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FACTORS CONTRIBUTING TO THE LOW ACADEMIC ACHIEVEMENT OF STUDENTS AT THE BASIC EDUCATION CERTIFICATE EXAMINATION IN SOME PUBLIC JUNIOR HIGH SCHOOLS OF A POLITICAL DISTRICT IN THE WESTERN REGION OF GHANA: STUDENTS' AND TEACHERS' PERSPECTIVE

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ABSTRACT: *The key to sustainable development of every nation is largely dependent on the quality of education that it offers to its citizens, more especially at the basic level. Therefore, any issue that may affect the aim of building and achieving quality education for national development needs to examined and addressed. This paper reports on an analysis of factors contributing to poor academic performance of students of a political district in the Western Region of Ghana, in the Basic Education Certificate Examinations (BECE). In all, four hundred and sixty* (460) *respondents comprising two hundred and thirty-eight (238) students and two hundred and twenty two* (222) *teachers were used for the research. Among other things, the study discovered that in all, there are eight dimensions underlying the poor performance of students at BECE in the political district, which accounted for;* 63.2% *of variance in students' response, and* 64.7% *of teachers' response in the original variables. In sum, the constructs considered to be contributing to poor performance were: teacher failures, parent shortcomings, reactive learning, passive learning, unfavourable economic conditions, uncongenial circumstances, administrative lapse, and truancy. Stakeholders of education are advised to focus on these dimensions to ensure quality education for sustainable national development.*

KEYWORDS: Poor Academic Performance, Factor Analysis, Principal Component Factoring

INTRODUCTION

The issue of poor academic performance has been a major problem in Africa of which Ghana cannot dissociate itself. Many governments including that of Ghana have made several efforts at curtailing if not eliminating the problem of poor academic performance more especially at the foundation stage of education. Poor academic performance can be explained from several perspectives, but it can also be considered as a situation where individual or group of students fail(s) to achieve certain minimum standards or benchmarks either in an examination or other assessments. Consequences of poor academic performance at the basic school, range from; low quality graduates who may not be able to pursue higher education, production of graduates who are not fit for national development.

In view of this negative impact, there has been a massive public uproar about poor performance at the basic schools in Ghana. Over the last couple of years, students' performance in the BECE has dropped tremendously and this has been a major concern of all stakeholders of education. For instance, it has been discovered that, over a couple of years, terminal performance of students as well as the overall students' performance in BECE in that political district has reduced drastically. It is against this background that this study solicited responses from students and teachers to identify factors that contribute to students' poor performance at the BECE and to propose ways of improving the situation. In summary, four hundred and sixty (460) respondents made up of two hundred and thirty-eight (238) students and two hundred and twenty two (222) basic school teachers were used. A questionnaire comprising 20 items for students and 24 items for teachers, that uses five-point Likert scale ranging from 'strongly agree to strongly disagree' was used for the data collection. The data collected was analysed using Statistical Products and Service Solutions (SPSS16). The factor analysis method used in this research is reviewed below.

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. In this respect, factor analysis seeks to examine interdependence that exists among variables and common constructs (factors) that governs a situation or phenomenon.

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

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

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

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

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

which presents 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 ith variable on the jth 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 $(\varepsilon_i, \varepsilon_j) = 0$, Cov $(F_i, \varepsilon_j) = 0$, and 0 is a null matrix.

Also the coefficients (pattern loadings) l_{ij}, $i = 1, 2, \dots, p$; $j = 1, 2, \dots, m$ 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 $X_1, X_2, \ldots, X_p$ are correlated because they are influenced by some common underlying dimensions (factors). The correlation among the indicator variables enhances the identification of the common latent factors as the indicator variables that are influenced by the same factor tend to 'load' highly on (have a high correlation coefficient with) that common factor and also amongst themselves (Everitt and Dunn 2001; Johnson and Wichern, 1992; Sharma,1996).

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. PC A is a mathematical procedure of data reduction technique that uses an orthogonal transformation to convert a set of observation 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, and the third principal component accounts for 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

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

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).

