

Article

Bayesian Hierarchical Modelling of Student Academic Performance: The Impact of Mathematics Competency, Institutional Context, and Temporal Variability

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Abstract: This study explores the multifaceted factors influencing academic performance among undergraduate students enrolled in Science, Technology, Engineering, and Mathematics (STEM) programs at a South African university. Employing a Bayesian hierarchical modelling approach, this research analyses data from 630 students collected over four academic years (2019–2023). The findings indicate that high school mathematics marks and progression rates serve as significant predictors of academic success, confirming the critical role of foundational mathematical skills in enhancing university performance. Interestingly, gender and age were found to have no statistically significant impact on academic outcomes, suggesting that these factors may be less influential in this context. Additionally, socio-economic status, represented by school quintiles, emerged as a substantial determinant of performance, highlighting disparities faced by students from disadvantaged backgrounds. The results underscore the necessity for targeted educational interventions aimed at bolstering the academic capabilities of students entering university, particularly those with weaker mathematics backgrounds. Furthermore, the study advocates for a holistic admissions approach that considers various attributes beyond standardized scores. These insights contribute to the existing literature on STEM education and provide practical recommendations for educators and policymakers aiming to foster equitable academic success among all students.

Keywords: academic performance; Bayesian hierarchical modelling; educational interventions; gender differences; socio-economic status; STEM education



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1. Introduction

Academic performance in Science, Technology, Engineering, and Mathematics (STEM) disciplines has been the subject of extensive scholarly investigation because of the critical roles these fields play in driving innovation and economic development (Kazu & Kurtoğlu Yalçın, 2021; Xu & Ouyang, 2022). Numerous studies have identified a range of factors that influence students' success in STEM programs, including prior academic achievement, socio-economic status, and institutional support (Goings & Boyd, 2024; Mosia & Egara, 2024a, 2024b; Munir et al., 2023; Okeke et al., 2025; Rickels, 2017). High school mathematics performance is widely recognised as a strong predictor of success in tertiary STEM education, with students who excel in mathematics more likely to perform well at university (Lubishtani & Avdylaj, 2023; Nitzan-Tamar & Kohen, 2022). However, there is ongoing

debate regarding the impact of demographic factors, such as gender and age, on academic outcomes in STEM fields, with mixed findings in the literature (Charlesworth & Banaji, 2019; Egara & Mosimege, 2023, 2024; Tandrayen-Ragoobur & Gokulsing, 2021).

In South Africa, this issue takes on additional complexity, as educational inequality is a persistent challenge, particularly for students from historically disadvantaged backgrounds (Spaull, 2013). Socio-economic status, often reflected in the quintile ranking of high schools, plays a significant role in shaping students' academic trajectories at the university level (Van Der Berg & Hofmeyr, 2018). Students from lower quintile schools, which typically have fewer resources and lower-quality teaching, face significant disadvantages when transitioning to higher education (Ogbonnaya & Awuah, 2019). These disparities highlight the importance of understanding the complex interplay between prior academic preparation, socio-economic background, and university performance in designing effective interventions to promote student success (Mosia et al., 2025; Schreiber & Yu, 2016).

In response to these challenges, this study builds on the existing body of work by employing a Bayesian hierarchical modelling approach to analyse the academic performance of undergraduate students enrolled in STEM programs at a South African university between 2019 and 2023. By examining both individual-level and structural factors, the study seeks to deepen our understanding of the key predictors of academic success in STEM, particularly the roles of high school mathematics marks and socio-economic status. The study also explores the impact of demographic factors, such as gender, on performance in STEM disciplines. Additionally, it aims to assess the efficacy of current admission and support strategies and provide recommendations for educational policymakers and practitioners seeking to foster equitable academic outcomes across diverse student populations.

1.1. Theoretical Framework

The theoretical foundation for this study is grounded in Human Capital Theory by Becker (1964), Constructivist Learning Theory by Vygotsky (1978), and Expectancy-Value Theory by Wigfield and Eccles (2000). Together, these frameworks provide a comprehensive understanding of how individual characteristics, prior academic performance, and demographic factors interact with the learning environment to influence academic success in university settings.

Human Capital Theory: Human Capital Theory posits that education enhances individuals' productivity and value in the labour market, leading to improved socio-economic outcomes. This study applies the theory beyond a narrow focus on Admission Point scores (APS) and high school mathematics marks by considering these indicators as part of a broader concept of academic capital. Academic capital encompasses the cumulative knowledge, skills, and learning habits students bring to university, which are critical for navigating the demands of higher education. In this context, high school mathematics marks and AP scores represent foundational components of human capital, reflecting cognitive readiness and prior academic achievement. However, the theory also implies that other factors, such as time management skills, problem-solving ability, and access to educational resources, are integral to understanding students' academic trajectories. This broader view allows for a more nuanced exploration of how human capital influences academic success.

Constructivist Learning Theory: Constructivist Learning Theory, particularly social constructivism, emphasises that learning is a dynamic process shaped by social interactions, prior knowledge, and the educational environment. Rather than focusing solely on progression rates, this study adopts a broader constructivist perspective by examining how students' interactions with peers, instructors, and institutional support systems influence their ability to build upon prior learning. Progression rate is viewed as an outcome of

cumulative and adaptive learning experiences, reflecting how students navigate challenges and integrate new knowledge. Additionally, the study considers the role of collaborative learning opportunities and formative feedback in fostering a deeper understanding of academic content, consistent with the constructivist emphasis on active and social learning processes.

