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A logistic regression analysis on factors affecting students' performance in Introductory mathematics: A case study from the University of Nigeria, Nsukka

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Abstract
A logistic model was fitted to data on some variables provided by questionnaire administered on 112 undergraduate students in introductory mathematics (MTH111) using the google form. The variables considered are gender, income, infrastructure, course presentation, rate of attendance, GPA, extra factors, study schedule, parental education qualification. The model also correctly classifies 82.2% of the overall cases; this is also an indication that the model is a good fit.

Keywords: Logistic model, introductory mathematics, Log odds ratio, academic performance, goodness of fit

Introduction

Mathematics is a basic course that student's study either in the primary level of education, secondary level of education and even up to tertiary stage, it is unavoidable. Mathematics achievement in Nigeria has been so frustrating, despite all the effort engaged to improve the study. Some students develop interest in mathematics from their primary stage and suddenly lose interest thereafter. One of the definitions given by Akindade (2011) opined that it is a field of study of size, numerations and the relations between them. Mathematics deals with logical reasoning and quantitative calculation. Its development has involved an increasing degree of idealization and abstraction of its subject matter. Mathematics is used for analyzing and communicating information and ideas to address a range of practical tasks and real-life problems. In 2004, Kitta defined mathematics as the language that helps us to describe ideas and relationships drawn from the environment. Since the 17th century, mathematics has been an indispensable adjunct to the physical sciences and technology, and in more recent times it has assumed a similar role in the quantitative aspects of the life sciences. Mathematics education is one of the subjects recognized as a major factor in development, causing national agenda to focus in this area.

More so, greater demand for economic, scientific and technological knowledge in the Nigerian development programmed has brought about the securing of an excellent mathematical knowledge at all levels of education, thus, increasing knowledge in mathematics of the future engineers, physicists, chemists, sociologists, industrial and medical personnel, as well as other sciences, including historians cannot be over emphasized The knowledge of mathematics has been expressed in the professional fields such as Agriculture, Medicine, Engineering and so on, which enhances the growth of a nation; and to a large extent these professional field contributes immensely to the technological growth of a nation. Of sad reflection over the years, Nigerian tertiary students' achievement in mathematics at the graduation level of the first degree examination has a relatively low rate. Discussing factors affecting students' academic performance will require us to look at the concept of poor performance. According to Aremu (2000), poor performance is a performance that adjudged by the examinees/testees and some significant as falling below an expected standard. The interpretation of this expected or desire standard is better appreciated from the perpetual cognitive ability of the evaluator of the performance. The evaluator or assessor can therefore give different interpretations depending on some factors while Abdullahi (2013) described poor academic performance as any performance that falls below a desired standard. The criteria of excellence can be from 40% to 100% depending on some subjective criteria of the evaluator or assessor. Just as in universities in Nigeria, any grade below 40% is considered as poor or failed

Introductory mathematics (MTH 111) is a compulsory first year course for nearly all students in the university of Nigeria, Nsukka particularly for those in the faculty of physical sciences. In the university of Nigeria and similar institutions, massive failure in elementary mathematics is one event that recurs in the system. Although failure is inevitable in the performance outcome of students; massive failure is worrisome. Over the years the students have a record of poor performance and this has been attributed to the fact that the course is challenging. For this fact, students resort to actions such as examination malpractice which equally includes hiring of machineries, bribing of lecturers, hacking of school sites and some other illegal indulgences not mentioned in this work. But despite all the supposed remedies students employ to get at least a pass mark, it is quite obvious that improvements are rarely made. This course is an essential basis for many advance courses in mathematics and other disciplines in the sciences. Some students find it difficult to graduate at times due to the perceived challenge in the course. Studies have shown that poor performance in calculus is not restricted to Nigeria but to Colleges and Universities of other countries. Study of students' performance is as old as the history of education. The analysis has started around thirties of the 20th century. Students differ in terms of gender, culture, family environment, financial status of parents, etc. while schools differ in number of students, the quality of teachers, infrastructure, location, assistance provided by the government, etc. According to the institute of Education, University of Cape Coast (U.C.C) Chief examiners report, the worst performance in the 2013 / 2014 academic year first semester examination for Colleges of Education in Ghana was in Mathematics (Numbers and Basic Algebra). The reports made available to the Colleges of Education indicated that 32.9% of the candidates who took the mathematics paper (Numbers and Basic Algebra) had the grades D or D+ and 20.9% failed in the subjects. Educators, trainers, and researchers have long been interested in exploring variables contributing effectively for quality of performance of learners. These variables are inside or outside school and affect students' quality of academic achievement. These factors may be termed as student factors, family factors, school factors and peer factors.

