International Journal of Statistics and Applied Mathematics

ISSN: 2456-1452
Maths 2017; 2(1): 42-49

www.mathsjournal.com
Received: 14-11-2016
Accepted: 16-12-2016

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Factors that associated with the academic performance of first year students at the national University of Lesotho: structural equation modelling approach

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Abstract
In this paper, the PLS-PM model has been estimated as to directly and indirectly identify factors that influence academic performance of the first year students at NUL. Sample used to utilise the task was 46. The estimated PLS-PM model was found stable and satisfying the SEM conditions. Several measure were established and found that 63% of variation of OWM is been explained by all those factors that are found to be significant. Also, seven factors were retained with factor loadings in the range of 0.4 to 0.81. Furthermore, the results of the discriminant analysis revealed that, 54% of female students are enrolled to the university while only 46% is for male students each year.

Keywords: Structural Equation Modelling, Partial Least Square Path Model, Discriminant Analysis

1. Introduction

In all countries of the world, education is the most important sector of living; hence the major resources are plunged into it as an investment to human resource and the development of the country. The educational performance is influenced by various components including admission points, socio economic status and school foundation. Acato (2006) [1]; Geiser and Santelices (2007) [18] all contend that admission points which are a reflection of the past performance has some impact on future performance of students. Tertiary institutions in Austria have found that a selection rank based on a student's overall performance is a predictor of success for most courses.

As documented by Berthelot, Ross, and Tremblay (2001) [5], the study agrees with the literature that admission points really distress the performance of university students and that is why the basic university entry admission points is a diploma points or mature age points. However, Berg (2012) [4] defines education as the conveyance of learning, aptitudes and information from teachers to students is lacking to capture what is truly vital about being and getting to be educated. Learning is taken to mean any change in behavior, knowledge, understanding, skills or capabilities which the greenhorn retains which cannot be ascribed simply to the physical growth or to the development of inherited behavior patterns.

In the current study, two techniques are used to check two different issues. The first technique is the use of the structural equation model (SEM) through employment of the Partial Least Square Path Model (PLS-PM) to identify the factors that influences the academic performance of first year students at the National University of Lesotho (NUL) directly and indirectly. And lastly, in assessing the enrollment rate at the university, the K^{th} nearest neighbor discriminant analysis with the discriminating factor as the sex structure of the student is engaged.

1.1 Literature review

There are different types of methods that have been used to model the factors that influence the academic performance of students. One of the mostly appropriate used methods is the application of linear regression analysis. However, in recent literature the focus had shifted from the multiple linear regression modelling to the structural equation modelling (SEM).

According to Brown (2015) [7] and Markus (2012) [34], SEM procedures allow researchers the flexibility and power to examine the relationships between observed and latent variables, as well as to test cross-group similarities and differences among latent variables. SEM is flexible in correcting the measurement of error and its assumptions are fewer compared to the classical methods (P. T. D. Little, 2013) [32].

Testing of latent differences between groups longitudinally in addition to contextual effects modelling is classified as other useful applications of SEM see the work of (T. D. Little *et al*., 2007) [33]. As Guo, Perron, and Gillespie (2009) [21] stated, SEM methods performs an increasingly significant role in developing knowledge for the profession of social work because it integrates both measurement and theory.

Provided that anatomical connections within a cluster of structures are known, the SEM allows strength of estimation by which each structure is been affected by its input structure. The linear correlation or covariance between measurements of activity obtained from different structures to derive structural coefficients is been exploit by the SEM. This correlations are assumed to reflect the power of the underlying causal process as Boucard, Marchand, and Noguès (2007) [6] has stated.

In the work of Chemers, Hu, and Garcia (2001) [8], the SEM is used with some laten variables and errors. Their study showed that the academic performance is been influenced by high school grade point average (GPA), academic self-efficacy (ASE), self-rated academic performance (ASR), academic expectations (ACAEXP); faculty ratings of academic performance, challenge-threat evaluations, optimism; health problems and adjustment. This hypothesized model is established through the path diagram.

