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Multivariate Study of the Use of Assessment Strategies and Cross Cutting Issues by Basic School Teachers: The Case of Ghana's New Curriculum

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Authors' contributions

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

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ABSTRACT

Ghana's new basic school curriculum requires teachers to use new teaching strategies that also address cross cutting issues in their teaching to enhance learning. This study sought to assess the use of assessment strategies by basic school teachers in Ghana. A sample size of 100 was computed at 95% confidence interval and randomly selected from the population. The features, strategies and principles underpinning *the assessment strategies* and cross cutting issues in Ghana's new curriculum for the basic school formed the basis of the construction of the 47 items used in the questionnaire. The internal consistency of the items used in the four point likert scale was high with Cronbach's Alpha coefficient of 0.995. Principal component analysis and multiple linear regressions were the main methods used for the analysis.KMO statistic of 0.921 and Bartlett's Test's Chi Square value was13684.049 with difference of freedom of 1081 and significance at 0.00000. Multiple extraction approaches were used to retain two components which explained about 91% of the variance. The first component named **Criterion motivation** explained

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about 61.7% of the variance and composed generally of assessment as-of- and - for learning strategies. The second component which was named **inclusion motivation,** generally loaded highly with the cross cutting issues and explaining about 28.6% of the total variance. Criterion and inclusion motivation were found to predict feedback with a high power of 94%.Criterion motivation was found to have a positive impact on feedback received from students and was statistically significant ($B = 0.746$, $P<0.001$). Again, there was a positive relationship between the inclusion motivation and feedback with a significant difference ($B = 0.232$, $P<0.001$).There were some disparities in the use of assessment strategies outlined in the new basic school curriculum for Ghana. Teachers were found to exhibit preference to some components of the assessment strategies recommended for use in the new curriculum at the detriment of others. It is recommended that the developed criterion motivation and inclusive motivation approaches are adopted in teaching in order to enhance maximum feedback from learners.

Keywords: Principal component analysis; multivariate; assessment strategies; Ghana; curriculum; cross cutting issues; basic school; teacher.

1. INTRODUCTION

Harlen [1] found that summative assessment and formative assessment when combined in educational practice, has the capacity to raise standards for all students. Contemporary, Educational Curriculum emphasizes the use of summative and formative assessment strategies by teachers as well as integrating cross cutting issues into the teaching and learning process. Ghana's new curriculum emphasizes seven (7) pedagogical approaches to teaching and learning. These include the following: (a)integration of assessment as learning, for learning and of learning into the teaching and learning processes and as an accountability strategy (b) questioning techniques that promote deep learning (c) positioning of inclusion and equity at the centre of quality teaching and learning(d) use of differentiation and scaffolding as teaching and learning strategies for ensuring that no learner is left behind (e) creation of learning-centred classrooms through the use of creative approaches to ensure learner empowerment and independent learning (f) use of Information Communications Technology (ICT) as a pedagogical tool and (g) identification of subject specific instructional expectations needed for making learning in the subject relevant to learners [2].

The implication of these pedagogical approaches is that each lesson that the teachers prepare must satisfy all approaches as outlined by the new curriculum. From the work of Wilie [3], during curriculum implementation, some aspects of pedagogical approaches receive less emphasis and attention from teachers (who are the sole implementers) during teaching and learning. It is against this backdrop that there is a need to use principal component analysis (PCA) to obtain a summary of the numerous pedagogical approaches proposed by the new curriculum without any loss of generality. This study will help identify the domains that predict feedback from learners with a high power. To that end, teachers will teach by focusing on identified domains that will yield the same outcome as using all the seven (7) approaches altogether.

2. LITERATURE REVIEW

Principal components analysis (PCA) has been extensively applied in diverse fields as a multivariate approach in reducing the dimension of data points so as to facilitate the interpretation and construction of predictive models [4].

Tulu et al. [5] examined the use of assessment techniques by secondary school teachers in Ethiopia using PCA. The study confirmed that there were three types of assessment techniques: Assessment OF learning, assessment FOR learning, assessment AS learning. Most of the teachers reported that assessment OF learning and assessment FOR learning to be the most common and dominant forms of assessments across language, sciences and social sciences. However, only the physical education teachers used assessment AS learning to assess their students.

Anwar [6] used principal component analysis in their work to evaluate the use of formative assessment in teaching. Likert scale with 11 items were constructed and administered to the students taking the course of Epidemiology in MD program of College of Medicine. Factor analysis was used to see similar pattern of responses in the Likert scale items. Two distinct factors were underlying student responses were retained. However, the researcher did not explore multiple extraction approaches such as parallel approaches and the Kaisor Eigen value greater than one rule. Decision on the number of components to retain was solely made using the scree plot which is widely known for its subjectivity.

