Using Poisson Regression Model and its Application in a University System (A Case Study of University of Benin)

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DOI: https://doi.org/10.51584/IJRIAS.2025.100800025

Received: 26 July 2025; Accepted: 31 July 2025; Published: 30 August 2025

ABSTRACT

In this study we need to understand the correlation between the qualities of performance at lower level courses that serve as prerequisites to higher level courses. In this study, we seek to employ two first year (100 Level) undergraduate Mathematics and two second year (200 Level) undergraduate Mathematics courses, respectively, which serve as prerequisites to four specific third year (300 Level) undergraduate Mathematics courses to test this correlation.

The method of poisson regression analysis was applied to find out which 100 and 200 Level Mathematics courses have impact on the performance in the 300 Level Mathematics courses comprising of MTH312, MTH313, MTH322 and MTH323 at the Department of Mathematics, University of Benin, Benin City, Nigeria.

From our study, it was discovered that only MTH110 showed a positive effect to the performance of three out of the four 300 level undergraduate courses, followed by MTH112 and MTH212 which had positive effect in one out of the four 300 level undergraduate courses respectively. To determine the quality of performance at higher level courses is of great interest.

INTRODUCTION

Analyzing and predicting educational progress has been an active area of research in recent times, [1]. According to [2], students' low academic performance at the end of a university degree has been a longstanding problem, especially among undergraduate students.

In time past, universities have been using various statistical techniques to analyze educational reports stored in the educational institute repository such as enrolment data, students' performance, teachers' evaluations, gender differences, among others. Multiple linear regression techniques may give a university the needed information to better plan students' enrolment, students' dropout, the identification of weak student early enough, and efficiently allocate resources with a precise approximation because of its ability of decision making. Through multiple linear regression analysis, a university could predict correctly which undergraduates will or will not successfully graduate. The institution could use this information to assist students that are to improve their academic performance. The prediction of student academic performance has long been regarded as an essential research topic in many academic disciplines because it benefits both teaching and learning. It helps Lecturers develop a good understanding of how well or poor the students in their classes will perform, Lecturers, Course Advisers can take proactive measures to improve student learning. [2] predicted students performance using Linear Regression Algorithm with the correlation of 0.9338 and the accuracy of 87.84%.

This study presents a model that predicts students' score for MTH312, MTH313, MTH322 and MTH323 using 100 and 200 level courses which include MTH110, MTH112, MTH212 and MTH222 without considering demographic, economic or socioeconomic factors and psychological effects on the students. It is assumes that from a managerial point of view, it is easier to use academic features which are the courses offered to predict students' performance than to use economic, social and psychological factors. Several studies used multiple linear regression analysis for regression task with respect to predicting academic performance of different educational levels.

RELATED LITERATURES

In [3] their study, predicted student academic performance in engineering courses using a machine learning technique. In their research, the input features included course grades from all semesters and the output variable was exam scores. The researchers discovered that SVMs are suitable for predicting an individual student's performance and that multi-linear regression is suitable for forecasting the performance of all students in a course. However, the authors were unable to justify why SVM was optimal as other machine learning techniques were not tested with the dataset. [4] forecast students' performances using machine learning techniques like c4.5 algorithm, Sequential Minimal Optimization (SMO), Naïve Bayes, k-Nearest Neighborhood (k-NN) and Multi-Layer Perceptron (MLP) with input features (e.g., gender, income, board marks, and attendance). Correlation-based feature selection (CBFS) techniques was applied to improve the model performances and it was determined that SMO achieves a higher effective average testing accuracy (66%) in comparison with other methods. [5] Predicted student performance using data mining techniques like Regression and decision trees to know the academic failure of students. [6] Showed the wave equations of the performance of the students. Their research clustered students using their academic performance as metric. They identified that apart from the challenges and costs involved in Educational Data Mining (EDM) implementation requires the privacy and ethics of all the stakeholders involved in the EDM process. However, this study was unable to assert a good predictive accuracy.