National Research Council in the late 1980s explains that students study of mathematics is getting worse worldwide especially with regard to the enrolment and performance of minority groups in mathematics and science courses. Several scholars have given reasons for these consistent poor performance in mathematics. Different sectors have contributed to the growth of mathematics and some policies have been put in place by the government, still it is largely observed that the performance of students in mathematics remains poor.

It was observed that students' performance in introductory mathematics varies from department to department across the university. It is of great expectation that less or no failure in introductory mathematics (MTH 111) should exist especially in mathematics department and other departments that are highly quantitative. But this is not the case as there are more failures than expected in these departments despite the fact they are majorly quantitative.

Logistic regression analysis extends the techniques of multiple regressions to research situations in which the outcome variable is categorical. Applications abound in the fields of medicine, social sciences and education. Logistic regression model deals with the relationship between a categorical variable in binomial form and various linear variables. Logistic regression is a statistical model that in its basic form uses a logistic function to model a binary dependent variable. Mathematically, a binary logistic model has a dependent variable with two possible values, such as pass/fail, male /female, which is represented by an indicator variable, where the two values are labeled "0" and "1". The two outcomes involved are mutually exclusive. Logistic regression equation becomes apparent when we have multiple levels in an explanatory variable or indeed multiple explanatory variables.

Some researchers like Onuoha (2002) [9] evaluated performance of statistics major students in mathematics and statistics courses in the University of Nigeria, Nsukka. The kruskal-wallis H-test result showed that academic performance in mathematics and statistics courses is dependent on the type of courses taken and the various years involved, and is independent of sex in both Mathematics and statistics courses. Abubakar and oguguo (2011) [8] conducted their study using multiple regressions to study the correlates between age and gender on academic achievement (CGPA) mathematics and science students. Based on the result, they discovered that gender was a better predictor. This further means that gender contributes more on academic performance of students. Ajogbeje in 2011 studied the effect of students' previous knowledge and semester scores on achievement of students in mathematics. The elementary units of the target population were obtained from SSCE and (MTH111, MTH112, MTH122, MTH211 and STA111) scores of students in environmental studies. The result showed that a lesser percentage of the total variation in CGPA were explained by the regression equation, which means that there were other factors rather than SSCE and the undergraduate courses, that have a higher effect on the performance studied the factors that influenced students' mathematics performance in some selected colleges of education in Ghana. The result revealed that lecture method of instruction, inadequate teaching and materials highly determines students' performance Murray in 2013 studied the factors that influenced mathematics achievement at the berbice campus. Employing multiple regression as a tool, he discovered from his study that there was a significant positive relationship between the dependent variable MTH 111 performance and the independent variables prior academic performance, self-efficacy, self- regulation, academic resources, learning styles and the result indicated that the best set of predictors for the mathematics performance on the first year course at the campus are prior academic achievement, learning styles and academic resources concluded based on the result of their study in the university of Paupa, Indonesia that students with high level of higher order thinking skills (HOTS) contributes immensely to students' academic achievement in mathematics studied the factors that affected underachievement in elementary mathematics in the University of Cebu, Philippine. In his study, he used chi-square to run the test and the result obtained from his study revealed that only the relationship between mathematics performance and students factors was significant. The students' factors include habits, attitudes and interests toward mathematics and time management which directly affect the performance of students in mathematics. Appah, odumosu and olisama in 2019 examined the factors which contribute to the mathematics word problem achievement of National Diploma Students' of Federal College of Forestry. Pearson Product Moment Correlation and multiple regressions were used. This study revealed that students' factors such as gender, students' interest in mathematics, students' attitude to mathematics, students' awareness of importance of mathematics to their course of study and their performance in English courses affect students' achievement in mathematics word problems positively. Ling and Luan (2019) examined the association between interest and mathematics performance among Malaysian students in a technology-enhanced learning environment. Using the Pearson product-moment correlation coefficient, the established a fact that association between interest and mathematics performance was weak for those who had a higher level of performance in mathematics but stronger for those with lower mathematics performance in their study concluded that mathematics achievements of university students in social sciences depend on the following factors: mathematics anxiety, mathematics confidence, students' engagement in a mathematics course, and background knowledge from secondary school. Based on their findings, they concluded that teaching in secondary school is a crucial determinant for success in mathematics at university. More importantly, It is an irrefutable fact that the success in learning the subject is contingent on myriad of factors such as school, students and teacher - all impinge on the learning of mathematics. This implies that there must be some factors militating against students' performance. The interest of this work therefore seek to identify such factors among the students in the Mathematics and Statistics department of the University of Nigeria, Nsukka in order to provide basis for improvement intervention strategy on course delivery.