On the other hand, Gursoy, Jurowski, and Uysal (2002) [22] proposed an SEM for the support of tourism development that is been influenced by the perception of its costs and benefits and also the state of the local economy. The model suggests that the perception is been influenced by the concern which residence have on their community, their emotional attachment to it, the degree to which they are environmentally sensitive, and the extent to which they use the same resource base that tourists use. To add on that, the state of local economy, influences the perception of the benefits and costs of tourism development. This is the argument from the model of (Gursoy *et al*., 2002).

There are different methods used when developing an SEM model. (1) The partial least square structural equation modelling (PLS-SEM) and covariance based structural equation modelling (CB-SEM). Sarstedt, Ringle, Henseler, and Hair (2014) [43] indicates that PLS–SEM is an increasing methodology in business researches. The increasing use of the PLS-SEM across a variety of disciplines has been documented by several studies such as of C. M. Ringle, Sarstedt, and Straub (2012) and Hair, Sarstedt, Pieper, and Ringle (2012) [23].

In the strategic management field, the long range planning has given three special issues to the method. Robins (2014) [41], provides a clear indication of the importance of PLS-SEM for research and practice. Developments in different researches shows the proponents and critics of PLS-SEM and heated debates on the method's advantages and disadvantages (Rönkkö, 2014, Goodhue, Lewis *et al*. 2012) [42, 19]. An outright rejection of any method is certainly not a good research practice and is unfounded in light of PLS-SEM's manifold advantageous features (Henseler, Ringle, & Sinkovics, 2009 and Hair, Ringle *et al*. 2011) [28]. However, Reinartz, Haenlein, and Henseler (2009) [37] emphasized that almost all methodological studies provide a balanced and constructive perspective capabilities and limitations on PLS-SEM.

Nevertheless, more of SEM literature has focus on the comparative studies of PLS-SEM with CB-SEM. The statistical comparison methods are significant in learning more about the situations where one method is used over the other. Sarstedt *et al*. (2014) [43] showed that the comparative study research has reached a point that requires a different angel and new arguments to pursue.

In contrast to others, Rigdon (2012) [38] argues that PLS-SEM must be fully emancipate itself from CB-SEM by forcing its prediction orientation other than aiming at testing the theory of the model. Is there really a dichotomy between predictive and explanatory modeling? Correspondingly prediction establishment has become one of the most recently cited reasons for choosing PL-SEM over CB-SEM. All the practical reviews of PLS-SEM used across different disciplines are evidences.(Rigdon, 2012) [38]. In any case, these audits likewise uncovers that instead of completely subscribing to predictive modeling, PLS-SEM specialists frequently outline their results as reporting in a corroborative sense. Instead, analysts ought to expand their focus; and furthermore considers prediction as an essential analysis objective (Rigdon, 2012) [38]. According to Diamantopoulos, Sarstedt, Fuchs, Wilczynski, and Kaiser (2012) [12], all things are considered in the very way of business exploration to look at levers with which to predict enhancements in organization performance and accordingly to give recommendations for decision making

Consequently, methodological papers for exploring the characteristics of PLS such as (Goodhue, Lewis, & Thompson, 2012; Lu *et al*. 2011 and Reinartz *et al*. 2009) [19, 37] have mostly focused on the statistical power thereof. Simulation of Monte Carlo had largely confirmed that the power of PLS is comparable to competing techniques; such as CB-SEM or regression on sum scores which propose that the researcher should not worry about the statistical power of the PLS. However, none of the extant simulation studies have investigated whether substantial collinearity in the structural model influences the adequacy and statistical power of path coefficient estimates obtained through variance-based SEM (Dijkstra & Henseler, 2015) [15]. The current study uses a PLS-Path modelling (PLS-PM). The choice of the PLS-PM is based on several advantages that it has as Henseler *et al* (2012) has indicated. The popularity of the PLS-PM among researcher is due to four significant advantages. Firstly, the PLS-PM encompasses no assumptions about the population or measurement scales. (Fornell & Bookstein, 1982) [17]. According to Bagozzi. and Yi (1994), when the distributions are highly skewed, for example the customer satisfaction studies such as of (Fornell, 1995), the PLS-PM can thus be used. GöTEBORG (2014) [20] who developed PLS path modeling, coined the term "soft modeling" because of PLS' rather soft assumptions.