[7] Examined student difficulties in a course on mathematics, system analysis, and design using data mining techniques. The paper examined student difficulties in a course on mathematics, system analysis, and design using data mining techniques. Test grades were used as input features and determined that Ada Boost was the best classifier for predicting the difficulties that students would experience in the subjects. Also, [8] carried out a predictive analysis on Students Academic Performance utilizing Naive Bayes Algorithm. The limitation of this study was that the research was conducted on few factors affecting academic performance. In [9], at-risk students in advance of the next course were identified. In their study, logistic regression, support vector machines (SVMs), decision trees (DTs), Artificial Neural Network (ANN) and a Naïve Bayes classifier (NBC) were used to identify at-risk students in advance of the next course. The study used input features, such as grades, attendance, quizzes, weekly homework, team participation, project milestones, mathematical modelling activity tasks, and exams from an offline course. Analysis of the results found that the NBC algorithm provided satisfactory accuracy (85%).

Similarly, [5] used discriminant analysis to identify major prerequisite for success in a specific course of study in a university system. They presented a case study with forty Industrial Mathematics majors where discriminant analysis was used successfully to determine the major prerequisite for success in Industrial Mathematics.

From the foregoing, previous studies have predicted students' academic performance both in forms of graduating CGPA and course grades for individual courses using various input features and factors. Despite all these findings, not much has been done in identifying prerequisite courses responsible for the consistent high failure rate of some higher level courses in a university system. In addition, no prior publication in literature that has reported significant correlation between academic success of higher level courses and academic success of their assumed prerequisite courses of lower levels.

The focus of this study is to predict the courses that leads to improved performance of MTH312, MTH313, MTH322 and MTH323 courses for full-time undergraduate students at the Department of Mathematics using 100 level foundation courses, such as (Algebra & Trigonometry) MTH110, (Calculus) MTH112, MTH212, MTH222 to predict MTH312, MTH313, MTH322 and MTH323 in the Department of Mathematics, Faculty of Physical Sciences, University of Benin, Nigeria.

Study Population

The population which this study focuses on is the 300 Level undergraduate students of the Mathematics Department, University of Benin from 2003/2004 session through 2022/2023 academic session. The 300 level courses have chosen which are, MTH312, MTH313, MTH322 and MTH323, which are offered by all the three course programmes.

Sample Size

The sample for the 2003/2004 through 2022/2023 contains number of students who failed the courses as mentioned. A total of records were used.

Measurement of Variables

The dependent variables and independent variables for the study were obtained from Mathematics Department bound results copies for each session.

Dependent Variables

The outcome variables otherwise known as the dependent variable in this study is MTH312 (Real Analysis III), MTH313 (Complex Variable Analysis I), MTH322 (Real Analysis IV) and MTH323 (Complex Variable Analysis II), here the students' population for failure are used to predict future outcome.

Independent Variables

The independent variables which are relevant for this study, in line with its objective of analyzing the cause of continuous failure in the aforementioned 300 level courses are: MTH110 (Algebra & Trigonometry), MTH112 (Calculus), MTH212 (Real Analysis I), and MTH222 (Real Analysis II). In other words these are the prerequisite courses for the four dependent variables.

Poisson Regression Model

$$\log(\lambda_i) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 \qquad (1)$$

Rationale for Poisson Regression

Given that our dependent variables represent counts of failures (nonnegative integers) in the four 300level courses, Poisson regression is more appropriate than linear regression because:

1. Nature of Data:

Failure counts are discrete events (0,1,2,... students failing)

The distribution is rights skewed (many courses with few failures, few with many failures)

2. Limitations of Linear Regression:

May predict negative failure counts (impossible values)

Assumes constant variance (homoscedasticity), which count data often violate

Doesn't account for the discrete nature of count outcomes

3. Poisson Advantages:

Specifically models count data

Uses a log link function to ensure predicted counts remain nonnegative

Accounts for variance increasing with the mean

3.5.2 Model Specification

For each target course (e.g., MTH312), the Poisson regression model is:

$$\log(\lambda_i) = \beta_0 + \beta_1(MTH110) + \beta_2(MTH112) + \beta_3(MTH212) + \beta_4(MTH222) \qquad (2)$$

Where:

λ_i = Expected failure count for academic session (i)

β_0 = Baseline failure rate (when all predictors=0)

$\beta_1\ to\ \beta_4$ = Coefficients for prerequisite course scores

Offset: If courses have varying enrolments, include log (enrolment) as an offset to model rates rather than counts

Estimation via Maximum Likelihood

Parameters are estimated by maximizing the Poisson likelihood function:

$$L(\beta) = \prod_{i=1}^{n} \frac{e^{-\lambda_i} \lambda_i^{y_i}}{y_i!} \qquad (3)$$

Where y_i is the observed failure count for session i.