Expectancy-Value Theory: Expectancy-Value Theory posits that students' academic performances are driven by their expectations of success and the value they assign to academic tasks. This framework is applied in this study not only to explore gender differences in motivation and performance but also to examine how students' self-efficacy, perceptions of course relevance, and future career aspirations influence their engagement with university mathematics. For instance, the theory highlights that students who perceive mathematics as valuable for achieving their personal or professional goals are more likely to persist and excel. It also considers how institutional practices, such as career counselling and mentorship, can shape students' expectancy beliefs and task values. By addressing these broader motivational factors, the study provides a more holistic understanding of how expectancy-value dynamics impact academic success.

1.2. Reviewed Studies

Several studies have explored the impact of high school mathematics marks on university-level academic performance. [Anderton et al. \(2017\)](#) found that completing advanced-level mathematics and physical science courses at secondary school was associated with a higher first-year GPA among health science students in Australia. Similarly, [Islam and Al-Ghassani \(2015\)](#) examined the predictive validity of high school performance for success in Calculus I at Sultan Qaboos University, with their analysis revealing that high school math scores positively influenced university-level calculus success, particularly for female students. [Lee et al. \(2021\)](#) demonstrated the utility of a Math-Up Skills Test (MUST) in predicting first-semester organic chemistry success, further emphasising the role of mathematical competency in academic achievement.

Research on gender differences in academic achievement presents mixed results. [Hsieh and Yu \(2023\)](#) found that male STEM students in Taiwan perceived higher gains in practical competence, although no gender differences were observed in achievement motivation. Conversely, [Pennington et al. \(2021\)](#) found that girls outperformed boys in standardised tests across various subjects, despite reporting lower self-concept in mathematics and science. [Yu and McLellan \(2019\)](#) reported that boys demonstrated lower academic engagement and higher self-handicapping behaviours, underscoring the complex relationship between gender, self-perception, and academic outcomes.

The influence of age on academic performance is also well-documented. [Casanova et al. \(2023\)](#) revealed a significant link between age and adaptation difficulties among first-year STEM students, although the direct relationship between age and dropout rates was insignificant. Studies by [Cáceres-Delpiano and Giolito \(2019\)](#) and [Nam \(2014\)](#) similarly highlighted that while older school entry age positively impacted academic achievement early on, this effect diminished over time. [Çelikkol \(2023\)](#) found that students who started school at an older age performed better in Turkish high school entrance exams.

The relationship between socio-economic status (SES) and academic performance has been widely studied across different contexts. [Liu et al. \(2020\)](#) found a moderate correlation between SES and academic achievement in China, with a stronger link to language-based subjects than mathematics. [Autor et al. \(2019\)](#) revealed that boys from disadvantaged backgrounds exhibited more behavioural problems and lower academic performances than girls from similar backgrounds. Other studies, such as those by [Singh and Choudhary \(2015\)](#) and [Munir et al. \(2023\)](#), confirmed that higher SES students consistently outperform

their lower SES peers, with parental involvement playing a key role in mitigating the effects of low SES on academic outcomes.

Admission Point Scores (APSs) are standardised metrics used in university admission processes to evaluate student readiness and predict academic success. Calculated from high school grades, APS serves as a key criterion in admission decisions. Studies, such as by [Edwards et al. \(2013\)](#), have shown that high school scores and aptitude tests, key components of APSs, are strong predictors of academic success in medical schools. [Molontay and Nagy \(2023\)](#) emphasised the potential of APSs in admissions when test design biases are addressed, while [Dabaliz et al. \(2017\)](#) demonstrated the predictive value of high school and standardised test scores for pre-clinical success. However, [Nagy and Molontay \(2021\)](#) noted that the predictive accuracy of APSs varies by discipline, underscoring the need for tailored approaches in admissions processes.

Progression rates are closely linked to academic success. [Simelane and Engelbrecht \(2023\)](#) measured the mathematical development of students in an academic development program at the University of Pretoria, finding improvements in mathematical skills but persistent struggles with fundamental topics. [Burns \(2011\)](#) noted that admission criteria such as GPA and science GPA were strong predictors of academic progression in graduate programs, while [Harding \(2012\)](#) found a positive correlation between progression exam scores and academic success in nursing education. These studies highlight the importance of progression metrics in predicting student retention and success.

Variability in student success across academic programs and years has been documented globally. [Brunner et al. \(2018\)](#) analysed cross-country variability in school performance and found significant differences influenced by sociodemographic factors. Similarly, [Sánchez et al. \(2020\)](#) reported small to moderate correlations between Student Evaluations of Teaching (SET) and academic outcomes in higher education, suggesting that prior academic achievement and institutional context play key roles in predicting student success. [Dabaliz et al. \(2017\)](#) highlighted the need for admission processes that account for the variability in predictive accuracy across disciplines, further reinforcing the importance of tailoring interventions to specific educational contexts.

Despite the wealth of research on factors influencing academic success, several gaps remain. The majority of studies focus on non-African contexts, limiting the generalisability of their findings to South African universities. Additionally, traditional statistical models like general linear models and hierarchical regression fail to capture the complexities of student performance, such as the interaction between mathematics competency, institutional factors, and temporal variability. Research on gender differences, SES, and admission point scores highlights inconsistent findings, necessitating a deeper understanding of how these factors interact in different contexts. To bridge these gaps, this study employs Bayesian Hierarchical Modelling, which provides a more comprehensive analysis of student performance by accounting for individual, institutional, and temporal variability. This approach enables more accurate predictions and insights, offering a comprehensive understanding of student success in diverse educational settings. Given the socio-economic disparities and wide variability in resources across South African schools, this model is particularly suited to identifying key factors and informing targeted interventions to improve academic outcomes.

