Modeling Students' Attendance with Respect to Lecturers' Qualities/Attributes

B. T. Babalola[1*], A. O. Olubiyi[1] and M. I. Adarabioyo[2]

[1]*Department of Statistics, Ekiti State University, Ado Ekiti, Ekiti State, Nigeria.*
[2]*Department of Mathematical and Physical Sciences, Afe Babalola University, Ado Ekiti, Ekiti State, Nigeria.*

Authors' contributions

This work was carried out in collaboration between all authors. Author BTB designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors AOO and MIA managed the analyses of the study and managed the literature searches. All authors read and approved the final manuscript.

Original Research Article

ABSTRACT

Aim: This research work was conceived and executed to investigate the impact of University lecturers' attitude inside and outside the lecture rooms on the students' decision on whether or not to attend their lectures.
Study Design: Questionnaires were randomly distributed to students.
Place and Duration of study: Ekiti State University, Ado-Ekiti, Nigeria. The study was carried out between November 2016 to April 2017.
Methodology: 300 University undergraduate students were sampled. Some basic factors (punctuality, charisma, motivation and so on) were considered as explanatory variables. Students' attendance was scaled in percentage and the predictors being categorical variables were measured using a Likert scale. The ordinal logistic regression was employed.
Results: The result shows that some of the factors significantly affect the students' attendance. Out

_____

Corresponding author: E-mail: teniolababa@gmail.com;

of all the 8 (eight) factors only 6(six) are actually statistically significant which are: punctuality, inspiration, eloquence, joviality, intelligence and motivation.
Conclusion: The fitted model can be used to predict the different probabilities of all the possible outcomes of any attendance to a certain degree given the conditions of the students involved.

1. INTRODUCTION

Education is the process of facilitating learning, or the acquisition of knowledge, skills, values, beliefs, and habits. Educational methods include storytelling, discussion, teaching, training, and directed research. Education can take place in formal or informal settings and any experience that has a formative effect on the way one thinks, feels, or acts may be consider educational. As an academic field, philosophy of education is "the philosophical study of education and its problems and its central subject matter is education, and its methods are those of philosophy".

Academic achievement or (academic) performance is the outcome of education. The extent to which a student, teacher or Institution has achieved their educational goals. Academic achievement is commonly measured by examinations or continuous assessment but there is no general agreement on how it is best tested or which aspects are most important.

Attendance is the concept of people, individually or as a group, appearing at a location for a previously scheduled event. Measuring attendance is a significant concern for many organizations and of course Universities, which can use such information to gauge the effectiveness of their efforts and to plan for future efforts.

DeKalb [1] reported that Students must be present in school in order to benefit from the academic program in its entirety. Schools and law enforcement officials are getting tough by enforcing laws that mandate school attendance and by holding parents responsible for their student's attendance. Student non-attendance is a problem that extends beyond the school. It affects the student, their families, and the community (DeKalb, 1999; U. S. Department of Education) [1].

Educators, parents, and politicians are continuously searching for that magic solution that will reform our public education system and establish a flawless system of education for our youth, by providing them with a quality education [2]. "The success of the school in carrying out its primary charge of educating and socializing students is contingent on students attending school regularly" [3]. Papadakis, S. [4], discussed the actions and benefits of an e-learning project called the eTwinning in is paper. One of the benefits of the scheme is to enhance lecturers and students ability to make use of new technologies.

Students' views about attendance policies are unclear. Chenneville and Jordan's [5] research showed that only 20% of students were in favour of attendance policies, yet 71% reported that they were less likely to miss classes for classes where an attendance policy was in place. Launius [6] found that 84% of (Psychology) undergraduates said their attendance would improve if they were to receive credit for attendance (rewards), and Gump's research [7] found that 66.7% of (Introduction to Japanese Culture) undergraduates indicated they would be persuaded to attend classes if credit was given for attendance.

Michael (2010), wrote an article titled "how to motivate your students to behave better, work harder and care for each other". He listed the steps involved in doing that. Brian (2017) wrote on how teachers' dress affects students. He concluded that the way a teacher/lecturer dresses can bring a connection(positive or negative) between the lecturer and the students.

