Factor Analysis of Issues Contributing to Examination Malpractice in a Tertiary Institution in Ghana

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Abstract
The success of every educational institution depends on its ability to observe its code of ethics in respect of all its operations to achieve its mission. This achievement, if persistently monitored and consolidated, will help raise the image of that institution and hence gain high public recognition, which will in the nutshell contribute to sustainable quality education. This research was necessitated by the recurrence of examination malpractice at all levels of basic, secondary and tertiary education in recent times in Ghana. This phenomenon of examination malpractice does not augur well for the education system of Ghana and for that matter the future of the nation, especially when all educational institutions have codes governing the conduct of examination. Therefore, any factor that is likely to undermine effort at ensuring adherence to the code of ethics ought to be identified and eliminated. This paper reports on an enquiry into factors contributing to examination malpractice at one of the tertiary institutions in Ghana. A sample size of two hundred and fifty (250) students was used for the study. Among other things, the research findings revealed that there are three dimensions contributing to examination malpractice in the tertiary institution, which accounted for 70.65% of the variance in the original variables. In sum, the issues considered to be contributing to examination malpractice in the tertiary institution are: misconduct of some lecturers and invigilators, societal moral decadence, and institutional failures. Staff and students of the polytechnic will do well to focus on these dimensions to safeguard the image of the institution.
Keywords: Examination Malpractice, Factor Analysis, Principal Component Factoring

1. Introduction

Education plays a very important role in development of every nation**.** In one dimension, it is seen as an instrument for; liberation of the minds of people, facilitation of social unity, and enhancing economic development. The educational system constitutes the principal tool for the development of important body of knowledge, skills, attitudes and values. The quality of life of the citizens of a nation depends to a large extent, the quality of education that it receives, hence it has become obligatory to have the best quality education for its citizens to fit into the ever changing society we find ourselves (Asiedu-Akrofi, 1978).

To achieve such quality education, one of the key factors that must not be discounted is academic performance. Academic performance may be looked at from various perspectives; one of such perspectives often used as a measure of academic performance is students' academic score or cumulative grade point average, CGPA. In general, students' academic score is measured through examination. 'The high premium attached to paper qualifications as prerequisite for admissions and gainful employment' (Adegoke, 2010)**,** has assumed such importance that all levels of our educational system have received much attention in respect of examination. Examination serves as an avenue through which we can assess and measure students' academic output and hence predict his/her knowledge, skills, and competence; on the job market, or the next level of education. Unfortunately, the rate at which examination is being compromised is becoming alarming. Examination malpractice has been occurring persistently in our educational institutions to the point where it is difficult to tell the difference between very hard working students and ordinary students. The tension and 'examination fever' that usually characterises school campuses prior to, and during examinations seem to have gone down. One of the generally held views and what appear to be the feelings of some students is that, after all, there are other means by which they can maneuver to pass their examinations so why study hard. This ill-opinion has run through our society to the point where people have begun to question the authenticity and credibility of the hard-earned certificates of some distinguished individuals and institutions. Some of the consequences of examination malpractice are that perpetrators of examination malpractice may displace their colleagues who have done honest work, academically, in areas such as searching for jobs, and admission into institutions of higher studies and the credibility of our society and educational system has been undermined. In this respect, some people with high academic credentials may not be able to demonstrate it on the field of work and this may lead to job inefficiency which will in turn affect the growth of our economy. As the Government of Ghana prepares to upgrade, and grant autonomy to the Polytechnics to run as Technical Universities, these ill-behaviours will not augur well for the institutions' image. Many institutions have prescribed punishments of various degrees for violation of examination rules, yet the frequency of the incidence of examination malpractice appears to be rising. The questions that arise are: Are these measures and punishment not enough to deter people from the act? If they are, why is it that examination malpractice seems to be on ascendancy? The researchers believe that there is more to punishment as a way of curbing examination malpractice. The researchers, therefore, tried to identify factors that contribute to examinations malpractice at the polytechnic. In doing this, data was obtained from two hundred and fifty (250) respondents who were interviewed through questionnaires comprising eleven items that uses five-point Likert scale ranging from 'strongly agree to strongly disagree'. The data collected was analysed using Statistical Products and Service Solutions (SPSS), Version 16. The factor analysis which was the main statistical tool used in this research is reviewed below.