Twene four et al. [7] in their work sought to identify a metric for measuring students' performance in the Department of Mathematics and Statistics of a public university in Ghana using Principal Component Analysis. Three principal components were retained as rules or indices for the classification of students' performance. A derivative of the first principal component, RSI, could serve as a new performance measure for the Department as it takes into consideration differences in the raw scores of the students. In their work, decision to retain factors was primarily based on Screen plot and Kaiser's Eigen value greater than 1 rule. However, recent studies have found parallel analysis to be the most robust method for retaining factors, which the authors did not consider in their work.

3. METHODS

The study used the survey approach to collect primary data. The research questionnaire had set of 47 questions. The questions covered strategies for assessment strategies (i.e assessment for-as-of learning) and cross cutting issues that the Basic school teachers are required to use in their teaching. The features, strategies and principles underpinning *Assessment as learning* formed the basis of the construction of the 47 text items used in the questionnaire in this study. The study involved a population of 132 basic school teachers from all regions of Ghana. A sample size of 100 was computed at 95% confidence interval and randomly selected from the population. The questionnaire consisted of a four point likert scale; Strongly Agree (SA), Agree (A), Disagree (D) and Strongly Disagree. These likert were weighted 4, 3, 2 and 1 respectively. For fulfilling the objectives Questionnaire was designed on 4 point Likert scale (where 4 is Strongly Agree and 1 is Strongly Disagree).

3.1 Sample Size Determination

The size of sample was computed at 95% confidence interval using the following model:

$$n = \frac{N}{1+Ne^2}$$

Where;

$n =$ sample size, $N =$ population, $e = error = 0.05$

$$n = \frac{132}{1+(132)(0.05)^2} \approx 100$$

3.2 Cronbach Alpha

It measures how closely related items in a group are (that's the internal consistency).Cronbach's alpha is a coefficient of reliability (or consistency).

It can be written as:

$$\alpha = \frac{N.\bar{c}}{\bar{v} + (N-1).\bar{c}}$$

Where; N represents the number of items, $\bar{c}$ is the average inter-item covariance among the items; $\bar{v}$ equals the average variance [8].

3.3 Construction of Principal Components

For a random vector, say, X, with domain $\Re^m$, will have a mean and covariance matrix of μ_X and Σ_X, respectively. $\lambda_1 > \lambda_2 > \cdots > \lambda_m > 0$ for an array of eigenvalues of Σ_X, so that the i-theigenvalue of Σ_X represents the largest i-th eigenvalue. Again, suppose a vector α_i denotes the i-th eigenvector of Σ_X corresponding to the i-th eigenvalue of Σ_X. We wish to derive principal components (PCs) form by considering the maximization of $\mathrm{var}[\alpha_1^T X] = \alpha_1^T \Sigma_X \alpha_1$, with respect to $\alpha_1^T \alpha_1 = 1$ (a typical optimization problem).

The Lagrange multiplier approach is then applied to solve the problem.
To that end,

$$L(\alpha_1, \phi_1) = \alpha_1^T \Sigma_X \alpha_1 + \phi_1(\alpha_1^T \alpha_1 - 1)$$

$$\frac{\partial L}{\partial \alpha_1} = 2\Sigma_X \alpha_1 + 2\phi_1\alpha_1 = 0 \quad \Rightarrow$$
$$\Sigma_X \alpha_1 = -\phi_1\alpha_1 \quad \Rightarrow$$
$$\text{var}[\alpha_1^T X] = -\phi_1\alpha_1^T \alpha_1 = -\phi_1.$$

Since $-\phi_1$ represent the eigenvalue of Σ_X, with α_1 denoting the respective normalized eigenvector, $\text{var}[\alpha_1^T X]$ is maximized when α_1 chosen as the initial eigenvector of Σ_X. To this end, $z_1 = \alpha_1^T X$ is reffered to as the first PC of X, with α_1 representing the vector of coefficients for z_1, where $\text{var}(z_1) = \lambda_1$.

To get the second PC, $z_2 = \alpha_2^T X$, we shall maximize $\text{var}[\alpha_2^T X] = \alpha_2^T \Sigma_X \alpha_2$ on condition that z_2 is not correlated with z_1. But $\text{cov}(\alpha_1^T X, \alpha_2^T X) = 0 \Rightarrow \alpha_1^T \Sigma_X \alpha_2 = 0 \Rightarrow \alpha_1^T \alpha_2 = 0$, which we will solve by maximizing $\alpha_2^T \Sigma_X \alpha_2$, on condition that $\alpha_1^T \alpha_2 = 0$, and $\alpha_2^T \alpha_2 = 1$. We again make use of the Lagrange multiplier approach.