Second, the sample size does not matter while deal with the PLS-PM because Chin and Newsted (1999) [9] showed that the PLS-PM can be used to estimate the relationship between the latent variables and several indicators. The complexity of the overall model hardly influences sample size requirements as the PLS-PM algorithm consists of OLS regressions for subparts of the focal path model. Third, it is easy to use a PLS-PM software with graphical user-interfaces like Smart-PLS C. Ringle, Wende, and Will (2007), or the PLS-PM module of XLSTAT software (Addinsoft, 2007) and the open packages like SEM-PLS Monecke and Leisch (2012) [35] have contributed to PLS-PM appeal.

Lastly, PLS-PM is preferred over CB-SEM when an improper or non-convergent results are likely so called Heywood cases, (Krijnen (Krijnen, Dijkstra, & Gill, 1998; Reinartz *et al*. 2009) [31, 37]. In a complex models for which the number of latent and manifest variables are high in relation to the number of observations, and the number of indicators per latent variable is low. The remaining part of the pater is structured as follows section 2 data description and materials used section 3 reports empirical analysis and results interpretation and section 4 discussion of the results from the study, conclusion on the study findings and recommendations.

2 Data and Materials

Data description

This study uses the cross-sectional data which was collected from the National University of Lesotho. The data is from the second year students of the class of Mathematics for Demography of the year 2015/2016 which consists of 46 observations and that is the population of the class. These class consists of BSc statistics and Demography students and Bachelor of Arts in Statistics and Demography. And STATA 13.0 for windows is used to analyses the data.

2.1 Material used

Partial Least Square Path Model (PLS-PM)

PLS-Path Modeling is the PLS approach for models of structural equations uses partial least squares method to estimate the coefficients of a structural equation system. The results obtained with technique are reliable as those based on covariance structure. However, the PLS-PM has fewer restrictions especially on the data distribution and sample size. These structural equations work like regression equations and the goal is to estimate their coefficients. However, the ordinary least squares (OLS) regression model is mostly spread due to its lack of application requirements. As the results, the measure used to evaluate the correctness of adjustment is the usual coefficient of determination. This coefficient can be estimated using OLS but if multicolinearity exists, either in the measurement model nor in the structural model, then the PLS regression method is been used. According to Henseler *et al*. (2010) [26], PLS is a family of altering least square algorithm and extend the principal component and canonical correlations analysis. The method was defined by Wold (1966, 1974, 1982) [\49, 50], for the analysis of high dimensional data in a low-structure environment and had undergone various extensions and modifications.

Henseler *et al*. (2010) [26], emphasized that the PLS-PMs are formally defined by two sets of linear equations which are the inner model and the outer model. The inner model indicates the relations between latent variables while the outer model indicates the relations between a latent variable and its observed indicators or manifest variables. The PLS-PM for the current study is depicted in figure 1

