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Structural equation modelling of academic performance in statistics degree programme: A case study of University of Ibadan

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Abstract

This paper is concerned with the structural equation modelling of the academic performance in Statistics degree programme. Structural equation modelling is a class of methodologies that represent hypotheses about variances and covariances of observed data in terms of structural parameters defined by a theoretical model. It takes a confirmatory approach to the multivariate analysis of structural theory which specified the causal relations among the multiple observed variables. The causal pattern of intervariable relations within the theory was specified a priori. Structural equation modelling evaluated two models – the measurement model and the structural model. The measurement model related observed responses or indicators to latent variables (confirmatory factor analysis), while the structural model specified relations among latent variables (path analysis). The direct and indirect effects of personal factor, psychological factor, institutional/environmental factor, family characteristics, social and religious factor on the academic performance of students were studied. The academic performance of students remains a top priority for students, parents, educators, researchers, administrators (management) and government. The extent to which the theoretical model is supported by sample data collected from undergraduate students of the Department of Statistics, University of Ibadan, was determined. There were 37 observed variables and 7 latent variables. The result indicated that the attitude of students towards learning had positive direct impact on academic performance, while psychological factor had negative influence on academic performance. Also, the structural equation model analysis with four basic fit indices suggested a reasonable model-data fit.

Keywords: Confirmatory factor analysis; path analysis; constructs; indicators; modification indices.

Introduction

Structural Equation Modelling is an approach that has been used in recent years. It is an extension of General Linear Model (GLM), which involves solving linear equations simultaneously. Structural equation modelling is a general term used to describe a large number of statistical models used to evaluate the validity of substantive theories with empirical data. The technique is used for testing and estimating causal relations using a combination of statistical and qualitative causal assumptions. One of the advantages of structural equation modelling is that it can be used to study the relationships among constructs that are indicated by multiple measures. The relationships are described by parameters, such as factor loadings, that indicate the magnitude of the effect (direct or indirect) that independent variables (either observed or latent) exert on dependent variables (either observed or latent). Historically, structural equation modelling was derived from the hybrid of two separate statistical traditions. The first tradition is factor analysis developed in the disciplines of psychology and psychometrics. The second tradition is simultaneous equation modelling developed mainly in econometrics, but having an early history in the field of genetics and introduced to the field of sociology under the name path analysis. The combination of these methodologies into a coherent analytic framework was based on the work of [16], [19] and [26]. It is widely applied in various disciplines including psychology, education, health science, behavioural science, market and management. It is appropriate for investigating achievement, economic trends, exercise, and health issues, family and peer dynamics, self-concept, psychotherapy, self-efficacy, depression and performance of students.

Previous studies revealed that little research has been done in assessing the factors affecting the academic performance of statistics students, and traditional statistical approaches to data analysis were used in specifying default models, assume measurement occurs without error. But, none of these researches focused on the collective influence of the academic-related factors in a single study. However, structural equation modelling allows the use of multiple observed variables to better understand the factors affecting the academic performance of students, specify the relationship among these factors and examine the contribution of each of the factors to the academic performance in statistics programme.

The students' academic performance plays an important role in producing the best quality graduates who will become great leaders and manpower for the country thus responsible for the country's economic and social development [2]. Students' academic performance measurement has received considerable attention in previous research. It is a challenging aspect of academic literature that students' performance are affected by social, psychological, demographical, economic, environmental (home and institution) and personal factors. These factors strongly influence the students' performances but these factors vary from person to person. There are so many factors that can improve students' academic performances and also so many factors that can lead to poor academic performance. Besides these factors, socioeconomic status is one of the most studied and discussed factor among educational professionals that made meaningful contributions towards determining factors affecting academic performances of students. The most prevalent argument is that the socioeconomic status of learners affects the quality of their academic performance [9]. The academic performance of students remains a top priority for students, parents, educators, researchers, administrators (management) and government. Different researchers agreed that a number of factors exert significant influence on the academic achievements of students in tertiary institutions. The environment, social and personal characteristics of students play an important role in their academic success. The school personnel, family and communities provide help and support to students for the quality of their academic performance. This study sought to investigate the research questions: what are the factors (personal, psychological, institutional/environmental, family characteristics, social and religious factor) affecting the academic performance in Statistics degree programme? Do the hypothesized relationships among these factors hold? For this study, the following factors were considered.