This research work is based on the outcomes of students non- attendance and attendance of lectures. We considered the causes of absenteeism of students. The research was designed to model undergraduate students' psychosocial perception of their lecturer's attitudes or qualities that may influence their decisions on whether to attend lectures or not. After listing some factors we thought could interest/disinterest a student about attending his/her lectures, the study is designed to determine which of the variable is statistically significant and consequently model the attendance.

Student's attendance was categorized into the following measurements below

1. 0% - 49% attendance(which can be seen as "good")
2. 50% - 74% attendance (which can be seen as "better")
3. 75% - 100% attendance.(which can be seen as "best")

The study is aimed at 1. modeling attendance outcomes (dependent variables) in terms of some predictors (independent variable). The model will enable us to obtain probabilities of each of the possible outcomes. 2. determining the goodness of fit of the model as the validity of the assumptions of the model and thereby offering useful suggestions and recommendations. 3. examining the relationship that exists between student's attendance and some predictor's factors viz: lecturer's charisma, lecturer's joviality, lecturer's punctuality, lecturer's outfits, lecturer's intelligence, lecturer's eloquence, lecturer's inspiration (inspiration that student gets from a lecturer) and lecturer's motivations. 4. obtaining the probability of students attending or not attending lectures with or without lecturers' qualities.

DEFINITION OF TERMS

- Attendance - The act of being present at a place.
- Charisma - Compelling attractiveness or charm that can inspire devotion in others.
- Punctuality -
- Outfit/grooming- The way someone cares for one's personal appearance, hygiene and clothing
- Inspirations - The process of being mentally stimulated to do or feel something, especially to do something creative.
- Eloquence - Fluent or persuasive speaking or writing.
- Joviality - The state or quality of being , merriment, jollity.
- Intelligence - The ability to acquire and apply knowledge and skills.
- Motivation – A reason or reasons for acting or behaving in a particular way, a sets of facts and arguments used in support of proposal
- Odds- It is a numerical expression of a likelihood possible event will occur. Odds are ratio of probability and its ranges from zero to infinity.

- Odds ratio – Is the ratio of ratios of probability.

1.1 Conceptual Frame Work of the Study

The model shows the identified factors and the supposed relationship these factors have on students' attendance.
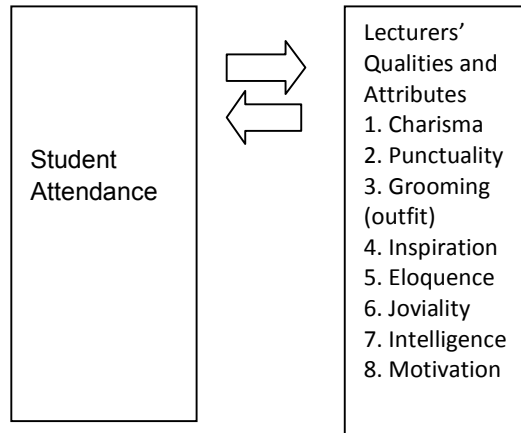
1.2 Conceptual Framework

Fig. 1. Diagram showing the relationship between student attendance and lecturers' qualities and attributes

2. MATERIALS AND METHODS

In this section, we present the material and methods employed in carrying out the research. The response variable which is students' attended was obtained as continuous data but was categorized into three groups. The predictor variables are qualitative in nature as such , they were measured using the likert scale. Their values were coded appropriately in order to allow for proper analysis of the data. The logistic regression is a suitable statistical method for handling data like this. It has some advantages over the ordinary least square regression especially when dealing with categorical data. These independent variables were modeled to reflect their relationship with the response variable using the ordinal logistic regression(which is used when the dependent variable can be ordered).

The method of analysis employed in this study is logistics survey model because it allows for accuracy of results especially when data are ranked or categorized and ordered. The data was collected using questionnaires. The

breakdown of methodology is stated in the remaining part of this section.

2.1 Logistics Regression

Logistic regression is a type of regression analysis used for predicting the outcome of a categorical dependent variable (a dependent variable that can take on a limited number of categories) based on one or more predictor variables. The probabilities describing the possible outcome of a single trial are modeled as a function of explanatory variables using a logistic function. Logistic regression measures the relationship between categorical dependent variable and usually a continuous independent variable, by converting the dependent variable to probability scores. Logistic regression can be binomial or multinomial.