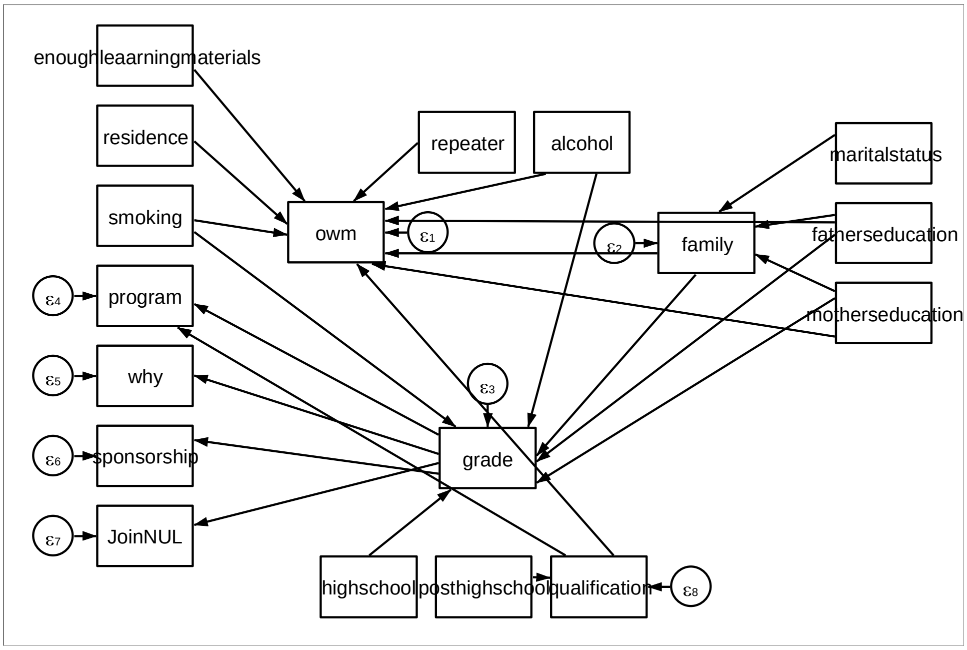

Fig 1: A Simple PLS-PM

Without losing generality, the latent and manifest variables are centered so that the location of parameters can be discarded in the following equations.

The inner model for latent variables is

$$\Xi = \Xi\beta + Z \tag{1}$$

where, Ξ is the vector of latent variables, β denotes the matrix of path coefficients and Z represents the inner model residuals. The basic PLS design assumes a recursive inner model that is subject to predictor specification. Thus the inner model constitutes a causal chain system. Hence predictor specification reduces equation 1 to

$$E(\Xi|\Xi) = \Xi\beta \tag{2}$$

As per work of Hanafi (2007) [24], there are two modes included in the PLS-PM of the outer models. This are among them mode A and mode. Mode B of the PLS-PM optimizes a correlation criterion while mode A tend to optimize the covariance criterion (A. Tenenhaus & Tenenhaus, 2011) [46]. On the other hand, Fornell and Bookstein (1982) [13] emphasized that statistical and theoretical reasoning and typically results from a decision to define an outer model as reflective or formative is subject to the choice of a certain mode.

Model estimation happens through an arrangement of regressions regarding weight vectors which fulfill the altered point equations upon convergence. Dijkstra (2010) [13], provides a general analysis of such equations and ensuing convergence issues. Wold (1982) [50], used a basic path modelling algorithm which includes the three stages as follows: (1) the iterative approximation of latent variable scores, (2) the estimation of outer weights, outer loadings and path coefficients and (3) the estimation of location parameters. However, the current studies uses only observed variables. In order to determine the path coefficients, a multiple linear regression is conducted in respect of each endogenous observed variables. The endogenous variable's scores are regressed on the observed variable scores.

