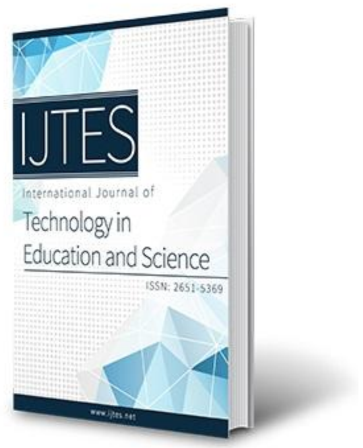

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Using Multinomial Logistic Regression Model to Predict the Effect of Social Media on Academic Performance of College Students

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Abstract

Social media networking has become an integral part of communication today, with widespread usage across various demographics. This study was conducted to investigate the impact of social media on student academic performance, recognizing its prevalence and influence in educational settings. A random sample of 1,692 students was selected to participate in the study. A multinomial logit model was developed to predict student performance based on significant predictors, including age, marital status, monthly budget for social networks, monthly stipend, and daily private study time on social media. The results showed that age, marital status, monthly social network subscription budget, monthly stipend, and private study time on social media were statistically significant. The likelihood of achieving a 2.40–3.49 CGPA was highly dependent on age, marital status, monthly budget for social media subscription, and private study time with p-values of 0.018, 0.000, 0.000, and 0.000 respectively. Those students who studied less than 1 hour and those who spent 1-2 hours daily on social media were more likely to attain a 2.40-3.49 CGPA. Additionally, a 1.50-2.39 CGPA was influenced by monthly stipend, marital status, and daily private study time on social media with p-values of 0.017, 0.000, and 0.000 respectively.

Introduction

Multinomial logistic regression (MLR) is employed when dependent variables involve three or more categories. This explains the correlation between the dependent variable and the independent variable when their values are obtained with rating scales (Hosmer et al., 2013). It is a simple extension of binary logistic regression that allows for more than two categories of the dependent or outcome variables. Like binary logistic regression, multinomial logistic regression uses maximum likelihood estimation to evaluate the probability of categorical membership. It does necessitate careful consideration of the sample size and examination for outlying cases. Like other data analysis procedures, initial data analysis should be thorough and include careful univariate, bivariate, and multivariate assessment. MLR is often considered an attractive analysis because; it does not assume normality, linearity, or homoscedasticity. MLR model is generally used when the categorical response variable has more than two levels or categories. MLR model permits simultaneous comparison of more than one difference; that is, the log odds of three or more differences are estimated simultaneously (Garson, 2009).

Social media is a computer-mediated tool that allows students to create, share, and exchange information, ideas, pictures, and videos for virtual communities and learners. It was widely accepted by the public. Numerous online networking platforms include but are not limited to Facebook, Twitter, Instagram, Pinterest, YouTube, LinkedIn, Google+, Flickr, Snapchat, Vine, and Tumblr. The capacity of social media networking to spread valuable data quickly has made it the quickest-developing method of association. It has also changed numerous businesses; however, the most impact of it is in classroom teaching and the overall education system. It is generally used regularly by millions of people across the globe for different reasons. A big portion of social media users are made up of youths and most of them are college students (Alwaleed Al-Hugail et al., 2014). Students have easy access to the internet and engage in social networking activities. Since its inception, the number of users has steadily increased, especially among students, who are subjected to a great deal of neglect and challenges in their academic performance, resulting in a rapid decline in educational quality (Shahbub Alam, 2021). Social media networking is sharing and generating knowledge, and these features are of great value in the context of higher education. It plays an important role in the field of education and student's life. It is easier and more convenient to access information, provide information, and communicate via social media. Teachers and students are connected and can make use of these social media platforms for the working of their education. Professors are expanding their social media usage to host live lectures, offer off-hours, support for students, or even host student debates. It helps teacher educators to be connected to their students off campus as well as with their ex-students. Teacher Educators use social media as a way of teaching by creating groups and accounts for students where the information can be accessed. Teacher educators can share ideas and point students to Skype, WhatsApp, LinkedIn, and Facebook. The advantages of using social media for educational purposes are far-ranging.