Binomial or binary logistic regression refers to the instance in which the observed outcome can have only two possible types (example: "stillbirth" or "livebirth"; "yes" or "no"). Multinomial logistic regression refers to cases where the outcome can have three of more possible types (example: "better" vs. "no change" vs. "worse"). Like other forms of regression analysis, logistic regression makes use of one or more predictor, variables that may either be continuous or categorical data. Also, like other linear regression models, the expected value of a Bernoulli distribution is simply the probability of a case.

In other words, in logistic regression, the base rate of a case for the null model is fit to the model including one or more predictors. Unlike ordinary linear regression, however, logistic regression is used in predicting binary outcomes rather than continuous outcomes. Given this difference, it is necessary that logistic regression take the natural logarithm of the odds (referred to as a logit) to create a continuous criterion. The logit of success is then fit to the predictors using regression analysis. The results of the logit are not intuitive, so the logit is converted back to the odds via exponential function or the inverse of the natural logarithm.

The logit is referred to as the link function in logistic regression, although the output in logistic regression is binomial and displayed in a contingency table, the logit is an underlying continuous criterion upon which linear regression is conducted.

2.1.1 Ordinal logistic regression

Ordinal logistic regression (often just called 'ordinal regression') is used to predict an ordinal dependent variable given one or more independent variables. It can be considered as either a generalization of multiple linear regressions or as a generalization of binomial logistic regression, but this guide will concentrate on the latter. As with other types of regression, ordinal regression can also use interactions between independent variables to predict the dependent variable.

For example, you could use ordinal regression to predict the belief that "tax is too high" (your ordinal dependent variable, measured on a 4-point Likert item from "Strongly Disagree" to "Strongly Agree"), based on two independent variables: "age" and "income". Alternately, you could use ordinal regression to determine whether a number of independent variables, such as "age", "gender", "level of physical activity" (amongst others), predict the ordinal dependent variable, "obesity", where obesity is measured using three ordered categories: "normal", "overweight" and "obese".

Ordinal variables may also be independent or intervening variables in structural equation models. For example, job tenure, a continuous variable, may depend on job satisfaction, an ordinal variable measured on a Likert scale, as well as on other variables. Job satisfaction in turn may depend on characteristics of individuals and their jobs. One solution to this problem is to assume that the ordered categories constitute a continuous scale. In addition, the models described here can be extended to allow for the discrete and continuous effects of ordinal variables.

2.1.2 Fitting a logistic regression

Before delving into the formulation of ordinal regression models as specialized cases of the general linear model, let's consider a simple example. To fit a binary logistic regression model, you estimate a set of regression coefficients that predict the probability of the outcome of interest. The same logistic model can be written in different ways. The version that shows what function of the probabilities results in a linear combination of parameters is

$$ln\left(\frac{prob(events)}{(1-prob(events))}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_K X_K$$

The quantity to the left of the equal sign is called a logit. It's the log of the odds that an event occurs. (The odd that an event occurs is the ratio of the number of people who experience the event to the number of people who do not. This is what you get when you divide the probability that the event occurs by the probability that the event does not occur, since both probabilities have the same denominator and it cancels, leaving the number of events divided by the number of non-events.) The coefficients in the logistic regression model tell you how much the logit changes based on the values of the predictor variables.

Defining the Event

In ordinal logistic regression, the event of interest is observing a particular score *or* less. For the rating of judges, you model the following odds:

P_1 = prob(score of 1) / prob(score greater than 1)
P_2 = prob(score of 1 or 2) / prob(score greater than 2)
P_3 = prob(score of 1, 2, or 3) / prob(score greater than 3)

The last category does not have an odds associated with it since the probability of scoring up to and including the last score is 1.

All of the odds are of the form = prob (score $\geq j$) / prob (score $> j$)

You can also write the equation as = prob (score $\geq j$) / (1 – prob (score)),

Since the probability of a score greater than j is 1 – probability of a score less than or equal to j.
The logit link function was used for this study.