To that end,

$$L(\alpha_2, \phi_1, \phi_2) = \alpha_2^T \Sigma_X \alpha_2 + \phi_1\alpha_1^T \alpha_2 + \phi_2(\alpha_2^T \alpha_2 - 1)$$
$$\frac{\partial L}{\partial \alpha_2} = 2\Sigma_X \alpha_2 + \phi_1\alpha_1 + 2\phi_2\alpha_2 = 0$$
$$\Rightarrow \quad \alpha_1^T(2\Sigma_X \alpha_2 + \phi_1\alpha_1 + 2\phi_2\alpha_2) = 0 \quad \Rightarrow \phi_1 = 0$$
$$\Rightarrow \Sigma_X \alpha_2 = -\phi_2\alpha_2 \Rightarrow \alpha_2^T \Sigma_X \alpha_2 = -\phi_2.$$

As $-\phi_2$ is the eigenvalue of Σ_X, where α_2 is the respective normalized eigenvector, we are able to maximize $\text{var}[\alpha_2^T X]$ when we select α_2 as the second eigenvector of Σ_X. As a result, $z_2 = \alpha_2^T X$ becomes the second PC of X, where α_2 represents the vector of coefficients for z_2, and $\text{var}(z_2) = \lambda_2$. Per the above results, we can deduce that the i-th PC $z_i = \alpha_i^T X$ is constructed α_i is chosen as the i-th eigenvector of Σ_X, which will then have the variance λ_i. We can conclude by the above results that PCA are the only set of linear functions of original data that are uncorrelated and have orthogonal vectors of coefficients.

PCA relies on either covariance matrix or the correlation matrix. The linear combination weights directly originate from combination eigenvectors of correlation matrix or covariance matrix.

Recall that for m variables, the $m \times m$ covariance or correlation matrix will contain the following sets:

$$\text{m eigenvalues } -\{l_1, l_2, \ldots, l_p\}$$
$$\text{m eigenvectors } -\{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_p\}.$$

We form each principal component (PC) when we consider the values of the elements of the eigenvalues as the weights of the linear combination.

Assuming that the k-theigenvector $\mathbf{e}_k = (e_{1k}, e_{2k}, \ldots, e_{pk})$, then the PCs $Y_1, \ldots$, are produced by

$$Y_1 = e_{11}X_1 + e_{21}X_2 + \ldots + e_{m1}X_m$$
$$Y_2 = e_{12}X_1 + e_{22}X_2 + \ldots + e_{m2}X_m \ldots$$
$$Y_m = e_{1m}X_1 + e_{2m}X_2 + \ldots + e_{mm}X_m$$

3.4 Multiple Linear Regressions

The data $(Y_1, z_{11}, z_{12}, \ldots, z_{1r}), (Y_2, z_{21}, z_{22}, \ldots, z_{2r}), \ldots, (Y_n, z_{n1}, z_{n2}, \ldots, z_{nr})$ will have the following multiple linear regression model:

$$Y_i = \beta_0 + \beta_1 z_{i1} + \beta_2 z_{i2} + \cdots + \beta_r z_{ir} + \varepsilon_i, i = 1, \ldots, n,$$

The terms satisfy the following properties:

$$1. E(\varepsilon_i) = 0; \quad 2.\ Var(\varepsilon_i) = \sigma^2; \quad 3. Cov(\varepsilon_i, \varepsilon_j) = 0, i \neq j$$

The matrix form of the above data is:

$$Y = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix} = \begin{bmatrix} \beta_0 + \beta_1 z_{11} + \cdots + \beta_r z_{1r} + \varepsilon_1 \\ \beta_0 + \beta_1 z_{21} + \cdots + \beta_r z_{2r} + \varepsilon_2 \\ \vdots \\ \beta_0 + \beta_1 z_{n1} + \cdots + \beta_r z_{nr} + \varepsilon_n \end{bmatrix} = \begin{bmatrix} \beta_0 + \beta_1 z_{11} + \cdots + \beta_r z_{1r} \\ \beta_0 + \beta_1 z_{21} + \cdots + \beta_r z_{2r} \\ \vdots \\ \beta_0 + \beta_1 z_{n1} + \cdots + \beta_r z_{nr} \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

Or

$$\begin{bmatrix} 1 & z_{11} & \cdots & z_{1r} \\ 1 & z_{21} & \cdots & z_{2r} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & z_{n1} & \cdots & z_{nr} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_r \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix} = Z\beta + \varepsilon$$

Where;

$$Y = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix}, Z = \begin{bmatrix} 1 & z_{11} & \cdots & z_{1r} \\ 1 & z_{21} & \cdots & z_{2r} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & z_{n1} & \cdots & z_{nr} \end{bmatrix}, \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}, \beta = \begin{bmatrix} \beta_0 \\ \beta_2 \\ \vdots \\ \beta_r \end{bmatrix}.$$

The error terms are; $1.\ E(\varepsilon) = 0;\ and\ \ 2. Cov(\varepsilon) = E(\varepsilon\varepsilon') = \sigma^2 I;$ [9,10].