The purpose of this study is to investigate the factors that influence academic success among undergraduate students enrolled in STEM programmes at a South African university. Specifically, the study aims to explore how high school mathematics marks, socio-economic status (represented by school quintiles), admission scores, age, and gender affect student performance, as measured by their average marks and progression rates. The study employs Bayesian hierarchical modelling to account for the nested structure of the data (students

within academic programmes and years), offering a comprehensive understanding of the individual- and group-level factors contributing to academic success.

1.3. Research Questions

1. To what extent do high school mathematics marks influence the academic performance of undergraduate STEM students at a South African university?
2. How does gender impact student academic success in STEM programmes?
3. How does age impact student academic success in STEM programmes?
4. What is the role of socio-economic status, represented by school quintiles, in shaping the academic outcomes of STEM students?
5. How do admission scores affect students' average marks and overall academic performance?
6. What impacts do progression rates have on students' average marks and overall academic performance?
7. What variability exists across different academic programmes and years in relation to student success, and how do these group-level factors influence academic outcomes?

1.4. Hypotheses

1. H_1 : High school mathematics marks have a significant positive effect on the academic performance of undergraduate STEM students.
2. H_2 : There is no significant difference in academic performance between male and female students enrolled in STEM programmes.
3. H_3 : Age has no significant effect on the academic performance of undergraduate STEM students.
4. H_4 : Socio-economic status, as represented by school quintiles, significantly influences the academic outcomes of STEM students.
5. H_5 : Admission Point (AP) scores do not significantly predict student academic performance in STEM programmes.
6. H_6 : Progression rates significantly positively impact the academic performance of students in STEM programmes.
7. H_7 : Variability in academic performance is significantly influenced by the academic programme and the year of study.

2. Materials and Methods

2.1. Research Design

This study employed a quantitative research design using a Bayesian hierarchical linear mixed-effects model to analyse the factors influencing academic performance among undergraduate students enrolled in Science, Technology, Engineering, and Mathematics (STEM) programmes at a South African university. The hierarchical nature of the data, with students nested within academic programmes and years, necessitated the use of a multilevel approach that accounted for both individual-level and group-level variability.

Hierarchical Bayesian Analysis

Hierarchical Bayesian analysis provides a flexible framework for understanding complex systems where data are nested within multiple levels. This method, grounded in Bayesian probability theory, enables researchers to combine individual-level data with group-level structures, allowing for a more nuanced understanding of variability and dependence in the data (Gelman et al., 2003). Educational research often involves such hierarchies, with students nested within classrooms, academic programmes, and institutions. Hierarchical Bayesian models are particularly well-suited for analysing these settings

because they naturally account for dependence and variation at multiple levels (Britten et al., 2021).

Educational data are inherently hierarchical. Students share contextual factors, such as curricula, teaching quality, and institutional resources, within their respective academic programmes and years. Traditional models often treat observations as independent, which can lead to incorrect inferences by ignoring shared influences within groups. Bayesian hierarchical models address this issue by explicitly modelling group-level effects through random variables. For example, Zhang et al. (2022) demonstrated how these models allow researchers to estimate both individual- and group-level parameters while incorporating uncertainty in a coherent probabilistic framework. The mathematical structure of a simple hierarchical Bayesian model is as follows:

$$y_{ij} \sim N(\mu_j, \sigma^2), \mu_j \sim N(\theta, \tau^2), \theta \sim N(\mu_0, \sigma_0^2),$$

where

- y_{ij} represents an observation at the individual level i within group j ;
- μ_j is the group-specific mean;
- θ is the overall mean across groups;
- τ^2 to σ^2 represent group-level and individual-level variances, respectively.

This structure enables the model to “borrow strength” across groups, stabilising estimates, particularly for groups with limited data (Huang, 2024). One of the key advantages of hierarchical Bayesian analysis is its ability to pool information across groups. By using partial pooling, the model avoids both extremes of no pooling (analysing each group independently) and complete pooling (treating all data as if they come from a single group). This is particularly useful in educational settings where some academic programmes or years have fewer students, as partial pooling helps stabilise estimates for smaller groups without overgeneralising from larger ones (Britten et al., 2021).

2.2. Sample and Sampling Procedure

The dataset included 630 undergraduate STEM students who were enrolled at the university between 2019 and 2023. After the exclusion of incomplete records, the final sample consisted of students with a mean age of 24 years (SD = 2.5). The gender distribution was approximately balanced (52% female, 48% male), and the racial composition was representative of the university’s demographics, as follows: African (60%), White (25%), Coloured (10%), and Asian (5%). The study employed stratified random sampling to ensure the inclusion of students from various STEM programmes and across academic years. Data were collected for variables such as high school mathematics marks, admission point (AP) scores, progression rates, age, and socio-economic status represented by school quintiles (ranging from Quintile 1 to Quintile 5).

2.3. Data Collection

Data on academic performance, including progression rates and average marks earned in each academic year, were obtained from the university’s academic records. Demographic and socio-economic data, such as age, gender, high school mathematics marks, AP scores, and school quintile, were retrieved from student enrolment records maintained by the university. All data collection procedures adhered to ethical guidelines, including obtaining the necessary approvals from the university’s ethics committee. Measures were taken to ensure the confidentiality and anonymity of the students, and data were used solely for the purposes of this study.

2.4. Measures

The key variables examined in this study are defined as follows: Mathematics marks refers to students' high school mathematics scores, which ranged from 50 to 100. Admission Point (AP) score represents the overall academic performance in high school, with a mean score of 35. Progression rate was defined as the ratio of credits passed to the total credits required, expressed as a percentage ranging from 0% to 100%. Socio-economic status (school quintile) categorised students into five quintiles, with Quintile 1 representing the lowest socio-economic background and Quintile 5 the highest. Lastly, average university marks serve as the outcome variable, representing students' average performance across all enrolled courses within an academic year, ranging from 0 to 100.