Personal factor

This factor measures individual's academic achievements and their demographical factors. This includes Cumulative Grade Point Average (CGPA), number of compulsory courses, number of elective courses, mode of admission, age, gender, students' proficiency in mathematics, marital status of the student, UTME (Unified Tertiary Matriculation Examination) score, interval between completion of secondary education and admission to university.

Family factor

This includes the family characteristics such as father's educational qualification, mother's educational qualification, marital status of the parents, father's occupation, mother's occupation, family size and position in the family.

Psychological factor

This measures students' motivation (measured using Academic Motivation Scale [25]. The AMS measures intrinsic motivation to know (IMTK), intrinsic motivation towards accomplishment (IMTA), intrinsic motivation to experience stimulation (IMES), extrinsic motivation; external regulation (EMER), introjected (EMIN), identified (EMID) and amotivation), self-efficacy (measured by [5] and [6], the scale considers activities that are performed by university students in their studies in general; class concentration, memorization, understanding, explaining concepts, discriminating concepts, and note-taking), anxiety (measured here by using the scale designed by [18] of the Test Procrastination Questionnaire TPQ), study effort, study strategy (measured by using Revised Study Process Questionnaire-2 Factors (R-SPQ-2F) which was designed by [7]. Deep Strategy is the strategy used by the student to "maximise meaning" in the material learnt and Surface Strategy is the use of rote learning or "memorisation" of facts, study time (shows how many hours the student devoted to self-study per day).

Institutional/environmental factor

This factor constitutes the university facilities available such as health facilities, hostel facilities, place of residence, library facilities, lecture halls, events and entertainment like campus politics, university entertainment, availability of learning materials, lecturers' role, tutorials, teaching method of lecturers, lecturers' attitude.

Social and religious factors

These constitute social media, religious and sport activities.

The aim of this study is to examine the important factors that affect the academic perfor-mance of students in Statistics degree programme. The objectives are to study the direct and indirect effects of personal, family characteristics, psychological, institutional/ environmental, social and religious factors on academic performance and to determine the extent to which the theoretical model is supported by sample data.

The rest of this paper is structured as follows; materials and methods which includes the data and the methodology used for this study. Analysis and discussion of the results are presented in using two-step approach. The conclusions and recommendations are also discussed.

Materials and methods

The study involved 208 questionnaires which were administered to the undergraduate students of the Department of Statistics, University of Ibadan, which included 65 students from 200 Level, 93 students from 300 Level and 53 students from 400 Level. The structure of the questionnaire included the demographical characteristics and the academic achievements of the students, family characteristics, psychological factor which measured the students' motivation using the Academic Motivation Scale (AMS) by [25], anxiety by [18], study strategy using Revised Study Process Questionnaire-2 Factors (R-SPQ-2F) designed by [7], self-efficacy by [5] and [6], study effort and time; environmental/institutional factor and social/religious factor. The Cronbach's Alpha (a measure of internal consistency) for this study was from 0.760-0.984, indicating a good and acceptable level of reliability for the scales used in the questionnaire. Structural equation modelling technique was employed to estimate, analyse and test the model specified which showed the relationships among observed and latent variables in the theoretical framework.In applying structural equation modelling, there are five basic steps as recommended by [8], [20], [23] and [24].

Model specification

Model specification involves using all of the available relevant theory, research, and information to develop a theoretical model. In other words, available information is used to decide which variables to include in the theoretical model, which implicitly also involves which variables not to include in the model and how these variables are related. The goal is to find the model that closely fits the covariance structure. We want to know the extent to which the true model that generated the data deviates from the implied theoretical model. If the true model is not consistent with the implied theoretical model, then the implied theoretical model is mis-specified. The difference between the true model and the implied-model may be due to errors of omission and/or inclusion of any variable or parameter.