Interpretation of Coefficients

Coefficients are interpreted as Incidence Rate Ratios (IRRs) after exponentiation:

$$IRR = e^B \qquad (4)$$

IRR > 1: Prerequisite score increases failure rate

IRR < 1: Prerequisite score decreases failure rate

IRR = 1: No effect

Example: If $\beta_{MTH110} = 0.05, then\ e^{0.05} \approx 1.05$ indicates a 5% higher failure rate per 1unit increase in MTH110 score.

Model Diagnostics

1. Goodness of Fit:

Deviance Test: Compare residual deviance to χ^2 distribution

Pearson Chi-Square: Assess over dispersion (if ratio >1, use negative binomial)

2. Residual Analysis:

Pearson residuals: Identify outliers

Deviance residuals: Check model fit

3. Over dispersion Check:

If variance > mean, use:

Negative binomial regression, or

Quasi-Poisson with scaled standard errors.

DATA ANALYSIS, RESULTS AND DISCUSSION

This chapter presents the data analysis in line with all the research questions raised in chapter one of this study. 100 level mathematics courses for first semester and first and second semester 200 level Real analysis course were used for analysis to predict success rate in 300 level mathematics courses, namely MTH312, MTH313, MTH322 and MTH323 which is the focus of this study. The estimates of beta were gotten which were used to build the respective models for the study.

Table 4.1: Descriptive Statistics of MTH312, MTH313, MTH322, and MTH323 Grades for 2003/2004 through 2022/2023 sessions

	N	Mean	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
MTH312F	18	132.50	3.894E3	.388	.536	-.668	1.038
MTH313F	18	149.67	2.645E3	.122	.536	-.531	1.038
MTH322F	18	199.50	1.174E4	-.078	.536	-1.437	1.038
MTH323F	18	116.17	2.374E3	1.473	.536	2.669	1.038
Valid N (listwise)	18						

From the descriptive statistics above since variance/mean ratio is less than 1.5 for all the dependent variables we will result to Poisson Regression. This also support the claim of poisson regression for count dataset.

Table 4.2 Fitting a Poisson Regression for 100 Level and 200 level Mathematics Courses with MTH312

Dependent Variable	MTH312F
Probability Distribution	Poisson
Link Function	Log

The table above shows that poisson regression is applicable to the data

Table 4.3 Variable Information for MTH312

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	MTH312F	18	51	258	132.50	62.399
Covariate	MTH110F	18	11	215	80.22	61.965
	MTH112F	18	9	158	77.44	50.883
	MTH212F	18	13	282	90.00	61.695
	MTH222F	18	10	142	45.44	40.226

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue VIII August 2025

The above table shows the descriptive statistics of the data used.

Table 4.4 Goodness of Fit for MTH312

	Value	df	Value/df
Deviance	167.008	13	12.847
Scaled Deviance	167.008	13	
Pearson Chi-Square	165.512	13	12.732
Scaled Pearson Chi-Square	165.512	13	
Log Likelihood	-142.984		
Akaike's Information Criterion (AIC)	295.967		
Finite Sample Corrected AIC (AICC)	300.967		
Bayesian Information Criterion (BIC)	300.419		
Consistent AIC (CAIC)	305.419		

From the above table, The scaled deviance (167.008) and Pearson Chi-Square (165.512) suggested reasonable model fit, though further refinement might be needed.

Table 4.5: Omnibus Test for MTH312

Likelihood Ratio Chi-Square	Df	Sig.
341.566	4	.000

The Poisson regression model for **MTH312** was statistically significant (Omnibus Test: $\chi^2 = 341.566$, $p < 0.001$), indicating that the predictors collectively influenced the outcome.