2.1.3 **Fitting an Ordinal Logit Model**

The Polytomous universal model or the SPSS ordinal logistic regression procedure is an extension or a special case of the general linear regression model. Logistic regression model is written as:

$$Y_i = x_i' \beta + \varepsilon_i \qquad (1)$$

The same logistic model can be written in different ways. The version that shows what function of the probabilities results in a linear combination of parameters is:

$$\ln\left(\frac{prob(event)}{1 - prob(event)}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k \qquad (2)$$

$$\ln\left(\frac{\sum \Pr(Y < j / X)}{1 - \sum \Pr(Y < j / X)}\right) = \alpha_j + \beta_i X_i$$
$$i=1,2,\dots\dots k \quad j=1,2,\dots\dots p-1 \qquad (3)$$

α_j or β_0 is called the threshold. β_j is called parameter estimates and X_i are sets of factors or predictors. The quantity on the left hand side of equation (3) is called logit and it is the log of odds that an event occurs. The method that will be used to find the parameter estimates (β_0, β_1,…… β_k) is the method of maximum likelihood function. The maximum likelihood estimate (MLE) can be obtained as follows;

Suppose Y ~ Bernoulli (π_i), where

$$\pi(x) = F (\alpha_1 + \beta_i X_i)$$

Then, the likelihood function is

$$L (\alpha, \beta/y) = \prod_{i=1}^{n} \pi(x_i)^{y_i} \left\{1 - \pi(x_i)\right\}^{1-y_i}$$

Let $\pi(x_i)$ be written as F_i, then

$$L(\alpha, \beta/y) = \prod_{i=1}^{n} F_i^{y_i} \left(1 - F_i\right)^{1-y_i}$$

The log likelihood is *Log L(α, β/y)*

$$= \sum_{i=1}^{n} \left\{y_i \log F_i + (1 - y_i) \log(1 - F_i)\right\}$$

By expanding the above expression, we have

$$= \sum_{i=1}^{n} \left\{y_i \log F_i + \log(1 - F_i) - y_i \log(1 - F_i)\right\}$$

$$= \sum_{i=1}^{n} \left\{y_i \log F_i + \log(1 - F_i) - y_i \log(1 - F_i)\right\}$$

This can also be rewritten as

$$= \sum_{i=1}^{n} \left\{y_i \log\left(\frac{F_i}{1 - F_i}\right) + \log(1 - F_i)\right\} \qquad (4)$$

The MLE values of α and β can be obtained by differentiating equation (4) with respect to α and β and the setting the two equations to zero and then solve.

$$\text{let } \frac{dF(w)}{dw} = f(w)$$

$$\text{then } \frac{\partial \log(1-F)}{\partial \alpha} = -\frac{f_i}{1-F_i} = -\frac{F_i f_i}{F_i(1-F_i)}$$

$$\frac{\partial}{\partial \alpha} \log\left(\frac{f_i}{1-F_i}\right) = \frac{f_i}{F_i(1-F_i)}$$

Therefore,

$$\frac{\partial}{\partial \alpha} \log L(\alpha, \beta / y) = \sum_{i=1}^{n} (y_i - F_i)\left(\frac{f_i}{1-F_i}\right) \quad (5)$$

By similar argument,

$$\frac{\partial}{\partial \beta} \log L(\alpha, \beta / y) = \sum_{i=1}^{n} (y_i - F_i)\left(\frac{f_i}{1-F_i}\right)x \quad (6)$$

It is better to set equation (5)and (6) to zero and then solve for α and β.

2.2 Sample and Data Collection

The sample consists of only year 2 – year 5 students in different faculties in Ekiti State University and 300 students were chosen randomly(simple random sampling) as the research sample for the data. Pre-degree and year 1 students were excluded from the sample .It is well known that a student of such level may not be able to say if a lecturer is good or not because they are just beginners and not all might know all the lecturers in general. The source of data collection adopted in this research is primary data through the use of questionnaire. The questionnaire contains questions about the students' demographical data(age, sex, level to mention a few). In another section of the questionnaire, questions was asked about lecturers' attitudes and qualities. The researchers' administered 300 copies of the questionnaire and the questionnaire was administered to undergraduate students of Ekiti State University.

2.2.1 ROC Curve

A measure of goodness-of-fit often used to evaluate the fit of a logistic regression model is based on the simultaneous measure of sensitivity (true positive) and specificity (true negative) for all possible cutoff points. First, the sensitivity in calculated and specificity pairs for each possible cutoff point and plot sensitivity on the y axis by (1-specificity) on the x axis. This curve is called the receiver operating characteristic (ROC) curve. The area under the ROC curve ranges from 0.5 and 1.0 with larger values indicative of better fit.