Structural Equation Modelling involves the evaluation of two models; measurement model and structural model. The measurement model:

$$Y = \Lambda_y \eta + \varepsilon \qquad .... (1)$$

$$X = \Lambda_x \xi + \delta \qquad .... (2)$$

The structural model:

$$\eta = B\eta + \Gamma\xi + \zeta \qquad .... (3)$$

where η is $m \times 1$ vector of endogenous latent variables, ξ is $n \times 1$ vector of exogenous latent variable, Y is $p \times 1$ vector of observed (dependent) variable, X is $q \times 1$ vector of observed (independent) variable, B is $m \times m$ matrix of structural coefficients, Γ is $m \times n$ matrix of structural coefficients, Λ_x is $q \times n$ matrix of factor loadings, Λ_y is $p \times m$ matrix of factor loadings. ζ is $m \times 1$ vector of error term, ε is $p \times 1$ vector of measurement error, δ is $q \times 1$ vector of measurement error, m is the number of endogenous latent variables, n is the number of exogenous latent variables.

The models in equations (1), (2) and (3) can be shown graphically using the path diagram in Figure 1. Many previous studies found that the attitude of students towards learning and some other factors such as environmental factor, parental factor, etc. affect students' performance. In this study, students' academic performance (η_2) denotes the dependent latent variable measured by the CGPA (Y_1), number of compulsory courses (Y_2), and number of elective courses (Y_3), registered by the students. Attitude of students towards learning (η_1) which also denotes a dependent latent variable measured by CGPA and predicted by a latent independent variable, 'psychological factor'. The model shown in Figure 1 was developed to indicate the effect of the following 6 factors; 'personal', 'psychological', 'family', 'institutional/environmental', 'social/religious' and 'attitude towards learning', each of which includes several observed variables (that is the indicators measuring these factors).

Family characteristics (Familyxter) measured by father's educational qualification (X_9), mother's educational qualification (X_{10}), marital status of parents (X_{11}), father's occupation (X_{12}), mother's occupation (X_{13}), family size (X_{14}) and position in the family (X_{15}). Psychological factor (Psycho) is measured by motiva-

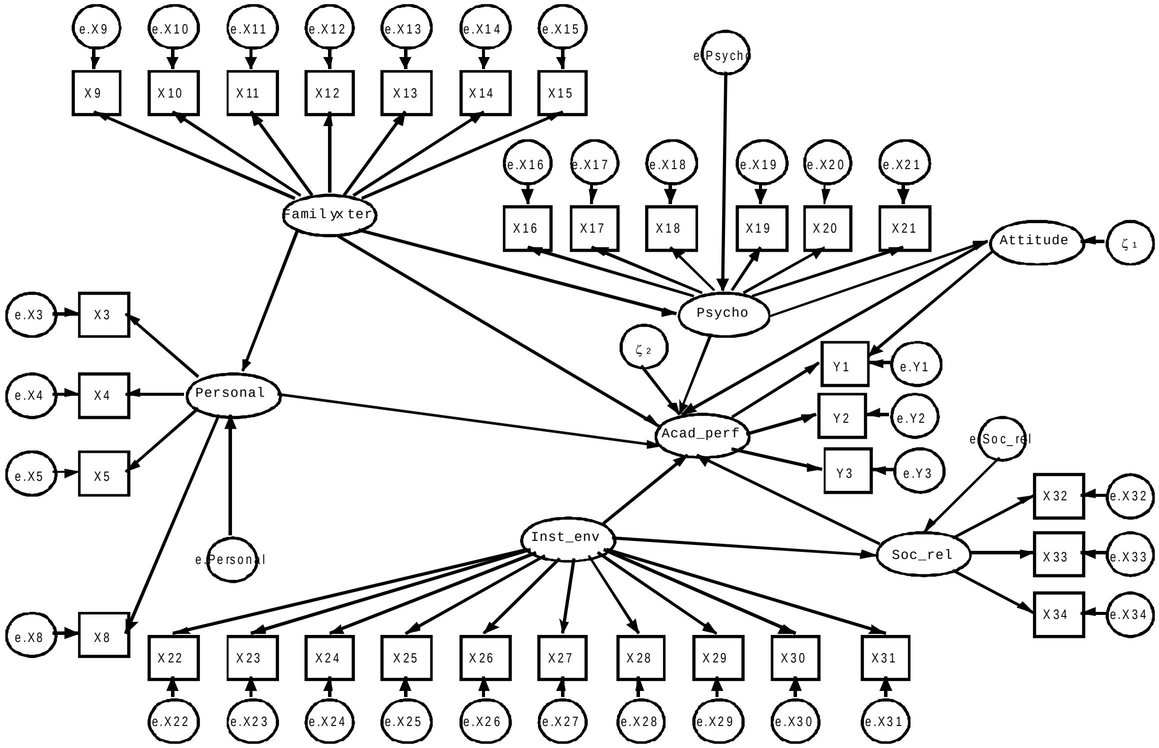

Figure 1. Model for academic performance.