Statement of the Problem

The Internet is the most important source of information and the growing dimensions of the use of social media by students cannot be underestimated. Students use social media anywhere and at any time where an internet connection is available to meet their educational needs (Dewing, 2010). On the contrary, some dangers are associated with social networking sites such as E-crime, internet addiction, laziness, standard crime like fraud, kidnapping, immoral acts like pornography, prostitution, and cyber-bullying (Odoh, 2014). Students at all levels, especially tertiary level have been engaged in the use of social networking sites (SNSs). It is therefore crucial to understand the degree to which social media impacts students' academic performance using a multinomial logistic regression model.

Aim and Objectives

This study aims to investigate the effects of social media on the academic performance of students using multinomial regression analysis. The specific objectives of the study are to:

i. Investigate the effect of daily private study time using social media on academic performance.
ii. Examine the effect of age distribution on academic performance
iii. Investigate the significance of monthly subscriptions for social networks on academic performance.

Background

Several studies have been conducted to assess the association between social media use by college students and academic performance. Foster et al. (2019) used an interview protocol to examine the influence of some selected demographic, homes-related, school-related, teachers-related, and pupils-related factors as predictors on pupils' Basic Education Certificate Examination (BECE) performance in mathematics as categorical response variable (upper grade, average grade, and lower grade) using multiple logit model. A combination of systematic and simple random sample of 62 pupils was selected from a cohort of BECE candidates of University Junior High School in Cape Coast municipality. The findings showed that the age of pupils and class size were significant in the two models. The findings in the first model show that the incidence of upper grades in BECE mathematics is largely dependent on the age of pupils and class size, with younger pupils exhibiting significantly upper grades than older pupils, and with pupils in smaller class sizes showing significantly upper grades than those in large class size respectively. In the second model, the occurrence of average grades in BECE mathematics is also largely dependent on the age of pupils and class size, with younger pupils exhibiting significantly average grades than older pupils, and with pupils in smaller class sizes showing significantly average grades than those in large classes respectively.

Other significant predictors in the first model are gender, school location, and homework, and in the second model, parental educational level. The study concluded that pupils who lack the benefit of the factors especially (school location, class size, self-homework undertaking, and parental education) have a high probability of recording poor performance (lower grades) at BECE mathematics. Mushtaq et al. (2018) investigated the positive and negative effects of social media on the academic performances of students at Alberoni University of Afghanistan. Using a quantitative approach to collect the relevant data, the authors administered 371 survey questionnaires among the undergraduates in nine faculties. The authors concluded that despite public views concerning the misuse of social media among students in society, most of the students were interested in using social media positively for their educations. The positive impacts of social media among undergraduates appeared to be higher as compared to negative impacts.

However, the results of ANOVA showed that there were no statistically significant differences between the positive and negative impact of social media and students' academic achievements. The authors concluded that educators and students could use social media as informational and communicational tools to improve the learning process. Alamri et al. (2020) examined the Social Media Applications (SMA) factors used for active collaborative learning (ACL) and engagement (EN) to assess the student's academic performance in measuring education sustainability, as well as examining their satisfaction from its use. The study employed constructivism theory and the technology acceptance model (TAM) as the investigation model. Using structural equation modeling for data analysis, the results showed that all the hypotheses were supported and positively related to sustainability for education, confirming significant relationships between the use of SMAs and the rest of the variables considered in the model (interactivity with peers (IN-P), interactivity with lecturers (IN-L), ACL, EN, perceived ease of use (PEOU), perceived usefulness (PU), SMA use, student satisfaction (SS), and students' academic performance (SAP). Palla and Sheikh (2021) investigated the impact of social media usage on the academic performance of college students in Kashmir, using a structured survey questionnaire. Their study findings showed that many of the students use social media networking sites to fulfill their educational needs. YouTube is the most used social media network among undergraduate students. Most of the students feel that social media networks are easy to use, and they have been using these sites for the past three years. Sivakumar (2020) examined the effects of social media on the academic performances of students in Cuddalore District. The survey method was adapted to collect the relevant data for the study.

