity of the study's results. The researcher also explained the purpose of the study and assured the students that their responses would remain confidential. Students were encouraged to complete the survey within twenty minutes, which included time for the general instructions.

After collecting all completed questionnaires, the researcher, with the assistance of the research adviser and a statistician, tallied the results and organized the data. Additionally, the researcher provided a letter signed by the school principal to the Gen-Math teacher and Senior High School Registrar, requesting the academic performance records of the students involved in the study.

Finally, the researcher analyzed the data using SPSS and AMOS and interpreted the results with confidence, integrity, and a commitment to preserving the confidentiality of the research.

Statistical Treatment

The study "Structural Equation Modelling of Mathematical Difficulties of Grade students in General Mathematics" will use descriptive statistics, Pearson's r correlation, and Structural Equation Modeling to calculate, formulate, and test the

For the variables and data collected in the study, descriptive statistics such as frequency, percentage, weighted mean, and standard deviation were used to organize and interpret the data among the student's demographic profile (number of hours of studying in a day, number of classmates in a classroom, general weighted average (GWA) grade in mathematics 10, and general average in grade 10), student engagement in learning mathematics (students interests, motivation and study habits), student learning environment in learning mathematics (classroom environment, home environment, and peer groups), availability of learning materials in learning mathematics (teaching strategies and learning materials (books, articles and technologies)), least learned competency and first quarter grade of students in Gen-Math.

Pearson r correlation used to analyze the relationships between the student's demographic profiles, indicators of student performance in mathematics, least learned competency, and the first quarter grade of the respondents in the subject Gen-Math. The researcher utilized the Statistical Package for the Social Sciences (SPSS), as described by Walberg (1981), to conduct the required calculations. Walberg's theory of educational productivity introduced in 1981, used SPSS to ensure accurate and reliable results which served as the foundation for further research in the field.

The Structural Equation Model (SEM) was employed to interpret and present the results in relation to the research objectives. By applying SEM, the researcher can define a priori relationships among the variables included in the model. This specification is essential for testing the academic achievement model developed from the literature review (Bhale & Bedi 2023). Thus, the AMOS was used to test the SEM to test the possible relationship between student performance indicators in mathematics. Furthermore, the significance of all tests is at 0.05 level of significance.

Ethical Consideration

The researcher ensures accurate and unbiased data collection by providing a questionnaire to participants and obtaining signed consent forms from parents. The consent forms outline the study's purpose, procedures, risks, benefits, and voluntary participation. Participants are informed about the advantages of the study, including gaining insights into their own thoughts and behaviors. They are assured of confidentiality, with responses used solely for academic purposes, and are told they can withdraw from the study at any time without pressure. Throughout the research, participants are protected from any physical or emotional harm.

RESULTS AND DISCUSSION

Table 1. The Demographic Profile of the Grade 11 Banga National High School.

Profile	Frequency (n=390)	Percentage (100%)
1.1 Highest Level of Education		
Completed Higher Education (e.g., Bachelor's degree, Master's degree, Doctorate)	7	1.79%
Some College or University Education (e.g., attending but not completed)	144	36.92%
Completed Secondary Education (e.g., high school diploma)	167	42.82%
Completed Primary Education	72	18.46
No formal education or Some primary education	0	0.00%
1.2 Household Income per Month		
P 40, 001.00– Above	1	0.26%
P 30,001.00 – P 40, 000.00	24	6.15%
P 20,001.00 – P 30,000.00	109	27.98%
P 10, 0001.00– P 20,000.00	160	41.03%
Below – P 10, 000.00	96	24.62%
1.3 Number of Hours Studying in a Day		
4.1 hrs. - Above	14	3.59%
3.1 hrs. – 4 hrs.	0	0%
2.1 hrs. – 3 hrs.	47	12.05%
1.1 hrs. – 2 hrs.	101	25.88%
Below – 1 hr.	229	58.72
1.4 General Weighted Average (GWA) in Mathematics 10		
90 – 100	146	37.44%
85 – 89	166	42.56%
80 – 84	61	15.64%
75 – 79	3	0.77%
Below – 75	0	0%
1.5 General Average in Grade 10		

90 – 100	159	40.77%
85 – 89	148	37.95%
80 – 84	71	18.21%
75 – 79	10	2.56%
Below – 75	0	0%

The findings of this study reveal important insights into the relationship between demographic factors and students' performance in General Mathematics. Notably, parental education level and household income play significant roles in shaping students' academic outcomes. These results align with previous research, which suggests that students from families with higher levels of education tend to perform better academically, benefiting from increased cognitive resources and more effective academic support (Morris et al., 2017). In contrast, students from families with lower educational backgrounds may experience limitations in academic guidance, especially when navigating complex educational decisions such as college applications (Lareau, 2018). Therefore, the findings emphasize the need for interventions that target parental involvement and provide additional resources to bridge these gaps.

Similarly, household income emerges as a critical factor influencing students' academic engagement. As highlighted by Davis-Kean (2017) and Sirin (2015), socio-economic status (SES) is linked to students' academic achievement, with lower household income often limiting access to resources such as tutoring, internet access, and books. While the study shows that a majority of students come from lower-income households, which could contribute to academic challenges, it also highlights the necessity of developing targeted policies and interventions to support these students in overcoming such socio-economic barriers.

The analysis also sheds light on students' study habits. The findings that a significant proportion of students study for less than one hour a day raise concerns about the quality and effectiveness of their study strategies. Previous research, such as Duckworth et al. (2019), stresses the importance of academic perseverance, self-regulation, and efficient time management in achieving academic success. Students in this study, particularly those spending teaching effective study techniques limited time studying, may benefit from and time management skills, which could lead to improved academic performance despite limited study time.

Moreover, the relationship between students' General Weighted Average (GWA) in mathematics and their grade 10 general average underscores the importance of consistent academic habits. Studies such as Schneider & Preckel (2017**)** have demonstrated that strong academic performance in earlier grades is a predictor of future success. Given that a large portion of students in this study achieved a GWA of 85 or above, it suggests that they are on track for success, but may still need continued support to maintain high performance, particularly in challenging subjects like mathematics.

In conclusion, this study provides valuable insights into the impact of demographic factors on students' academic performance in mathematics. By recognizing the complex interplay of parental education, household income, and study habits, educational stakeholders can develop more targeted interventions that address the unique needs of Grade 11 students. Future research should explore the effectiveness of such interventions and further investigate the roles of teacher quality and school resources in shaping students' academic success, especially for those from disadvantaged backgrounds (Cheung & Andersen, 2020).

The Level of Students' Engagement in Learning Mathematics.

Indicators	Mean	SD	Interpretation
1. I am willing to ask for help in math when I do not understand something.	3.92	4.54	Minimal Support Needed
2. I use online mathematical tools in learning mathematics.	3.44	4.52	Moderate Support Needed

3. I give time to view video tutorial and read online materials in mathematics lessons.	2.99	1.04	Significant Support Needed
4. I practice solving problems in mathematics before the start of lesson.	2.92	1.03	Intensive Support Required
5. I am willing to spend extra time working on math problems outside of class.	2.60	1.04	Maximum Support Required
Section Mean	**3.18**	**1.86**	**Significant Support Needed**

The results of the study highlight key aspects of student engagement in mathematics, shedding light on the moderate willingness of Grade 11 students to seek help when they face challenges. The highest mean of 3.92 for seeking help, with a standard deviation of 4.54, indicates that students generally feel comfortable asking for assistance when they do not understand something in General Mathematics. This finding aligns with the work of Sezer and Ozdemir (2020), who emphasized that students with stronger self-regulation skills are more likely to seek help when needed, which can contribute to better performance in the subject. The willingness to ask for help is an important indicator of student engagement, as it reflects an active approach to learning rather than passive avoidance of difficulties.