tion (X_{16}), self-efficacy (X_{17}), anxiety (X_{17}), study strategy (X_{18}), study effort (X_{19}), and study time (X_{20}). Personal factor (Personal) is measured by gender (X_3), age (X_4), marital status of the student (X_5) and interval between completion of secondary education and admission to university (X_8). Social and religious factor (Soc_rel) is measured by social media (X_{32}), religious activities (X_{33}), sport activities (X_{34}). Institutional and environment factor (Inst_env) is measured by health facilities (X_{22}), hostel facilities (X_{23}), tutorial (X_{24}), politics (X_{25}), events and entertainment (X_{26}), library (X_{27}), lecture delivery and materials (X_{28}), lecturer's attitude (X_{29}), lecture halls (X_{30}) and place of residence (X_{31}).

Model identification

Model identification depends on the amount of information in the sample variance-covariance matrix *S* necessary for uniquely estimating the parameters of the model. A model is identified if the model degree of freedom is at least zero [20].

Model estimation

A properly specified structural equation model often has some fixed parameters and some free parameters to be estimated from the data. Fixed parameters are not estimated from the data and are typically fixed at 0 (indicating no relationship between variables) or 1.0. Free parameters are estimated through iterative procedures to minimize a certain discrepancy or fit function between the observed covariance matrix (data) and the model-implied covariance matrix (model). Definitions of the discrepancy function depend on specific methods used to estimate the model parameters. The method of estimation is maximum likelihood. This method assumes multivariate normal distribution of the data for the dependent (i.e. endogenous) variable. We want to obtain estimates for each of the parameters specified in the model that produce the implied covariance matrix Σ, such that the parameter values yield a matrix as close as possible to S, our sample covariance matrix of the observed or indicator variables.

Derivation of the fitting function

Let Y be a multivariate normal distribution. The likelihood of Y is given as:

$$L = \left(2\pi|\Sigma|\right)^{\frac{-N}{2}} \exp\left\{-\frac{1}{2} y'\Sigma^{-1} y\right\} \quad .... (4)$$

$$\log L = \log\left(\left(2\pi|\Sigma|\right)^{\frac{-N}{2}} \exp\left\{-\frac{1}{2} y'\Sigma^{-1} y\right\}\right)$$

$$\log L = \frac{-N}{2}\log\left(2\pi\right) - \frac{N}{2}\log|\Sigma| - \frac{1}{2} y'\Sigma^{-1} y$$

$$y'\Sigma^{-1}y = trace(NS\Sigma^{-1}) = Ntrace(S\Sigma^{-1})$$

$$\log L = \frac{-N}{2}\log(2\pi) - \frac{N}{2}\log|\Sigma| - \frac{1}{2}Ntrace(S\Sigma^{-1}) \quad \ldots . (5)$$

The fitting function is defined as:

$$F_{ML} = -\log L/N + \log L_{H_1}/N \quad \ldots . (6)$$

where $\log L_{H_1}$ is the log-likelihood of the standard model given the sample size N. It is defined as:

$$\log L_{H_1} = -\frac{N}{2}\log(2\pi)\log|S| - \frac{N}{2}(p+q) \quad \ldots . (7)$$

$(p + q)$ is the number of observed variables.

$$F_{ML} = -\left(-\frac{N}{2}\log(2\pi) - \frac{N}{2}\log|\Sigma| - \frac{1}{2}Ntrace(S\Sigma^{-1})\right) +$$

$$\left(-\frac{N}{2}\log(2\pi) - \frac{N}{2}\log|S| - \frac{1}{2} - \frac{N}{2}\log|S| - \frac{N}{2}(p+q)\right)$$

$$= \frac{N}{2}\log|\Sigma| + \frac{1}{2}Ntrace(S\Sigma^{-1}) - \frac{N}{2}\log|S| - \frac{N}{2}(p+q)$$

$$= \frac{N}{2}\left[\log|\Sigma| + \frac{1}{2}trace(S\Sigma^{-1}) - \log|S| - (p+q)\right]$$