$w_i' \cdot w_i = 1 \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . . (1)$

$w_i' \cdot w_j = 0 \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . . (1)$ 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 $\mu' = (\mu_1, \mu_2, \dots \dots, \mu_p)$ 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 $\mathrm{E}(Z_i) = 0$, $\mathrm{Var}(Z_i) = 1$ for all $i = 1,2, \dots, p$ 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, $C' = [c_1, c_2, \dots, c_p]$ are then given by $C = A'Z$ where $A = [e_i, e_2, \dots, e_p]$, with $e_i s$, $i = 1,2, \dots, p$ being the eigenvectors of ρ. The eigenvalue- eigenvectors pairs $(\lambda_{1,}\ e_1), (\lambda_{2,}\ e_2), \dots, (\lambda_{p,}\ e_p)$ 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 $\mathrm{Var}(C_i) = e_i' \rho e_i = \lambda_1$ 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.

RESULTS

Table 1: KMO and Bartlett's Test

	Students' Response	Teachers' Response
KMO	0.866	0.732
Bartlett's Test: Approx. Chi-Square	495.799	580.680
Df	21	105
Sig.	0.000	0.000

Source: Results from analysis of field work data, 2016

To verify that our data is suitable for factor analysis, we check the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO), and Bartlett's Test of Sphericity, for the sample size and the appropriateness of the correlation matrix for factor analysis. From the results presented in Table 1, it could be seen that the values of the KMO, obtained from students' and teachers' responses are respectively 0.866 and 0.732 (which are greater than the minimum recommended value of 0.5 (Sharma, 1996)). The corresponding values for the Bartlett's test are 0.000 each, which is less than 0.05 indicating that the tests are significant. This indicates that at least, some of the variables are correlated amongst themselves. Hence the data are appropriate for factor analysis.

Table 2: Communalities

Variable (students' response)	**Initial**	**Extraction**
My parents do not assist me in doing my homework	1.000	0.962
My class teacher does not check my attendance to school regularly	1.000	0.568
My teacher does not give me class work after class lessons regularly	1.000	0.595
My class teacher fails to discuss previous lessons before he starts teaching	1.000	0.620
My teacher does not regularly use diagrams, tables, charts and graphs as practical in teaching	1.000	0.571
My teacher does not spend much time on weak students	1.000	0.583
My teacher fails to conduct mental drill during class lessons	1.000	0.524
Variable (teachers' response)	**Initial**	**Extraction**
Students are not regular and punctual to school	1.000	0.759
Students do not participate in my class effectively	1.000	0.674
Students do not do class work regularly	1.000	0.667
Students do not do homework regularly	1.000	0.647
The outcome of students' class work and homework is not encouraging	1.000	0.535
Students skip classes during market days to assist their parents to sell their wares	1.000	0.592
Students do other menial jobs to support themselves with their school needs	1.000	0.690
Large class size in my school contributes to poor academic performance in BECE	1.000	0.717
Routine supervision of lesson notes and teaching is not done in my school regularly	1.000	0.691

Mock examinations conducted in my school every year is inadequate for students preparing for BECE	1.000	0.579
Parents fail to provide the needed learning materials for their wards' studies	1.000	0.724
My students are unable to honour their study time table	1.000	0.603
Students do not revise materials taught frequently	1.000	0.662
Students are unwilling to initiate learning themselves	1.000	0.540
Students in my school hardly do discovery learning	1.000	0.630

Source: Results from analysis of field work data, 2016

The communalities (extraction) are shown in Table 2. In PCF, all variables are assigned an initial variance (total communality) of one, as we have stated earlier. The final communalities of each variable indicate the variance for each variable accounted by the chosen factor solution. Analysis of the students' and teachers' responses revealed that seven and fifteen variables were maintained respectively in the final factor solution. The other variables were removed from the