4. RESEARCH QUESTIONS

(a) What are the components that predict feedback oflearners with high power, with regards to the pedagogical approachesoutlined in Ghana's new Basic Education Curriculum?
(b) What is the relationship between each of these components in (a) in relation to feedback from learners?

5. ANALYSIS AND RESULTS

The Cronbach's Alpha coefficient of 0.995 suggests a very high internal consistency(reliability) of the items.

Table 1. Cronbach'salpha reliability test

Reliability statistics		
Cronbach's Alpha	**Cronbach'salpha based on standardized items**	**N of items**
.995	.995	47

Table 2. KMO and Bartlett's test

KMO and Bartlett's test		
Kaiser-Meyer-Olkinmeasure of sampling adequacy		.921
Bartlett's test of sphericity	Approx. Chi-square	13684.049
	df	1081
	Sig.	.000

5.1 Kaiser-Meyer-Olkin – Measure of Sampling Adequacy

Kaiser-Meyer-Olkin Measure of Sampling Adequacy is an index for comparing the modulus of the observed correlation coefficient to the modulus of the partial correlation coefficient. It is the basis for determining the appropriateness of factor analysis. Values within the interval of 0.5-1.0 indicate adequacy of the data for factor analysis. From the above table, the KMO statistic of 0.921 means that there is no error in 92% of the sample; and the remaining 8% there some sort of error may occur.

5.2 Bartlett's Test of Sphericity

Bartlett's Test of Sphericity measures the strength of the relationship among the variables. It is based on the null hypothesis that the variables are uncorrelated in the population (thus, it assumes the population matrix is an identity matrix).In the table above, Bartlett's Test's Chi Square value is 13684.049, DF=1081, significance at 0.00000.This is an indication that the correlation matrix is not an identity matrix (thus, we reject the null hypothesis).The significance is an indication that our correlation matrix for our measured variables is significantly different from an identity matrix which is consistent with the assumption that the matrix should be treated as factorable. This shows that the Bartlett's test of sphericity is highly sufficient for the data under study.

By inspecting the Scree plot, it can be seen thatcorresponding eigenvaluesproduced a departure from linearity coinciding with a 3-factor result. To this end, this test indicates that the data should be analyzed for3 factors. This method is however known for its element of subjectivity.

The Kaiser's eigenvalue >1 rule requires factors with eigenvalues exceeding 1 to be the only ones to be retained. To that end, three factors will be retained with respect to this method.

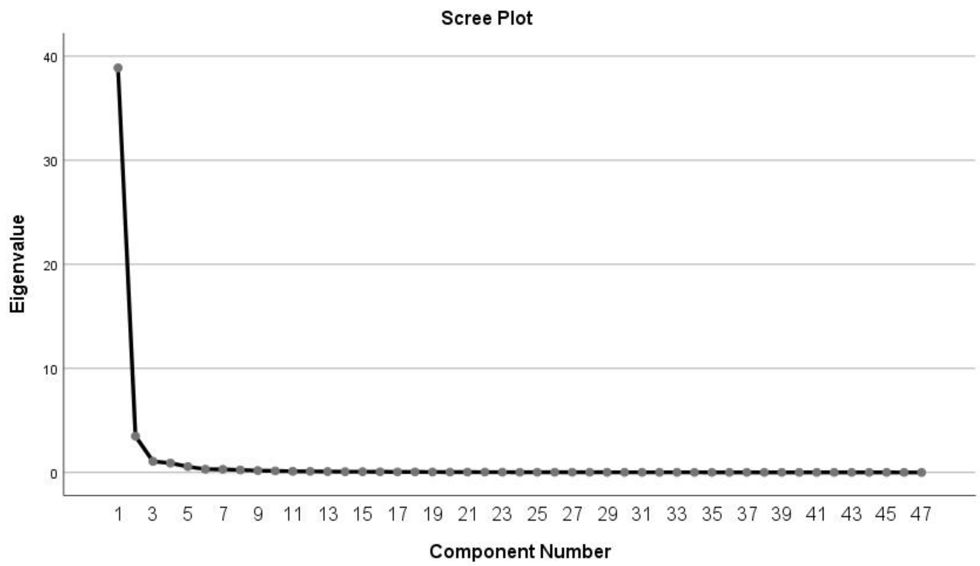

Fig. 1. Scree plot test

Table 3. The Kaiser'sEigenvalue > 1 Rule

Component	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	38.876	82.715	82.715	38.876	82.715	82.715	23.007	48.952	48.952
2	3.481	7.407	90.122	3.481	7.407	90.122	10.961	23.321	72.273
3	1.065	2.266	92.387	1.065	2.266	92.387	9.454	20.115	92.387
4	.897	1.909	94.297						
5	.558	1.186	95.483						