Table 4.6: Tests of Model Effects

Source	Type III		
	Wald Chi-Square	Df	Sig.
(Intercept)	10761.626	1	.000
MTH110F	202.528	1	.000
MTH112F	17.398	1	.000
MTH212F	.271	1	.603
MTH222F	2.477	1	.116

The above table shows the effect of the predictor variables in the model. All the lower levels courses are showing significant except for MTH222 which is not significant.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue VIII August 2025

Table 4.7: Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	4.439	.0428	4.355	4.523	10761.626	1	.000
MTH110F	.006	.0005	.006	.007	202.528	1	.000
MTH112F	-.002	.0005	-.003	-.001	17.398	1	.000
MTH212F	.000	.0006	-.002	.001	.271	1	.603
MTH222F	.001	.0008	.000	.003	2.477	1	.116
(Scale)	1[a]						
The above table further confirms the effects of the lower level courses on MTH312							
Significant Predictors:							

MTH110F ($\beta = 0.006$, $p < 0.001$) had positive and significant effect on MTH312 performance.

MTH112F ($\beta = -0.002$, $p < 0.001$) had a negative but significant impact.

Non-Significant Predictors:

MTH212F ($\beta = 0.000$, $p = 0.603$) and MTH222F ($\beta = 0.001$, $p = 0.116$) did not significantly predict MTH312 performance

DISCUSSION OF RESULTS

The Poisson regression analysis revealed that MTH110F had a strong positive effect on MTH312F performance ($\beta = 0.006$, $p < 0.001$), suggesting that higher scores in this foundational course predict better outcomes in the advanced course. In contrast, MTH112F showed a small but significant negative association ($\beta = -0.002$, $p < 0.001$), which may indicate differences in course difficulty, content alignment, or student preparedness. The model's goodness of fit statistics (deviance/df ≈ 12.8) suggest possible over dispersion, implying that a negative binomial regression might better account for excess variability.

The Omnibus Test confirmed the model's overall significance ($\chi^2 = 341.566$, $p < 0.001$), but MTH212F ($p = 0.603$) and MTH222F ($p = 0.116$) were non-significant predictors, indicating they do not meaningfully influence MTH312F outcomes. This could imply that these intermediate courses lack direct relevance or that their content does not transfer effectively to MTH312F. Further refinement such as addressing over-dispersion or exploring interactions could strengthen the model's explanatory power.

Table 4.8 Fitting a Poisson Regression for 100 Level and 200 level Mathematics Courses with MTH313

Dependent Variable	MTH313F
Probability Distribution	Poisson
Link Function	Log

The table above shows that poisson regression is applicable for the data to be used.

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Table 4.9 Variable Information for MTH313

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	MTH313	18	58	250	149.67	51.426
Covariate	MTH110	18	11	215	80.22	61.965
	MTH112	18	9	158	77.44	50.883
	MTH212	18	13	282	90.00	61.695
	MTH222	18	10	142	45.44	40.226

The above table shows the descriptive statistics of the data used.

Table 4.10: Goodness of Fit for MTH313

	Value	Df	Value/df
Deviance	192.581	13	14.814
Scaled Deviance	192.581	13	
Pearson Chi-Square	199.245	13	15.327
Scaled Pearson Chi-Square	199.245	13	
Log Likelihood	-157.354		
Akaike's Information Criterion (AIC)	324.708		
Finite Sample Corrected AIC (AICC)	329.708		
Bayesian Information Criterion (BIC)	329.160		
Consistent AIC (CAIC)	334.160		

From the above table, the scaled deviance (192.581) and Pearson Chi-Square (199.245) suggested reasonable model fit.

Table 4.11: Omnibus Test or MTH313

Likelihood Ratio Chi-Square	Df	Sig.
117.934	4	.000

The Poisson regression model for **MTH313** was statistically significant (Omnibus Test: χ^2 = 117.934, $p < 0.000$), indicating that the predictors collectively influenced the outcome.

Table 4.12: Test of Model Effect

Source	Type III		
	Wald Chi-Square	Df	Sig.

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(Intercept)	15050.613	1	.000
MTH110F	23.762	1	.000
MTH112F	9.010	1	.003
MTH212F	19.372	1	.000
MTH222F	3.600	1	.058

The above table shows the effect of the predictors in the model. It shows that only MTH110, MTH112 and MTH212 proved significant with a p.value of 0.000, 0.003 and 0.000 respectively while MTH222 proved insignificant with a p-value of 0.0058.

Table 4.13: Parameter Estimates for MTH313

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	4.759	.0388	4.683	4.835	15050.613	1	.000
MTH110F	.002	.0004	.001	.003	23.762	1	.000
MTH112F	-.001	.0005	-.002	.000	9.010	1	.000
MTH212F	.003	.0006	-.001	.004	13.372	1	.000
MTH222F	-.001	.0007	-.003	4.548E-5	3.600	1	.058
(Scale)	1						

The table above shows the actual significance of each predictor variable.