2.5. Statistical Analysis

To examine the factors influencing academic performance, a Bayesian hierarchical linear mixed-effects model was employed. This model accounted for both fixed and random effects, capturing the nested structure of the data. The random intercepts for academic programmes (Plan Code) and academic years were included to account for variability across these groups. The fixed effects included high school mathematics marks, AP scores, progression rate, gender, age, and socio-economic status (school quintile).

Bayesian hierarchical modelling was chosen for its ability to simultaneously estimate individual-level and group-level effects and handle the nested data structure. The model specification included the following: *Fixed effects*: High school mathematics marks, gender, AP scores, age, progression rate, and school quintile. *Random Effects*: Academic programme and academic year were treated as random effects to account for unobserved heterogeneity. The priors used in the Bayesian model included normal distributions for the regression coefficients, with a ridge prior ($N[0, 1^2]$) to regularise the estimates and mitigate overfitting. The random effects were assigned a Cauchy distribution to accommodate substantial variability across programmes and years, given its heavy-tailed nature and flexibility for modelling extreme values or outliers.

Before conducting the Bayesian analysis, a Pearson correlation matrix was computed to examine the relationships between key variables. This helped identify potential multicollinearity issues, which were further assessed through the posterior correlation matrix of fixed-effect parameters. No significant multicollinearity was observed, as most predictors exhibited low to moderate correlations.

The convergence of the Bayesian model was evaluated using the Rhat diagnostic, with all estimates showing excellent convergence (Rhat = 1.00). The reliability of the parameter estimates was further supported by the narrow credible intervals for significant predictors.

3. Results

3.1. Descriptive Statistics

The study analysed data from 630 undergraduate students enrolled in Science, Technology, Engineering, and Mathematics (STEM) programs at a South African university between 2019 and 2023. After excluding incomplete records, the final sample included students from first-year, second-year, and third-year. The mean age was 24 years (SD = 2.5). The gender distribution was approximately balanced, with 52% female and 48% male students. The racial composition was representative of the university's demographics, as follows: African (60%), White (25%), Coloured (10%), and Asian (5%). High school Mathematics marks ranged from 50 to 100, with a mean of 75 (SD = 12), indicating a generally strong mathematical background of the students enrolled in these programmes.

The Admission Point (AP) scores had a mean of 35 (SD = 7), reflecting potentially varied academic performance of student from their overall high school performance. In

addition, the study explored the students' socio-economic status which was represented by school quintiles. The distribution of the foregoing quintiles was as follows: Quintile 1 (10%), Quintile 2 (15%), Quintile 3 (20%), Quintile 4 (25%), and Quintile 5 (30%). Further, the study calculated the student progression rate, which is calculated as the ratio of credits passed to the total credits required and had a mean of 0.75 (SD = 0.15).

A mean progression rate of 0.75 indicates that, on average, students are successfully completing 75% of their credits registered for within the expected timeframe. This metric is crucial for assessing students' academic progress and identifying potential obstacles to timely programme completion. The standard deviation of 0.15 reflects a moderate level of variability in progression rates, suggesting that while the majority of students progress close to the average rate, a subset of students is experiencing either significantly faster or slower progress. This variability may contribute to extended time to graduation for some students or potentially increased risk of attrition, particularly for those at the lower end of the progression rate distribution.

3.2. Bayesian Hierarchical Modelling Empirical Study

To investigate the factors influencing average university marks among STEM students, a Bayesian linear mixed-effects model was employed. The model accounted for the hierarchical structure of the data by including random intercepts for academic programmes and academic years. The fixed effects included high school mathematics marks, gender, admission point scores, school quintile, age, and progression rate. The choice was informed by data generation process. The dataset under examination included undergraduate students enrolled in various STEM (Science, Technology, Engineering, and Mathematics) programmes across multiple academic years at a South African university. This inherently hierarchical or nested structure—students nested within academic programmes and academic year—necessitates an analytical approach that can appropriately account for the non-independence of observations within these groups, hence our choice of Bayesian Hierarchical modelling, as it allows us to simultaneously estimate individual-level and group-level (programme and year) effects on student success, as measured by the average mark obtained by the student in a given academic year. This is how the hierarchical model was specified mathematically.

$$\text{Average Mark}_{(ijk)} = \beta_0 + \beta_1(\text{High School Math Marks})_{(ijk)} + \beta_2(\text{Gender})_{(ijk)} + \beta_3(\text{Admission Point Scores})_{(ijk)} + \beta_4(\text{School Quintile})_{(ijk)} + \beta_5(\text{Age})_{(ijk)} + \beta_6(\text{Progression Rate})_{(ijk)} + u_j + v_k + \epsilon_{(ijk)}$$

where,

- i indexes individual students;
- j indexes academic programmes;
- k indexes academic years;
- β_0 is the overall intercept;
- β_1 to β_6 are the fixed effect coefficients;
- u_j represents the random intercept for academic programme j ;
- v_k represents the random intercept for academic year k ;
- $\epsilon_{(ijk)}$ is the residual error term.

The analysis starts off by presenting the correlation matrix between the variables. The correlation matrix presented in Figure 1 below highlights the relationships between key academic variables among undergraduate STEM students at a South African university. Understanding these associations provides foundational insights into factors influencing academic performance.