Table 3: Total Variance Explained

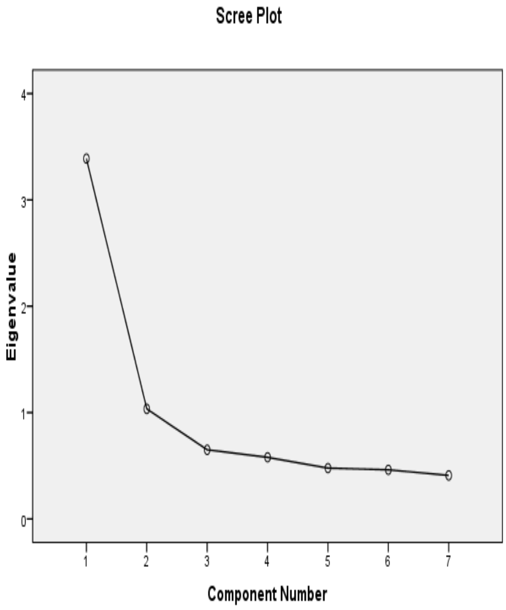
	Initial Eigenvalues (Students' Data)			Initial Eigenvalues (Teachers' Data)		
Component	Total	% of Variance	Cumulative (%)	Total	% of Variance	Cumulative (%)
1	3.389	48.410	48.410	3.409	22.726	22.726
2	**1.034**	**14.774**	**63.184**	1.654	11.025	33.751
3	0.650	9.282	72.466	1.373	9.156	42.907
4	0.579	8.274	80.740	1.143	7.618	50.525
5	0.478	6.823	87.563	1.082	7.212	57.737
6	0.462	6.597	94.160	**1.049**	**6.995**	**64.733**
7	0.409	5.840	100.00	0.750	4.998	69.731
8				0.745	4.968	74.699
9				0.692	4.611	79.310
10				0.654	4.361	83.671
11				0.586	3.904	87.575
12				0.560	3.733	91.308
13				0.504	3.361	94.669
14				0.439	2.928	97.596
15				0.361	2.404	100.00

Source: Results from analysis of field work data, 2016

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 at least 0.50. This means that at least 50% of the initial communality of each of the retained variables was accounted for in the final factor solution. The factor solution is considered to be adequate if at least half of the variance of each variable is shared with the factors (Sharma, 1996). 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 retained in the final factor solution. The results of Table

3 suggest we extract two and six components, respectively, from the variables in the students' and teachers' data.

The eigenvalues of the components extracted in the students' data and that of the teachers' data are 3.389, and1.034, and 3.409, 1.654, 1.373, 1.143, 1.082, and1.049 respectively. The two factor solutions account for 63.184%, and 64.733% of the initial variability in the data respectively**.** It is customary to consider more than one criterion in the extraction of the components for the final solution, as it serves as a guarantee that the final factor solution is more acceptable. In this regard, the Kaiser's criterion, the scree plots and the percentage of the initial total variance explained were considered. Kaiser's criterion suggests retaining two (2) and six (6) components; respectively, from students' and teachers' data as these components have eigenvalues greater or equal to one.



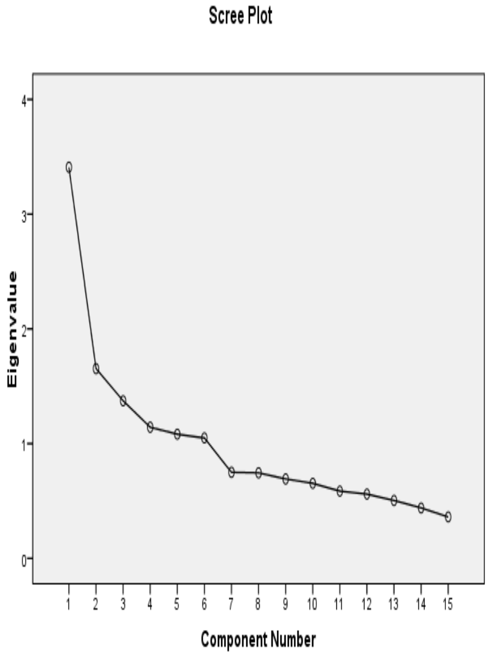


Fig 1: Eigenvalues against component no. **Fig 2: Eigenvalues against component no.**

Figure 1 suggests the extraction of two (2) components from the students' data while Figure 2 appear to suggest the extraction of six (6) components from teachers' data respectively, as there appear to be a major change in the direction of the curve of the scree plot at the second and sixth components respectively. The remaining components of Figures 1 and 2 have eigenvalues lower than one (1). The two factor solutions suggested by the Kaiser criterion accounted for 63.2% and 64.7% of the total variance explained in the case of the students' data and the teachers' data respectively. These two values are greater than the suggested minimum of 60% (Hair et al) overall variance explained. The first two components in the case of the students' data and the first six in the case of teachers' data were retained as the final factor solution as these factor solutions satisfy both the Kaiser and the minimum variance explained criteria. They also represent a more conservative solution than the ones suggested by the scree plots.

Number of Factors Extracted

Having considered analysis of total variance explained and the scree plot, we now turn our attention to the component matrix. This shows the loadings of each of the items on the components. At a cut- off value of 0.5 we see that the retained (variables) load on the first two and six components of the students' and teachers' data respectively.