However, while students demonstrated a moderate tendency to ask for help, they showed a slightly lower inclination towards using online mathematical tools (mean = 3.44, SD = 4.52), which suggests that digital learning tools could be underutilized in supporting their academic performance. In today’s digital age, incorporating online resources can significantly enhance learning by providing diverse, interactive tools to deepen understanding. The study suggests that further efforts to increase the adoption of digital learning tools in mathematics could provide more engagement opportunities for students and accommodate various learning styles, as suggested by Zimmerman (2015), who highlighted the role of technology in enhancing self-regulated learning.

The findings also point to a lack of motivation when it comes to spending extra time on mathematics outside of class (mean = 2.60, SD = 1.04), which was interpreted as “maximum support required.” This suggests that many students may not view additional practice as a valuable way to improve their mathematical understanding. Booth and Newton (2018**)** pointed out that spending more time on mathematical problems is essential for students' engagement, as it allows them to develop more sophisticated problem-solving strategies. The students’ reluctance to spend extra time on mathematics indicates a need for structural changes in how time is allocated for learning. Extended time for problem-solving, whether in the classroom or through structured homework programs, could be a viable solution to address these challenges.

Moreover, students' practice of solving problems before the lesson (mean = 2.92, SD = 1.03) was similarly rated as requiring intensive support. This is consistent with research by Zimmerman (2015), who argued that self-regulation in learning is critical for students' academic success. Excessive dependence on external support (e.g., pre-class problem-solving) can limit students' ability to develop independent problem-solving skills, which are necessary for success in mathematics and other STEM fields. The findings underscore the need for balanced instructional strategies that encourage student autonomy in learning, while still providing necessary support when students face difficulties.

Despite the challenges, students demonstrated a moderate level of engagement (mean = 3.18, SD = 1.86) in learning mathematics, with a clear need for intervention to improve their academic performance. This reflects Booth and Newton’s (2018) assertion that allowing additional time for problem-solving, along with fostering student autonomy and self-regulation, can significantly enhance academic engagement. The results indicate that extended classroom time or structured homework programs that emphasize active engagement in problem-solving could improve student outcomes in mathematics.

In conclusion, the study emphasizes the importance of student engagement in mathematics and the need for interventions to improve students' willingness to seek help, use online tools, and spend more time on problem-solving. By improving self-regulation, offering more practice opportunities, and integrating technology into learning, student engagement and academic performance can be enhanced. Future research should investigate the effectiveness of these interventions, particularly in STEM education.

Table 3. The Level of Students Learning Environment in Mathematics

Indicators	Mean	SD	Interpretation
1. The teacher uses a variety of teaching methods to help me understand mathematics.	3.71	1.13	Moderate Support Needed
2. I have access to resources that enhance my understanding of the subject.	3.22	0.97	Significant Support Needed
3. There is family interaction when I need help to understand lessons in mathematics.	2.45	1.15	Intensive Support Required
4. There is enough space for studying and reviewing lessons in mathematics in our home.	2.87	1.10	Significant Support Needed
5. I have teamwork and collaborative efforts with my peers in learning mathematics.	3.46	1.12	Moderate Support Needed
Overall Mean	**3.14**	**0.70**	**Significant Support Required**

The findings from Table 3 highlight the importance of both classroom and home learning environments in shaping students' academic success in mathematics. Teachers who use a variety of teaching methods are instrumental in creating a more engaging and effective learning environment, with a high mean score indicating that diverse instructional strategies positively influence students' academic outcomes. This aligns with Casinillo and Guarte's (2018) study, which found that strategies like computer-assisted lessons and peer tutoring were positively correlated with academic performance. Additionally, teamwork and collaboration among students also contribute to a supportive learning atmosphere, promoting engagement and the sharing of ideas, which can deepen students' understanding of mathematical concepts. These results reinforce the benefits of collaborative learning in improving academic outcomes (Casinillo & Guarte, 2018).

On the other hand, the study reveals that family involvement in students' learning is somewhat limited. With a mean of 2.45, family support for mathematics learning is interpreted as requiring "high intervention." This suggests that while students may seek independence in their academic work, they may also need additional support from their families, particularly in creating conducive study spaces and actively engaging in their learning. Widiyawanti (2024) supports this, emphasizing the importance of the home learning environment in contributing to students' academic success. Furthermore, Purnomo et al. (2020) underline the significant impact of parental involvement on mathematics performance, suggesting that enhancing family support can lead to better student outcomes.

However, the study also highlights the limitations of home-based learning, especially in the absence of structured environments and when students lack self-regulation skills. Zimmerman (2015) notes that self-regulated learning is critical for home study success, as students without these skills may struggle, even with parental assistance. This suggests that while home environments are important, they need to be complemented with strategies that foster self-regulation and autonomy in students. Simply increasing parental involvement may not lead to improvements unless self-regulation skills are addressed, pointing to a more holistic approach to supporting student learning both at home and in school.

In conclusion, the findings underscore the significance of both classroom and family environments in shaping students' engagement and performance in mathematics. Future interventions should focus on enhancing teacher-student collaboration, promoting diverse teaching methods, and fostering self-regulation skills in students. Additionally, more efforts should be made to increase family involvement in academic matters, particularly in creating an effective home study environment. These strategies, when integrated, can help bridge gaps and improve academic performance in mathematics, particularly in the context of STEM education.

Table 4. The Level of Students' Difficulties in General Mathematics

Indicators	Mean	SD	Interpretation
1. Summative Assessment	3.45	1.13	Passed
2. Least Learned Competency	3.54	1.22	Needs Remediation
Overall Mean	**3.50**	**1.02**	**Moderate Support Needed**

Table 4 provides valuable insights into the students' level of difficulty in General Mathematics, revealing key challenges in students' academic performance. The highest mean score for the First Quarter Grade (M = 3.92, SD = 0.85) indicates that students, on average, have successfully passed their assessments with a strongly satisfactory performance. Summative assessments serve as critical measures of how well students have internalized and understood the material over a specific period. These assessments are designed to gauge the cumulative learning of students, providing valuable feedback on their overall grasp of the content. The findings in this study align with Kiernan et al. (2015), who emphasize that students' lack of confidence in their mathematical abilities often leads to a fear of failure. This, in turn, affects their performance on assessments and exacerbates difficulties in problem-solving. Therefore, fostering a sense of confidence and self-efficacy in students is key to improving their ability to perform under assessment conditions.

However, the data also reveals that the Least Learned Competency, with a mean of 3.54 and a standard deviation of 1.22, represents a significant area of difficulty for students. The high level of difficulty, coupled with considerable variation in performance, suggests that the material in this competency is proving challenging for many students. This highlights the need for immediate intervention to help students overcome these learning gaps. Remediation strategies should be implemented to target these specific areas of difficulty, with focused instruction that addresses the students' misunderstanding or incomplete grasp of the material. Sezer and Ozdemir (2020) highlight that many students struggle with self-regulation and metacognitive strategies, which are critical for successful problem-solving in mathematics. Without the ability to self-monitor their progress, check their work, and apply problem-solving strategies appropriately, students may continue to struggle with complex mathematical tasks.