Methodology

Logistic regression allows the effect of independent variable(s) on one binary dependent variable to be tested. It is predominantly used to assess relationships between the binary dependent variable and each independent variable whilst controlling for the other independent variables but also produces a model which can be used for prediction. Logistic regression analysis involves one dependent variable (binary or categorical variable) and two or more independent variables. For a logistic regression, the predicted dependent variable is a function of the probability that a particular subject will be in one of the categories. It uses the concepts of odds ratio to calculate the probability and the outcome in logistic regressions is often coded as 0 and 1, where 1 indicates that the outcome of interest is present and 0 indicates that the outcome of interest is absent.

Its salient feature is that there is a binary response of interest and the predictor variables are used to model the probability of that response. Here the binary response variable, Y is the grade of the students in the course. That is:

- Grades D – F, coded as 0; regarded as students at risk of being successful in MTH111
- Grades A – C, coded as 1; regarded as students not at risk of being successful in MTH111.

The predictor variables are the factors being investigated for possible influence on the response variable. To determine the factors that affect students' performance in introductory mathematics (MTH111), the independent variables are: gender, infrastructure, course presentation, rate of attendance, GPA, extra factors, study schedule, parental education qualification and socioeconomic status (income), GPA, level of infrastructure, while the dependent variable (binary outcome) is the grade of students in introductory mathematics (MTH111).

2.1.1 Model Specification

Binary logistic regression being the appropriate model for the study attempts to model the relationship between dependent variable and two or more independent variables by fitting a linear equation to the observed data. It uses the concepts odd ratios to calculate the probability, that is, the ratio of the odds of an event happening to its not happening;

$$\text{Odds} = {}^{p}/_{1-p}$$

The odds ratio helps identify how likely an exposure is to lead to a specific event. The larger the odds ratio, the higher odds that the event will occur with exposure. Odds ratio smaller than one imply the event has fewer odds of happening with the exposure.

The multiple logistic models can then be expressed as:

$$\hat{p}=\left(\frac{b_0+b_1X_1+b_2X_2+b_3X_3+b_4X_4+b_5X_5+b_6X_6+b_7X_7+b_8X_8+b_9X_9}{1+\exp(b_0+b_1X_1+b_2X_2+b_3X_3+b_4X_4+b_5X_5+b_6X_6+b_7X_7+b_8X_8+b_9X_9)}\right)$$

Where

$\hat{p}$ is the expected probability that the outcome is present; b_0 and b_7 are the regression coefficients while the X_1 through X_9 are distinct independent variables;

X_1 = students grade point average (GPA)
X_2 = parental income of student
X_3 = infrastructure in the classroom
X_4= course presentation
X_5= rate of attendance
X_6=gender
X_7=study schedule
X_8= extra factors
X_9 = parental education qualification.

The log of the odds that the outcome is present is specified as:
In

$$\left(\frac{P}{1-P}\right)=b_0+b_1x_1+b_2x_2+b_3x_3+b_4x_4+b_5x_5+b_6x_6+b_7x_7+b_8x_8+b_9x_9.$$

The odds ratio is a ratio of two sets of odds: the odds of the students' to get a 'pass' in MTH111 versus the odds of the students' with no pass (fail) in MTH111.

In

$$\left(\frac{pass}{1-Pass}\right)=b_0+b_1x_1+b_2x_2+b_3x_3+b_4x_4+b_5x_5+b_6x_6+b_7x_7+b_8x_8+b_9x_{9.}$$

2.1.2 Assumptions of the model

1. Dependent variable should be measured on a dichotomous scale; binary outcome, $\hat{Y}$= Fail (0) and Pass (1)
2. There should be absence of outliers
3. The predictor variables should not be highly correlated.
4. Observations are independent of each other.

Note: logistic regression makes no assumptions about the distributions of the predictor variables

2.1.2.1 Verification of model assumptions

1. The dependent variable is a binary outcome, that is, $\hat{Y}$(odd ratio) = Fail (0) and Pass (1)
2. To detect the potential outliers, the normal probability plot and the scatter plot were used and presented below.