2. Materials and Methods

This section briefly discusses factor analysis and the fundamental equations that were used to analyse the data. Factor analysis is a statistical technique used to describe, if possible the covariance relationships among many variables in terms of a few underlying but unobservable random quantities called factors (Johnson and Wichern, 1992). The technique comprises common factor analysis and principal components analysis. In this respect, factor analysis seeks to examine the interdependence that exists among variables and common constructs (factors) that governs a situation or phenomenon.

2.1 *The Orthogonal Factor Model*

In a multivariate setting, if observable random variable X, has p components, with the mean μ and covariance matrix, Σ, then the factor model postulates that X is linearly dependent upon a few factors $F_1, F_2, F_3, \dots, F_m$; where m is far less than p; and p additional source of variation $\varepsilon_1, \varepsilon_2, \varepsilon_3, \dots, \varepsilon_p$ called errors or sometimes specific factors (Johnson and Wichern, 1992). In this situation, the factor model is

$$X_1 - \mu_1 = \ell_{11}F_1 + \ell_{12}F_2 + \cdots + \ell_{1m}F_m + \varepsilon_1$$

$$X_2 - \mu_2 = \ell_{21}F_1 + \ell_{22}F_2 + \cdots + \ell_{2m}F_m + \varepsilon_2$$

$$\vdots \qquad \vdots \qquad \vdots \qquad \vdots \quad \vdots \qquad \vdots$$

$$X_p - \mu_p = \ell_{p1}F_1 + \ell_{p2}F_2 + \cdots + \ell_{pm}F_m + \varepsilon_p$$

which is presented in matrix notation as $(X-\mu)_{(p\times 1)} = L_{(p\times m)}F_{(m\times 1)} + \varepsilon_{(p\times 1)}$.

The coefficient ℓ_{ij} is called the loading of i^{th}variable on the j^{th} factor. L is the matrix of factor loadings. In an orthogonal factor model, the data is analysed based on assumption that the factors and specific error terms are all independent. In this case we can mathematically write that:

$[F] = (m\times 1)$ $[\varepsilon] = (p\times 1)$ $(F) = (m\times m)$

Cov (ε_i, ε_j) = 0, Cov (F_i, ε_j) = 0, and 0 is a null matrix. Also the coefficients (pattern loadings) l_{ij} , i = 1, 2, . . . , p; j =1, 2, . . . , m are the same as the simple correlations (structure loadings) between the indicator variables X_i and the factors F_j , and the variance (communality) that X_i shares with F_j is given by $l^2{}_{ij}$ (Sharma, 1996). Thus the total communality of an indicator variable X_i with all the m common factors is given by$l^2{}_{i1} + l^2{}_{i2} + \cdots + l^2{}_{im}$.

It should be noted that, the observable variables $X_1, X_2, \dots, X_p$ are correlated because they are influenced by some common underlying dimensions (factors). Indicator variables that are influenced by common latent factors tend to have high correlation among each other and also with the common latent factor. This is the basis for identifying the underlying factors. (Everitt and Dunn 2001; Johnson and Wichern, 1992; Sharma, 1996).

2.2 *Principal Component Factoring*

This is one of the most frequently used methods of factor analysis which uses principal component analysis (PCA) to extract factors influencing many observed variables by examining correlation among them. PCA is a mathematical procedure for data that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables. This transformation is such that the first principal component (PC) has the largest possible variance in the data; the second PC accounts for maximum variance that was not accounted for by the first PC; the third principal component accounts for the highest of the remaining variance that was not accounted for by the first and second components, and so on (Johnson and Wichern, 1992; Shama, 1996; Everrit and Dunn, 2001).