Table 4: Rotated Component Matrix (Students' Response)

Variable	Component 1	Component 2
My class teacher fails to discuss previous lessons before he starts teaching	0.775	
My teacher does not give me class work after class lessons regularly	0.763	
My teacher does not spend much time on weak students	0.760	
My class teacher does not check my attendance to school regularly	0.752	
My teacher does not regularly use diagrams, tables, charts and graphs as practical in teaching	0.746	
My teacher fails to conduct mental drill during class lessons	0.709	
My parents do not assist me in doing my homework		0.980

Source: Results from analysis of field work data, 2016

This suggests that two and six-factor solutions are likely to be more appropriate in the data collected from students and teachers correspondingly. Hence, per these three criteria of eigenvalue-greater-one rule, scree plot and the percentage of variance explained, two and six factors are retained for interpretation. The seven variables from students' responses and fifteen variables from teachers' responses to be considered are shown in Tables 4 and 5 respectively.

Table 5: Rotated Component Matrix (Teachers' Response)

Variable	Component					
	1	2	3	4	5	6
V_1	0.776					
V_2	0.731					
V_3	0.703					
V_4	0.578					
V_5	0.524					
V_6		0.778				
V_7		0.673				
V_8		0.584				
V_9			0.790			
V_{10}			0.706			
V_{11}				0.765		
V_{12}				0.653		
V_{13}					0.826	
V_{14}					0.630	
V_{15}						0.839

Source: Results from analysis of field work data, 2016

Interpretation of Output

Tables 4 and 5 present the results of the rotation of the initial factor solutions. It can be seen that after Varimax rotation**,** 7 variables are retained to constitute the two components (factor) solution of the students' data, and fifteen variables to constitute six components (factor) of the teachers' data. These variables are defined as; $v_1 -$ students do not revise materials taught frequently, $v_2 -$ students in my school hardly do discovery learning, $v_3 -$ students are unwilling to initiate learning themselves, $v_4 -$ my students are unable to honour their study time table, and $v_5 -$ the outcome of students' class work and homework is not encouraging, to constitute component1. For component2, the variables are; $v_6 -$ students do not do classwork regularly, $v_7 -$ students do not do homework regularly, $v_8 -$ students do not participate in my class effectively. Component3 is made up of; $v_9 -$ students do menial job to support themselves with their school needs, and $v_{10} -$ students skip classes during market days to assist their parents to sell their wares. $V_{11} -$ large class size in my school contributes to poor academic performance in BECE, and $v_{12} -$ parents fail to provide the needed learning materials for their wards' studies, constitute compnent4. Also, $v_{13} -$ routine supervision of lesson notes and teaching is not done in my school regularly, and $v_{14} -$ mock examinations conducted in my school every year is inadequate for students preparing for BECE, constitute component5. The sixth component comprises; $v_{15} -$ students are not regular and punctual to school.

Based on these factor solutions, the dimensions influencing poor academic performance in BECE are named as follows:

Students' Response

Factor1**:** Teacher failures

Factor 2: Parent shortcomings

Teachers' Response

Factor 1: Reactive learning

Factor 2: Passive learning

Factor 3: Unfavourable economic conditions

Factor 4**:** Uncongenial circumstances

Factor 5**:** Administrative lapse

Factor 6**:** Truancy

CONCLUSION

Inferring from above analyses, we conclude that for the political district in the Western Region of Ghana to succeed in getting rid of poor academic performance at BECE, it must persistently inspect all facets of it operations in respect of; teachers and parents collaborating to discharge their full responsibilities towards students' education, involving students in diverse active learning exercises to develop skills in constructing and using knowledge, by creating enabling economic and other congenial atmosphere that promote learning, and honouring administrative duties, more especially the ones that check students' attendance to school. This will help improve the performance of its basic school graduates which will serve as bedrock for quality education for national development. The findings in this study support the literature of researchers such as; Ansu (1989), Anamuah-Mensah et al. (2007), and Oppong-Sekyere et al. (2013), who discovered that factors attributed to teachers, students and parents are the causes of low academic performance of students at basic level. In this research, only one political district was used. It is therefore recommended that in future research, more districts are covered to enable us establish concrete external validity about the study results**.** Also, responses were solicited from only students and teachers: it is suggested that in future research, feed-back is sought from principal stakeholders such as parents, and other civil society organisations.

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