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Factor Analysis Model for Diagnostic Assessment and Instructional Approaches in Ghana's New Curriculum: The Case of Differentiation, Scaffolding and Inclusion

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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 OH managed the analyses of the study and also managed the literature searches. All authors read and approved the final manuscript.

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ABSTRACT

Ghana's new Basic Education Curriculum emphasizes on ensuring that every learner benefits from the teaching and learning process. The study used the survey research design aimed at determining the predictive power with which use of Scaffolding, Differentiated techniques and Inclusion approaches predict diagnostic assessment. The features, strategies and principles underpinning instructional Scaffolding, Differentiation and Inclusion approaches as well as Diagnostic assessment formed the basis of the construction of 14 text items used in the questionnaire in this study. The study involved a population of 132 basic school teachers from sixteen (16) regions of Ghana. A sample size of 100 was computed at 95% confidence interval and randomly selected from the population. The reliability of the items was assessed with Cronbach's Alpha (0.976). Bartlett's test of sphericity was statistically significant (P< 0.01, Chi-square

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=3077.529, DF=91), and the KMO statistic was 0.924. All multiple extraction approaches such as Parallel analysis, Kaiser's criterion and Scree test suggested retaining two factors. Varimax rotated matrix was used to generate factor scores for modeling the relationships between diagnostic assessment and inclusion, differentiated techniques as well as Scaffolding using multiple linear regressions. From the results, Scaffolding (B_1 = .744, B_2 =.185, F= 466.442, P<0.001), Differentiated approaches (B_1 = .516, B_2 =.400, F=312.809, P<0.001) and Inclusion (B_1 =.512, B_2 =.373, F= 213.375, P<0.001) pedagogical approaches were statistically significant and positively related to diagnostic assessment. Scaffolding, Differentiated approaches and Inclusion approaches were found to have predictive power of 91%, 87% and 82% respectively. Instructional Scaffolding was found to be the most efficient predictor of diagnostic assessment. This study provides scientific evidence that the Scaffolding, Inclusion and Differentiated techniques outlined in Ghana's new Curriculum provides sufficiently for Diagnostic assessment although it was not explicitly stated in it. It is therefore recommended for Ghana Education service to run a continuous training programme for teachers in efficient use of these techniques for effective teaching and learning.

Keywords: Factor analysis; scaffolding; differentiated techniques; inclusion; diagnostic assessment; Ghana; education.

1. INTRODUCTION

Ann et al. [1] argued from their study that any curriculum that seeks to support students' success must provide for three types of assessments namely; Pre-assessment (Diagnostic), Formative and Summative Assessment.

Educators need to detect students' mathematical ability at an early stage before teaching them new content [2]. Diagnostic assessment facilitates teachers' collection of data to guide the progress of their own classes. It enables their practice to be more 'evidence-informed' in the sense that they can base decisions about the pace and sequence of instruction on better evidence of their students' current ideas and understandings [3].

All Classroom assessments fall under summative, diagnostic, and formative. However, none in itself is a sufficient tool to maximize students' learning [4]. In spite of the importance of assessment in education today, few teachers receive much formal systematic training in assessment design or analysis. Teachers' assessment literacy is low and most teachers have difficulty in using assessment appropriately [5].

Obadare-Akpata,[6] examined the need to integrate diagnostic assessment (DA) in teaching and learning process to serve as quality control measures in the education system. He identified large class size, non-inclusion of DA in the curriculum; lack of commitment on the part of teachers as well as lack of motivation of teachers by their employers as factors that hinder implementation of DA in schools. Dayo [7] in his work found teachers who use DA are able to identify students with learning difficulties for remediation measures before they are engaged in any standardized test or certification.

Betts et al. [8] found that schools with mandatory diagnostic math testing produce positive gains than those with voluntary use DA tests by individual teachers (does not convey the same apparent benefits). They explained that diagnostic tests result in specific interventions and more accurate grouping, which tend to have positive effects. According to them, DA should be continuous in its usage rather than temporary. It has the capacity to boost achievement by providing information to help teachers and counselors better offer timely interventions to students.

In the work of Sun et al. [9] it was established that diagnostic assessment provides detailed information about students' strengths and weaknesses and highly effective means of providing effective feedback for teachers to improve their teaching practice. The study further found that most teachers have difficulty in using assessment to improve their teaching.