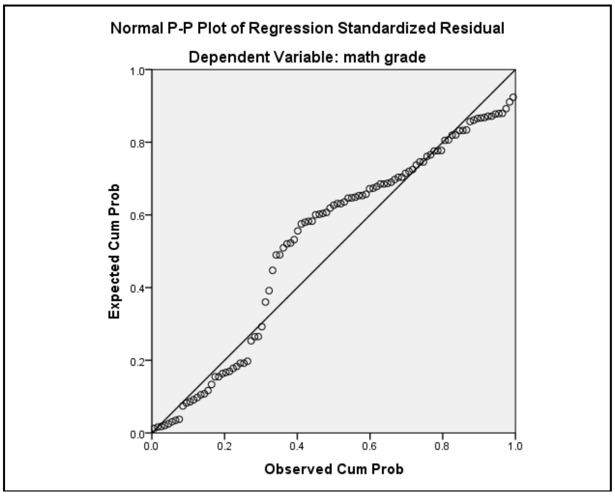

Fig 1: Normal probability plot of regression standardized residual

From the above plot, there are no indication of any outlier. This is because the data points are clustering close to the line.

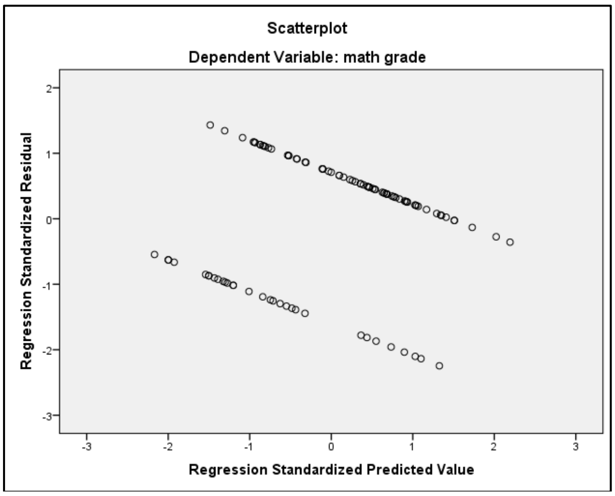

Fig 2: Scatter plot of regression standardized predicted value

Based on the data points represented in figure 2, it shows that there are no outliers. This is because the points formed two parallel lines. The points are approaching being outliers but they are not outliers.

3. To check for multicollinearity among the predictor variables, the variance inflation factor and the tolerance limit were used.

(a) Variance Inflation factor

The VIF is calculated for all independent variables of a model. From a mathematical point of view, the VIF measures the increase of the variance in comparison to an orthogonal basis. The VIF of the k^{th} variable is defined by the following formula:

$VIF_k = 1/(1-R^2_k)$,

Where R^2_k is the goodness of fit of the linear model for a particular variable X_k based on all other variables.

(b) Tolerance – This is the inverse of the VIF

As a rule of thumb, the VIF of all variables should be less than 10 in order to avoid troubles with the stability of the coefficients. That is:

VIF > 10 – indicates high correlation among predictor variables or Tolerance < 0.10

Table 1: Collinearity diagnostics

Model		Collinearity Statistics	
		Tolerance	**VIF**
1	Grade point average	.898	1.114
	Parental income	.941	1.062
	Infrastructure in the hall	.792	1.263
	Course introduction and presentation	.813	1.230
	Rate of attendance	.903	1.107
	Gender of students	.903	1.108
	Students study time	.948	1.055
	Extra factors	.820	1.219
	Parents education qualification	.884	1.131

a. Dependent Variable: math grade

From table 1, the predictor values in the VIF column are all less than 10 and those in the Tolerance column are all greater than 0.1, this indicates absence of multicollinearity in the independent variables. This means that there are no linear dependence among the variables.

2.2 Data Analysis and presentation of results

2.2.1 Goodness of fit of the model

The goodness of fit a model measures how well the model describes the response variable. Assessing goodness of fit involves investigating how close values predicted by the model are to the observed values.

Statistic used in testing the fit of the model is as follows:

(a) Nagelkerke R square

Is an adjusted version of the Cox & Snell R-square that adjusts the scale of the statistic that cover the full range from 0 to 1.

$$\text{Nagelkerke } R^2 = \left(\frac{1-\frac{L_0}{L_1}}{1-L_0^{2/n}}\right)^{2/n}, \; 0 < R^2 < 1.$$

Where

L_0 is the null model and L_1 is the full model.