3. RESULTS AND DISCUSSION

This section presents the results and implications of the findings. Table 1 shows the frequencies of the three groups of the students' attendance.

Table 1. Students' attendance

Percentage of lectures	No of students attending	Percentage
0%-49%	32	10.7%
50%-75%	102	34%
76%-100%	166	55.3%

Descriptive statistics show that students who attended 0% - 49% lectures, 50% - 75% and 76% - 100% are 32(10.7%), 102(34%) and 166(55.3%) respectively.

From Table 2, we can see that 94% of the students confessed that a lecturer's charisma is one of the qualities that influence student's attendance while 6% of the remaining students said it does not affect anything. On the other hand, 75.3% of the same students said that lecturer's punctuality is one of the qualities that influence student's attendance while 24.7% of the remaining students said No. Furthermore, 83.7%, 82.3%, 81%, 83.3%, 84.7%, 81%, of the same students said Yes that lecturer's outfits, lecturer's inspiration (inspirational word from the lecturer's statement during lectures), lecturer's eloquence, lecturer's joviality, lecturer's intelligence, and lecturer's motivation as one of the qualities that influences student's attendance while 24.7%, 16.3%, 17.7%, 19%, 16.7%, 15.3% and 19% of the remaining students said No.

3.1 Overall Model Test

We need to determine whether the model improves our ability to predict the outcomes.

Link function: logit

The Table 3 gives the results for the data imputed and its can be interpreted this way:

H_0: Model 1 = Model 2
H_1: Model 1 ≠ Model 2

Table 2. Summary of students' perceptions of reasons for attending lectures due to lecturers' qualities or attitudes

Lecturers' Qualities and Attributes	(No. of Students) Yes	Percentage	(No of students) No	Percentage
Charisma	282	94%	18	6%
Punctuality	226	75.33%	74	24.7
Grooming (Outfit)	251	83.7%	49	16.3%
Inspiration	247	82.3%	53	17.7%
Eloquence	243	81%	57	19%
Joviality	250	83.3%	50	16.7%
Intelligence	254	84.7%	46	15.3%
Motivation	243	81%	57	19%

Table 3. Model Fitting information

Model	-2 Log Likelihood	Chi-Square	Df	Sig.
Intercept Only	**308.505**			
Final	**91.621**	**216.884**	**8**	**.000**

Where model 1 is a model without any predictor i.e. intercept model and model 2 is a model with predictors. Since the Chi-square value which is 216.884 > 15.51= $\chi^2_{(0.05,\ 8)}$ and with is p-value =0.00<0.05, we then rejects the null hypothesis that states that the model without predictors is good as model with predictors. (i.e. we rejects that all explanatory variables are equal to zero).

3.2 Goodness of Fit Test

We can test the goodness of fit using the result obtained from our analysis provided by Table 4 compared to the tabulated values of Chi-square.

Table 4. Goodness-of-Fit

	Chi-Square	Df	Sig.
Pearson	58.052	92	.998
Deviance	59.094	92	.997

Link function: logit

H_0: Model fits is good
H_1: Model fits is not good

Good models have large observed significance levels since the goodness of fit measures have large observed significance level that is 0.998(Pearson) and 0.997(deviance) are relatively high when compared with the normal significant level (0.05), coupled with the fact that χ^2 = 58.052 < $\chi^2_{(0.05,\ 92)}$ =115.39 and P = 0.05 < 0.998 for Pearson and χ^2 =59.094 < $\chi^2_{(0.05,\ 92)}$ =115.39 and p-value = 0.05 < 0.997= P for value for deviance measure. This shows that the

observed data is consistent and it fits the model well. Since we are accepting the null hypothesis we can conclude that the model is good.

Table 5. Measuring strength of association

Cox and Snell	.515
Nagelkerke	.629
McFadden	.389

The pseudo R square were calculated based on the likelihood ratio and they are presented in Table 5.

The Nagelkerke has the highest among the pseudo R square and its value is 0.629. This reveals that the explanatory variable can account or explains 62.9% proportions of the total variation in the variable outcome. This shows a relatively high proportions and excellent predictors of the dependent. Cox-Snell and McFadden gave 0.51 and 0.389 respectively.

3.3 Test of Parallelism

When we fit logistic regression, we assume that the relationship between the independent variables and the logit are the same for all logits. This assumption is tested in Table 6.