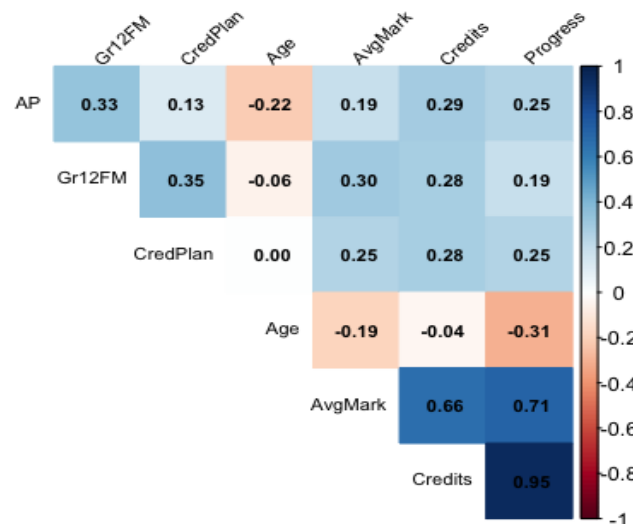


Figure 1. Pearson correlation matrix of key variables.

This figure displays the correlations between key academic variables among undergraduate STEM students at a South African university. The abbreviations used in the matrix are as follows:

- AP: admission point score;
- Gr12FM: Grade 12 final mathematics mark (NSC);
- CredPlan: total credit plan;
- Age: age of student;
- AvgMark: average university mark;
- Credits: credits passed;
- Progress: progression rate.

The correlation matrix in Figure 1 highlights several key relationships influencing academic performance among undergraduate STEM students at a South African university. High school mathematics marks exhibit a moderate positive correlation with both admission scores ($r = 0.33$) and average university marks ($r = 0.30$), emphasising the critical role of mathematical proficiency in academic success. Notably, average marks are strongly positively correlated with credits passed ($r = 0.71$) and progression rate ($r = 0.66$), underscoring the importance of consistent academic progression for achieving high performance. The exceptionally high correlation between credits passed and progression rate ($r = 0.95$) indicates that students who meet their credit requirements are likely to advance smoothly through their programmes. Conversely, age shows a negative correlation with both credits passed and progression rate ($r = -0.31$), suggesting that older students may encounter challenges in maintaining steady academic progress. These findings collectively highlight the significance of strong foundational skills in mathematics, the necessity of supporting continuous academic advancement, and the importance of addressing the unique needs of older students to enhance overall academic outcomes in STEM disciplines. High correlations among certain predictors (e.g., credits_pass and progression_rate) may indicate multicollinearity, which can complicate the interpretation of regression coefficients. Bayesian hierarchical modelling helps mitigate some issues related to multicollinearity by appropriately accounting for hierarchical structures and borrowing strength across groups.

3.3. Testing Existence of Multicollinearity

Figure 2 below present the results of posterior correlation matrix of the fixed effects parameters indicate that most predictors in the Bayesian multilevel model exhibit low to moderate correlations, suggesting minimal multicollinearity and enhancing the reliability

of the coefficient estimates. Specifically, the intercept has a modest negative correlation with high school mathematics marks ($r = -0.20$) and age ($r = -0.26$), while high school mathematics marks and AP scores are moderately negatively correlated ($r = -0.21$). Among socio-economic indicators, school Quintiles 2 and 3 ($r = 0.53$) and Quintiles 4 and 5 ($r = 0.65$) show substantial positive correlations, reflecting that students from adjacent quintiles share similar socio-economic backgrounds. In contrast, other predictor pairs, such as gender and progression rate, exhibit weak or negligible correlations (e.g., $r = 0.17$ between gender and Quintile 5), indicating that these variables contribute independently to academic performance.

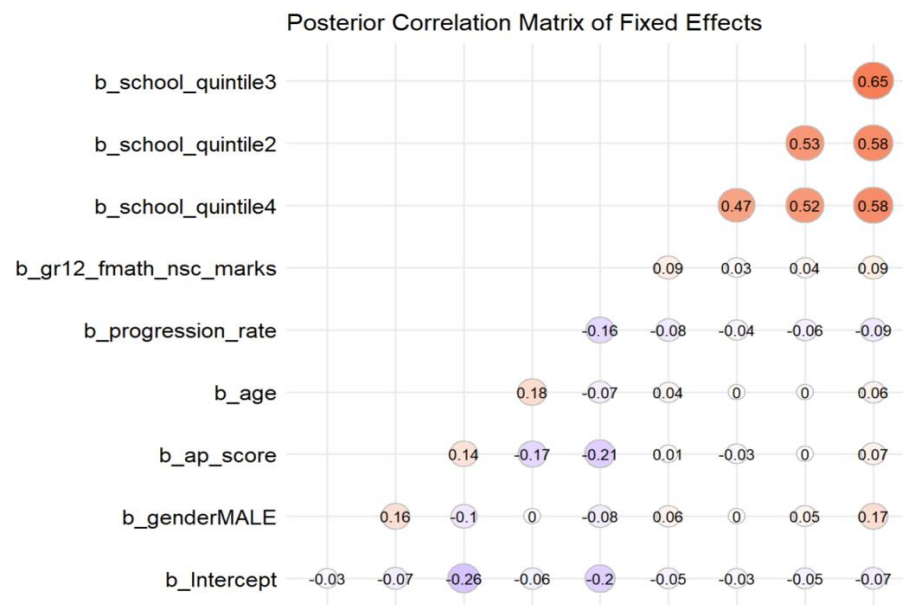


Figure 2. Posterior correlation matrix of the fixed effects, with Quintile 1 as the reference.

Figure 2 displays the posterior correlation matrix of fixed effects to assess potential multicollinearity among the following key variables:

- b_school_quintile3: Students from schools in the third socio-economic quintile;
- b_school_quintile2: Students from schools in the second socio-economic quintile;
- b_school_quintile4: Students from schools in the fourth socio-economic quintile;
- b_gr12_fmath_nsc_marks: Grade 12 final mathematics marks (NSC);
- b_progression_rate: Progression rate, calculated as the ratio of credits passed to total credits required;
- b_age: Age of the student;
- b_ap_score: Admission Point Score (AP Score), reflecting the student's overall high school academic performance;
- b_genderMALE: Gender, specifically male students in the sample;
- b_Intercept: Intercept term in the statistical model, representing the baseline level of the outcome variable when all predictors are set to zero.