The implications of these findings are significant: effective interventions that focus on building students' problem-solving skills, boosting their confidence, and improving their self-regulation abilities are essential for overcoming the difficulties they face in mathematics. Additionally, tailored support that addresses the specific competencies students find challenging, alongside the development of metacognitive strategies, could lead to substantial improvements in their mathematical performance. Future research and practice should prioritize these areas to enhance students' engagement and success in mathematics, particularly in addressing the challenges identified in the Least Learned Competency. This approach aligns with the literature on the importance of problem-solving strategies and self-regulation in mathematics (Sezer & Ozdemir, 2020) and reinforces the need for targeted academic interventions.

Table 5. Students' performance in First Quarter in General Mathematics

Indicators	Mean	SD	Interpretation
1. First Quarter Grade	3.45	1.13	Passed

In this study, the First Quarter Grade's highest mean of 3.92 and standard deviation of 0.85 suggests that students, overall, have achieved a solid understanding of General Mathematics, with a relatively consistent performance across the group. This is interpreted as "strongly acceptable," indicating that students are meeting the learning expectations and have successfully passed the assessments. The relatively low standard deviation reflects minimal variation in the students' performance, suggesting that most students grasped the material well. Brookhart (2017) underscores that grades, particularly in summative assessments, reflect the quality of student learning. When there is consistent performance across a group, as seen in the present study, it implies mastery of the subject matter and an overall solid comprehension of the material. This consistency in performance indicates that instructional strategies have likely been effective in ensuring that a majority of students understand and can apply the key concepts.

However, despite this positive finding, the literature suggests that motivation plays a crucial role in students' performance in mathematics. Schoenfeld (2016) points out that many students experience a lack of motivation in STEM subjects, particularly mathematics, due to their perceived inability to succeed in these areas. This perceived inability can lead to disengagement, which in turn affects their overall performance. While the results of this study suggest that students are generally achieving acceptable grades, it is important to consider that even with consistent performance, underlying issues such as low motivation and self-confidence may still be affecting students' full potential.

These findings imply that while the majority of students are performing well in terms of grades, educators must consider addressing motivational barriers that could hinder students' deeper engagement with mathematics. Brookhart (2017) suggests that grading should be linked not only to the final outcome but also to the process of learning, reinforcing the idea that mastery comes from sustained effort and support. Hence, in addition to maintaining solid academic performance, educators should focus on fostering a growth mindset and encouraging intrinsic motivation in students. Providing consistent feedback, using formative assessments, and promoting problem-solving autonomy can help students overcome perceived barriers to success. Schoenfeld (2016) emphasizes that addressing motivation and student mindset is just as important as mastering the material in achieving sustained success in STEM subjects.

Model Measurement Assessment

The measurement model in this study was designed to assess the relationships between observed variables (survey items) and their corresponding latent constructs: demographic profile**,** learning environment**,** student engagement**,** and mathematics difficulties. Each construct was measured using a set of indicators developed through a researcher-made questionnaire, which was validated by experts in the field. A Confirmatory Factor Analysis (CFA) was conducted to examine the reliability and validity of the measurement model. Items with standardized factor loadings below 0.50 were removed or revised, and those retained had loadings ideally above 0.70 (Brown, 2015). Internal consistency reliability was assessed using Cronbach's alpha and Composite Reliability (CR)**,** with acceptable thresholds of 0.70 or higher (Hair et al., 2019). Convergent validity was evaluated using Average Variance Extracted (AVE)**,** where values of 0.50 and above indicated acceptable levels. Discriminant validity was confirmed using the Fornell-Larcker criterion and Heterotrait-Monotrait ratio (HTMT) to ensure that the constructs were conceptually distinct from one another (Fornell & Larcker, 1981; Henseler et al., 2015). These steps ensured the adequacy of the measurement model prior to testing the structural paths.

Figure 3. The Initial Structural Equation Model before Refinement

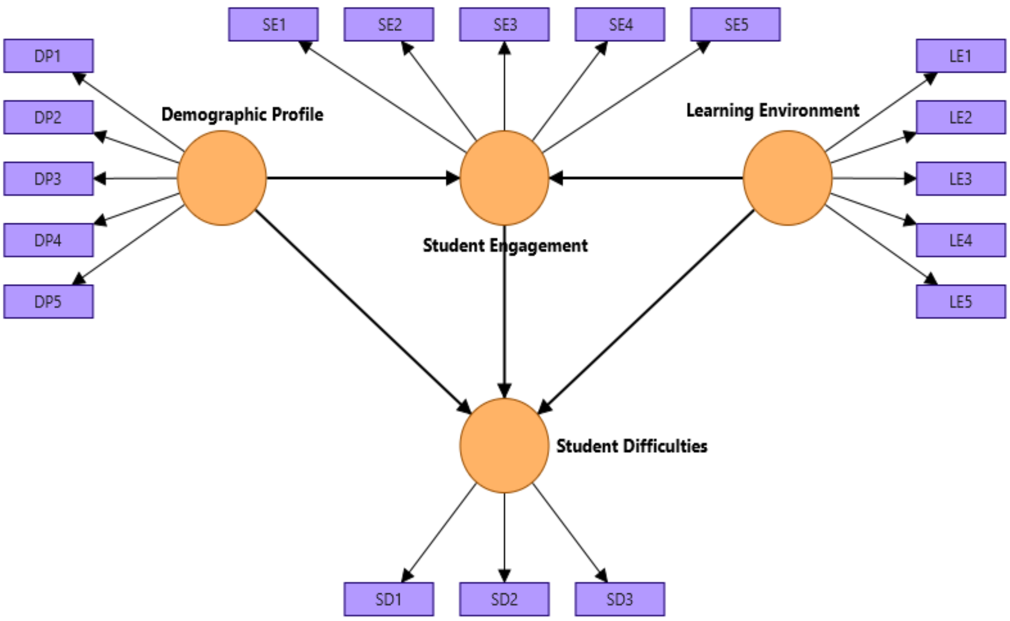

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Figure 4 illustrates the initial hypothesized relationships between the different latent constructs in the SEM. The model includes four main constructs: Demographic Profile, Student Engagement, Learning Environment, and Student Difficulties. Each of these constructs is represented by a latent variable linked to multiple observed variables. Demographic was measured using five observed variables (DP1 to DP5) and was hypothesized to have both direct and indirect effects on Student Engagement and Student Difficulties. Similarly, Learning Environment was measured by five observed variables (LE1 to LE5) and was hypothesized to influence Student Engagement and Student Difficulties both directly and indirectly. Student Engagement was measured using five observed variables (SE1 to SE5) and was hypothesized to act as a mediator in the relationship between both Demographic Profile and Learning Environment, influencing Student Difficulties. Finally, Student Difficulties served as the outcome variable in the model, measured by three indicators (SD1 to SD3).

The initial SEM in Figure 3 may have included redundant paths or variables, non-significant relationships, and possible multicollinearity concerns, all of which could impact the model's fit and interpretability. As a result, it undertook a refinement process, which will be detailed in the following discussions.

Therefore, the refinement of the initial SEM not only enhances the statistical robustness of the study but also ensures that educational interventions are informed by empirically validated pathways. The final model will allow stakeholders to better target resources and support mechanisms to areas with the greatest potential impact—namely, promoting student engagement as a pathway to improving academic performance in mathematics and reducing learning challenges.