The scaffolding teaching strategy provides individualized support based on the distance between what children can do by themselves and the next learning that they can be helped to achieve with competent assistance [10]. Scaffolding in education refers to the use of a variety of instructional techniques aimed at moving learners progressively towards stronger understanding and ultimately greater independence in the learning process. It has a number of advantages which include (1) provides learners a simplified version of a lesson, assignment, or reading, and then gradually increases the complexity, difficulty, or sophistication over time (2) describe or illustrate a concept, problem, or process in multiple ways to ensure understanding (3) give learners an exemplar or model of an assignment they will be asked to complete (4) give learners a vocabulary lesson before they read a difficult text (5) describe the purpose of a learning activity clearly and the learning goals they are expected to achieve; and (6) describe explicitly how the new lesson builds on the knowledge and skills learners were taught in a previous lesson [11].

Differentiation is a process by which differences (learning styles, interest and readiness to learn) between learners are accommodated so that all learners in a group have the best possible chance of learning. Differentiation could be by content, tasks, questions, outcome, groupings and support. Differentiation as a way of ensuring each learner benefits adequately from the delivery of the curriculum can be achieved in the classroom through i) task ii) support from the Guidance and Counselling Unit and iii) learning outcomes. Differentiation by task involves teachers setting different tasks for learners of different abilities. E.g. in sketching the plan and shape of their classroom some learners could be made to sketch with free hand while others would be made to trace the outline of the plan. Differentiation by support involves the teacher giving the needed support and referring weak learners to the Guidance and Counselling Unit for academic support. Differentiation by outcome involves the teacher allowing learners to respond at different levels. Weaker learners are allowed more time for complicated tasks [11].

Inclusion is ensuring access and learning for all learners especially those disadvantaged. All learners are entitled to a broad and balanced curriculum in every school in Ghana. The daily learning activities to which learners are exposed should ensure that the learners' right to equal access and accessibility to quality education is met. The Curriculum suggests a variety of approaches that address learners' diversity and their special needs in the learning process. When these approaches are effectively used in lessons, they will contribute to the full development of the learning potential of every learner. Learners have individual needs, learning experiences and different levels of motivation for learning. Planning, delivery and reflection on daily learning experiences should take these differences into consideration. The curriculum therefore promotes: (1) learning that is linked to the learner's background and to their prior experiences, interests, potential and capacities (2) learning that is meaningful because it aligns with learners' ability (e.g. learning that is oriented towards developing general capabilities and solving the practical problems of everyday life); and b(3)the active involvement of the learners in the selection and organisation of learning experiences, making them aware of their importance and also enabling them to assess their own learning outcomes [11].

2. REVIEW OF RELATED LITERATURE

A recent study by Kaoropthai et al. [12] revealed a positive relationship between scaffolding and diagnostic strategies when the two strategies were used to help University students who had learning difficulties in English language subject. The prediction accuracy of the system was 95.5%. The model developed by this study was able to diagnose the students' strengths and weaknesses, and predict what skills each type of students urgently needs to learn to scaffold them one step further in their academic reading ability. Diagnostic assessment has been found to model Inclusion, Scaffolding and Differentiated learning approaches [13].

Shim et al. [2] compared diagnostic test with students' academic achievement. The results of the study indicated that students who performed well in their diagnostic test also performed well in their mathematics final assessments. Likewise, those who did not perform well in their diagnostic test obtained poor results in their final mathematics assessment. Their results corroborated the study of Carmody et al. [14] who found a significant positive correlation between the students' diagnostic test and the final examination and that of Sheridan,[14] study also found a positive correlation between mathematics diagnostic testing and the semester 1 mathematics test result.

Lertporn et al. [15] used factor analysis to develop and examine the quality of a diagnostic test for the scientific literacy characteristics of primary students. The findings revealed that the sample group had a misconception of scientific literacy characteristics in terms of knowledge and context. Factored questions provided interesting information that the teaching and learning approaches used by science teachers could build positive attitudes in group activities. They explained that information from the diagnosis assessment enable teachers to view students' defects clearly. Teachers emphasized for diagnostic assessment to be used side by side of formative assessment and summative assessment in order to maximize teaching and learning. This, they believe has the potential to enable teachers monitor changes in students' conceptions after teaching and learning has been reformed, and to improve the students' conceptions.