Let θ denote the ML estimate under H_o, the maximum likelihood fitting function is defined as:

$$F_{ML} = \log|\Sigma(\theta)| + trace(S\Sigma^{-1}(\theta)) - \log|S| - (p+q) \quad \ldots . (8)$$

where $\theta = (B, \Gamma, \Lambda_y, \Lambda_x, \Phi, \Psi, \Theta_\varepsilon, \Theta_\delta)$ . . . . (9)

Newton-Raphson algorithm is used to minimize the fitting function F_{ML}. A step in the Newton-Raphson algorithm is generally defined by

$$\hat{\theta}^{(i+1)} = \hat{\theta}^{(i)} - \left[\frac{\delta^2 FML}{\delta\theta\delta\theta'}\right] - 1\left[\frac{\delta_{FML}}{\delta\theta}\right] \quad \ldots . (10)$$

Model testing

The two most popular ways of evaluating model fit are those that involve the χ^2 goodness of fit statistics and fit indexes. The χ^2 goodness of fit statistic assesses the magnitude of discrepancy between the sample and fitted covariance matrices, and it is the product of the sample size minus one and the minimum fitting function. The statistics can be derived from various estimation methods that vary in the degrees of sensitivity to the distributional assumptions, and the one derived from maximum likelihood (ML) under the multivariate normal assumption is the most widely used summary statistic for assessing model fit. In this study, the criteria used for an indication of a good model-data fit are a non-significant, χ^2 CFI $\geq$, TLI $\geq$, SRMR $\leq$, RMSEA $\leq$ 0.05. This cutoff was specified by [14].

Model modification

When the hypothesized model is rejected, based on goodness of fit statistics, then the next step is to modify the model and subsequently evaluate the new modified model. This is aided by modification indices and sometimes in conjunction with the expected parameter change (EPC) statistics. *Modification index* is an estimate of how much the χ^2 will be reduced if we estimate a particular extra parameter. *Expected Parameter Change (EPC)*is the expected size of change in the parameter estimate when a certain fixed parameter is freely estimated.

From the model specified above, the relationship between the measurement and structural models is further defined by the two-step approach to structural equation modelling proposed by [3] and [15]. The two-step approach emphasizes the analysis of the measurement and structural models as two conceptually distinct models. This approach expanded the idea of assessing the fit of the structural equation model among latent variables (structural model) independently of assessing the fit of the observed variables to the latent variables (measurement model). The basis for the two-step approach is given by [17] who argued that testing the initially specified theory (structural model) may not be meaningful unless the measurement model holds. This is because if the chosen indicators for a construct do not measure that construct, the specified theory should be modified before the structural relationships are tested.

Results and discussion

Table 1 presents the descriptive statistics of some variables in the target population; it shows the mean, standard deviation, minimum value and maximum value. From the available record in the department, students admitted through Direct Entry (DE) are approximately 55.3% and UTME students are44.7% and we also found that 68.75% of the students are male and 31.25% are female.

Structural equation modelling was used to analyze the relationship among personal factor *(Personal)*, family characteristics *(Familyxter)*, psychological factor *(Psycho)*, institutional factor *(Inst_env)*, social/religious factor *(Soc_rel)*, attitude towards learning *(Attitude)* on academic performance *(Acad_perf)* of students using Stata 12. Using the two-approach for this study, we conducted a confirmatory factor analysis on each of the latent variables whose indicators are more than 3.The indicators with high factor loadings (0.35 as the threshold) and statistically significant at significance level of 5% were used for the study. The observed variables X_3, X_{13}, X_{14}, X_{15}, X_{19}, X_{24}, X_{25}, X_{31}, X_{33}, X_{34}, were removed from the model in Figure 1. This is shown in Table 2, the factor loadings λ_3, λ_{11}, λ_{14}, λ_{15}, λ_{19}, λ_{24}, λ_{25}, λ_{31}, λ_{33}, and λ_{34}, which represent 'gender', 'marital status of parents', 'family size', 'position in the family', 'study strategy', 'tutorials', 'politics', 'place of residence', 'religious activities' and 'sport' respectively are all non-significant.