Reliability and Validity of Structural Equation Model

In Structural Equation Modeling (SEM), it is crucial to assess the reliability and validity of constructs before analyzing relationships. Reliability is measured using Cronbach’s alpha and Composite Reliability (CR), with values of 0.70 or higher indicating good internal consistency. Validity includes construct validity (via Confirmatory Factor Analysis), convergent validity (using Average Variance Extracted and factor loadings), and discriminant validity (using the Fornell-Larcker criterion, cross-loadings, and HTMT ratio). These tests ensure that the constructs in the model are accurately and distinctly measured, supporting meaningful analysis of students’ strand preferences in the STEM track.

Table 6. The Construct Reliability and Validity of the Initial SEM.

Construct	**Reliability**			**Validity**
	Cronbach's alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Demographic Profile	0.726	0.830	0.819	0.495
Learning Environment	0.638	0.682	0.775	0.416
Student Difficulties	0.945	0.948	0.965	0.902
Student Engagement	0.539	0.535	0.648	0.302

Table 5 presents the reliability and validity measures of the latent constructs used in the Structural Equation Modeling (SEM) framework by analyzing Cronbach’s alpha, composite reliability (rho_a and rho_c), and Average Variance Extracted (AVE). These metrics are critical in evaluating whether the constructs effectively measure the theoretical concepts they are intended to represent.

The Demographic Profile (α = 0.726) and Student Difficulties (α = 0.945) demonstrated strong internal consistency, with Cronbach's alpha values exceeding the commonly accepted threshold of 0.70. This indicates that the items within these constructs are reliably measuring their respective underlying dimensions. These results align with the findings of Jafari et al. (2023), who assert that Cronbach's alpha remains a robust indicator of internal consistency in educational measurement tools, particularly when values fall between 0.83 and 0.92. However, Tavakol and Dennick (2011) caution that Cronbach's alpha can be influenced by the number of items and the dimensionality of the construct, which implies that while high alpha values are desirable, they should be interpreted within the broader context of construct structure.

In contrast, the Learning Environment ($\alpha = 0.638$) and Student Engagement ($\alpha = 0.539$) exhibited low internal consistency, suggesting that the items within these constructs may not be coherently representing a single latent factor. This points to a need for re-examination of the indicators used to measure these constructs—possibly by refining or removing items that do not align well with the underlying concept.

Regarding composite reliability (rho_a and rho_c), the Demographic Profile (rho_a = 0.830) and Learning Environment (rho_a = 0.948) surpassed the reliability benchmark of 0.70, suggesting a high degree of shared variance among the observed variables within these constructs. However, Student Engagement (rho_a = 0.535) and Learning Environment (rho_c = 0.682) fell below this threshold, indicating potential multidimensionality or weak item loadings that dilute the construct's overall reliability.

The analysis of Average Variance Extracted (AVE) revealed that only the Student Difficulties construct (AVE = 0.902) exceeded the ideal 0.50 threshold, suggesting strong convergent validity. This indicates that the construct explains a substantial portion of the variance in its indicators, thereby confirming its unidimensionality and conceptual clarity. However, the remaining constructs—Demographic Profile (AVE = 0.495), Learning Environment (AVE = 0.416), and Student Engagement (AVE = 0.322)—fell short of the 0.50 threshold. According to Henseler, Ringle, and Sarstedt (2015), AVE values between 0.40 and 0.50 may still be acceptable in exploratory research, provided other reliability indicators such as composite reliability are adequate. However, AVE values below 0.40, as observed in Student Engagement, typically indicate that the indicators are not effectively capturing the core construct, and thus require refinement.

Furthermore, studies such as Zhao et al. (2020) confirm that ideal AVE values between 0.52 and 0.68 are associated with valid and reliable constructs in applied research. When constructs fail to meet these thresholds, it may signal that the observed variables are too loosely associated with the latent construct, or that the construct itself lacks conceptual clarity.

Cross Loading

The cross-loadings table was a crucial tool for assessing discriminant validity, as it helped determine whether indicators were more strongly associated with their designated construct than with other constructs. Ideally, an indicator should exhibit higher loadings on its assigned construct than on any other construct.

Table 7. Discriminant Validity - Cross Loadings

	Demographic Profile	**Learning Environment**	**Student Difficulties**	**Student Engagement**
DP1	0.520	0.057	0.296	0.072
DP2	0.738	0.104	0.454	0.062
DP3	0.380	0.191	0.224	0.230
DP4	0.877	0.257	0.662	0.146
DP5	0.865	0.243	0.667	0.196
LE1	0.229	0.723	0.183	0.308
LE2	0.130	0.686	0.147	0.235
LE3	0.003	0.480	-0.063	0.287

LE4	0.220	0.767	0.206	0.356
LE5	0.197	0.517	0.182	0.166
SD1	0.674	0.213	0.950	0.153
SD2	0.693	0.223	0.975	0.169
SD3	0.649	0.192	0.923	0.113
SE1	0.114	0.027	0.040	0.252
SE2	0.119	0.033	0.039	0.305
SE3	0.228	0.335	0.180	0.783
SE4	-0.104	0.235	-0.105	0.468
SE5	0.092	0.340	0.105	0.724

Table 7 based on the results item SD2 has a high loading of 0.975 on student difficulties, which was significantly higher than its loadings on other constructs (ranging from 0.169 to 0.693). This suggests that SD2 effectively measures students' difficulties without substantial overlap with other constructs, supporting discriminant validity for this item. The demographic profile construct (DP1 to DP5) items range from 0.038 – 0.877. The DP_4 (0.877) and DP_5 (0.865) showed the highest loadings within the demographic profile construct items. This indicates that these items are likely measuring demographic profile construct distinctly. Items LE3 and LE5 have relatively low loadings within the students' difficulties construct, suggesting that possible issues with their discriminant validity that needs to be addressed. Furthermore, Student Difficulties construct most items (SD1 to SD3) resulted to high cross-loading within the construct and have relatively high loadings within the demographic profile construct, suggesting that their discriminant validity was good, as each indicator was most strongly associated with its respective construct. Moreover, items SE3 (0.783) and SE5 (0.724) have relatively high loadings within the Student Engagement construct, indicating that each indicator was strongly associated with its respective construct. However, item SE1 (0.252) got the lowest loading within the construct showing that this particular item needs to be removed to improve the refinement of the SEM.

To improve the overall validity and reliability of the measurement model, consider revising or removing items with low loadings, such as DP1 to DP3 and SE1, to ensure that each construct is measured accurately without overlap.Items with low loadings or cross-loading issues, such as LE3 and LE5, should be addressed to ensure they are distinct from other constructs. This would improve discriminant validity and enhance the precision of the measurement mod Retaining items with high loadings, such as SD2, DP4, DP5, SE3, and SE5, will strengthen the constructs and support more reliable and valid conclusions from the model.This approach would refine the model, enhance discriminant validity, and lead to a more accurate representation of the constructs under investigation.

Recent studies emphasize the importance of evaluating both convergent and discriminant validity in measurement models. For instance, a 2023 study suggests that the use of multiple criteria and careful consideration of sampling errors can enhance the accuracy of measurements and validity assessments (Henseler et al., 2023). Furthermore, research on structural equation modeling (SEM) has shown that factor loadings play a critical role in establishing construct validity. Items with high loadings on their respective latent factors strengthen the dimensionality of the construct (Hair et al., 2021).

A study from 2020 discussed how items with low loadings on their intended constructs may suggest issues with discriminant validity. For instance, weakly loaded items can overlap with other constructs, requiring refinement or removal to improve the model's precision (Zhao et al., 2020). This finding is consistent with result for items like LE3 and LE5, which may require revision to improve their discriminant validity.