Nur et al. [16] used factor analysis to investigate the underlying causes of effective learning through learning styles that may help to improve performance and achievement in the classrooms. The results suggested five learning key factors (LKF) which account for 67.404% of the total variance with considerably reduce the complexity of the data set by using these components with 33% loss of information. Kaiser-Meyer-Olkin value was 0.621 and small values of the significance level of Bartlett's test of sphericity (0.000) indicated factor analysis was feasible for this data set. Varimax rotation with Kaiser normalization was performed and five factors solution was revealed labelled as attention and concentrating, visual learners, audio learners, kinaesthetic learners and cognitive factors. Main findings suggested that the result of 15-items scale was much more reliable instruments than the initial 27-items scale with Cronbach's alpha correlation coefficients of 0.735.

Musa et al. [17] used factor analysis to study the low achievement of second year secondary school students in Khartoum state in mathematics. The factors extracted explained 79% of the total variance. School environment is the first factor, which represents 13% of the total variance explained, the second factor is mathematics achievement, which represents 10.7% of the total variance explained, and the third factor is the education of parents, which represents 5.39% of the total variance.

A study in Ghana sought to model the use of assessment strategies and crosscutting issues using principal component analysis. Two components named, Criterion motivation and Inclusion motivation were found to predict feedback from students with a power of 94%. The study confirmed that the basic school teachers exhibited preference to some components of the assessment strategies at the expense of others [18].

Recent studies in Ghana [19,20] have shown significant differences between demographic variables of basic school teachers (such as teaching division, sex and years of teaching experience) and the use of formative and summative assessment strategies. This raises the concern that professional teachers still need in-service professional training for effective use of the teaching strategies recommended in the curriculum.

3. PROBLEM STATEMENT

Diagnostic assessment is the process of coming to understand a student's current learning needs well enough to plan for the best possible instructional processes and outcomes for each learner whose academic welfare is the teacher's responsibility. Unfortunately, teachers often do prescribe without a diagnosis [21].

Ghana's new curriculum for the basic level stresses the use of formative and summative assessment strategies, leaving out diagnostic assessment. Existing scientific literature, [1] supports integration of these three forms of assessment for effective teaching and learning. Ghana's Curriculum also stresses the need for teachers to satisfy cross cutting issues (stressing use of scaffolding and differentiation approaches, inclusion, and equity and inclusivity) which by their characteristics seek to offer remediation to vulnerable groups. It is imperative to assess the relationship between these strategies and diagnostic assessment. There is also evidence in literature (from the introduction) supporting that teachers voluntarily incorporate diagnostic assessment in their teaching.

4. METHODS

The study used the survey approach. The features, strategies and principles underpinning *instructional Scaffolding, Differentiation and Inclusion approaches as well as Diagnostic assessment* formed the basis of the construction of 14 text items used in the questionnaire in this study. The study involved a population of 132 basic school teachers from the sixteen regions of Ghana. A sample size of 100 was computed at 95% confidence interval and randomly selected from the population. The reliability of the items was assessed with Cronbach's Alpha (0.976). 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. Factor analysis was performed on the responses of the teachers on their use of diagnostic test. The factors retained through multiple extraction approaches were used to model the relationship that Scaffolding, Differentiation and Inclusion approaches have with Diagnostic assessment. From the rotated component matrix, loadings greater than or equal to 0.3 were retained as significant contributors. These were used to generate factor scores for modeling the relationships between diagnostic assessment and inclusion, differentiated techniques as well as Scaffolding using multiple linear regressions. After developing these instruments, the content and face validity was done by experts in the Quality Assurance department of the Holy Child College of Education to determine the appropriateness of the instruments. Participants gave their consent for their responses to be used for the purpose of research. The duration for responding to the items was 2 hours. Since the respondents were guided to provide answers item by item, there were no missing data. SPSS and Microsoft Excel were used for the data analysis. Yamane's Formula for Sample Calculation was used [22].

4.1 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, $e = error = 0.05$

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

4.2 Factor Analysis Model

The factors can be expressed as linear combinations of the observed variables.

$$F_i = W_{i1}X_1 + W_{i2}X_2 + W_{i3}X_3 ... + W_{ik}X_k$$

Where,

F_i = estimate of i th factor
W_i = weight or factor score coefficient
k = number of variables

X = an n × 1 random vector of observed random variables X_1 , X_2 , X_3 ,..., X_n.
It is assumed that E(X)= 0 E(XX')= R_{xx} ,
a correlation matrix with unities in the main diagonal F = an m × 1 vector of m common factors F_l , F_2 ,..., F_m

It is assumed that E(F) = 0 E(FF')= R_{ff} , a correlation matrix U = an n × 1 random vector of the n unique factor variables, U_l , U_2 ,..., U_n.