2.2 Goodness-of-Fit Indices for PLS Path Modelling.

After estimating the PLS-PM, the goodness of fit (GoF) is piloted as to universally validate the PLS-PM. This criterion was proposed by M. Tenenhaus, Amato, and Esposito Vinzi (2004) [47] and it is specifically as follows (Esposito Vinzi, Trinchera, Squillacciotti, & Tenenhaus, 2008) [15]:

$$GoF = \sqrt{\frac{[\sum_{j=1}^{J}\sum_{q=1}^{Pj} Cor^2(X_{qj},\hat{\xi}j)]x[\sum_{j*=1}^{J*} R^2(\hat{\xi}j*,\{\hat{\xi}j'sexplaining\hat{\xi}j*\})]}{[\sum_{j=1}^{J} Pj]xJ*}} \quad (3)$$

with J being the number of observed variables in the model and J*<J is the number of endogenous observed variables. $Cor\left(x_q j, \hat{\xi} j\right)$ is the correlation between the q^th reflective indicator of the j^th observed variable and the corresponding observed variable scores $R^2\left(\hat{\xi}j *, \{\hat{\xi}j'sexplaining\ \hat{\xi}j *\}\right)$is the R^2 value of the regression that links the j*^th endogenous observed variable to its explanatory observed variables.

To check whether The National University of Lesotho is helping in an attempt to make university education universal by the year 2020, the assessment of enrolment to the university by sex structure is made. These assessment is done through a nonlinear discriminant analysis of which Otsu (1982) [36] derived an optimal nonlinear discriminant (ONDA)by assuming the underlying probabilities. In his work, he showed that the optimal non-linear discriminant mapping is closely related to Bayesian posterior probabilities. Following this approach, these paper proposes the nonlinear discriminant analysis by utilizing the logistic discriminant analysis.

2.2.2 The K^th Nearest Neighbor Discriminant analysis

The k-nearest neighbor is a nonparametric pattern classifier which yield good classification accuracy.in the two class situation, similar samples are mostly likely to have the same aposteriori probabilities. Kim, Choi, Moon, and Mun (2011) [30], established the k nearest neighbor discriminant comparison with quadratic discriminant and linear discriminant analysis in classification of electromyogram signals based on the wrist-motion directions. They indicated that the k^th algorithm predicts the test of sample category according to the k training samples; which are the nearest neighbors to the test sample and finally classifies the sample or observation to the category which has the largest category probability.

Suppose that an object belongs to one set of m mutually exclusive populations $p_1, p_2, \ldots, p_j$. And also class X is the same feature vector as all the training samples, then d_i is s one of the neighbors in the training set $y\left(d_i, p_j\right) \in \{0,1\}$ indicates whether d_i belongs to class p_j and $sim(X, d_i)$ is the similarity function for X and d_i. Then, the probability density function $P(X, d_i)$ for the feature data X, given class p_j is presented as follow

$$P\left(X, p_j = \sum_{d_i \in KNN} sim(X, d_i) * y\left(d_i, p_j\right)\right) \quad (4)$$

$sim(X, d_i)$ is calculated using the Euclidean distance, cosine, and correlation methods (Toussaint, 2005) [48]. However, in this study, the Euclidean distance method is selected because it is often used as the distance metric. The k-value is a client characterized constant number of neighbor elements and an un-labelled vector is grouped by doling out the label that occurs most regularly among the k preparing samples closest to the query point. In this study, the k-value is at first altered at 5 and it will be discussed in the discussion. As per the name of the k neighbors and the distribution of the similarity value, the class of the input vector X was discriminated.

3 Empirical analysis

This section provides and discusses the preliminary and primary analyses results**.**

3.1 Preliminary results

In this section the preliminary data analyses are conducted with the purpose of assessing the behavior of the data set. In the current study, the adoption of the descriptive statistics is used to provide a sound understanding of the data. Table 1 presents the summary statistics from the survey data on factors that influence the academic performance of students.

Table 1: Exploratory data analysis

			Joint Statistic	
Variable	**Pr (skewness)**	**Pr (kurtosis)**	**Adj Chisq**	**Prob (chisq**
Owm	0.1783	0.4719	2.47	0.29
Gender	0.5891			
Grade	0.1724	0.3385	2.95	0.23

The results from table 1 reveals that observation, Overall weighted mean(OWM) is normally distributed because the associated probability value of both skewness and kurtosis jointly is 0.2909 which is greater than 5% and therefore conclude that the observation is normally distributed together with gender and grade and generally the data is jointly normally distributed.