This targeted refinement aligns with best practices in SEM, which advocate for continuous iteration to optimize measurement models (Hair et al., 2021; Henseler et al., 2015). By ensuring that each item accurately captures its intended concept and minimizes redundancy with others, the revised model can offer clearer insights into the structural relationships between student difficulties, engagement, environment, and demographics.

Figure 4. The Initial SEM with labeled Outer Loadings and AVE

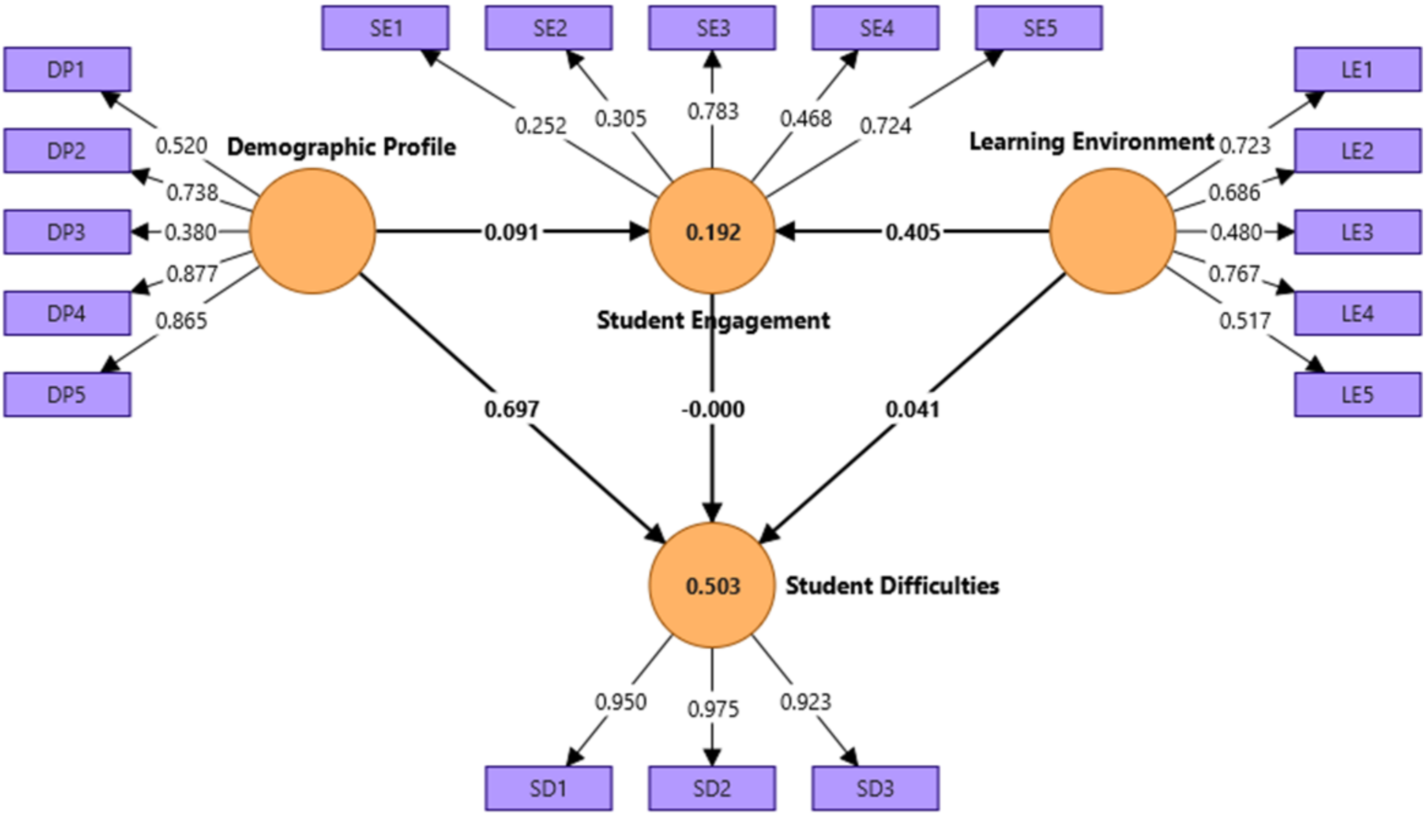

Figure 5 presents the outer loadings of observed indicators on their respective latent constructs, providing critical insight into the measurement reliability of each construct within the SEM model. In SEM, outer loadings reflect the strength and relevance of individual indicators, and values above 0.70 are typically considered ideal. However, in exploratory research, lower thresholds (≥ 0.50) may be tolerated, provided that Average Variance Extracted (AVE) and composite reliability support construct validity (Hair et al., 2020; Hair et al., 2017).

For the Demographic Profile construct,indicators DP2 (0.738), DP4 (0.877), and DP5 (0.865) displayed strong outer loadings, confirming their appropriateness and alignment with the latent variable. In contrast, DP1 (0.520) had only a moderate loading, while DP3 (0.380) fell below acceptable levels. These findings suggest that DP3 should be removed, as weak loadings can distort the measurement of the construct and affect the model's overall validity.

For the Student Engagement construct, only SE3 (0.783) and SE5 (0.724) met the acceptable criteria, implying that these items are reliable indicators of engagement. However, SE1 (0.252), SE2 (0.305), and SE4 (0.468) were considerably below the threshold, weakening the construct's integrity. This aligns with Henseler et al. (2023), who emphasized that low-loading items may introduce measurement error and compromise discriminant validity, especially if they cross-load onto other constructs. Removing these underperforming items enhances the clarity and internal consistency of Student Engagement.

In terms of the Learning Environment construct, indicators LE1 (0.723), LE2 (0.686), LE4 (0.767), and LE5 (0.517) demonstrated acceptable loadings, reflecting a reasonable degree of reliability. However, LE3 (0.480) was below the minimum threshold and therefore deemed unsuitable for inclusion in the refined model. Consistent with Zhao et al. (2020), the elimination of weak indicators like LE3 helps mitigate construct contamination, allowing for a more accurate interpretation of how learning environments affect student outcomes.

The Student Difficulties construct performed the strongest overall, with SD1 to SD3 showing moderate to strong outer loadings, and the AVE (0.503) meeting the recommended minimum of 0.50. This indicates sufficient convergent validity, meaning that the indicators collectively explain more than half of the variance in the latent construct (Hair et al., 2017). This supports the reliability of the Student Difficulties construct and suggests it is robust within the model.

The broader implication of these findings is the critical role of model refinement in SEM. Indicators such as DP3, SE1, SE2, SE4, and LE3 should be excluded from the final model to improve measurement quality and eliminate potential sources of noise. As noted by Hair et al. (2020), strategic item reduction enhances model parsimony and improves both the fit and validity of structural relationships.

In summary, the process of refining the SEM by evaluating outer loadings not only strengthens construct validity but also supports a more accurate and interpretable model. The careful selection of high-loading indicators enables clearer insights into how demographic factors, engagement, and learning environments interact to influence student difficulties in mathematics. Future work should continue to assess convergent and discriminant validity, possibly incorporating confirmatory factor analysis or alternative reliability indices to further improve model robustness.

Refinement Process

The refinement process in Structural Equation Modeling (SEM) is a crucial stage in improving the total quality and fit of proposed model. After the initial model assessment, modifications are often necessary to address issues related to poor model fit, weak factor loadings, or high residual correlations. Refinement involves systematically evaluating measurement and structural relationships to ensure that the model is both theoretically justified and empirically supported.