It is assumed that E(U) = O; E(UU') = I

The unique factors are normalised to have unit variances and are mutually uncorrelated.

A = an n × m matrix of coefficients called the factor pattern matrix

V = an n × n diagonal matrix of coefficients for the unique factors

The observed variables, which are the coordinates of X, are weighted combinations of the common factors and the unique factors. The fundamental equation of factor analysis can then be written as:

X = AF + VU

The correlations between variables in terms of the factors may be derived as follows:

R_{xx} = E(XX') = E{(AF + VU)(AF + VU)'} = E{(AF + VU)(F'A' + U'V')} = E(AFF'A' + AFU'V' + VUF'A'+ VUU'V') = $AR_{ff}A' + AR_{fu}V' + VR_{uf}A' + V^2$

Given that the common factors are uncorrelated with the unique factors, we have

$R_{fu} = R_{uf} = 0$

Hence, $R_{xx} = AR_{ff}A' + V^2$

Suppose that we subtract the matrix of unique factor variance, V^2, from both sides. We then obtain

$R_{xx} – V^2 = AR_{ff}A'$

Rxx is dependent only on the common factor variables, and the correlations among the variables are related only to the common factors.

Let Rc = Rxx – V^2

be the reduced correlation matrix. We have already defined the factor pattern matrix A. The coefficients of the factor pattern matrix are weights assigned to the common factors when the observed variables are expressed as linear combinations of the common and unique factors. We now define the factor structure matrix. The coefficients of the factor structure matrix are the covariances between the observed variables and the factors. The factor structure matrix is helpful in the interpretation of factors as it shows which variables are similar to a common factor variable. The factor structure matrix, A_s , is defined as

A_s = E(XF') = E[(AF + VU)F'] = AR_{ff} + VR_{uf} = AR_{ff}

Thus, the factor structure matrix is equivalent to the factor pattern matrix A multiplied by the matrix of covariances among the factors R_{ff}.

Substituting A_s for AR_{ff}, the reduced correlation matrix becomes the product of factor structure and the factor pattern matrix:

Rc = $AR_{ff}A'$ = A_s A' [23].

4.3 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:

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

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 ; $1.\ E\left(\varepsilon\right) = 0;\ and\ \ 2. Cov\left(\varepsilon\right) = E\left(\varepsilon\varepsilon'\right) = \sigma^2 I;$ [24].

5. HYPOTHESES

5.1 Hypothesis 1

H_{01}: There is no significant difference between impact of diagnostic assessment and differentiated approaches

5.2 Hypothesis 2

H_{02}: There is no significant difference between impact of diagnostic assessment and Scaffolding techniques

5.3 Hypothesis 3

H_{03}: There is no significant difference between impact of diagnostic assessment and Inclusion techniques

6. RESEARCH QUESTIONS

1. What is the power with which use of differentiated approaches suggested in Ghana's new curriculum predicts diagnostic assessment?
2. What is the power with which use of Scaffolding technique suggested in Ghana's new curriculum predicts diagnostic assessment?
3. What is the power with which use of Inclusion technique suggested in Ghana's new curriculum predicts diagnostic assessment?

6.1 Observations from Correlation Matrix

The correlation matrix shows that all correlations are greater than 0.30and were all statistically significant among the 14 correlation coefficients.

Bartlett's test of sphericity was statistically significant ($P< 0.01$, Chi-square =3077.529, DF=91), and the KMO statistic was 0.924. The KMO statistics of 0.924 is an indication of the appropriateness (meritorious) of the correlation matrix for factor analysis. Kaiser-Meyer-Olkin Measure of Sampling Adequacy values which are greater than 0.7 by rule of thumb approach is considered a good indication that factor analysis will be useful for the variables under study [25].

The Bartlett's test of Sphericity tests the difference between the correlation matrix for variables and the identity matrix. Bartlett's Test of Sphericity obtained for the data was 3077.529 and p-value was 0.000; an indication of a significant difference which makes it inferable 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 is a strong indication that the Bartlett's test of sphericity is highly sufficient for the data under study. Based on KMO and Bartlett's Test of Sphericity factor analysis is appropriate for analyzing the correlation matrix.