(b) Hosmer-Lemeshow test

This is a goodness of fit test for logistic regression, especially for risk prediction models. A goodness of fit test tells you how well your data fits the model. The Hosmer-Lemeshow test statistic is calculated with the following formula.

$$G^2_{HL} = \sum_{j=1}^{10} \frac{(O_j - E_j)^2}{E_j(1 - E_j/n_j)} \sim \chi^2_8$$

Where:

χ^2 = chi squared.

n_j = number of observations in the j^{th} group.

O_j = number of observed cases in the j^{th} group.

O_j = number of expected cases in the j^{th} group.

Σ = summation notation.

(c) Omnibus test

The omnibus test is a likelihood-ratio chi-square test of the current model versus the null (in this case, intercept) model. The significance value of less than 0.05 indicates that the current model outperforms the null model.

2.2.1.1 Statistical test for model fit

H_0: the model is not a good fit to the data

H_1: the model is a good fit to the data

$\alpha = 0.05$

Test statistic

$$G_{HL}^2 = \sum_{j=1}^{10} \frac{(O_j - E_j)^2}{E_j(1 - E_j/n_j)} \sim \chi_8^2$$

Where
χ^2 = chi squared.
n_j = number of observations in the j^{th} group.
O_j = number of observed cases in the j^{th} group.
O_j = number of expected cases in the j^{th} group.
Σ = summation notation

Decision rule: Reject H_0 if p-value is less than 0.05
Output

Table 2: Omnibus Tests of Model Coefficients

		Chi-square	DF	Sig.
Step 1	Step	43.303	26	.018
	Block	43.303	26	.018
	Model	43.303	26	.018

From Table 2, the full model represents significant improvement in model fit relative to the intercept only model. It also shows that at least one of the population regression slopes is non-zero, $\chi^2(26) = 43.303$, $P < 0.05$.

Table 3: Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1.	81.255[a]	.349	.492

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

From the model summary in table 3, between 35% and 49% of the variance in the dependent variable is explained by the model. Basically, the pseudo R^2 (Nagelkerke R Square) indicate that 49.2% of the variability in the log odds ratio is explained by the independent variables.

Table 4(a): Hosmer and Lemeshow Test

Step	Chi-square	DF	Sig.
1.	7.406	8	.494

Table 4(b): Contingency Table for Hosmer and Lemeshow Test

		Math grade = Fail		Math grade = Pass		Total
		Observed	Expected	Observed	Expected	
Step 1	1.	9	8.603	1	1.397	10
	2.	6	6.746	4	3.254	10
	3.	6	5.549	4	4.451	10
	4.	4	3.915	6	6.085	10
	5.	1	2.470	9	7.530	10
	6.	1	1.945	10	9.055	11
	7.	3	.983	7	9.017	10
	8.	1	.552	9	9.448	10
	9.	0	.231	10	9.769	10
	10.	0	.005	10	9.995	10

Based on the results presented in Table 4(a &b), it shows that the logistic model is a good fit to the data, ($p > 0.05$)

Table 5: Classification Table[a]

Observed			Predicted		
			Math grade		Percentage Correct
			Fail	Pass	
Step 1	Math grade	Fail	21	10	67.7
		Pass	8	62	88.6
	Overall Percentage				82.2

a. The cut value is .500

The classification table shows percentage accuracy in classification by the model. It shows that out of the 112 students predicted not to pass the examination, we have 67.7% students correctly predicted by the model not to pass the examination. More so, 88.6% were predicted by the model to pass the examination among those predicted to pass the examination. The overall classification of the model shows that 82.2% of all the cases were correctly predicted by the model.