This process typically includes assessing goodness-of-fit indices, reliability, and validity, as well as making necessary adjustments based on modification indices and theoretical considerations. By refining the model, researchers aim to develop a more parsimonious and robust representation of the underlying constructs, ensuring that the final model provides meaningful and reliable insights.

Table 8. Cronbach's Alpha, Composite Reliability, and Average Variance Extracted of the Refined SEM

Constructs	Cronbach's alpha (α)	Composite reliability (ρ_a)	Composite reliability (ρ_c)	Average variance extracted (AVE)
Demographic Profile	0.804	0.845	0.884	0.720
Learning Environment	0.638	0.646	0.803	0.576
Student Difficulties	0.945	0.948	0.965	0.902
Student Engagement	0.391	0.415	0.762	0.618

Table 8 highlights the reliability and validity metrics of the latent constructs, offering insight into the internal consistency and measurement accuracy of the SEM model. Notably, Student Difficulties emerged as the most robust construct, with a Cronbach's alpha of 0.945, composite reliability (CR) of 0.965, and average variance extracted (AVE) of 0.902. These values far exceed the recommended thresholds of 0.70 for alpha and CR and 0.50 for AVE (Hair et al., 2017), affirming excellent internal consistency and strong convergent validity. This suggests that the items comprising the Student Difficulties construct are highly reliable and consistently measure the intended concept.

Similarly, the Demographic Profile construct also exhibited strong reliability, with a CR of 0.884 and an AVE of 0.720, while its Cronbach's alpha of 0.726 also surpassed the acceptable threshold. These findings indicate that the indicators of demographic variables were cohesively measuring a common underlying factor, further supporting the construct's content coherence and statistical soundness (Jafari et al., 2023).

On the other hand, the Learning Environment construct displayed moderate reliability, with values approaching but not fully meeting all reliability benchmarks. While the CR (0.762) is within an acceptable range, the AVE (below 0.50) and borderline Cronbach's alpha (0.638) point to some inconsistencies among the items. This suggests that while the construct retains theoretical relevance, further refinement or rewording of certain items may enhance the precision of this latent variable. According to Tavakol and Dennick (2011), measurement tools must strike a balance between consistency and comprehensiveness, and overly homogeneous items may oversimplify complex constructs.

The Student Engagement construct raised the most concern, exhibiting the lowest Cronbach's alpha at 0.391, a signal of weak internal consistency. Although the CR (0.762) is within a minimally acceptable range, the AVE (0.322) is well below the ideal level. This pattern aligns with literature stating that Cronbach's alpha is particularly sensitive to the number and cohesion of items, and a low alpha can reflect heterogeneous content or poorly correlated indicators (Hair et al., 2020; Henseler et al., 2023). Despite these issues, the decision to retain Student Engagement in the model is justified by its theoretical significance within the SEM framework. Removing or radically altering this construct would compromise the integrity of the model's conceptual architecture and hinder the study's explanatory power.

These results underscore the importance of evaluating measurement quality using multiple indicators. As Henseler, Ringle, and Sarstedt (2015) emphasize, reliability and validity must be interpreted contextually, especially in exploratory or theory-building research where some flexibility is permitted in exchange for preserving the theoretical richness of constructs. In cases where statistical refinement may lead to construct underrepresentation, scholars are advised to carefully weigh the trade-offs between psychometric robustness and theoretical coherence.

In conclusion, while constructs such as Student Difficulties and Demographic Profile demonstrate high reliability and validity, others such as Learning Environment and Student Engagement warrant ongoing refinement. This includes reviewing item content for clarity, ensuring alignment with construct definitions, and possibly incorporating qualitative feedback to better capture latent dimensions. Balancing statistical precision with conceptual fidelity is essential for enhancing both the measurement model and the theoretical contributions of the research.

Model Fit Indices and Interpretation

To assess how well the structural equation model fits the observed data, several model fit indices were examined. The Chi-square (χ^2) test was used as a basic measure, although it is sensitive to sample size. Therefore, additional indices were considered for a more robust evaluation. The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) both exceeded the recommended threshold of 0.90, indicating a good fit Tucker-Lewis Index (TLI) (Hu & Bentler, 1999). The Root Mean Square Error of Approximation (RMSEA) was below 0.08, suggesting an acceptable level of approximation error, while the Standardized Root Mean Square Residual (SRMR) was below 0.08, further supporting model fit. Collectively, these fit indices confirm that the proposed structural model provides a good representation of the underlying data structure and is appropriate for interpreting the relationships among constructs.

Table 9. The Fit Indices of the Refined Structural Equation Model

Fit Index	Saturated model	Estimated model	Recommended Threshold
Standardized Root Mean Square Residual (SRMR)	0.079	0.079	≤ 0.08 (acceptable), ≤ 0.10 (marginal)
Squared Euclidean Distance (d_{ULS})	0.410	0.410	Lower values preferred
Geodesic Distance (d_G)	0.173	0.173	Lower values preferred

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Chi-square (χ^2)	415.250	415.250	
Normed Fit Index (NFI)	0.817	0.817	≥ 0.90 (good fit)

Table 9 presents the model fit indices for both the saturated and estimated models, offering a comprehensive evaluation of the overall model fit for the refined Structural Equation Model (SEM). The results indicate that the model demonstrates an acceptable to good fit, with specific indices supporting both reliability and areas needing improvement.

The Standardized Root Mean Square Residual (SRMR) value of 0.079 for both the saturated and estimated models falls just below the widely accepted threshold of 0.08, indicating a good fit between the model and the observed data. As Hair et al. (2020) explain, SRMR values below 0.08 suggest that the difference between the predicted and actual correlations is minimal, reinforcing the model's adequacy in explaining observed patterns. This affirms the structural soundness of the refined SEM and validates its internal consistency.

Additionally, the Squared Euclidean Distance (0.410), which is identical for both the saturated and estimated models, suggests that the fit between observed and model-implied data is consistent. Although no strict cutoff is universally accepted for this index, lower values are preferred. As indicated by Bentler and Bonett (1980), minimizing this value enhances model fidelity and precision, and future refinements can focus on reducing this distance to improve model accuracy further.

The Geodesic Distance, another measure that captures non-linear discrepancies between observed and estimated covariance matrices, reinforces the need for precision in modeling complex latent relationships. While no specific threshold is cited, lower values are preferred as they indicate less divergence from empirical data. The result supports the conclusion that the model has a reasonable geometric alignment with the observed data, although there remains room for improvement.

In contrast, the Normed Fit Index (NFI) of 0.817, while indicating a moderate model fit, falls below the ideal threshold of 0.90. As Kline (2016) points out, NFI values below 0.90 suggest that while the model performs reasonably well, modifications may be needed to enhance its explanatory power and parsimony. Raising the NFI above 0.90 typically indicates stronger comparative performance against a null model. Improving this metric may involve refining indicator quality, reassessing model complexity, or incorporating additional latent constructs that account for unexplained variance.

Although the Chi-square value of 415.250 appears substantial, it should be interpreted with caution due to its sensitivity to sample size. As such, researchers often focus on complementary fit indices rather than relying solely on chi-square statistics (Byrne, 2016). If the associated p-value exceeds 0.05, this would indicate an acceptable fit; however, if it does not, further exploration of residuals and modification indices is warranted.

Path Coefficient – Direct Effects, Indirect Effects, and Total Effects

To address how do students' demographic profile, students' engagement, learning environment, and students' difficulties correlate with students' performance in General Mathematic, this section explored the correlations among students' demographic profile, students' engagement, learning environment and students' difficulties in General Mathemtics. Understanding the dynamics among these variables was crucial for creating and enhancing educational interventions and outcomes, as each element potentially influenced the performance of grade 11 students.