Communalities are the representation of 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.

From the Scree plot, it is clear that corresponding eigenvalues produced a departure from linearity coinciding with a 2-factor result. To this end, this test indicates that the data should be analyzed for 2 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, two factors will be retained with respect to this method.

Parallel analysis was performed with parameters of 14 assessment indicator variables with 100 observations. Percentile Eigen value was set at 95 and with the default set to generate 100 correlation matrices. The Eigenvalues 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 1. Reliability statistics

Reliability Statistics		
Cronbach's Alpha	**Cronbach's Alpha Based on Standardized Items**	**N of Items**
.976	.975	14

Table 2. Correlation matrix

Correlation Matrix[a]		**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**	**M**	**N**
Correlation	A	1.000	.926	.885	.965	.941	.979	.878	.533	.490	.561	.914	.890	.808	.490
	B	.926	1.000	.832	.898	.945	.910	.881	.477	.439	.502	.911	.850	.801	.438
	C	.885	.832	1.000	.913	.864	.903	.837	.698	.642	.735	.851	.874	.837	.642
	D	.965	.898	.913	1.000	.926	.986	.878	.563	.518	.593	.904	.913	.816	.518
	E	.941	.945	.864	.926	1.000	.938	.932	.467	.430	.492	.968	.868	.818	.430
	F	.979	.910	.903	.986	.938	1.000	.888	.545	.501	.573	.913	.904	.815	.501
	G	.878	.881	.837	.878	.932	.888	1.000	.431	.397	.454	.965	.875	.769	.397
	H	.533	.477	.698	.563	.467	.545	.431	1.000	.928	.966	.430	.622	.778	.939
	I	.490	.439	.642	.518	.430	.501	.397	.928	1.000	.901	.396	.573	.768	.986
	J	.561	.502	.735	.593	.492	.573	.454	.966	.901	1.000	.453	.655	.788	.911
	K	.914	.911	.851	.904	.968	.913	.965	.430	.396	.453	1.000	.857	.766	.395
	L	.890	.850	.874	.913	.868	.904	.875	.622	.573	.655	.857	1.000	.872	.572
	M	.808	.801	.837	.816	.818	.815	.769	.778	.768	.788	.766	.872	1.000	.769
	N	.490	.438	.642	.518	.430	.501	.397	.939	.986	.911	.395	.572	.769	1.000
Sig. (1-tailed)	A		.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	B	.000		.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	C	.000	.000		.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	D	.000	.000	.000		.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	E	.000	.000	.000	.000		.000	.000	.000	.000	.000	.000	.000	.000	.000
	F	.000	.000	.000	.000	.000		.000	.000	.000	.000	.000	.000	.000	.000
	G	.000	.000	.000	.000	.000	.000		.000	.000	.000	.000	.000	.000	.000
	H	.000	.000	.000	.000	.000	.000	.000		.000	.000	.000	.000	.000	.000
	I	.000	.000	.000	.000	.000	.000	.000	.000		.000	.000	.000	.000	.000
	J	.000	.000	.000	.000	.000	.000	.000	.000	.000		.000	.000	.000	.000
	K	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000		.000	.000	.000
	L	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000		.000	.000
	M	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000		.000
	N	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	

a. Determinant = 5.073E-15

Table 3. KMO and Bartlett's test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.924
Bartlett's Test of Sphericity	Approx. Chi-Square	3077.529
	df	91
	Sig.	.000

Table 4. Communalities

Communalities		
	Initial	**Extraction**
A	1.000	.944
B	1.000	.905
C	1.000	.898
D	1.000	.944
E	1.000	.961
F	1.000	.953
G	1.000	.909
H	1.000	.959
I	1.000	.952
J	1.000	.938
K	1.000	.945
L	1.000	.889
M	1.000	.893
N	1.000	.962