Significant Predictors

MTH110F ($\beta = 0.002$, $p < 0.001$) had positive and significant effect on MTH312 performance.

MTH212F ($\beta = 0.003$, $p = 0.001$) also had positive and significant effect on MTH312 performance.

Non-Significant Predictors:

MTH112F ($\beta = -0.002$, $p < 0.000$) had a negative but significant impact.

MTH222F ($\beta = 0.001$, $p = 0.116$) did not significantly predict MTH312 performance

Discussion of result

The Poisson regression analysis for MTH313 performance revealed several key insights about the relationship between prerequisite mathematics courses and student achievement. The model showed statistically significant positive effects from both the foundational course MTH110F ($\beta = 0.002$, $p < 0.001$) and the intermediate course MTH212 ($\beta = 0.003$, $p < 0.001$), suggesting that strong performance in these courses consistently predicts better outcomes in MTH313. Interestingly, MTH112 demonstrated a small but significant negative relationship ($\beta = -0.001$, $p = 0.003$), which may reflect differences in curriculum alignment or varying levels of course difficulty that could potentially hinder subsequent performance. The 200-level course MTH222 showed a marginally insignificant effect ($\beta = -0.001$, $p = 0.058$), indicating it may have limited predictive value for MTH313 success.

These findings collectively suggest that while most prerequisite courses positively influence advanced performance, certain courses may need curriculum review to better support student progression.

Table 4.14: Fitting a Poisson Regression for 100 Level and 200 level Mathematics Courses with MTH322

Dependent Variable	MTH322F
Probability Distribution	Poisson
Link Function	Log

The table above is used to demonstrate that poisson regression can be used for the data for MTH322.

Table 4.15: Variable Information for MTH322

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	MTH322F	18	40	347	199.50	108.351
Covariate	MTH110F	18	11	215	80.22	61.965
	MTH112F	18	9	158	77.44	50.883
	MTH212F	18	13	282	90.00	61.695
	MTH222F	18	10	142	45.44	40.226

The above table shows the descriptive statistics of the data used.

Table 4.16: Goodness of fit for MTH322

	Value	Df	Value/df
Deviance	922.297	13	70.946
Scaled Deviance	922.297	13	
Pearson Chi-Square	908.237	13	69.864
Scaled Pearson Chi-Square	908.237	13	
Log Likelihood	-523.564		
Akaike's Information Criterion (AIC)	1.057E3		
Finite Sample Corrected AIC (AICC)	1.062E3		
Bayesian Information Criterion (BIC)	1.062E3		
Consistent AIC (CAIC)	1.067E3		

From the above table, the scaled deviance (922.297) and Pearson Chi-Square (908.237) suggested reasonable model fit.

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Table 4.17: Omnibus Test for MTH322

Likelihood Ratio Chi-Square	Df	Sig.
196.993	4	.000

The poisson regression model for MTH322 was statistically significant (Omnibus Test: Chi-square 196.993, p-value < 0.001) indicating that the predictors collectively influenced the outcome.

Table 4.18: Test of Model Effects for MTH322

Source	Type III		
	Wald Chi-Square	Df	Sig.
(Intercept)	19704.117	1	.000
MTH110F	114.098	1	.000
MTH112F	24.698	1	.000
MTH212F	20.022	1	.000
MTH222F	1.261	1	.262

The above table shows the effect of the predictor variables in the model. All the lower levels courses are showing significant with p<0.001 except for MTH222 which has a p-value of 0.262 which indicate that it is not significant.

Table 4.19: Parameter estimate for MTH322

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	Df	Sig.
(Intercept)	4.970	.0354	4.901	5.039	19704.117	1	.000
MTH110F	.004	.0004	.003	.005	114.098	1	.000
MTH112F	.002	.0004	.001	.003	24.698	1	.000
MTH212F	-.002	.0005	-.003	-.001	20.022	1	.000
MTH222F	.001	.0006	.000	.002	1.261	1	.262
(Scale)	1						

Significant Predictors:

The above table further confirms the effects of the lower level courses on MTH322

MTH110F ($\beta = 0.006$, $p < 0.001$) had positive and significant effect on MTH322 performance.