The row labeled null hypothesis contains -2loglikelihood for the constrained model. The model that assumes the lines or planes are parallel. The row labeled general is for the model with separate planes or lines. The entry labeled chi square is the difference between the two -

2loglikelihood value. The χ^2 value = 14.128 compared with χ^2 (0.05, 8) = 15.51 and p = 0.05 < p–value = 0.129. This shows that we have chosen the right link function and this gives the assumption to proportional odds since we do not have any sufficient evidence to reject the null hypothesis(which states that there is no significant difference between the regression co-efficient across the response categories) suggesting that the model assumption of equality is satisfied.

3.4 Parameter Estimates

In this section, we discussed the estimated parameters and interpreted them.

Here we are going to use the Wald's statistic to find out which of the predictors are significant to the outcome variable. The Wald's statistic is the square of the ratio of the co-efficient to its standard error based on the observed significance level.

3.4.1 Tests for parameter significance

3.4.1.1 Lecturer's charisma

H_0: LC = 0 (lecturer's charisma has no influence on student attendance)

H_1: LC ≠ 0 (lecturer's charisma has influence on student attendance)

3.4.1.2 Test statistic

$$Z = \frac{LC}{S.E\ (LC)} = \frac{0.088}{0.595} = 0.1478$$

Z = 0.1478
$Z^2 = 0.022 < \chi^2$ (0.05, 1) = 3.841 and P-value = 0.882 > 0.05 = α

Table 6. Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	Df	Sig.
Null Hypothesis	91.621			
General	74.494	14.128	8	.129

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories'

a. *Link function: Logit.*

Table 7. Parameter Estimates

		Estimate	Std. error	Wald	Df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[atten = 2]	-5.988	.704	12.981	1	.000	1.157	3.919
	[atten = 3]	-1.254	.925	61.854	1	.000	5.460	9.085
Location	[charisma=1]	.088	.595	.022	1	.882	-1.079	1.255
	[charisma=2]	0[a]	.	.	0	.	.	
	[punctuality=1]	1.141	.388	8.642	1	.003	.380	1.902
	[punctuality=2]	0[a]	.	.	0	.	.	
	[outfits=1]	.673	.491	1.880	1	.170	-.289	1.635
	[outfits=2]	0[a]	.	.	0	.	.	
	[insp=1]	1.406	.478	8.646	1	.003	.469	2.343
	[insp=2]	0[a]	.	.	0	.	.	
	[ello=1]	1.748	.478	13.372	1	.000	.811	2.685
	[ello=2]	0[a]	.	.	0	.	.	
	[jov=1]	1.226	.558	4.819	1	.028	.131	2.320
	[jov=2]	0[a]	.	.	0	.	.	
	[intelli=1]	1.203	.558	4.642	1	.031	.109	2.297
	[intelli=2]	0[a]	.	.	0	.	.	
	[motiv=1]	1.042	.461	5.114	1	.024	.139	1.945
	[motiv=2]	0[a]	.	.	0	.	.	

It is evident that the Wald's statistic is lesser than the chi square critical, so we conclude that the null hypothesis (H_0) needs to be accepted and we say that lecturer's charisma does not have any influence on student's attendance.

3.4.1.3 Lecturer's punctuality

The Wald's statistic is greater than the chi square critical, so we conclude that H_0 needs to be rejected. The implication of this is that lecturer's punctuality has influence on student's attendance. Since it is significant, we can say how punctual a lecturer is in going for his/her lectures stimulates students to attend such lecturer's lectures.

3.4.1.4 Lecturer's outfits

The Wald's statistic is lesser than the chi square critical, so we conclude that H_0 needs to be accepted and we can then say that lecturer's outfits does not have any influence on student's attendance.

3.4.1.5 Lecturer's inspirations

It is evident that the Wald's statistic is lesser than the chi square critical, so we conclude that H_0 needs to be accepted and we say that lecturer's outfits does not have any influence on student's attendance. Furthermore, this very variable has the largest beta value and it is statistically significant, which means that it has a great effect on students' attendance.

3.4.1.6 Lecturer's eloquence

We conclude that H_0 needs to be rejected and we say that lecturer's eloquence has influence on student's attendance. Since it is significant, we can say how eloquent a lecturer is in delivering his /her lecture stimulates students to attend such lecturer's lectures.