Extraction Method: Principal Component Analysis

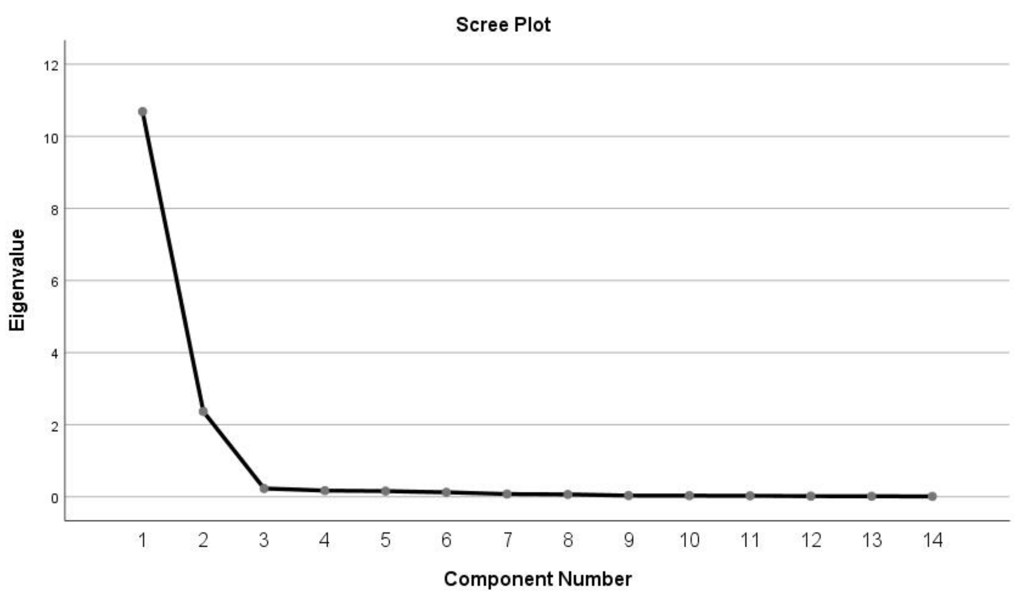

Fig. 1. Scree plot test

Table 5. Total variance explained by retained components

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	10.687	76.335	76.335	10.687	76.335	76.335	8.192	58.517	58.517
2	2.366	16.900	93.235	2.366	16.900	93.235	4.861	34.718	93.235
3	.229	1.635	94.870						
4	.171	1.222	96.092						
5	.156	1.116	97.208						
6	.124	.883	98.092						
7	.075	.534	98.626						
8	.064	.456	99.082						
9	.033	.233	99.315						
10	.030	.213	99.528						
11	.027	.192	99.720						
12	.016	.111	99.831						
13	.013	.096	99.928						
14	.010	.072	100.000						

Extraction Method: Principal Component Analysis

Table 6. Parallel analysis (Monte Carlo PA Output)

Component Number	Actual eigenvalue from PCA	Random order from parallel	Decision
1	10.687	1.690047	Accept
2	2.366	1.499665	Accept
3	.229	1.372039	Reject
4	.171	1.266552	Reject
5	.156	1.169666	Reject

Table 7. Rotated component matrix

Rotated Component Matrix[a]		
	Component	
	1	2
A	.956	
B	.956	
C	.935	
D	.925	.311
E	.925	
F	.921	
G	.912	.334
H	.843	.421
I	.802	.505
J	.689	.647
K		.955
L		.950
M		.941
N	.311	.917

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

Using the rule of the thumb, loadings below 0.3 were considered not significantly contributing to the components.

6.2 Decision on Factors to Maintain from Multiple Extraction Approaches

To prevent over- and under-extraction errors, multiple extraction approaches such as Scree test, Kaiser Criterion and parallel analysis were employed as a way to validate the number of components to retain. All three approaches, Scree test and Kaiser's Eigen vale greater than 1 rule and parallel analysis suggested maintaining two factors. 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 by making the large loadings larger and the small loadings smaller within each component. The first component explains about 76.3% of the total variance. Also, the second component explains about 16.9% of the total variance. In total, the two factors accounted for about 93.2% of the variance.

Factor scores can be used instead of the original variables in subsequent multivariate analysis such as multiple linear regression.

6.3 Modeling of the Relationships

From the rotated component matrix, loadings greater than or equal to 0.3 were retained. These were used to generate factor scores for modeling the relationships between diagnostic assessment and inclusion, differentiated techniques as well as Scaffolding using multiple linear regressions.

The relationship between differentiated approaches and diagnostic assessment was positive was and statistically significant (B_1 = .516, B_2 =.400, F=312.809, P<0.001). The R-square value of 0.866 shows that the regression model explains about 87% of the variance. In other words, use of differentiated approaches in teaching predicts the same output as using diagnostic assessment with a predictive power of 87%.