Table 4. Parallel analysis(Monte Carlo PA Output)

Component number	Actual eigenvalue from PCA	Random order from parallel	Decision
1	38.876	2.661375	Accept
2	3.481	2.451178	Accept
3	1.065	2.300507	Reject
4	.897	2.172024	Reject
5	.558	2.059007	Reject

Parallel analysis was performed with parameters of 47assessment indicator variables with100 observations. Percentile Eigen value was set at 95 and with the default set to generate 100 correlation matrices. The Eigen values computed from the randomly generated correlation matrices of the parallel analysis were compared with the Eigen values extracted from the data set.The factors having Eigen values (from the data set) exceeding that from that *Monte Carlo PA Output* were retained with those failing the threshold jettisoned. To that end, 2 factors were accepted and retained.

Table 5. Total variance explained by PCA

Total variance explained									
Component	**Initial eigenvalues**			**Extraction sums of squared loadings**			**Rotation sums of squared loadings**		
	Total	**% of variance**	**Cumulative %**	**Total**	**% of variance**	**Cumulative %**	**Total**	**% of variance**	**Cumulative %**
1	38.876	82.715	82.715	38.876	82.715	82.715	28.976	61.651	61.651
2	3.481	7.407	90.122	3.481	7.407	90.122	13.381	28.471	90.122
3	1.065	2.266	92.387						
4	.897	1.909	94.297						
5	.558	1.186	95.483						
6	.308	.656	96.140						
7	.296	.629	96.769						
8	.235	.500	97.269						
9	.182	.388	97.657						
10	.142	.303	97.960						
11	.110	.234	98.193						
12	.104	.221	98.415						
13	.082	.174	98.589						
14	.070	.148	98.737						
15	.067	.142	98.879						
16	.057	.122	99.001						
17	.050	.107	99.107						
18	.044	.094	99.201						
19	.038	.081	99.282						
20	.033	.070	99.353						
21	.030	.063	99.416						
22	.028	.060	99.476						
23	.024	.051	99.527						
24	.023	.048	99.575						
25	.022	.047	99.622						
26	.020	.042	99.664						
27	.018	.038	99.702						
28	.016	.034	99.736						
29	.014	.030	99.766						
30	.014	.029	99.795						
31	.013	.027	99.822						
32	.012	.025	99.847						
33	.010	.022	99.869						
34	.009	.020	99.889						
35	.009	.018	99.907						
36	.008	.017	99.924						
37	.007	.014	99.938						
38	.006	.013	99.951						
39	.006	.012	99.963						
40	.005	.011	99.974						
41	.004	.008	99.982						
42	.003	.007	99.989						
43	.002	.005	99.993						
44	.002	.003	99.997						
45	.001	.002	99.999						
46	.000	.001	100.000						
47	.000	.000	100.000						

Extraction Method: Principal Component Analysis

5.3 Decision on Factors to Maintain from Multiple Extraction Approaches

To avoid over- and under-extraction errors, multiple extraction approaches such as Scree test, Kaiser Criterion and parallel analysis were employed. The Scree test and Kaiser's Eigen vale greater than 1 rule suggested maintaining three factors. However, the parallel analysis approach suggested maintaining two factors. Past studies which have compared the three methods of deciding the number of factors to retain have found that the results from the parallel analysis were more robust compared to the Scree test and Kaiser's Eigen value greater than 1 rule [4]. As a result, PCA with 2 components was forced.

In order to maximize high item loadings and minimizes low item loadings, rotation was employed to obtain a solution which is more interpretable and simplified and parsimonious. The most commonly used rotation technique; Orthogonal Varimax was used to produce uncorrelated factor structures.Its goal is to minimize the complexity of the components bymaking the large loadings larger and the small loadings smaller within each component.The first component explains about 82.7% of the total variance. Also, the second component explains about 7.4% of the total variance.In total, the two factors accounted for about 90.1% of the variance.

All assessment for learning and assessment as learning principles were loaded highly on the first component.With the exception of two variables (ASO 27 and ASO 28), all assessment as learning principles were loaded on the first component. With respect to cross cutting issues, 4 principles and 5 principles were loaded highly on the first and second components respectively.