3.4.1.7 Comment

The β (regression coefficient) value which is 1.748 is positive, which means that for a higher value of lecturer's eloquence, there are better chances or a higher probability on student's attendance.

3.4.1.8 Lecturer's joviality

It is evident that the Wald's statistic is greater than the chi square critical, so we conclude that H_0 needs to be rejected and we say that lecturer's joviality has influence on student's attendance. Since it is significant, we can say how jovial a lecturer is in delivering his /her lecture stimulates students to attend such lecturer's lectures.

The β (regression coefficient) value which is 1.226 is positive, which means that for a higher value of lecturer's joviality, there is better chance or a higher probability on students' attendance.

3.4.1.9 Lecturer's intelligence

Based on what we have above, we conclude that H_0 needs to be rejected and we say that lecturer's intelligence has influence on student's attendance. Since it is significant, we can say how intelligent a lecturer is in solving problems and explains them when delivering his /her lecture stimulates students to attend such lecturer's lectures.

3.4.1.10 Lecturer's motivation

We can safely conclude that H_0 needs to be rejected and we say that lecturer's motivation has influence on student's attendance. Since it is significant, we can say how lecturer motivates when delivering his /her lecture stimulates students to attend such lecturer's lectures.

3.5 The Logisitic Regression Model

Here, we are interested in extracting the logistic regression models from the result in the table above. The predictors considered are all positive as regard to attendance. The estimates of the regression parameters are in the column labeled "estimate". We will generate 3 logit models.

Where i = 0, 1, 2,…,k

$$ln\left(\frac{prob(events)}{(1-prob(events))}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8$$

$$ln\left(\frac{prob(events)}{(1-prob(events))}\right) = -5.988 + 0.088X_1 + 1.141X_2 + 0.673X_3 + 1.406X_4 + 1.748X_5 + 1.226X_6 + 1.203X_7 + 1.042 X_8$$

$$ln\left(\frac{prob(events)}{(1-prob(events))}\right) = -1.254 + 0.088X_1 + 1.141X_2 + 0.673X_3 + 1.406X_4 + 1.748X_5 + 1.226X_6 + 1.203X_7 + 1.042X_8$$

3.5.1 Predicting probabilities using the model

P_1 (y=1) = β_0

$$ln\left(\frac{P_1}{(1-P_1)}\right) = \beta_0$$

P_1 =probability of having 50% - 75% attendance without the combination of all influence of lecturer's attitude (all explanatory variable is equal to zero i.e fall under boundary)

$P_1 = \frac{1}{1+e^{-(-5.988)}} = 0.0025$

$P_2(y= 1 \text{ or } 2) = \beta_0$

$ln\left(\frac{P_2}{(1-P_2)}\right) = \beta_0$

P_2= probability of having 50% - 75% or 76% - 100% (50% - 100%) attendance without the combination of all influence of lecturer's attitude (all explanatory variable is equal to zero i.e fall under boundary)

$P_2 = \frac{1}{1+e^{-(-1.254)}} = 0.22$

P_3 = probability of having 76% - 100% attendance without the combination of all influence of lecturer's attitude (all explanatory variable is equal to zero i.e fall under boundary)

$P_3(y=3) = P(y= 1 \text{ or } 2) - P(y=1) = 0.22 - 0.0025 = 0.21$

P_0= probability of having 0% - 50% attendance without the combination of all influence of lecturer's attitude (all explanatory variable is equal to zero i.e fall under boundary)

$P_0 = 1 - (\text{prob. } y = 1 \text{ or } 2) = 1 - 0.22 = 0.78$

The probability of a student who says all the predictors considered in this study(that is,lecturer's charisma, lecturer's punctuality, lecturer's outfits, lecturer's inspiration, lecturer's eloquence, lecturer's joviality, lecturer's intelligence and lecturer motivation) do not influence his/her attendance, the probability that such a student would have 0% - 59% in attendance is 0.78, the probability of having 50% - 75% in attendance is 0.0025, the probability of having 76% - 100% attendance is 0.21.

3.5.2 Interpretation of the regression coefficient and the exponential values

The value of the exponential of the regression coefficient can be easily calculated. This gives us the direct relationship between the odds and the regressors. Minitab analysis was later used in deducing the odds ratio .