Overall, the correlation structure supports the model's integrity by demonstrating that the fixed effects are largely uncorrelated, thereby reducing concerns about multicollinearity and allowing for clear interpretation of each predictor's unique impact on students' average marks.

3.4. Motivation for the Choices of Priors

The regression coefficients represent the fixed effects in the model. Each coefficient β_j (where $j = 1, 2, \dots, p$ for p predictors) is assigned a normal prior distribution centred at

zero with a standard deviation of one. This prior is known as a ridge prior and serves to shrink the coefficients toward zero, promoting regularisation and mitigating overfitting.

$$\begin{aligned}\beta_j &\sim N(0, 1^2) \text{ for each } j = 1, 2, \dots, p. \\ \beta_0 &\sim N(0, 5^2) \\ \sigma_k &\sim \text{Cauchy}(2) \text{ for each random effect } k.\end{aligned}$$

Notation Explanation

- β_j is the regression coefficient for the j th predictor;
- β_0 is the intercept of the regression model;
- σ_k : is the standard deviation of the k th random effect (e.g., for academic programs or years);
- $N(\mu, \sigma^2)$ is the normal (Gaussian) distribution with the mean, μ , and variance, σ^2 ;
- $\text{Cauchy}(x_0, \gamma)$ is the Cauchy distribution with the location parameter, x_0 , and scale parameter, γ .

The choice of these priors is motivated by the fact that for regression coefficient ridge prior encourages the model to favour smaller coefficients unless the data strongly suggest otherwise, thereby reducing overfitting and enhancing model generalisability. For the intercept, it allows for the baseline level of the outcome variable to vary widely, accommodating diverse starting points across different groups or conditions. Finally for random effects regularisation it provides a robust prior for scale parameters, allowing for the possibility of substantial group-level variability while avoiding overly restrictive assumptions.

The analysis in Table 1 reveals that mathematics marks and progression rate are significant fixed-effect predictors of student success (measured as the average performance overall for enrolled courses). Specifically, for each additional point in mathematics marks, the expected increase in a student's average performance is 2.13 units (95% CI: [1.45, 2.82]), indicating a strong positive association. Similarly, progression rate has a substantial positive effect, with an estimate of 7.66 units (95% CI: [7.02, 8.30]), underscoring its critical role in influencing the student average performance. In contrast, gender (Male), AP score, and age do not exhibit statistically significant effects, as their 95% credible intervals include zero (gender: [−1.94, 0.27]; AP score: [−0.52, 0.74]; and age: [−0.82, 0.44]). These findings suggest that while academic performance and progression metrics are pivotal, demographic factors such as gender and age may have limited impact within the scope of this model. All fixed-effect estimates demonstrated excellent convergence diagnostics (Rhat = 1.00), ensuring reliable parameter estimation.

Regarding the random effects in Table 2, significant variability was observed across the grouping factors plan code, school quintile, and year. Plan code accounted for an estimated 4.26 units of variability (95% CI: [2.58, 6.76]), indicating that different academic programmes substantially influence the outcome variable. School quintile exhibited a particularly large estimate of 50.11 units (95% CI: [2.39, 114.84]), although the wide credible interval suggests considerable uncertainty, potentially due to limited data or high inherent variability within this grouping. Year contributed an estimated 13.76 units of variability (95% CI: [1.11, 84.13]), highlighting significant year-to-year differences in the outcome. All random effect estimates also showed perfect convergence diagnostics (Rhat = 1.00), confirming the robustness of the model's hierarchical structure. These random effects underscore the importance of accounting for unobserved heterogeneity across different academic programs, institutional quintiles, and temporal contexts, thereby enhancing the model's explanatory power.

Table 1. Posterior estimates of fixed effects in the Bayesian multilevel regression model.

Predictor	Estimate	Est. Error	<i>l</i> –95%CI	<i>U</i> –95%CI	Rhat
Mathematics Marks	2.13	0.35	1.45	2.82	1.00
Gender (Male)	−0.84	0.57	−1.94	0.27	1.00
AP Score	0.11	0.32	−0.52	0.74	1.00
Age	−0.19	0.32	−0.82	0.44	1.00
Progression Rate	7.66	0.32	7.02	8.30	1.00

Table 2. Posterior estimates of random effects in the Bayesian multilevel regression model.

Grouping Factor	Estimate	Est. Error	<i>l</i> –95%CI	<i>U</i> –95%CI	Rhat
Plan Code	4.26	1.06	2.58	6.76	1.00
School Quintile	50.11	30.96	2.39	114.84	1.00
Year	13.76	24.91	1.11	84.13	1.00

3.5. Summary of Findings

Research Question 1: To what extent do high school mathematics marks influence the academic performance of undergraduate STEM students at a South African university? H_1 : High school mathematics marks have a significant positive effect on the academic performance of undergraduate STEM students.

The Bayesian hierarchical model results show that high school mathematics marks significantly positively influence the academic performance of undergraduate STEM students. For every additional point in high school mathematics marks, the expected increase in the student's average university marks is 2.13 units (95% CI: [1.45, 2.82]), suggesting a strong positive association between high school mathematics proficiency and academic success in university (see Table 1). These findings support Hypothesis 1, confirming that students with stronger mathematical backgrounds tend to perform better in STEM programmes.

Research Question 2: How does gender impact student academic success in STEM programmes? H_2 : There is no significant difference in academic performance between male and female students enrolled in STEM programmes.