If $X_1, X_2, \ldots, X_p$ and $w_{ij}, i = 1,2, \ldots, p, j = 1,2, \ldots, p$ are the observed variables and respective coefficients (weights), then the PCs; $C_1, C_2, \ldots, C_p$ are given by

$$C_1 = w_{11}X_1 + w_{12}X_2 + \cdots + w_{1p}X_p$$
$$C_2 = w_{21}X_1 + w_{22}X_2 + \cdots + w_{2p}X_p$$
$$\vdots \quad \vdots \quad \vdots \quad \vdots$$
$$C_p = w_{p1}X_1 + w_{p2}X_2 + \cdots + w_{pp}X_p$$

To restrain the variance of the $C_i s$, $i = 1,2, \ldots, p$ from increasing, and ensure that the new axes representing the $C_i s$ are orthogonal (uncorrelated), the weights, $w_{ij}, i = 1,2, \ldots, p, j = 1,2, \ldots, p$ are estimated based on equations 1 and 2 below (Johnson and Wichern, 1992; Shama, 1996; Everrit and Dunn, 2001).

$$w_i' \cdot w_i = 1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$
$$w_i' \cdot w_j = 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1) \text{ for all } i \neq j$$

Where $w_i' = (w_{i1}, w_{i2}, \ldots\ldots, w_{ip})$. The original variables X_i with mean μ_i and standard deviation, σ_{ii}, $i = 1,2, \ldots, p$ could be transformed into new components by $Z_i = \frac{X_i - \mu_i}{\sigma_{ii}}$, for $i = 1,2, \ldots, p$. The resulting variables could be used to form the PCs (Johnson and Wichern, 1992). The vector of standardised variables, Z could be written in vector notation as $\left(V^{\frac{1}{2}}\right)^{-1}(X - \mu)$ where $\mu' = (\mu_1, \mu_2, \ldots\ldots, \mu_p)$ and $V^{\frac{1}{2}}$ is the standard deviation matrix given by $V^{\frac{1}{2}} = \begin{bmatrix} \sigma_{11} & 0 & \cdots & 0 \\ 0 & \sigma_{22} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_{pp} \end{bmatrix}$. In which case E$(Z_i) = 0$, Var $(Z_i) = 1$ for all $i = 1,2, \ldots, p$ and $Cov(Z) = \left(V^{\frac{1}{2}}\right)^{-1} \Sigma \left(V^{\frac{1}{2}}\right)^{-1} = \rho$ where the variance-covariance matrix, Σ and the correlation matrix, ρ of X are given

$$\Sigma = \begin{bmatrix} \sigma_{11}^2 & \sigma_{12}^2 & \cdots & \sigma_{1p}^2 \\ \sigma_{21}^2 & \sigma_{22}^2 & \cdots & \sigma_{2p}^2 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{p1}^2 & \sigma_{p2}^2 & \cdots & \sigma_{pp}^2 \end{bmatrix}$$

$$\rho = \begin{bmatrix} \frac{\sigma_{11}^2}{\sigma_{11}\sigma_{11}} & \frac{\sigma_{12}^2}{\sigma_{11}\sigma_{11}} & \cdots & \frac{\sigma_{1p}^2}{\sigma_{11}\sigma_{pp}} \\ \frac{\sigma_{21}^2}{\sigma_{11}\sigma_{22}} & \frac{\sigma_{22}^2}{\sigma_{22}\sigma_{22}} & \cdots & \frac{\sigma_{2p}^2}{\sigma_{22}\sigma_{pp}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\sigma_{p1}^2}{\sigma_{11}\sigma_{pp}} & \frac{\sigma_{p2}^2}{\sigma_{22}\sigma_{pp}} & \cdots & \frac{\sigma_{pp}^2}{\sigma_{pp}\sigma_{pp}} \end{bmatrix}$$

and $\rho_{ij} = \frac{\sum_{k=i}^{n}(X_{ki} - \mu_i)(X_{kj} - \mu_j)}{n}$, $i \neq j$ is the covariance between variables X_i and X_j, each of which has n observations respectively. The PCs, $C' = [c_1, c_2, \ldots, c_p]$ are then given by $C = A'Z$ where $A = [e_i, e_2, \ldots, e_p]$, with $e_i s$, $i = 1,2, \ldots, p$ being the eigenvectors of ρ. The eigenvalue- eigenvectors pairs $(\lambda_1, e_1), (\lambda_2, e_2), \ldots, (\lambda_p, e_p)$ of ρ are such that $\lambda_1 \geq \lambda_2 \geq \cdots, \lambda_p \geq 0$,

$e_i' \cdot e_j = 0$, $e_i' \cdot e_i = 1$ and Var $(C_i) = e_i' \rho e_i = \lambda_1$ and