3.2 The PLS-PM

Since the study revealed that the data is normally distributed, then the PLS-PM model as proposed in section 2.1 is estimated and the results are presented in table 2.

Table 2: Maximum Likelihood Estimates of the Estimated PLS-PM

Structural		coef	std err	z	prob
family<-					
	marital	2.595	0.7038	3.69	0.00
	mother	0.59368	0.2079	2.86	0.04
grade<-					
	family	0.1053074	0.0434239	2.43	0.02
	smoking	0.5499	0.1226866	4.48	0.00
program<-					
	grade	1.095588	0.0807151	13.57	0.00
why<-					
	grade	0.2058824	0.0761058	2.71	0.007
sponsorship<-					
	grade	0.9558824	0.0772337	13.21	0.00
Join_NUL<-					
	grade	0.448679	0.0540267	8.3	0.00
	high school	0.1451377	0.0363158	4	0.00
OWM<-					
	program	7.087895	1.82638	3.88	0.00
	residence	6.309379	2.19344	2.88	0.004
	smoking	9.173336	2.492498	3.68	0.00
	mother	4.608991	0.8891806	5.18	0.00
var(e.family)		4.469597	0.9319753		
var(e.grade)		0.3804242	0.0779324		
var(program)		0.8860294	0.1847499		
var(e.why)		0.7877238	0.1642518		
var(e.sponsorship)|		0.7116368	0.1483865		
var(e.JoinNUL)		0.0862575	0.0179859		
var(e.owm)|		53.29359	11.11247		

Table 2 presents the estimate PLS-PM. Only the reported paths were found significant at 5% level of significance while other paths were found insignificant. In addition to that, all the regression coefficients are all positive this indicates that there is a positive linear relationship between all the regression models and the paths that presents the independent variables within the path model.

3.2.2 Goodness of Fit Test

After model fitting, goodness of fit is established to test whether the model is good to fit the data. The reported goodness of fit statistic is in table 3. Since the calculated probability value of the chi-square statistic is 0%, the study concludes that the model is not good enough to fit the given data. According to Kenny and McCoach (2003), this biasness of the goodness fit is caused by the larger number of variables that are been used to estimate the model. Because as the number of the variables increase, the ratio of the chi-square also increases. However, Tanaka (1987) [45], showed that is difficult to launch a accurate decision rule for determining sample size based on the existing Monte Carlo evidence. But the problem of selecting an appropriate sample size is tied to both the ratio of number of variables to number of subjects and the ratio of number of parameters to be estimated to the number of subjects.

One other interesting reported statistic is the coefficient of determination. The reported overall R^2 is 0.6285534. This implies that 63% of variation of the overall weighted mean (owm) is explained by program that the student is enrolled to, the grade that s (he) got from final year of high school, why did the student did not enrolled with National University of Lesotho (NUL), sponsorship, whether they have enrolled straight after completing their high school and finally the family size that they are living within it. With this information in table 3, the study then concludes that the model is a good model to fit and determine the factors that influence academic performance. Also, the Wald test is used to support that the model is significant by test the hypothesis that the coefficients of the model and the joint coefficients are insignificant. The test follows a chi-square test and all the coefficients of the model and the joint coefficients are found to be significant hence the model is said to be good model. The Wald test results are presented in table 4. According to Harrell Jr (2001) [25], these test on both models with dichotomous variables and continuous variables.