The analysis indicates that gender is not a significant predictor of academic performance in STEM programmes. The coefficient for gender is −0.84 (95% CI: [−1.94, 0.27]), with a credible interval that includes zero, suggesting no statistically significant difference between male and female students' performance (see Table 1). Therefore, Hypothesis 2 is supported, indicating no significant gender-based disparities in academic outcomes for STEM students.

Research Question 3: How does age impact student academic success in STEM programmes? H_3 : Age has no significant effect on the academic performance of undergraduate STEM students.

The model results show that age does not significantly influence student academic performance in STEM disciplines. The estimated effect of age is −0.19 (95% CI: [−0.82, 0.44]), with the credible interval crossing zero, indicating no statistically significant relationship between age and academic outcomes (see Table 1). This finding supports Hypothesis 3, suggesting that age does not play a significant role in determining student success in this context.

Research Question 4: What is the role of socio-economic status, represented by school quintiles, in shaping the academic outcomes of STEM students? H_4 : Socio-economic status, as represented by school quintiles, significantly influences the academic outcomes of STEM students.

The random effect estimates indicate substantial variability across school quintiles, with the estimated effect of school quintiles being 50.11 units (95% CI: [2.39, 114.84]) (see

Table 2). Although the wide credible interval suggests some uncertainty, the findings indicate that socio-economic status, represented by school quintiles, plays a significant role in influencing academic performance, supporting Hypothesis 4. Students from lower quintiles may face greater challenges in their academic progression, underscoring the impact of socio-economic factors on educational outcomes in STEM fields.

Research Question 5: How do admission scores affect students' average marks and overall academic performance? H_5 : Admission Point (AP) scores do not significantly predict student academic performance in STEM programmes.

The model results show that AP scores do not significantly affect academic performance, with an estimated coefficient of 0.11 (95% CI: $[-0.52, 0.74]$), and the credible interval includes zero (see Table 1). This finding supports Hypothesis 5, indicating that AP scores are not a strong predictor of student success in STEM programmes once other factors like mathematics marks and progression rates are accounted for.

Research Question 6: What impact do progression rates have on students' average marks and overall academic performance? H_6 : Progression rates significantly positively impact the academic performance of students in STEM programmes.

Progression rate is identified as a significant positive predictor of academic performance, with an estimated effect of 7.66 units (95% CI: $[7.02, 8.30]$) (see Table 1). This substantial positive effect suggests that students who maintain higher progression rates, indicating consistent academic progress, are more likely to achieve better academic outcomes. Hypothesis 6 is strongly supported, emphasising the importance of timely credit completion for academic success in STEM disciplines.

Research Question 7: What variability exists across different academic programmes and years in relation to student success, and how do these group-level factors influence academic outcomes? H_7 : Variability in academic performance is significantly influenced by the academic programme and the year of study.

The random effect estimates reveal significant variability across both academic programmes and years. Specifically, the academic programme (Plan Code) accounted for 4.26 units of variability (95% CI: $[2.58, 6.76]$), while year contributed 13.76 units of variability (95% CI: $[1.11, 84.13]$) (see Table 2). These findings support Hypothesis 7, highlighting that the academic programme and the year of study significantly impact student performance. The wide credible intervals for year variability suggest fluctuations in performance across different cohorts or academic years, potentially due to external factors influencing university outcomes.

4. Discussion

The findings of this study, analysed using a Bayesian hierarchical model, provide critical insights into the factors influencing the academic performance of undergraduate STEM students. These findings are grounded in the following three theoretical frameworks: Human Capital Theory (Becker, 1964), Constructivist Learning Theory (Vygotsky, 1978), and Expectancy-Value Theory (Wigfield & Eccles, 2000). These theories offer explanations for the significant relationships observed between prior academic achievement, progression rates, demographic factors, and academic outcomes.

The significant positive effect of high school mathematics marks on university academic performance is supported by Human Capital Theory, which posits that education enhances individual productivity and success. Students with stronger mathematical backgrounds demonstrated better academic performance, a finding aligned with research by Anderton et al. (2017) and Islam and Al-Ghassani (2015). These studies similarly found that high school mathematics marks predict success in university-level courses, particularly in STEM-related subjects. The results from Lee et al. (2021) further emphasise that

early assessments of mathematical skills are reliable predictors of academic achievement in university, suggesting that mathematical competence forms a critical part of students' human capital. This finding underscores the importance of robust high school mathematics preparation as a key factor in fostering future success in higher education, reinforcing the need for continued emphasis on mathematics education at the secondary level.

While Expectancy-Value Theory suggests that gender-based differences in expectations and self-concept could influence academic performance, the study found no significant difference in performance between male and female students. This aligns with [Hsieh and Yu \(2023\)](#), who also observed no significant gender differences in achievement motivation despite differences in perceived competence. However, some research, such as by [Pennington et al. \(2021\)](#) and [Yu and McLellan \(2019\)](#), highlights gender differences in engagement and self-handicapping behaviours, though these did not appear to affect academic performance in this study. The absence of significant gender effects in this context suggests that the educational environment in South African STEM programs may mitigate gender-based disparities commonly observed in other regions. This is a positive indication that STEM education in this context supports equitable outcomes, regardless of gender.

This study found no significant effect of age on academic performance, which is consistent with [Casanova et al. \(2023\)](#), who found only weak links between age and academic adaptation. Similarly, [Cáceres-Delpiano and Giolito \(2019\)](#) noted that the early advantage of older students diminishes over time. This suggests that while age may influence early educational outcomes, it has little long-term impact on university performance, particularly in a context where cumulative learning and progression play a more significant role in academic success. This finding further supports Constructivist Learning Theory, which highlights that academic success is more dependent on cumulative knowledge than on the age of the student.