Table 1. Descriptive statistics

Variables	Mean	Standard deviation	Minimum	Maximum
Age (X_4)	23	3	18	41
CGPA (Y_1)	4.2	1.2	1.8	6.8
Number of compulsory courses (Y_2)	18.6	7.6	9	34
Number of elective courses (Y_3)	2.6	1.9	1	9

Table 2. Factor loadings and their standard errors (S.E.).

Factor loading	Coefficient	S.E	Factor loading	Coefficient	S.E	Factor loading	Coefficient	S.E
λ_2	0.0002*	0.0008	λ_{15}	-0.0855*	0.0741	λ_{26}	0.5816	0.0705
λ_4	0.8864	0.0671	λ_{16}	0.3524	0.1289	λ_{27}	0.6543	0.0650
λ_5	0.4282	0.0687	λ_{17}	0.5526	0.1841	λ_{28}	0.5463	0.0740
λ_8	0.8002	0.0647	λ_{18}	0.3757	0.1232	λ_{29}	0.4819	0.0777
λ_9	0.9708	0.0763	λ_{19}	0.0339*	0.1198	λ_{30}	0.5055	0.0738
λ_{10}	0.7322	0.0641	λ_{21}	0.3132	0.1240	λ_{31}	0.1335*	0.8995
λ_{11}	-0.1257*	0.0728	λ_{22}	0.3870	0.0825	λ_{32}	0.5091	0.5098
λ_{12}	0.3721	0.0700	λ_{23}	0.4796	0.0757	λ_{33}	0.1885*	0.1999
λ_{13}	0.5058	0.0870	λ_{24}	0.1308*	0.0903	λ_{34}	0.2094*	0.2192
λ_{14}	-0.1597*	0.0758	λ_{25}	-0.2194*	0.0880			

The factor-loadings having * are non-significant at significance level of 5%.

There are 22 observed variables in the model; the amount of information in the covariance matrix is 253, 1 constrained parameter, 54 free parameters which included: 17 factor loadings, 9 structural paths, 26 error variances, 2 latent exogenous variable variances. We estimated the parameters of the model as follows; the factor loading (λ_4, λ_9, λ_{16}, λ_{22}, λ_{32}) of the first indicator of each of the latent variables and a structural path is fixed at 1.0 (fixed parameter), the other factor loadings (λ_5, λ_8, λ_{10}, λ_{12}, λ_{13}, λ_{17}, λ_{18}, λ_{21}, λ_{23}, ... λ_{26}, ..., λ_{30}) and the structural coefficients (γ_{21}, γ_{22}, γ_{23}, γ_{24}, γ_{25}, γ_{13}, β_{21}) which represent the relationships among latent variables are estimated.

The original model has its log likelihood = -4038.21 with 22 iterations $\chi^2 = 357.54$, $p = 0.000$ with 199 degrees of freedom. The unstandardized and standardized estimates for the original model were presented in Table 3. By using Hu-Bentler (1999) cutoff criteria for fitting model, all the fit indices do not meet the specified cut off, hence, the model does not fit. That is, the hypothesized structural equation model is not reasonable; some modification might allow us to achieve a more acceptable model to data fit. The model in Figure 2 was modified by allowing error covariance of (interval between admission and year of 1st O' level attempt) and (Acad_perf) to be freely estimated with modification index of 35.762 and EPC of 0.8223.

Also, reported in Table 3 are the unstandardized and standardized estimates of the factor loadings and structural coefficients for the modified model $\chi^2 = 241.91$.

The fit to the data is statistically reasonable, therefore, the final model improved with *RMSEA* = 0.043, *SRMR* = 0.081, *TLI* = 0.932, *CFI* = 0.921 and we concluded that the model in Figure 2 reproduces the sample covariance matrix. SEM analysis with 4 basic indices; RMSEA, SRMR, CFI and TLI indicated that the data have a reasonable fit.