Table 8. Predictors and their corresponding log odds and odds ratios

Predictors	Log odds(β)	Odds ratios
Lecturer's charisma	0.088	1.09
Lecturer's punctuality	1.141	3.13
Lecturer's outfits	0.673	1.96
Lecturer's inspiration	1.406	4.08
Lecturer's eloquence	1.748	5.74
Lecturer's joviality	1.226	3.41
Lecturer's intelligence	1.203	3.33
Lecturer's motivation	1.042	2.84

For the two variables lecturer's outfit and charisma, we would say that for a unit increase in them, the odds of having" 0-49% attendance" versus the other outcomes decreases by 0.088 and 0.673 respectively , given that the other variables are held constant.

For lecturer's punctuality, inspiration, eloquence, joviality, intelligence, and motivation, the odds increase by 1.141, 1.406, 1.748, 1.226, 1.203 and 1.042 respectively.
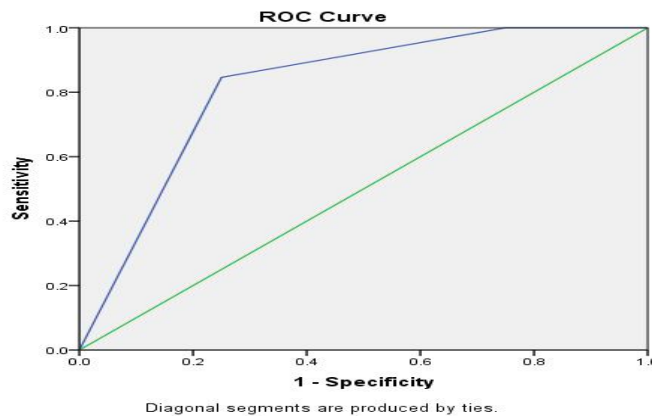

Fig. 1. Sensitivity and specificity
Area Under the Curve

Table 9. ROC table for Lecturer's charisma

Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
			Lower Bound	Upper Bound
.817	.137	.882	.549	1.000

Interpretation : Lecturer's charisma is not statistically significant but there is high sensitivity and specificity, the area specifies that is a better fits for the model. i.e lecturer's charisma is good for the model. "Joviality" has a low sensitivity and specificity while "punctuality, eloquence, intelligence and motivation " all have moderate sensitivity and specificity. "Oufit and Inspiration" have high sensitivity and specificity values.

3.6 Measure of Reliability

The Cronbach alpha value for this study is 0.878 which is a good one .The Cronbach alpha approaches 1 as the number of items in the scale approaches infinity. In other words, the higher the α coefficient, the more the items have shared covariance and probably measure the same underlying concept.

4. CONCLUSION

The fitted model above can be used to predict the different probabilities of all the possible outcomes of any attendance to a certain degree given the conditions of the students involved. As discovered during the course of this study, some of the explanatory variables actually affect the outcome of a student's attendance therefore lecturers and Institutions should strictly look into the factors that may dictate the students' attendance as we all know that students gain on knowledge from attending lectures than staying back from lecture. This will inadvertently culminate into better academic performances and of course better quality of education.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. DeKalb J. Student truancy. (Report No. EDO-EA-99-1). Washington, DC: Office of Educational Research and Improvement. (ERIC Document Reproduction Service No. ED429334); 1999.

2. Edwards S. Creating professional learning communities. Symposium Conducted at the Summer Leadership Academy, Springfield Public Schools, and Springfield, Missouri. Effect on attendance, participation, and exam performance. Computers & Education. 2002;52:868–881.

3. Smith W. An evaluation of the attendance policy and program and its perceived effects on high school attendance in Newport News Public Schools; 1998.

4. Papadakis S. Creativity and innovation in European education. 10 years eTwinning. Past, present and the future. International Journal of Technology Enhanced Learning. 2016;8, 3/4:279-296.

5. Chenneville T, Jordan C. Impact of attendance policies on course attendance among college students. Journal of the Scholarship of Teaching and Learning. 2008;8(3):29- 5.

6. Launius MH. College student attendance: Attitudes and academic performance. College Student Journal. 1997;31:86-92.

7. Gump SE. Keep students coming by keeping them interested: Motivators in class attendance? College Student Journal. 2004;38(1):157-160.