Table 3: Equation Level Goodness of Fit

Response observed	variance					
	fitted	predicted	residual	R-squared	mc	mc2
family	5.47	1.001598	4.469597	0.1830675	0.4278639	0.1830675
grade	0.47	0.0909127	0.3804242	0.1928826	0.4391841	0.1928826
program	1.45	0.565752	0.8860294	0.389695	0.6242556	0.389695
why	0.81	0.0199788	0.7877238	0.0247354	0.1572748	0.0247354
sponsorship	1.14	0.4306657	0.7116368	0.3770155	0.6140158	0.3770155
Join-NUL	0.19	0.1086833	0.0862575	0.5575193	0.7466722	0.5575193
OWM	178.37	125.0746	53.29359	0.7012158	0.8373863	0.7012158
overall				0.628045		

Table 4: Wald Test for significance of the equations

	Chi-sqr	df	prob
observed			
family	259.4	2	0
grade	311.5	2	0
program	184.24	1	0
why	7.32	1	0.0068
sponsorship	174.62	1	0
Join-NUL	661.18	2	0
owm	3141.12	4	0

3.2.3 Stability test of the SEM Model

After doing all necessary tests of the model, the other test to be constructed is the Stability analysis of simultaneous equation systems. This criteria was used by Shorten, Wirth, Mason, Wulff, and King (2007) [44] in their work where they reviewed stability of switched and hybrid systems. Nevertheless, in the current study the stability test is used on linear systems of equation. And the results are presented in table 5.

Table 5: Eigenvalue stability condition

Eigenvalue	Modulus
0	0
0	0
0	0
0	0
0	0
0	0
0	0

Since, all the Eigenvalues lies within the unit circle, this implies that the estimated SEM satisfies the stability condition and final model is presented in figure 2 with direct and indirect effects to the OWM.

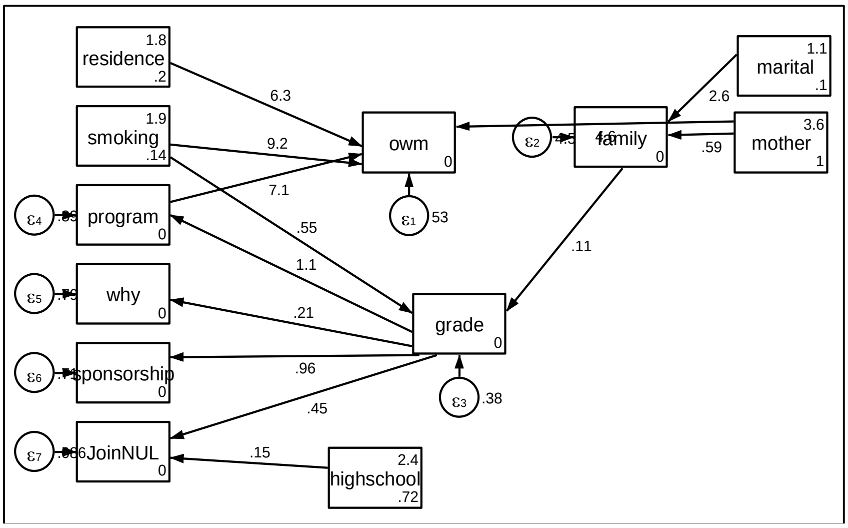

Fig 2: the final PLS-PM

3.3 Discriminant analysis

To check whether The National University of Lesotho is complying with the policy of version 2020 by making a university education universal, the discriminant analysis is established. This followed a Kth nearest neighbor algorithm for those variables that were identified as factors that directly and indirectly influence the academic performance of students. Table 6 presents the results.

Table 6: classification of enrollment by sex structure

	Classified		
True Gender	Female	Male	Total
Female	25	0	25
Male	21	0	21
Total	46	0	46
Priors	0.5435	0.4564	

There are two things to be noted out here. (1), the enrollment to the university seems to be biased. There are more female students enrolled than male students. (2) The probability at which female students are enrolled is higher than that of male students by 8.71%. This resulted from the prior statistic. The probability that females are enrolled at the university 54.35% each year while that of males is 46%. This indicates that by 2020, the university will be having more females with the growth rate of 8.71% which then violates the policy of vision world of the universal education by the year 2020.