2.2.2 Significance of model coefficients

Wald test: Wald chi square statistics are used to test the significance of individual coefficients in the model and are calculated as

$$W = \left(\frac{B_j^2}{S_{B_j}}\right) \sim \chi^2$$

Likelihood ratio test
The likelihood ratio test for a particular parameter compares the likelihood of obtaining the data when the parameter is zero (L_0) with the likelihood (L_1) of obtaining the data evaluated at the MLE of the parameter. It indicates the overall goodness of fit of the model. The test statistics is calculated as:
$-2 \times \text{In(likelihood ratio)} = -2 \times \text{In}\,(L_0/L_1) = -2 \times (\text{InL}_0 - \text{InL}_1)$

Table 6: Variables in the Equation

		B	S.E.	Wald	DF	Sig.	Exp(B)
Step 1[a]	GPA			3.200	3	.362	
	GPA (1)	-.682	1.810	.142	1	.706	.506
	GPA (2)	-1.327	1.056	1.581	1	.209	.265
	GPA (3)	-.018	.995	.000	1	.986	.982
	income			.318	2	.853	
	Income (1)	.738	1.376	.288	1	.592	2.092
	Income (2)	.386	1.268	.093	1	.761	1.472
	infrastructure			3.359	3	.340	
	Infrastructure (1)	.624	2.044	.093	1	.760	1.867
	Infrastructure (2)	-1.445	1.458	.982	1	.322	.236
	Infrastructure (3)	-1.687	1.440	1.371	1	.242	.185
	course_presentation			.500	3	.919	
	course_presentation (1)	1.262	2.073	.371	1	.543	3.533
	course_presentation (2)	.600	1.715	.123	1	.726	1.823
	course_presentation (3)	.369	1.689	.048	1	.827	1.447
	lectures_attended			.790	3	.852	
	lectures_attended (1)	20.294	28366.253	.000	1	.999	651209482.217
	lectures_attended (2)	-.213	.869	.060	1	.806	.808
	lectures_attended (3)	-.665	.755	.776	1	.378	.514
	Gender (1)	-2.156	.723	8.888	1	.003	.116
	study_time			5.461	3	.141	
	study_time (1)	1.619	.920	3.100	1	.078	5.050
	study_time (2)	-.101	.848	.014	1	.905	.904
	study_time (3)	22.264	18168.656	.000	1	.999	4665890252.008
	extra_factors			.212	4	.995	
	extra_factors (1)	-19.989	16084.813	.000	1	.999	.000
	extra_factors (2)	-20.038	16084.813	.000	1	.999	.000
	extra_factors (3)	-19.662	16084.813	.000	1	.999	.000
	extra_factors (4)	-19.884	16084.813	.000	1	.999	.000
	edu_qualification			4.024	4	.403	
	edu_qualification (1)	.240	1.225	.038	1	.845	1.271
	edu_qualification (2)	.117	1.048	.012	1	.911	1.124
	edu_qualification (3)	-.377	1.111	.115	1	.734	.686
	edu_qualification (4)	-1.595	1.103	2.089	1	.148	.203
	Constant	22.621	16084.813	.000	1	.999	6673445038.049

a. Variable(s) entered on step 1: GPA, income, infrastructure, course_presentation, lectures_attended, gender, study_time, extra_factors, edu_qualification.

The results in table 6 show that only one variable was identified to have significant regression coefficient β. This is gender. It shows that as we move from male to female on gender, the predictive logits of a student falling into the pass category is decreasing. Hence, it is the only variables that contributed significantly to the predictive ability of the model. Column seven of Table 6 gives the values of the corresponding estimated odds ratios, that is, e^{β}. The estimate value for gender is 0.116. This estimate is quite low and indicate that with gender, students not at risk of being successful in the course have lower odds ratio than those at risk. It also shows that for every one unit increase for gender, the odds of a student passing is changing by a factor of 0.116. Now the model becomes:

$$\text{In}\left(\frac{pass}{1-Pass}\right) = 20.465 + 2.156*\text{gender}$$

Summary and Conclusion

A logistic model was fitted to data on some variables provided by questionnaire administered on 112 undergraduate students in introductory mathematics (MTH111). The variables considered are gender, income, infrastructure, course presentation, rate of attendance, GPA, extra factors, study schedule, parental education qualification. From the Neglerke R^2, 49.2% variation in the log odds ratio was explained by fitting the independent variables. The unexplained variation is 51.8%; this is quite high, implying that there are other important independent variables which are not included in the regression model. The Hosmer Lemeshow test shows that the model is a good fit. The model also correctly classifies 82.2% of the overall cases; this is also an indication that the model is a good fit. Only one variable made significant contribution to the predictive ability of the model. The overall model was statistically significant when compared to the null model, χ^2 (26) = 43.303, p(0.018) < 0.05 The results showed that there are other important independent variables not identified but could be accommodated in the model. This could form the basis for further investigation. Expanded questions on the socioeconomic status of the students are suggested as one of the areas that could be further investigated

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