It was concluded that despite public views concerning the misuse of social media among students in society, most of the school students were interested in using social media positively for their academic purposes. However, the results of ANOVA showed that there were significant differences between academic achievement and impact of social media among Students. The authors suggested that educators and students could use social media as teaching and learning tools to ease and improve the learning process. Contrary to Sivakumar's (2020) results, Lau (2017) examined whether and how social media usage and social media multitasking predict academic performance among university students. From a sample of 348 undergraduate students at a comprehensive university in Hong Kong, the study found that using social media for academic purposes was not a significant predictor of academic performance as measured by cumulative grade point average, whereas using social media for nonacademic purposes (video gaming in particular) and social media multitasking significantly negatively predicted academic performance. Gaspar et al. (2017) focused on the use of a multinomial logistic regression model to analyze the determinants of students' academic performance in mathematics. A simple random sample of 393 students was selected from a cohort of first-year students of Zamse Senior High/Technical in the Bolgatanga Municipality. A questionnaire was used to gather data from the students. The results indicated that the occurrence of good performance in mathematics is largely dependent on the sex of students with male students showing significantly good performance than female students. Another significant predictor of good academic performance in mathematics was the age of students, with younger students exhibiting good academic performance than older students.

Mother's employment also contributed significantly to good performance in mathematics with students whose mothers were employed showing better academic performance than their counterparts whose mothers were not employed. Abiodun et al. (2015) examined the academic performance of undergraduate students using multinomial logistics regression and their findings showed that the sex of students and mode of admission significantly affect the level of academic performance and that male students were likely to have higher performance than female students. The residential status of students was also found to have a significant effect on the academic performance of undergraduate students with residential students exhibiting a higher performance compared to non-residential students.

Method

Multinomial Logistic Regression Model

The multinomial Logistic Regression model is believed by many statisticians to be the most important tool that can be applied to analyze categorical data. It is employed when dependent variables involve three or more categories. This explains the correlation between the dependent variable and the independent variable when their values are obtained with rating scales (Hosmer et al., 2013).

Sources of Data

This study was focused on the academic performance of students, a case study of Joseph Sarwuan Tarka University, Makurdi Benue State, Nigeria. The participants were enrolled during the 2018-2019 academic year. Data associated with their academic performance were collected as well as their demographic and social media data such as Cumulative Grade Point Average (CGPA), monthly subscription to social networks, daily private study time on social media, age, marital status, monthly stipend, and residency. Five academic departments were randomly selected including Mathematics, Statistics & Computer Science, Animal Breeding, Crop & Environmental Protection, Agricultural Economics, and Soil Science. A random sample of 1,692 students was selected to participate in the study. A total of 877 responses were received yielding a 51% return rate as presented in Table 1.

Table 1. Sample selection with the number of responses

Department	Sample	Response
Animal Breeding	400	196
Agric. Economics	291	166
Crops & Environmental Protection	221	141
Math/Stat./Computer Science	538	225
Soil Science	242	149
Total	**1692**	**877**

Statistical Model

The general multinomial logit model is given as:

$$log\left(\frac{\pi_i}{1-\pi_i}\right) = \beta + \sum_{j=1}^{p} \beta_i X_j \quad (1)$$

where π is a conditional probability of the form $p(y = 1/x_1, \ldots\ldots x_p)$. That is, it is assumed that success is more or less likely depending on the combination of values of the predictor variables. With logistic functions given as:

$$\pi_i = \frac{e^{\beta+\sum_{j=1}^{p}\beta_i X_j}}{1+e^{\beta+\sum_{j=1}^{p}\beta_i X_j}} \quad (2)$$

$$1-\pi_i = \frac{1}{1+e^{\beta+\sum_{j=1}^{p}\beta_i X_j}} \quad (3)$$

where $j = 1,2,3,..,p;\ i = 1,2,\ldots,n.$

Let y denote the level of the student's Cumulative Grade Point Average (CGPA).