Table 6. Rotated component matrix[a]

Rotated component matrix[a]		
	Component	
	1	**2**
ASF1	.807	
ASF2	.911	
ASF3	.895	
ASF4	.908	
ASF5	.845	
ASF6	.671	
ASF7	.833	
ASF8	.927	
ASF9	.728	
ASF10	.672	
ASF11	.649	
ASF12	.686	
ASF13	.708	
ASF14	.829	
ASF15	.809	
ASF16	.877	
ASO17	.923	
ASO18	.752	
ASO19	.684	
ASO20	.893	
ASO21	.696	
ASO23	.904	
ASO25	.679	
ASO26	.856	
ASO27		.673
ASO28		.744
ASA29	.912	
ASA30	.908	
ASA31	.893	
ASA32	.853	
ASA33	.870	
ASA34	.863	
ASA35	.927	
CCI36	.884	

Rotated component matrix[a]		
	Component	
	1	2
CCI37	.869	
CCI38		.953
CCI39		.947
CCI40		.936
CCI41	.901	
CCI42	.785	
CCI43		.692
CCI44		.952
AFOA45	.898	
AFOA46	.926	
AFOA47	.728	
AFOA48	.867	
AFOA49	.914	

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 3 iterations

Table 7. Components and their square loading

Component 1	Square loadings	Component 2	Square loadings
0.807	0.650486	0.357	0.127282415
0.911	0.83042	0.347	0.120497176
0.895	0.800914	0.383	0.14656774
0.908	0.823584	0.315	0.099264482
0.845	0.713695	0.458	0.210090044
0.671	0.45028	0.661	0.437500392
0.833	0.693826	0.465	0.216350059
0.927	0.859313	0.288	0.082929906
0.728	0.529431	0.591	0.349153293
0.672	0.451139	0.665	0.442040367
0.649	0.420866	0.593	0.351793844
0.686	0.470639	0.663	0.439384995
0.708	0.501235	0.605	0.36648624
0.829	0.686414	0.400	0.160134946
0.809	0.654773	0.504	0.253785072
0.877	0.768491	0.415	0.172452838
0.923	0.852162	0.276	0.075945537
0.752	0.565382	0.581	0.337565507
0.684	0.46718	0.653	0.425761975
0.893	0.796585	0.255	0.06483714
0.696	0.484662	0.653	0.425934448
0.904	0.817156	0.325	0.10567901
0.679	0.460393	0.668	0.446028803
0.856	0.732441	0.431	0.185782597
0.644	0.414219	0.673	0.453422364
0.521	0.271456	0.744	0.553300667
0.912	0.831867	0.329	0.108230934
0.908	0.82507	0.272	0.07424426
0.893	0.797455	0.324	0.105071778
0.853	0.72739	0.335	0.112405332
0.870	0.756347	0.352	0.124084373
0.863	0.744146	0.431	0.185799068
0.927	0.859986	0.299	0.089243048
0.884	0.780591	0.401	0.160461738
0.869	0.754797	0.297	0.087953366
0.195	0.037879	0.953	0.908897525
0.147	0.021717	0.947	0.896622991
0.234	0.054621	0.936	0.876141176
0.901	0.811031	0.286	0.08151997
0.785	0.616486	0.501	0.250888378
0.622	0.386484	0.692	0.478213548

Component 1	Square loadings	Component 2	Square loadings
0.145	0.02095	0.952	0.905808512
0.898	0.807269	0.378	0.143182244
0.926	0.8575	0.295	0.087148927
0.728	0.530022	0.614	0.376600655
0.867	0.752094	0.428	0.183036657
0.914	0.834981	0.309	0.095759
Sum of square loading	28.97583	Sum of square loading	13.38128534
%Varaiance Explained	**61.65069**	**%Varaiance Explained**	**28.47081987**
Total Variance	**90.1%**		

Table 8. Communalities

Communalities		
	Initial	**Extraction**
ASF1	1.000	.778
ASF2	1.000	.951
ASF3	1.000	.947
ASF4	1.000	.923
ASF5	1.000	.924
ASF6	1.000	.888
ASF7	1.000	.910
ASF8	1.000	.942
ASF9	1.000	.879
ASF10	1.000	.893
ASF11	1.000	.773
ASF12	1.000	.910
ASF13	1.000	.868
ASF14	1.000	.847
ASF15	1.000	.909
ASF16	1.000	.941
ASO17	1.000	.928
ASO18	1.000	.903
ASO19	1.000	.893
ASO20	1.000	.861
ASO21	1.000	.911
ASO23	1.000	.923
ASO25	1.000	.906
ASO26	1.000	.918
ASO27	1.000	.868
ASO28	1.000	.825
ASA29	1.000	.940
ASA30	1.000	.899
ASA31	1.000	.903
ASA32	1.000	.840
ASA33	1.000	.880
ASA34	1.000	.930
ASA35	1.000	.949
CCI36	1.000	.941
CCI37	1.000	.843
CCI38	1.000	.947
CCI39	1.000	.918
CCI40	1.000	.931
CCI41	1.000	.893
CCI42	1.000	.867
CCI43	1.000	.865
CCI44	1.000	.927
AFOA45	1.000	.950
AFOA46	1.000	.945
AFOA47	1.000	.907
AFOA48	1.000	.935
AFOA49	1.000	.931

Extraction Method: Principal Component Analysis

The sum of square loadings for components helps decide the number of components to be retained or extracted.