The significant influence of socio-economic status (SES) on academic outcomes found in this study aligns with existing research by [Liu et al. \(2020\)](#) and [Autor et al. \(2019\)](#), all of whom identified SES as a critical factor in shaping academic success. Students from higher SES backgrounds consistently outperform their lower SES peers, a trend confirmed by [Singh and Choudhary \(2015\)](#) and [Munir et al. \(2023\)](#). Human Capital Theory helps explain this relationship, as students from higher SES backgrounds are more likely to have access to better educational resources and support systems, allowing them to accumulate greater academic capital. The challenges faced by students from lower SES backgrounds reflect the broader systemic barriers that inhibit their academic success.

Contrary to Human Capital Theory predictions, this study found that Admission Point (AP) scores did not significantly predict academic performance, aligning with the mixed results from studies like [Edwards et al. \(2013\)](#) and [Nagy and Molontay \(2021\)](#). While AP scores can reflect certain aspects of prior academic achievement, they may not capture the full range of skills and attributes needed for success in STEM programs. [Molontay and Nagy \(2023\)](#) also suggested that admission scores' predictive accuracy varies by discipline, which may explain the limited predictive power of AP scores in this study. This finding suggests that STEM programs may benefit from more comprehensive admission criteria that go beyond standardised test scores and better capture the factors that contribute to student success in higher education.

The study found that progression rates were a significant predictor of academic performance, reinforcing Constructivist Learning Theory. This finding aligns with research by [Simelane and Engelbrecht \(2023\)](#), who demonstrated that consistent academic progression improves mathematical competency and academic success. [Brunner et al. \(2018\)](#) and [Sánchez et al. \(2020\)](#) also identified progression as a key indicator of future success, particularly in programs with high academic demands. The positive relationship between

progression rates and academic outcomes underscores the importance of supporting students' continuous academic progress, as it reflects their ability to integrate prior knowledge and adapt to new challenges.

The significant variability in academic performance across academic programs and years highlights the importance of context-specific factors in shaping academic success. Nagy and Molontay (2021) also emphasised the variability of admission score predictive accuracy across disciplines, further supporting the need for tailored educational interventions. This result is consistent with Brunner et al. (2018), who found that sociodemographic factors contribute to cross-country differences in school performance. The variability suggests that institutional and program-specific factors play a critical role in shaping student outcomes, with some programs offering more supportive environments for student success than others.

5. Conclusions

This study provides valuable insights into factors influencing academic performance among undergraduate STEM students at a South African university. By employing a Bayesian hierarchical model, the research identified key predictors of academic success, including high school mathematics marks and progression rates. These findings highlight the importance of a strong mathematics foundation for university success, particularly in STEM disciplines, and emphasise the role of socio-economic status in shaping academic outcomes, suggesting a need for targeted support for disadvantaged students.

A notable strength of this study is its comprehensive analysis, integrating multiple theoretical frameworks, such as Human Capital Theory, Constructivist Learning Theory, and Expectancy-Value Theory. This approach offers a deeper understanding of the complex interplay between individual characteristics, prior academic achievement, and demographic factors.

Recognising the interdependence between secondary and tertiary education, we emphasise the need for university-led initiatives, such as “math-bridge” programmes, to bridge gaps in students' mathematical competencies. Additionally, leveraging technological tools, such as computer algebra systems, can further support learning and reduce the cognitive load for students. These strategies, combined with tailored support systems for socio-economically disadvantaged students, can help promote equitable academic outcomes.

5.1. Limitation

Several limitations exist in this study despite the insight it provides into factors influencing academic performance among STEM students. Firstly, the focus on a single South African university limits the generalisability of the findings, as different institutions may yield varying outcomes. Future research should involve multiple universities or diverse contexts to improve external validity. Secondly, the study examined key factors like high school mathematics marks and progression rates but did not account for other influences such as learning styles, motivation, or family support. Incorporating these variables could provide a more comprehensive understanding of student performance. Thirdly, the cross-sectional design restricts causal interpretations, as data were collected at a single point in time. Longitudinal studies would offer a clearer understanding of how these factors influence academic success over time. Lastly, the study focused on grades as the primary measure of academic success. Future research should explore other dimensions, such as student satisfaction, retention, or employability, to provide a more holistic view of academic achievement.

5.2. Educational Implications and Recommendations

The findings from this study carry significant implications for educational policy and practice, particularly in STEM education at the university level. First, the strong positive relationship between high school mathematics marks and academic performance highlights the need for greater emphasis on mathematics education in secondary schools. To address this, educational authorities and tertiary institutions should collaborate to enhance mathematics education, focusing on both curriculum development and targeted support mechanisms. Initiatives such as enrichment programs, after-school tutoring, and workshops should be designed to address the needs of students who may struggle with mathematics while fostering curiosity and motivation for learning. Furthermore, universities can support this effort by offering bridging courses and integrating technological tools to help students build foundational mathematical competencies.

The study also underscores the importance of tracking students' progression rates. Universities should implement systems that closely monitor student progression rates throughout their academic journey, including regular assessments of academic performance and proactive outreach to identify those at risk of falling behind.

The significant influence of socio-economic status on academic performance suggests that universities must continue to address the disparities faced by students from lower socio-economic backgrounds. Developing comprehensive support systems, including financial aid, access to affordable housing, and resources like textbooks and technology, will help level the playing field for these students.

Finally, although admission scores did not significantly predict performance in this study, universities should reconsider their reliance on standardised admission criteria. A more holistic approach to admissions, considering factors such as motivation, extracurricular achievements, and resilience may offer a better indication of students' potential for success in STEM fields.

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