$\sum_{i=1}^{p} Var(C_i) = \sum_{i=1}^{p} Var(Z_i) = \rho$. In this case, the percentage of variance explained by the C_i is given by the $\frac{\lambda_i}{p}$. The correlation between a given PC, C_i and a given standardised variable, Z_j is referred to as the loading of Z_j on C_i and is given by $Corr(C_i, Z_j) = e_{ij}. \lambda_j^{\frac{1}{2}}$. The loading reflects the extent to which each

Z_j influences C_i considering the effect of other variables, Z_k , $j \neq k$ (Hair et al, 2006; Johnson and Wichern, 1992; Shama,1996). In PCF, the initial communalities of the indicator variables are one. The following section presents the results of the analysis of the data described in the introduction, using principal component factoring.

3. Results

Table 1: Data Suitability Test for Factor Analysis

Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.642
Bartlett's Test of Sphericity Approx. Chi-Square	173.380
d. f.	15
Sig.	0.000

Source: Results from analysis of field work data, 2015

To verify that our data is suitable for factor analysis, we check the Kaiser-Meyer-Olkin Measure of Sampling Adequacy, and Bartlett's Test of Sphericity, for the sample size and the appropriateness of the correlation matrix for factor analysis respectively. From Table 1, it could be seen that the value of the KMO is 0.642 (which is greater than the minimum thresh hold of 0.5 (Sharma, 1996)) and the Bartlett's test has a p-value of 0.000 which is less than the significance value 0.05 indicating that the test is significant. This indicates that at least, some of the variables are inter-correlated, the sample size is adequate. Hence the data is appropriate for factor analysis.

3.1 *Number of Factors Extracted*

To determine the number of factors to extract, we need to consider the Kaiser's criterion. In this situation, all factors with eigenvalues more than or equal to 1 are considered.

Table 2: Communalities

Variable	Initial	Extraction
Poor invigilation is conducted in my school during examination	1.000	0.765
There is absence of effective counseling in my school	1.000	0.711
There is prevailing level of immoralities in our society	1.000	0.790
Bribery in our society is very high	1.000	0.612
Leakage of answer materials to some students by some invigilators and lecturers during examination	1.000	0.686
Altering of grades by some lecturers in exchange for personal gain	1.000	0.675

Source: Results from analysis of field work data, 2015

The communalities (extraction) are shown in Table 2. In PCF, all variables are assigned an initial variance (total communality) of one (1), as explained earlier. The final communalities of each variable indicate the variance explained by each component (factor solution) for the chosen variables. Six out of the initial eleven (11) variables were retained in the final factor solution. The other five variables were removed from the analysis because of lower communalities of less than 0.50 threshold value, or they were cross-loading (loading on more than one factor) in the exploratory analysis. Using the results of Table 2, we can see that all the final communalities are more than 0.50. This means that at over 50% of the initial communality of each variable was accounted for in the final factor solution. The factor solution is considered to be satisfactory if at least half of the variance of each variable is shared with the factors (Sharma, 1996).

Using results of Table 3 we observe that the first three components have eigenvalues (2.093, 1.127 and 1.019). These three components account for a total of 70.649% the variance as shown in the cumulative % column of Table 3. Hence we consider the first three components for further analysis.

Table 3: Total Variance Explained

Component	Initial Eigenvalues	% of Variance	Cumulative (%)
1	2.093	34.878	34.879
2	1.127	18.783	53.662
3	**1.019**	**16.987**	**70.649**
4	0.654	10.897	81.546
5	0.587	9.790	91.336
6	0.520	8.664	100.00