Communalities represent the amount of the variable's variance that is accounted for by the components (so far as the loadings are correlations between variables and components are orthogonal, a variable's communality represents the R^2 of the variable predicted from the components).Communality represents the sum of square loading for each variable across factors.

5.4 Naming Components

All assessment for learning and assessment as learning principles were loaded highly on the first component. With the exception of two variables (ASO 27 and ASO 28), all assessment as learning principles were loaded on the first component. Again, all of the other forms of assessment were all loaded highly on component1. As a result this coupled with the fact that the first component explains about 61.7% of the variance, it was named **Criterion referenced domain.** The second component was generally loaded highly with the cross cutting issues and explaining about 28.6% of the total variance. To that end, the component was named **inclusion domain.**

Table 9 shows that the teachers lacked some expertise in items that have their respective percentage variance less than 1. To that end, the teachers lacked skills to use assess to find out what confusions, preconceptions, or gaps students may have. Again, teachers require skill to use interactive assessment that identifies particular learning need of students or groups. Finally, with respect to assessment for learning, teachers require lacked skills to provide description of processes during their teaching.

With regards to Table 10, teachers seem to have to some extent explored the various components of assessment as learning strategy although at a low variance explained.

The findings from Table 11 shows that teachers exhibited inadequate skills to report students' learning based on evidence obtained from variety of contexts and applications. Teachers also showed some shortfalls in use of transparent approaches to interpretation of achievement of students.

Table 9. Analysis of *Assessment for learning*

Text items for *Assessment for learning*	**% variance** $\left(\frac{L}{n}\right) \times 100$	**Loading (L)**
Students are assessed more than once during the learning process	1.384012	0.650485658
Students are made to understand exactly what they are to learn	1.76685	0.830419596
Students are made to understand exactly what is expected of them	1.704072	0.800913868
Feedback and advice is provided to students on how to improve their work	1.752307	0.823584234
Students are assessed to find out what students know and can do	1.518501	0.713695404
Students are assessed to find out what confusions,preconceptions,or gaps students may have	0.958043	0.450280352
The variety of feedback collected about students learning provides the basis to move students learning forward	1.476226	0.693826384
The variety of feedback collected about students learning help me decide on groupings, instructional strategies and resources	1.828326	0.859313313
Interactive assessment is provided that is aligned with the instructions	1.126448	0.529430726
Interactive assessment that identifies particular learning need of students or groups are provided	0.95987	0.451138952
Description of processes are provided	0.89546	0.42086626
Interactive assessment that select and adapt materials and resources are provided	1.00136	0.470639241
Interactive assessment that creates differentiated teaching strategies and learning opportunities are provided	1.066456	0.501234507
Interactive assessment that aid individual students to improve their in learning are provided	1.460455	0.686413939
Interactive assessment that provides immediate feedback and direction to students are given	1.393135	0.654773383
Assessment that is inclusive of all learners are given	1.635088	0.768491195
Total Variance	**21.92661**	

n is the number of variables in the complete data (47)

Table 10. Analysisof Assessment as learning

Text items for Assessment as learning	% Variance	Loading
Students are assessed in ways that make them learn about themselves as learners and become aware of how they can learn	1.696711761	0.797454527
Students are assessed in ways that make them reflect on their own work on regular basis through self an peer assessment	1.547639172	0.727390411
Students are assessed in ways that help them take responsibility for their own learning and monitoring future directions	1.609249766	0.75634739
Provisions are made for the development of independent learners	1.583289232	0.744145939
Provisions are made for regular and challenging opportunities to practice to improve confidence	1.829758323	0.859986412
Provisions are made for safe environment for students to take chances and where support is readily available	1.660831635	0.780590869
Provisions are made for assessment that requires students to ask questions about their learning	1.605950081	0.754796538
Total Variance %	**11.53342997**	

Table 11. Analysis of assessment of learning

Text items for Assessment of learning	%variance	Loadings
Students' learning are reported based on evidence obtained from few context and applications	1.813111649	0.852162475
Students' learning are reported accurately	1.202940465	0.565382019
Students' learning are reported based on evidence obtained from variety of contexts and applications	0.993999463	0.467179748
The rationale for undertaking a particular assessment of learning at a given time is provided	1.694862234	0.79658525
Processes that make it possible for students to demonstrate their competence and skill are provided	1.031196446	0.48466233
Public and defensible reference points for making judgements are provided	1.738629864	0.817156036
Transparent approaches to interpretation are provided	0.979558937	0.4603927
Description of assessment processes are provided	1.558385656	0.673
Strategies for recourse in the event of disagreement about decisions are provided	1.431914894	0.744
Total Variance %	**12.44459961**	