$y_1 = 1: 3.50 - 4.49(second\ class\ upper).$
$y_2 = 2: 2.50 - 3.49(second\ class\ lower)$
$y_3 = 3: 1.50 - 2.49(third\ class\ lower)$

Then the logic function of a student scoring second class lower, and third class lower relative to second class upper can be modeled in two logits as follows:

$$\text{Log}\left(\frac{\pi(y=2/xiAGE+\cdots+MRS)}{\pi(y=1/xiAGE+\cdots+MRS)}\right) = \beta + \beta_{21}AGE + \cdots + \beta_{26}MRS \quad (4)$$

$$\text{Log}\left(\frac{\pi(y=3/xiAGE+\cdots+MRS)}{\pi(y=1/xiAGE+\cdots+MRS)}\right) = \beta + \beta_{31}AGE + \cdots + \beta_{36}MRS \quad (5)$$

Hence, the corresponding probabilities for equations 4 and 5 are:

$$\pi i\ (second\ class\ upper) = \frac{1}{1 + \sum_{j=1}^{2} e^{\beta_j x_i}} \quad (6)$$

$$\pi i\ (second\ class\ lower) = \frac{e^{\beta+\beta_2 x_i}}{1+\sum_{j=1}^{2} e^{\beta_j x_i}} \quad (7)$$

$$\pi i\ (third\ class\ ) = \frac{e^{\beta+\beta_3 x_i}}{1 + \sum_{j=1}^{2} e^{\beta_j x_i}} \quad (8)$$

Statistical software was used to fit the models, and the maximum likelihood (ML) method was used to estimate the model parameters (Chatterjee & Handi, 2006). The dependent variable is the student's CGPA which has three categorical levels with second class upper (3.50-4.49) coded as 1, second class lower (2.40-3.49) coded as 2, and third class (1.50-2.39) coded as 3.

Assumptions of the Multinomial Logistic Regression Model

Some assumptions of multinomial logistic regression are defined below:

i. Dependent variables should be measured at the nominal level with more than or equal to three values.
ii. It should have one or more independent variables that are continuous, ordinal, or nominal (including dichotomous variables). However, ordinal independent variables must be treated as being either continuous or categorical.
iii. It should also have independence of observations, and the dependent variable should have mutually exclusive and exhaustive categories (i.e. no individual belonging to two different categories).
iv. There should be no multicollinearity. Multicollinearity occurs when you have two or more independent variables that are highly correlated with each other.

The method of maximum likelihood estimates the parameters of the multinomial logistic regression model by maximizing the likelihood function.

$$g(y_1, \ldots, y_1) = \prod_{i=1}^{n}\left[\frac{n!}{\prod_{j=1}^{J} y_{ij!}} \prod_{j=1}^{J} p_{ij}{}^{y_{ij}}\right] \quad (9)$$

The log-likelihood function of the parameters to be estimated is:

$$L(\beta) = \sum_{i=1}^{n}\sum_{j=1}^{J-1}\left(y_{ij}\sum_{k=0}^{k} x_{ik}\,\beta_{ki}\right) - n_i \log\left(1 + \sum_{j=1}^{J-1}\exp\left(\sum_{k=0}^{K} x_{ik}\beta_{kj}\right)\right) \tag{10}$$

The significance of a single predictor variable in logistic regression is tested using the likelihood ratio test and Wald statistic. 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 maximum likelihood estimate of the parameter. The test statistic is defined as G (likelihood test) is compared with Chi-square distribution with 1 degree of freedom.

$$G = -2\ln\frac{L0}{L1} = -2(\ln L_0 - \ln L_1) \tag{11}$$

A Wald test was conducted to measure the significance of each independent variable toward the dependent variable.

$$W_k = \left(\frac{\widehat{\beta}_k}{standard\ error\ (\widehat{\beta}_k)}\right)^2 \tag{12}$$

$\hat{\beta}_k$ is the $k-th$ estimated regression coefficient.

Pseudo R square has been developed in logistic regression to provide measures of the usefulness of the model. The Cox and Snell's R square is given as:

$$R^2 = 1 - \left[\frac{L(M_{intercept})}{L(M_{full})}\right]^{2/n} \tag{13}$$

The Nagelkerke's R square is given as:

$$R^2 = \frac{1-\left[\frac{L(M_{intercept})}{L(M_{full})}\right]^{2/n}}{1-[L(M_{intercept})]^{2/n}} \tag{14}$$

$L(M_{intercept})$ is the likelihood of the intercept model,

$L(M_{full})$ is the likelihood of the full model.