MTH112F ($\beta = 0.002$, $p < 0.001$) had a negative but significant impact.

Non-Significant Predictors:

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MTH212F ($\beta = -0.000$, $p = 0.603$) and MTH222F ($\beta = 0.001$, $p = 0.116$) did not significantly impact MTH322 performance.

Discussion of Analysis

The Poisson regression analysis for MTH322 performance revealed significant positive relationships with both 100-level mathematics courses. MTH110 showed a particularly strong positive effect ($\beta = 0.004$, $p < 0.001$), indicating that foundational mathematical skills substantially contribute to success in the advanced course. Similarly, MTH112 demonstrated a positive association ($\beta = 0.002$, $p < 0.001$), suggesting that it is also helpful. Surprisingly, MTH212 showed significance, negative effect ($\beta = -0.002$, $p < 0.001$), which may indicate potential curriculum misalignment or that certain intermediate concepts might not effectively prepare students for MTH322. The 200-level course MTH222 showed no significant relationship ($p = 0.262$), suggesting it has minimal predictive value for MTH322 performance. These findings highlight the varying degrees of influence that different prerequisite courses have on advanced mathematics achievement.

Table 4.20 Fitting a Poisson Regression for 100 Level and 200 level Mathematics Courses with MTH323

Dependent Variable	MTH323F
Probability Distribution	Poisson
Link Function	Log

The above table shows that the data is fit for poisson regression

Table 4.21: Variable Information for MTH323

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	MTH323F	18	53	255	116.17	48.728
Covariate	MTH110F	18	11	215	80.22	61.965
	MTH112F	18	9	158	77.44	50.883
	MTH212F	18	13	282	90.00	61.695
	MTH222F	18	10	142	45.44	40.226

The above table shows the descriptive statistics of the data used for the dependent and independent variables.

Table 4.22: Goodness of Fit

	Value	df	Value/df
Deviance	286.744	13	22.057
Scaled Deviance	286.744	13	
Pearson Chi-Square	320.129	13	24.625
Scaled Pearson Chi-Square	320.129	13	
Log Likelihood	-202.075		

Akaike's Information Criterion (AIC)	414.150		
Finite Sample Corrected AIC (AICC)	419.150		
Bayesian Information Criterion (BIC)	418.602		
Consistent AIC (CAIC)	423.602		

From the above table, the scaled deviance (192.581) and Pearson Chi-Square (199.245) suggested reasonable model fit.

Table 4.23: Omnibus Test

Likelihood Ratio Chi-Square	Df	Sig.
26.657	4	.000

The poisson regression model for MTH322 was statistically significant (Omnibus Test: Chi-square 26.667, p-value < 0.000) indicating that the predictors collectively influenced the outcome.

Table 4.24: Tests of Model Effects

Source	Type III		
	Wald Chi-Square	Df	Sig.
(Intercept)	10853.524	1	.000
MTH110F	1.956	1	.162
MTH112F	2.381	1	.123
MTH212F	3.737	1	.053
MTH222F	17.312	1	.000

The above table shows the effect of the predictor variables in the model. All the lower levels courses has a p-value greater 0.01 MTH110; p-value = 0.162, MTH112; p-value = 0.123; and MTH212; p-value = 0.053 except for MTH222 alone that has a p-value of 0.000.

Table 4.25: Parameter Estimates for MTH323

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	Df	Sig.
(Intercept)	4.668	.0448	4.580	4.755	10853.524	1	.000
MTH110F	.001	.0005	.000	.002	1.956	1	.162
MTH112F	.001	.0005	.000	.002	2.381	1	.123
MTH212F	.001	.0007	-1.824E-5	.003	3.737	1	.053
MTH222F	-.003	.0008	-.005	-.002	17.312	1	.000

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(Scale)	1						
The above table further confirms the effects of the lower level courses on MTH323							

Significant Predictors

MTH222 ($\beta = -0.003$, $p < 0.001$) was found to be significant but has a negative impact on MTH323 performance.

Non Significant Predictors

MTH110F ($\beta = 0.001$, $p < 0.162$) has insignificant effect on MTH323 performance.

MTH112F ($\beta = 0.001$, $p < 0.123$) has insignificant impact on MTH323 performance.

MTH212F ($\beta = 0.001$, $p = 0.053$) and has insignificant impact on MTH323 performance.