Table 12. Prediction of feedback from students (Model Summary)

Model summary				
Model	**R**	**R square**	**Adjusted R square**	**Std. error of the estimate**
1	.971[a]	.942	.941	.195

a. Predictors: (Constant), inclusion domain, Criterion referenced domain

Table 13. Prediction of feedback from students (ANOVA)

ANOVA[a]						
Model		**Sum of squares**	**df**	**Mean square**	**F**	**Sig.**
1	Regression	60.454	2	30.227	791.228	.000[b]
	Residual	3.706	97	.038		
	Total	64.160	99			

a. Dependent Variable: ASF8
b. Predictors: (Constant), inclusion domain, Criterion referenced domain

Criterion motivation was found to have a positive impact on feedback received from students and was statistically significant (B =0.746, P<0.001). Again, there was a positive relationship between the inclusion motivation and feedback with a significant difference (B = 0.232, P<0.001). The R-square value of 0.942 shows that the regression model explains about 94% of the variance. There was a significant difference among the use of assessment strategies by the teachers (P=0.00., F= 791.228).

Table 14. Prediction of feedback from students (Coefficients)

Model		Coefficients[a] Unstandardized coefficients B	Std. error	Standardized coefficients Beta	t	Sig.	95.0% confidence interval for B Lower bound	Upper bound
1	(Constant)	3.280	.020		167.813	.000	3.241	3.319
	Criterion domain.	.746	.020	.927	37.989	.000	.707	.785
	inclusion domain	.232	.020	.288	11.802	.000	.193	.271

a. Dependent Variable: ASF8

6. DISCUSSION

Overall, the study found that, the two components named criterion motivation and inclusion motivation explained about 91% of the variance in the original data set. These domains predicted feedback from learners with a high power of 94%. Criterion motivation was found to have a positive impact on feedback received from learners. Again, there was a positive relationship between the inclusion motivation and feedback from learners. The implication of these findings is that when teachers teach using the model developed by this study, they are sure to obtain a maximum feedback from learners under their tutelage with a predictive power of 94%.

In this study, teachers were found to exhibit preference to some components of the assessment strategies recommended for use in the new curriculum at the detriment of others. Teachers used *Assessment for learning most accounting for a total variance of* 21.9%. Assessment of learning was the next preferred with a total variance of 12.4%. Assessment as learning was the least used with a total variance of 11.5%. This conclusion is similar to the findings by Tulu et al. [5] who also found assessment for and assessment of learning to be the most used approaches in teaching among Ethiopian teachers.

From the results teachers lacked adequate skills to assess to find out the confusions, preconceptions, or gaps students may have. Again, teachers require skill to use interactive assessment that identifies particular learning need of students or groups. With respect to assessment for learning, teachers require lacked skills to provide description of processes during their teaching. The findings from also made evident that teachers exhibited inadequate skills to report students' learning based on evidence obtained from variety of contexts and applications. Teachers also showed some shortfalls in use of transparent approaches to interpretation of achievement of students. These findings are similar to that of Wilie [3] who found that there are certain aspects of formative assessment that are underemphasized by teachers.

7. CONCLUSION

Overall, these analyses indicated that two components named criterion motivation and inclusion motivation explained about 91% of the variance in the original data set. These components predicted 94% of feedback from students (P=0.00., F= 791.228). There were some disparities in the use of assessment strategies outlined in the new basic school curriculum for Ghana. Teachers were found to exhibit preference to some components of the assessment strategies recommended for use in the new curriculum at the detriment of others. They used *Assessment for learning* mostly, accounting for a total variance of 21.9%. Assessment of learning was the next preferred with a total variance of 12.4%. Assessment as learning was the least used with a total variance of 11.5%.

8. LIMITATIONS OF THE STUDY

Our sample consisted of predominantly class teachers, we cannot be certain this is representative of our current teaching population. Findings were limited to 100 randomly selected basic school teachers and might differ with larger population.

9. IMPLICATION FOR FURTHER STUDY

Future studies could use PCA to investigate the proposed model in this research and its impact on academic achievement in the case of high and low rated schools.

10. RECOMMENDATIONS

It is recommended that the developed criterion motivation and inclusive motivation approaches are adopted in teaching in order to enhance maximum feedback from learners.

CONSENT

As per international standard or university standard written participant consent has been collected and preserved by the author(s).

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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