McFadden's R square, which is defined as:

$$R^2McF = 1 - \frac{\ln L_M}{\ln L_0} \tag{15}$$

Where L_0 is the value of the likelihood function for a model with no predictors (i.e. with intercept only), and L_M is the likelihood function for the model being estimated. The ratio of the McFadden R square indicates the level of improvement over the intercept model offered by the full model.

Results

This section presents the results of the findings. It presents the result of model fitting information, goodness of fits, pseudo-R-square, likelihood ratio test, and parameter estimates. Chi-square statistics were used to assess the overall effectiveness of the model. Table 2 indicates that the model fits the data significantly better than the null model since the p-value (sig.) is less than 0.05

Table 2. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ration Test		
	-2Log Likelihood	Chi-Square	df	Sig
Intercept Only	1245.738			
Final	1060.484	185.255	30	0.000

The value of the Chi-square statistic might not indicate how strong or the extent to which the association between the dependent variable and the independent variables is. As a result, the Pseudo R-squared measures were used to determine the strength of association. Considering Table 3, all three measures (Cox and Snell, Nagelkerte & McFadden) values indicate weak correlations between the dependent variable and the set of independent variables since the values are greater than 0.05.

Table 3. Pseudo R-Square

Cox and Snell	0.190
Nagelkerke	0.216
McFadden	0.099

The Likelihood ratio test is used to assess the contribution of each variable to the model. Table 4 shows that each variable contributes significantly to the model except location since p-values are less than 0.05.

Table 4. Likelihood Ratio Test

Effect	Model Fitting Criteria	Likelihood Ratio Test		
	-2Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	1060.484	0.000	0	.
Age	1089.500	29.017	6	0.000
MRS	1098.059	37.576	2	0.000
Loc	1061.229	0.746	2	0.689
MTS	1085.586	25.102	6	0.000
MTB	1118.280	57.797	8	0.000
PST	1106.360	45.876	6	0.000

Note: MRS (Marital status), Loc (Location), MTS (Monthly subscription), MTB (Monthly budget), and PST (Private study time on social media).

The goodness of fits is used to assess the model whether the model adequately fits the data. The result of the goodness of fits from Table 5 indicates that in the predictions by the model, the observed values were significantly different from the predicted values hence the model does not adequately fit the data since the p-value is less than 0.05.

Table 5. Goodness of Fits

	Chi-Square	df	Sig
Pearson	983.124	232	0.000
Deviance	912.999	232	0.000

The parameter estimates table summarizes the effect of predictor variables.

Table 6. Parameter Estimates

CGPA		B	Sig.	Exp(B)
	Intercept	-1.863	0.08	
	Age-1	3.371	0	29.115
	Age-2	1.976	0.025	7.214
	Age-3	2.124	0.016	8.363
	Age-4	0	.	.
	MRS-1	-2.249	0	0.106
	MRS-2	0	.	.
	Loc-1	-0.077	0.676	0.926
2.40-3.49	Loc-2	0	.	.
	MTS-1	0.651	0.289	1.918
	MTS-2	0.765	0.207	2.148
	MTS-3	0.038	0.096	3.14
	MTS-4	0	.	.
	MTB-1	0.963	0.001	2.62
	MTB-2	0.974	0	2.649
	MTB-3	0.038	0.918	1.038
	MTB-4	-0.316	0.427	0.729
	MTB-5	0	.	.
	PST-1	1.872	0	6.502
	PST-2	1.096	0.001	2.992
	PST-3	0.563	0.079	1.756
	PST-4	0	.	.
	Intercept	-0.311	0.752	.
	Age-1	0.399	0.655	1.49
	Age-2	-0.587	0.438	0.556
	Age-3	0.044	0.954	1.045
	Age-4	0	.	.