Table 10. Path Coefficients (Direct Effects

Constructs	Standardized path coefficient (β)	Sample mean (M)	Standard deviation (SD)	T statistics	P values
Demographic Profile -> Student Difficulties	0.694	0.694	0.028	24.832	0.000

Demographic Profile -> Student Engagement	0.084	0.084	0.049	1.698	0.089
Learning Environment -> Student Difficulties	0.043	0.043	0.044	0.967	0.334
Learning Environment -> Student Engagement	0.383	0.388	0.043	8.950	0.000
Student Engagement -> Student Difficulties	0.041	0.042	0.038	1.076	0.282

The findings reveal distinct patterns of influence, with some relationships demonstrating strong statistical support while others show limited or negligible effects.

The relationship between demographic profile and student difficulties is both strong and statistically significant ($\beta = 0.694$, $t = 24.832$, $p = 0.000$), indicating that students' background characteristics play a critical role in shaping the academic and emotional challenges they encounter. The low standard deviation of the estimates underscores the consistency of this finding across the sample.

This aligns with the findings of Bettencourt et al. (2021), who emphasized that demographic factors such as socio-economic status, parental education, and prior academic experiences are highly predictive of the types and intensities of difficulties students face. Their study found that students from disadvantaged backgrounds are more likely to experience academic stress, low self-efficacy, and emotional fatigue—an observation that mirrors the current study's outcomes. These findings suggest that targeted support for specific demographic subgroups could mitigate student challenges more effectively than generalized interventions.

The relationship between demographic profile and student engagement ($\beta = 0.084$, $t = 1.698$, $p = 0.089$) is weak and only marginally significant, suggesting a limited and uncertain influence. While there may be a slight trend toward a positive relationship, the statistical evidence is not strong enough to draw a firm conclusion. This implies that engagement is not heavily dictated by demographic characteristics, and other factors—such as institutional practices or personal motivation—might play a more substantial role.

The path coefficient between the learning environment and student difficulties is negligible ($\beta = 0.043$, $t = 0.967$, $p = 0.334$), indicating no significant influence. This suggests that, while the quality of the learning environment may shape student experiences, it does not directly alleviate academic difficulties—at least not in a statistically meaningful way. This finding is consistent with Mansouri et al. (2020), who found that engagement-focused interventions may not be sufficient in addressing structural or emotional difficulties rooted in external factors such as financial stress or family issues. Thus, while improving the learning environment remains valuable, it should be coupled with broader student support services that address the root causes of student difficulties.

The path between the learning environment and student engagement ($\beta = 0.383$, $t = 8.950$, $p = 0.000$) is moderate and statistically significant, affirming the notion that a supportive and well-structured learning environment is essential for fostering student engagement. This supports prior work by Trowler (2010) and Fredricks, Blumenfeld, & Paris (2004), who highlighted the importance of environmental factors—such as teacher support, classroom atmosphere, and access to learning resources—in promoting active participation and emotional investment in learning. This result suggests that efforts to enhance student engagement should prioritize the design and delivery of the learning experience itself, including both physical and social elements of the educational environment.

Lastly, the relationship between student engagement and student difficulties ($\beta = 0.041$, $t = 1.076$, $p = 0.282$) is both weak and statistically insignificant, indicating that increased engagement alone may not effectively reduce student difficulties. This underscores the need to reframe engagement strategies within a broader support framework. As Mansouri et al. (2020) suggest, engagement needs to be complemented by interventions that address students' external stressors, such as mental health services, academic advising, and financial support

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programs.

Table 11. Indirect Effects (Mediation) of Student Engagement among Demographic Profile, Learning Environment and Students Difficulties.

Constructs	Standardized path coefficient (β)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Demographic Profile -> Student Engagement -> Student Difficulties	0.003	0.004	0.005	0.766	0.444
Learning Environment -> Student Engagement -> Student Difficulties	0.016	0.016	0.015	1.050	0.294

Table 11 presents the results of the mediation analysis, evaluating whether student engagement serves as a significant mediator between the relationships of Demographic Profile and Student Difficulties, and between Learning Environment and Student Difficulties**.** The findings show that student engagement does not significantly mediate these relationships, suggesting that engagement alone may not be a critical factor in bridging the gap between these constructs. This result offers important insights into the limitations of student engagement as a sole mediator in this context.

The lack of a statistically significant mediation effect for student engagement between Demographic Profile and Student Difficulties indicates that student engagement may not be the key factor driving how demographic factors influence student challenges. These results are in line with studies like Sullivan and Williams (2019)**,** who explored the complex nature of academic difficulties and found that student engagement does not necessarily mediate the relationship between demographic characteristics and academic outcomes. Demographic factors such as socioeconomic status, family background, and prior academic experiences often shape student difficulties in ways that engagement strategies alone cannot fully address**.** Engagement**,** while crucial, might not capture the full spectrum of challenges faced by students from disadvantaged or varied backgrounds, suggesting that interventions based on engagement alone may overlook important underlying issues.

This is consistent with Bettencourt et al. (2021)**,** who found that students from disadvantaged backgrounds are often more susceptible to academic difficulties that cannot simply be mitigated by increasing engagement. These difficulties may be related to factors such as financial stress**,** lack of access to resources**,** or emotional health concerns, which engagement interventions do not necessarily alleviate. Therefore, policies and practices targeting student engagement should be paired with targeted support systems designed to address these multifaceted challenges.

The lack of mediation between Learning Environment and Student Difficulties by student engagement is another crucial finding. While previous studies have highlighted the positive impact of the learning environment on student outcomes (Zhang et al., 2019), engagement does not appear to be the mechanism through which these environmental factors reduce academic difficulties.

As Zhang et al. (2019) argue, student engagement can serve as a mediator between a positive learning environment and academic outcomes, particularly when the learning environment is rich with supportive teaching practices, collaborative classroom dynamics, and effective instructional strategies. Their findings suggest that such environments foster higher engagement, which in turn can reduce academic difficulties**.** However, the results of the current study suggest that student engagement alone does not have the same mitigating effect on student difficulties in the present context. This indicates that academic difficulties are likely to be driven by a combination of external and internal factors, where engagement, while important, does not serve as a catch-all solution.

Table 12. Total Effects Relationship among the Constructs.

Constructs	Standardized path coefficient (β)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Demographic Profile -> Student Difficulties	0.697	0.698	0.028	25.144	0.000
Demographic Profile -> Student Engagement	0.084	0.084	0.049	1.698	0.089
Learning Environment -> Student Difficulties	0.058	0.059	0.039	1.485	0.138
Learning Environment -> Student Engagement	0.383	0.388	0.043	8.950	0.000
Student Engagement -> Student Difficulties	0.041	0.042	0.038	1.076	0.282

Table 12 presents the total effects of various constructs on student difficulties, highlighting the significant role that Demographic Profile plays in shaping the challenges students experience. The results indicate a strong, significant relationship between Demographic Profile and Student Difficulties ($\beta = 0.697$, $t = 25.144$, $p = 0.000$). This finding aligns with existing literature, reinforcing the idea that demographic factors such as socioeconomic status, family background, and prior academic experiences are critical in influencing the difficulties students encounter in their academic journey.