Also, the standardized coefficient in Table 3 represent the factor loadings between the indicators and their construct. The 3 indicators of **Personal** have high factor loadings and are statistically significant ($p<0.05$). Among the 4 indicators of Familyxter, X_9

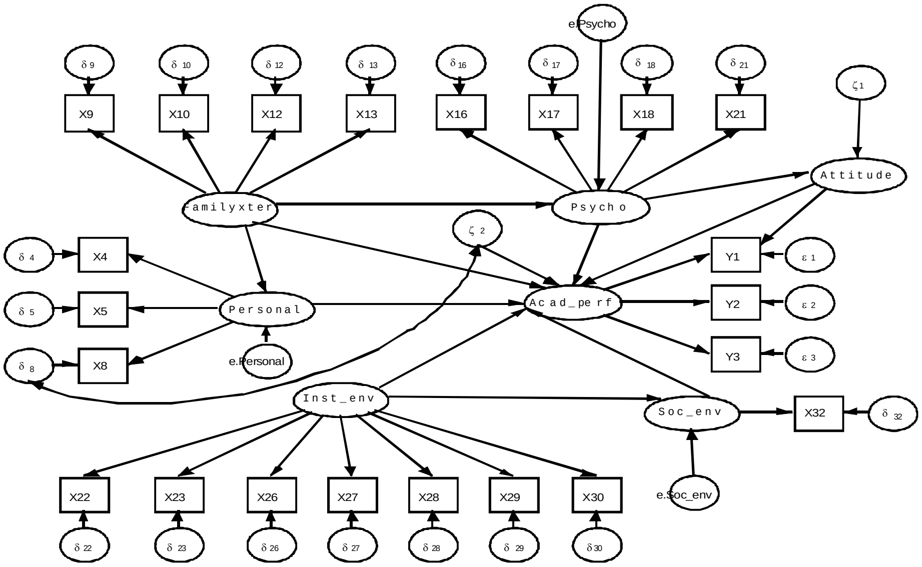

Figure 2. Modified structural equation model for academic performance.

Table 3. Maximum likelihood estimates of academic performance.

	Original model		Modified model	
	Unstandardized	Standardized	Unstandardized	Standardized
Structural path				
γ_{21}	-0.0867	-0.3294	-0.0147	-0.1091
γ_{22}	-0.1094	-0.1866	-0.0039	-0.0109
γ_{23}	-0.1345	-0.2188	0.2873	0.3567
γ_{24}	0.3219	0.1569	0.1492	0.0999
γ_{25}	0.0472	0.0730	0.0139	0.0483
β_{21}	1.0000*	0.2086	1.0000*	0.5247
γ_{1}	0.1283	1.0000	-0.3620	-0.8563
Familyxter$\rightarrow$Personal	-1.1390	-0.5114	-1.4269	-0.5422
Familyxter$\rightarrow$Psycho	0.0048	0.0051	-0.0688	-0.1560
Inst_env$\rightarrow$Soc_rel	-0.0962	-0.0303	-0.0895	-0.0163
Measurement				
λ_{4}	1.0000*	1.0000	1.0000*	1.0000
λ_{5}	0.0175	0.4523	0.0175	0.4530
λ_{8}	0.7904	0.8306	0.7908	0.8307
λ_{9}	1.0000*	0.8793	1.0000*	0.7609
λ_{10}	0.7530	0.7902	1.0100	0.8986
λ_{12}	0.1887	0.3193	0.1790	0.2566
λ_{13}	0.1626	0.2254	0.2678	0.3145
λ_{16}	1.0000*	0.6340	1.0000*	0.2485
λ_{17}	0.2270	0.2423	1.2388	0.5220**
λ_{18}	0.3845	0.2180	0.0392	0.0087**
λ_{21}	0.1441	0.2162	0.4746	0.2767**
λ_{22}	1.0000*	0.5613	1.0000*	0.4169
λ_{23}	0.8995	0,5473	1.1733	0.5027
λ_{26}	1.0191	0.5302	1.4928	0.5497
λ_{27}	1.1404	0.6345	1.7091	0.6705
λ_{28}	0.7216	0.4436	1.0901	0.4729
λ_{29}	0.4540	0.2993	0.7398	0.3447
λ_{30}	0.6771	0.3996	1.0309	0.4294
λ_{32}	1.0000*	0.8650	1.0000*	1.0000
λ_{Y_1} $(Acad_{perf})$	1.0000*	0.5394	1.0000*	0.3033
λ_{Y_1} $(Attitude)$	0.1231	0.0139	-3.4541	-0.5497**
λ_{Y_2}	-8.4926	-0.8895	-16.4990	-0.9970
λ_{Y_3}	-2.1752	-0.8907	-3.6186	-0.8554
χ^2	357.54		241.91	
df	199		198	
RMSEA	0.08		0.04	
SRMR	0.10		0.08	
CFI	0.761		0.932	
TLI	0.728		0.921	