CGPA		B	Sig.	Exp(B)
	MRS-1	-0.954	0.049	0.385
	MRS-2	0	.	.
	Loc-1	-0.189	0.39	0.828
1.50-2.39	Loc-2	0	.	.
	MTS-1	0.996	0.153	2.708
	MTS-2	0.345	0.619	1.412
	MTS-3	-0.928	0.354	0.395
	MTS-4	0	.	.
	MTB-1	0.261	0.479	1.298
	MTB-2	0.473	0.15	1.605
	MTB-3	0.947	0.018	2.579
	MTB-4	0.925	0.021	2.522
	MTB-5	0	.	.
	PST-1	0.803	0.181	2.232
	PST-2	0.497	0.122	1.644
	PST-3	-0.76	0.027	0.468
	PST-4	0	.	.

Note: Age (1: below 20, 2: 20-25, 3: 26-30, 4: 30 and above); Marital Status (MRS) (1: single, 2: married); Location (Loc) (1: On-campus, 2: Off-campus); Monthly Stipend (MTS) (1: less than $20, 2: $20-$40, 3: $40-$50, 4: $50 and above); Monthly Budget for social media (MTB) (1: below $2, 2: $2-$4, 3: $4-$6, 4: free mode, 5: $6 and above); Daily Private Study Time on social media (PST) (1: less than 1hr, 2: 1-2hrs, 3: 3-4hrs, 4: 4hrs and above).

Regarding the two logistic regression models, the “second class upper (3.50-4.49)” forms the baseline category against which the other two classes are directly compared. From Table 7, Age-1, Age-2, Age-3, MRS-1, MTB-1, PST-1, and PST-2 were significant in 2.40-3.49 while MST-1, MTB-3, MTB-4, and PST-3 were significant in 1.50-2.39.

Table 7. Logit Parameter Estimates

Predictor		Coefficient	P	Exp(B)
Logit 1	Constant	0.5538	0.346	
	Age	-0.3520	0.018	0.70
	MRS	2.0602	0.000	7.85
	Loc.	0.1503	0.401	1.16
	MTS	0.0893	0.503	1.09
	MTB	-0.3493	0.000	0.71
	PST	-0.4893	0.000	0.61
Logit 2	Constant	-0.1856	0.789	
	Age	0.2653	0.123	1.30

Predictor		Coefficient	P	Exp(B)
	MRS	1.0597	0.017	2.89
	Loc	0.2126	0.312	1.24
	MTS	-0.5995	0.000	0.55
	MTB	-0.0164	0.824	0.98
	PST	-0.5373	0.000	0.58

Table 7, logit 1 (second class lower) shows that Age, Marital status, monthly budget for network subscription, and daily private study time on social media were significant. In contrast, marital status, monthly stipend, and daily private study time on social media were significant in logit 2 (Third class lower).

$$\mathrm{Log}\left(\frac{\pi(y=2/Age+..+PST}{\pi(y=1/xiAge+..+xiPST}\right) = 0.5538 - 0.3520Age + 2.0602MRS - 0.3493MTB - 0.4894PST \tag{16}$$

$$\mathrm{Log}\left(\frac{\pi(y=3/MRS+...+xiPST}{\pi(y=1/MRS+.\ ..+PST}\right) = -0.1856 + 1.0597MRS - 0.5995MTS - 0.5373PST \tag{17}$$

Discussion

The result from Table 2 indicates that the model fits the data significantly better than the null model since the p-value is less than 0.05. Considering the values in Table 3, all three values indicate weak correlations between the dependent variable and the set of independent variables. From Table 4, the results showed that each variable has a significant contribution to the model except location since p-values are less than 0.05. The result of the goodness of fits from Table 5 showed that in the predictions by the model, the observed values were significantly different from the predicted values hence the model does not adequately fit the data since the p-value is less than 0.05. From Table 6, the results of the second class lower relative to second class upper showed that students who are below age 20yrs, 20 to 25yrs, and 26 to 30yrs are more likely to obtain second class lower relative to second class upper than those above 30yrs of age with significance values 0.0, 0.025, 0.016 respectively, controlling other predictor variables.