Source: Results from analysis of field work data, 2015

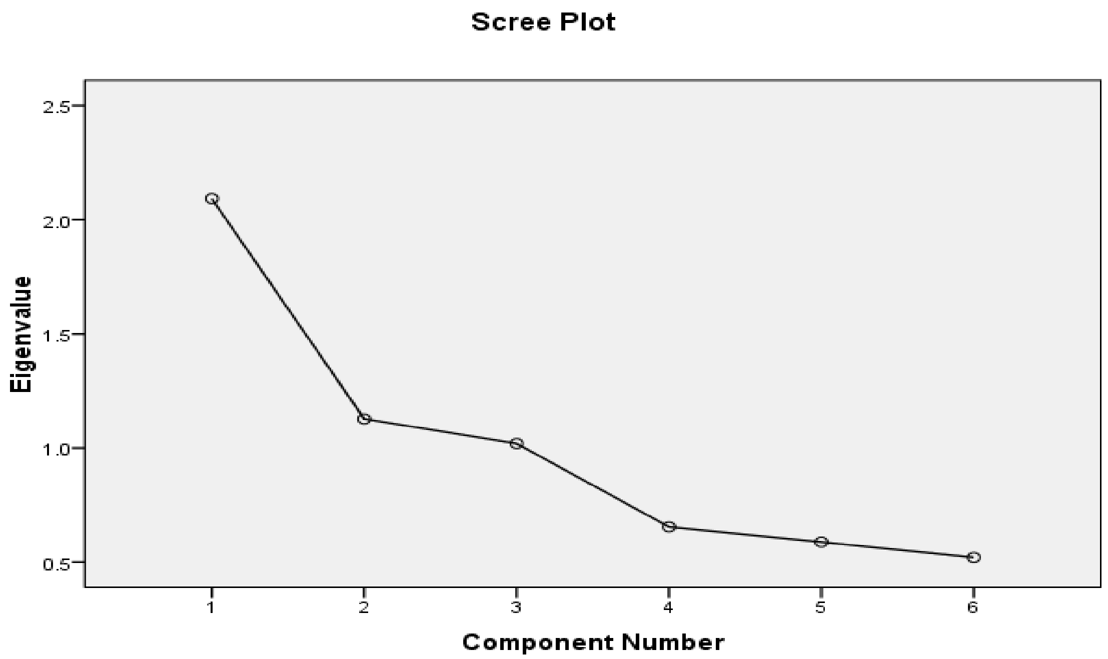

Figure 1: Plot of eigenvalues against component number

From Figure 1, we observe that there are clear breaks at second and fourth components. This makes the scree plot, in this situation, not helpful in terms of the number of new variables to retain. Since the three components selected by Kaiser's criterion together explain over 70% of the variability in the data, more than the recommended minimum of 60% (Hair et al., 2006), the first three components are retained as being enough to explain the factor structure of the data.

The six variables associated with the retained components are shown in Table 4. These are: altering of grades by some lecturers in exchange for personal gain, leakage of answer materials to some students by some invigilators and lecturers during examination, prevailing level of immoralities in our society, very high bribery in our society, poor invigilation conducted in the school during examination, and absence of effective counseling in the school.

3.2 *Interpretation of Output*

Table 4 is result of the Varimax rotation of the initial factor solution. It can be seen from the table that the variables: (altering of grades by some lecturers in exchange for personal gain and leakage of answer materials to some students by some invigilators and lecturers during

Table 4: Rotated Component Matrix

	Component		
Variable	1	2	3
Altering of grades by some lecturers in exchange for personal gain	0.811		
Leakage of answer materials to some students by some invigilators and lecturers during examination	0.792		
There is prevailing level of immoralities in our society		0.888	
Bribery in our society is very high		0.652	
Poor invigilation is conducted in my school during examination			0.844
There is absence of effective counseling in my school			0.751

Source: Results from analysis of field work data, 2015

examination; (prevailing level of immoralities in our societies and very high bribery in our societies; (poor invigilation conducted in the school during examination and absence of effective counseling in the school, load significantly on components 1, 2, and 3 respectively. Thus the components thought to be underlying dimensions influencing examination malpractice at the institution, are named as follows:
Factor1: Misconduct of some lecturers and invigilators
Factor 2: Societal moral decadence
Factor 3: Institutional failures

4. Conclusion

Judging from above, we conclude that for the tertiary institution to succeed in eradicating examination malpractice, it must persistently examine all aspects of its operations in respect of examinations, more especially, the conduct of some of its lecturers and invigilators and enforce the institutional measures dealing with examination malpractice to curtail the problem. This will help project the image of the institution high in the competitive tertiary education level. The study was restricted to few variables and also small sample size. It is therefore suggested that in future research, more variables, as well as tertiary institutions are covered so that the external validity of the study results can be firmly established. Further, responses were solicited from only students: it is recommended that in future research, feed-back is sought from lecturers and administrators, and other principal stakeholders.

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