4 Discussion, Conclusion and Recommendations

4.1 Discussion

The study has developed the SEM through the development of PLS-PM. In the hypothesis model, only seven significant factors were retained. And in the same final estimated model, all the estimated parameters were found significant towards estimating the overall weighted mean of the second year students. Nevertheless, the overall goodness of fit was not satisfactory. It was reported as 0% which means the model is not good enough to fit the given data at hand. The cause of this results is due to a small sample size where the study uses only 46 students as the sample. Also, Wolf, Harrington, Clark, and Miller (2013) [51], indicated that the sample size play a vital role in the model estimation and validity of the model and tested different samples sizes and found that a sample of 200 and above is the best sample for goodness of fit of the model. Furthermore, there is an entangling factor of inclination in the chi-square test. Given that there is no specification error, the evaluated chi-square is not an unbiased estimator; the amount of bias is reliant on the sample size. That is, for a fixed sample size, the average value of chi-square tends to be larger than its degrees of freedom, its expected value. In terms of Curran, West, and Finch (1996), The chi-square test is asymptotic and so it is exact only when the sample sizes are large. With small samples, the value of chi-square overestimates its theoretical value.

Following the work of Curran, Bollen, Paxton, Kirby, and Chen (2002) [10], the study the biasness of the chi square and found the same results of Curran that, at fixed sample size, the more the number of indicators are increased, the value of the chi square worsen because the value of the test statistic become significantly large. The larger the degrees of freedom, the greater the bias appears to be.

Nonetheless, when the number of variables are decreased in the preceding study, the SEM becomes inconsistent with the theoretical model and therefore have to increase the number of variables in the study and finally retain only seven significant factors with different factor loadings. Again, the study go through the testing of the stability of the estimated model and found that all the factors were stable at eigenvalues within the unit root test.

The study also went on to check whether the university is achieving the significant enrollment as per 2020 vision by making university education universal. The Kth nearest neighbor discriminant model was established with the aim of classifying the enrollment my sex structure of the students and also, the results brought out some biasness in the university enrolment. More female are being enrolled as per men. The rate at which female students are being enrolled is 54% which is higher than of male students by 8%.

4.2 Conclusion

The study had managed to find those factors that are significantly influence the academic performance of first year students at The National University of Lesotho. The study revealed that there are factors that influence academic performance directly and those that influence it indirectly. Factors that influences the overall weighted mean directly are the marital status of the student, the education the mother of a student, the program at which a student is enrolled to, the age of the student and finally the smoking habits of the student. While on the other hand, factors such as grade of the student from high school influence OWM of the student indirectly.

Having adopted the SEM, also the study revealed that the school library does not have enough learning materials. The books within the Thomas Mofolo library are of old editions. Also, the access of the materials is not easy.

4.3 Recommendations

In conclusion of the study, few recommendations need to be establish. Firstly, since it is going to take a longer time to re-evaluate the structure of the library in terms of updating the books, journals, manuscripts and many other materials that helps in development of the students, the school should adopt the short term migration policy of introducing the supplementary instructors (SI) where extra classes are been introduced to those modules that have a high likelihood of being repeated by students with the senior students facilitating those classes at their own spare time. Example of such kind of modules are introduction to Statistics I (ST 1311) Statistical methods I (ST 2421) and many others in each department. In implementing the SI facilitator, will have significant role in the performance of the students because some students are free when they are with their peer than their lecturers. Secondly, the school must make sure that the internet services is accessible and it is stable all the times so that students can access internet material at any time of the day. Thirdly, the school must introduce a new way of teaching by improving the lecture halls in such a way that all of them have multimedia facilities and also programs such as statistics and economics must have appropriate laboratories for practical sessions together with appropriate software for those particular modules.

Not all modules are to be taught in the classroom, some modules like for example categorical data analysis, methods of multivariate techniques, time series and forecasting, design of experiment and sampling, econometrics techniques, and many others, need to be always be taught in the practical labs with those relevant software.

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