In order words, students who are below 20 years of age are 29 times more likely to have second class lower than those above 30 years. Students aged 20 to 25 are 7 times more likely to obtain second class lower than those of 30 years and above and those of age 26 to 30 are 8 times more likely to obtain second class lower than those of age 30 and above considering the odds values. The result further indicated that students who are married are more likely to have second class lower relative to second class upper than the single with a p-value of 0.0 holding other predictor variables constant. This means that students who are married are 9 times more likely to have second class lower than the single. The result also showed that students who budgeted below \$2 and \$2 to \$4 for monthly network subscriptions are more likely to obtain second-class lower relative to second-class upper than those budgeted \$6 and above with p-values 0.001, and 0.0 respectively. In other words, students who budgeted below \$2 and \$4 to \$6 are 3 times more likely to have second class lower than those budgeted \$6 and above. Interestingly, students who spent less than 1hr, and those who spent 1hr to 2hrs for private studies on social media are more likely to obtain second-class lower relative to second-class upper than those who spent 3hrs and above with significance values 0.00, 0.001 respectively controlling other predictor variables. In order words, students who spent less than 1 hour for private studies on social media are 7 times more likely to obtain second class lower, and those who spent 1 to 2 hours are 3 times more likely to obtain second class lower.

The results of third class lower relative to second class upper showed that those students who budgeted \$4 to \$6 for monthly network subscription and those using free mode are more likely to obtain third class relative to second class upper than those budgeted \$6 above with significance values 0.018 and 0.021 respectively. This means that students who budgeted \$4 to \$6 and those using free mode are 3 times more likely to obtain third class than those who budgeted \$6 and above.

From Table 7, logit 1 (second class lower) showed that Age, Marital status, monthly budget for network subscription, and daily private study time on social media were significant indicating that the chance of having second class lower instead of second class upper is largely dependent on age, marital status, monthly budget and daily private study time on social media with significance values 0.018, 0.000, 0.000 and 0.000 respectively. Also, from logit 2 (third class lower), marital status, monthly stipend, and daily private study time on social media were significant which indicated that the chance of obtaining third class instead of second-class upper is significantly dependent on marital status, monthly stipend and monthly budget with p-values 0.017, 0.000, and 0.000 respectively.

Conclusion

A multinomial logit model was developed to predict the students' performance based on significant predictors. The findings showed that age, marital status, monthly budget for social networks, and daily private study time were significant for the second class while marital status, monthly budget for network subscription, and private study time were also significant for the third class. The finding in the second class lower versus second class upper showed that the chance of obtaining second class lower is largely dependent on age, marital status, monthly budget for subscription, and private study time. Also, students who are below age 30yrs exhibit significantly second class lower than those of 30yrs and above, students who are married obtained second class lower than the single ones, those budgeted below \$2, \$2 to \$4 for monthly network subscription exhibiting significantly second class lower than those budgeting \$6 above, finally, those that spent less than 1hr, 1 to 2hrs on daily private study time obtained second class lower than those spent 4 hours and above.

In the third class lower, the occurrence of third class is also largely dependent on marital status, monthly budget for social media, and daily private study time. Single students significantly obtain third class, those budgeted \$4 to \$6 for monthly network subscription, and those using free mode significantly exhibit third class. Finally, students that spent 3hrs to 4hrs for private studies on social media also significantly exhibit third class lower.

Recommendations

Based on the findings, the following recommendations are made:

i. Students who spend less time on private study using social media are more likely to obtain lower academic grades. Institutions should encourage students to allocate more time for focused academic work, perhaps by providing training on effective study habits, reducing distractions, and promoting digital literacy that emphasizes academic use of social media.
ii. The result showed that younger students (below 30 years) are more likely to obtain second-class lower relative to second-class upper. To address this issue, universities could implement targeted interventions, such as academic support programs, counseling, or time management workshops for students in this age group to enhance their academic performance.
iii. The analysis shows that students with lower monthly budgets for network subscriptions are more likely to perform poorly. Institutions could provide subsidized or free access to educational resources, especially internet access, to students who are financially constrained. This would help reduce the impact of budget limitations on their academic outcomes.
iv. For Students with a limited monthly stipend, particularly those budgeting less than $6 for network subscriptions monthly or using free modes, increasing financial support or scholarships for students may help in improving academic performance. This could involve collaborations with telecommunications companies to provide affordable internet packages for students

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