MTH222F ($\beta = -0.003$, $p = 0.000$) has a negative and has insignificant impact on MTH312 performance

Discussion of Results

The Poisson regression analysis for MTH323F revealed a strikingly different pattern compared to other mathematics courses. Among all prerequisite courses examined, only MTH222F showed a significant relationship with MTH323F performance, demonstrating a negative effect ($\beta = -0.003$, $p < 0.001$). This unexpected finding suggests that stronger performance in this intermediate course might actually correlate with lower scores in MTH323F, potentially indicating curriculum misalignment or differing cognitive demands between the courses. Notably, none of the other courses - including foundational courses MTH110F ($p = 0.162$) and MTH112F ($p = 0.123$) - showed statistically significant effects, while MTH212F approached marginal significance ($p = 0.053$). These results imply that MTH323F may require substantially different skills than those emphasized in most prerequisite courses, or that other unmeasured factors play a more crucial role in student success.

SUMMARY AND CONCLUSION

This research presents a comprehensive summary of the study's findings, conclusions drawn from the analysis, and practical recommendations. The contributions to knowledge and suggestions for future research are also highlighted.

Findings

The study yielded the following key findings:

For MTH312:

MTH110F showed a significant positive effect ($\beta = 0.006$, $p < 0.001$), enhancing MTH312 performance.

MTH112F had a small but significant negative impact ($\beta = 0.002$, $p < 0.001$).

MTH212F and MTH222F were non-significant predictors ($p > 0.05$).

For MTH313:

MTH110F ($\beta = 0.002$, $p < 0.001$) and MTH212F ($\beta = 0.003$, $p < 0.001$) positively influenced performance.

MTH112F showed a negative effect ($\beta = 0.001$, $p = 0.003$).

MTH222F was marginally insignificant ($p = 0.058$).

For MTH322:

MTH110F ($\beta = 0.004$, $p < 0.001$) and MTH112F ($\beta = 0.002$, $p < 0.001$) had positive effects.

MTH212F showed a negative association ($\beta = 0.002$, $p < 0.001$).

MTH222F was non-significant ($p = 0.262$).

For MTH323:

Only MTH222F was significant but negatively correlated ($\beta = 0.003$, $p < 0.001$).

Other prerequisites (MTH110F, MTH112F, MTH212F) showed no significant impact ($p > 0.05$).

General Observation: Success in prerequisite courses does not consistently translate to success in 300 level courses, indicating potential curriculum misalignment.

RECOMMENDATIONS

Based on the findings, the following recommendations are proposed:

1. **Curriculum Redesign:**

Revise content of MTH112F and MTH212F to address their negative/insignificant effects on advanced courses.

Investigate the unexpected negative correlation between MTH222F and MTH323F performance.

2. **Instructional Improvement:**

Assign experienced faculty to teach 200level courses to strengthen foundational knowledge.

Develop bridging programs to smooth the transition from 200level to 300level courses.

3. **Model Refinement:**

Use alternative models (e.g., negative binomial regression) to address overdispersion in the data.

Contribution to Knowledge

This study provides empirical evidence that:

Not all prerequisite courses equally prepare students for advanced mathematics.

Curriculum alignment issues may exist, particularly for intermediate courses (MTH212F, MTH222F).

Success in prerequisites does not guarantee success in 300 level courses, challenging traditional assumptions.

Summary

The study analyzed the relationship between 100/200 level mathematics courses and performance in 300level courses (MTH312MTH323) at the University of Benin from 2003/2004 to 2022/2023. Using Poisson regression, the analysis revealed that:

MTH110F consistently supported success in advanced courses.

Other prerequisites (MTH112F, MTH212F, MTH222F) showed mixed or negative effects, suggesting curriculum gaps.

Over dispersion in the data indicates the need for more robust modeling approaches.

Suggestions for Further Studies

Future research should:

1. Investigate other 200 and 300level courses to identify additional predictors of success.

2. Examine non academic factors (e.g., teaching quality, student engagement) influencing performance.

3. Conduct longitudinal studies to assess the impact of curriculum reforms on student outcomes.

Conclusion

The study concludes that while foundational courses like MTH110F enhance advanced performance, other prerequisites may hinder success due to misalignment. Addressing these issues through targeted curriculum reforms and experienced instruction could significantly improve student outcomes in 300level mathematics courses.

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