* Fixed parameters, all factor loadings are significant except ** marked.

(father's educational qualification) and X_{10} (mother's educational qualification) have high factor loadings (λ_9 and λ_{10}) and all the indicators are statistically significant (p<0.05). The study also indicated that all the indicators of Inst_env are significant with X_{22} (health facilities), X_{23} (hostel facilities), X_{26} (events and entertainment), X_{27} (library), X_{28} (lecture delivery and materials), and X_{30} (lecture halls) having high positive factor loadings. The X_{16} (motivation) have its factor loading λ_{16} =0.25 and p = 0.00; this is significant. X_{17}, X_{18} and X_{21} are not statistically significant but a positive loading with psychological factor.

From the model in Figure 2, there are 10 structural paths with personal, family characteristics having a negative direct influence of -0.1091, -0.0109 respectively on academic performance, psychological factor also have negative impact of -0.8563 on attitude towards learning. Also institutional/environment, social/religious and attitude towards learning have positive influence on academic performance of students. All the latent exogenous variables (personal factor, family characteristics, psychological, institutional/environment factor, social/religious factor) and attitude towards learning have direct effect on academic performances; psychological factor have direct effect on attitude towards learning. There is indirect effect of family characteristics on attitude towards learning through a mediator (intervening variable), psychological factor serves as the mediator. Also, family characteristics, psychological factor and institutional/environment factor have indirect effect on academic performance with total effects 0.0627, -0.0926 and 0.0991 respectively.

From the model, the relationship can be stated as:

$$\begin{aligned} Acad\_perf = {} & 0.5247\ Attitude - 0.1091\ Personal \\ & + 0.06627\ Familyxter - 0.0926\ Psycho \\ & + 0.0991\ Inst\_env + 0.0483\ Soc\_ret \end{aligned}$$

Conclusions and recommendations

In the past, the majority of students in statistics degree programme are admitted through UTME, whereas now, students admitted through Direct Entry (DE) are approximately 55.3% and UTME students are 44.7%. This study shows that 'gender', 'marital status of parents', 'family size', 'position in the family', 'place of residence', 'religious activities' and 'sport activities' do not affect the academic performance of students. The result also reveals that the model respecified is supported by the data collected. CGPA positively affect academic performance, number of compulsory and elective courses negatively affect academic performance, it is reasonable that if a student registered for more than the necessary number of compulsory (this applies to students that failed compulsory courses in the previous session thereby increases in the subsequent session) and elective courses, the student should expect a low CGPA, which in turn affect the academic performance of the student. Library facilities, health facilities, lecture delivery and materials positively affect students' performance.

The result also indicates that family characteristics do not affect personal factor. Personal, family characteristics, psychological, institutional/environmental, social/religious factor and attitude towards learning affect performance of students. There is indirect effect of family characteristics on attitude of students towards learning. Also, personal, family characteristics, psychological, institutional and social/religious factor have direct influence of -0.1091, -0.0109, 0.3567, 0.0999 and 0.0483 respectively and indirect impact of 0, 0.0736, -0.0008 and 0 respectively on academic performance.

Based on the finding of this study, we recommend the following for students, lecturers and the school/department administrators:

(i) Students should register for stipulated number of compulsory and elective courses and make use of the library more often.

(ii) Lecturers should improve their method of lecture delivery, update their lecture materials and emphasize the real application of statistics by adding more applied courses in the programme.

(iii) The school/department administrators should design and implement policies to improve the quality of education by providing more library facilities, health facilities, events and entertainment so as to improve students' motivation, attitude towards learning and teaching procedures.

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