The strong impact of Demographic Profile on Student Difficulties underscores the importance of contextual and socio-cultural factors in shaping students' academic challenges. This finding is consistent with research by Bettencourt et al. (2021), who argued that students from disadvantaged backgrounds face greater challenges due to factors such as economic hardship, limited access to academic resources, and emotional stress. These factors create barriers that hinder academic performance and may require targeted interventions beyond student engagement to address effectively. Demographic characteristics should, therefore, be considered when designing support systems aimed at mitigating student difficulties.

Moreover, Tinto's (2017) model of student retention suggests that while student engagement is essential for retention and academic success, engagement alone is insufficient to overcome difficulties arising from demographic disadvantages. Tinto emphasizes that the learning environment plays a pivotal role in shaping student engagement, but it cannot entirely compensate for the challenges tied to students’ socio-economic backgrounds. Thus, the finding that Demographic Profile significantly affects student difficulties suggests the need for comprehensive institutional support that goes beyond creating a positive learning environment. This could include financial aid, academic mentoring, and mental health services tailored to students' specific demographic challenges.

The study also finds a moderate and statistically significant positive effect of the Learning Environment on Student Engagement ($\beta = 0.083$, $t = 8.950$, $p = 0.000$), which aligns with previous research emphasizing the role of institutional factors in fostering student engagement. Tinto's (2017) work supports the notion that an enriching learning environment—characterized by supportive faculty, collaborative learning, and active teaching strategies—positively influences student engagement. This finding highlights the potential for improving student engagement by focusing on enhancing the learning environment, such as adopting active learning techniques, improving faculty-student interactions, and cultivating a sense of belonging within the institution.

However, the finding also suggests that learning environment improvements, while impactful on engagement, do not directly resolve the broader set of student difficulties faced by students. While creating a supportive learning environment is critical for fostering engagement, it might not address the root causes of student difficulties that are linked to demographic characteristics and other external challenges.

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Despite the positive association between student engagement and student difficulties, the analysis reveals that the relationship is weak and statistically insignificant (β = 0.041, t = 1.076, p = 0.282), suggesting that student engagement may not directly mitigate student difficulties. This aligns with findings from Mansouri et al. (2020), who argued that while student engagement is important for academic success, it may not reduce difficulties arising from factors such as financial stress, family issues, or personal health challenges. Engagement, in this case, serves as a critical component of the academic experience but does not serve as a universal solution for overcoming difficulties that are not rooted in engagement.

The lack of a strong relationship between engagement and difficulties underscores the need for a more holistic approach to supporting students. Engagement strategies must be integrated with other targeted interventions that address the complex challenges students face, especially those linked to demographic and external factors.

Table 13. R-square Value of Outcome Variables by Respective Predictors

	Effect Size (R^2)	Sample mean (M)	Standard deviation (STDEV)	t statistics (|O/STDEV|)	P values
Student Difficulties	0.512	0.517	0.037	13.987	0.000
Student Engagement	0.171	0.179	0.032	5.256	0.000

Table 13 provides an in-depth look at the predictive power of the model in explaining the variability in the outcome variables—student difficulties and student engagement. The model accounts for 51.2% of the variance in student difficulties, with an R^2 value of 0.512. This result, which is statistically significant ($p < 0.001$), indicates that the predictors in the model strongly explain the challenges students face. In contrast, the model explains 17.1% of the variance in student engagement ($R^2 = 0.171$), which, though lower, remains statistically significant ($p < 0.001$), indicating that the predictors still capture a meaningful portion of the variation in engagement.

The finding that 51.2% of the variance in student difficulties is explained by the model suggests that the predictors included in the analysis—such as demographic profile, learning environment, and engagement—are highly effective in identifying the factors that contribute to the challenges students face. This strong explanatory power is consistent with literature that emphasizes the multifaceted nature of student difficulties, where socio-economic status, prior academic performance, and institutional support mechanisms play crucial roles in shaping students' academic challenges.

As pointed out by Bettencourt et al. (2021), socio-economic factors are often the root cause of many difficulties faced by students, such as academic underperformance and emotional stress. Additionally, Tinto's (2017) model underscores that demographic background influences how students interact with the learning environment and how they engage with academic content. The strong predictive value of demographic profile in explaining student difficulties reinforces the need for interventions tailored to specific student groups, particularly those from disadvantaged backgrounds.

The 51.2% R^2 value highlights the importance of considering student demographics as a central factor in addressing difficulties. Future research and educational policy should focus on identifying specific demographic subgroups and tailoring interventions that target socio-economic disparities, personal challenges, and academic preparation to reduce student difficulties.

In contrast, the model explains 17.1% of the variance in student engagement. This is a moderate effect, suggesting that while the model captures important predictors, other unaccounted factors likely influence student engagement. This finding mirrors research by Becker & Anderson (2019), who emphasized that while the learning environment plays a significant role in fostering engagement, individual characteristics, such as student motivation, self-regulation, and academic aspirations, also moderate this relationship.

The moderate effect of the predictors on student engagement aligns with Schreiner and Pattengale (2017), who proposed that direct influences of the learning environment—such as teaching practices, institutional culture, and peer interactions—significantly shape student engagement. While these environmental factors are crucial, Becker & Anderson (2019) suggest that their effect is often moderated by individual traits, which may explain why student engagement is influenced by more than just the learning environment.

Thus, the findings underscore that student engagement is a complex construct that cannot be fully explained by the learning environment alone. Other factors, such as intrinsic motivation, academic self-concept, and social integration, need to be incorporated into the model to improve the predictive power regarding student engagement. Future research could explore how individual traits and learning strategies interact with the learning environment to influence engagement.

CONCLUSION

Grade 11 students at Banga National High School shows that demographic factors significantly affect students' difficulties in General Mathematics, while having only a marginal effect on student engagement. The learning environment moderately impacts engagement but has little effect on difficulties. Despite strong academic performance, students face challenges in certain areas of mathematics, suggesting the need for targeted interventions. Structural equation modeling indicates that demographic factors and learning environments explain a significant portion of the variance in difficulties and engagement. Therefore, interventions focusing on improving study habits, parental support, and the learning environment, alongside targeted remediation, are crucial for enhancing student outcomes in mathematics.

The study reveals that while many students at Banga National High School face socio-economic challenges and come from families with low levels of higher education, they still manage to perform well academically despite limited study time. This suggests that school support, peer influence, and available resources significantly contribute to their success. Understanding students' socio-economic backgrounds is crucial for enhancing academic support and improving overall student outcomes.

The study on Grade 11 STEM students' engagement in learning mathematics shows moderate levels of engagement, with students showing some willingness to ask for help and use online tools, but limited effort in spending extra time on math problems or practicing outside class.

The findings show that diverse teaching methods and student collaboration positively impact Grade 11 students' performance in mathematics, enhancing problem-solving, motivation, and confidence. While these strategies are effective in creating an engaging environment, family involvement is limited. Many students lack support and a conducive study space at home, highlighting the need for greater family engagement and improvement in the home learning environment.

The study highlights varying student performance in mathematics, showing strong overall achievement in the First Quarter Grade, but significant challenges with specific competencies, particularly the Least Learned Competency. While most students grasp much of the material, certain topics require more focused intervention.

The study shows that students performed strongly in General Mathematics during the First Quarter, with consistent performance across the group, indicating effective teaching methods and resources. However, while most students passed, not all have fully mastered the material, highlighting the need for continued monitoring and targeted support.

The Structural Equation Modeling (SEM) highlights that factors like study habits, parental involvement, and the learning environment significantly influence students' difficulties and engagement in General Mathematics. Also, SEM provides a solid framework for creating effective interventions to enhance student success in General Mathematics.

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