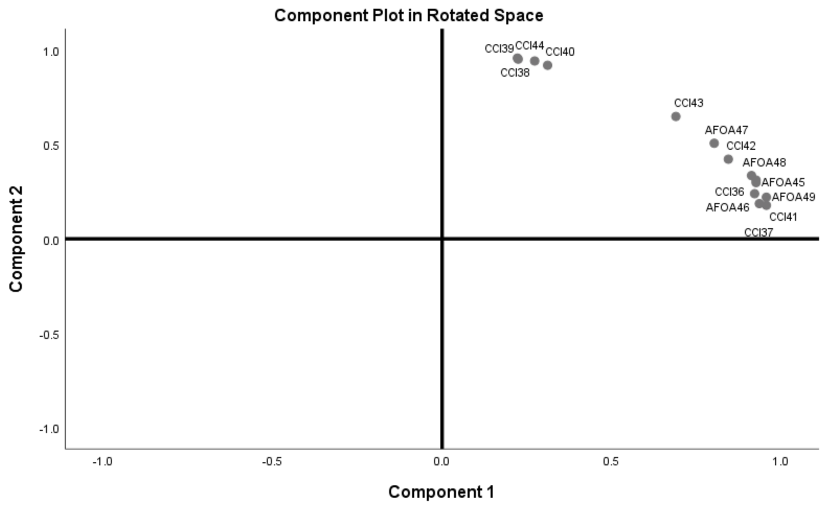

Fig. 2. Factor loading plot

Table 8. Model summary for differentiated instructional approach

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	.930[a]	.866	.863	.260

a. Predictors: (Constant), REGR factor score 2 for analysis 1, REGR factor score 1 for analysis 1

Table 9. ANOVA output for differentiated instructional approach

ANOVA[a]						
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	42.206	2	21.103	312.809	.000[b]
	Residual	6.544	97	.067		
	Total	48.750	99			

a. Dependent Variable: ASF10
b. Predictors: (Constant), REGR factor score 2 for analysis 1, REGR factor score 1 for analysis 1

Table 10. Regression coefficients for differentiated instructional approach

Coefficients[a]								
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**T**	**Sig.**	**95.0% Confidence Interval for B**	
		B	**Std. Error**	**Beta**			**Lower Bound**	**Upper Bound**
1	(Constant)	2.950	.026		113.577	.000	2.898	3.002
	REGR factor score 1 for analysis 1	.516	.026	.736	19.775	.000	.464	.568
	REGR factor score 2 for analysis 1	.400	.026	.570	15.316	.000	.348	.452

a. Dependent Variable: ASF10

Table 11. Model summary for scaffolding instructional approach

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	.952[a]	.906	.904	.250

a. Predictors: (Constant), REGR factor score 2 for analysis 1, REGR factor score 1 for analysis 1

Table 12. ANOVA output for scaffolding instructional approach

ANOVA[a]						
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	58.117	2	29.059	466.442	.000[b]
	Residual	6.043	97	.062		
	Total	64.160	99			

a. Dependent Variable: ASF8
b. Predictors: (Constant), REGR factor score 2 for analysis 1, REGR factor score 1 for analysis 1

The relationship between Scaffolding approaches and diagnostic assessment was positive was and statistically significant (B_1 = .744, B_2 =.185, F= 466.442, P<0.001). The R-square value of .906 shows that the regression model explains about 91% of the variance. In other words, use of scaffolding approaches in teaching predicts the same output as using diagnostic assessment with a predictive power of 91%.

Table 13. Regression coefficients for scaffolding instructional approach

Coefficients[a]								
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**95.0% Confidence Interval for B**	
		B	**Std. Error**	**Beta**			**Lower Bound**	**Upper Bound**
1	(Constant)	3.280	.025		131.412	.000	3.230	3.330
	REGR factor score 1 for analysis 1	.744	.025	.924	29.644	.000	.694	.793
	REGR factor score 2 for analysis 1	.185	.025	.229	7.355	.000	.135	.234

a. Dependent Variable: ASF8

Table 14. Model summary for inclusion instructional approach

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	.903[a]	.815	.811	.305

a. Predictors: (Constant), REGR factor score 2 for analysis 1, REGR factor score 1 for analysis 1

Table 15. ANOVA output for inclusion instructional approach

ANOVA[a]						
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	39.721	2	19.861	213.375	.000[b]
	Residual	9.029	97	.093		
	Total	48.750	99			

a. Dependent Variable: ASF13
b. Predictors: (Constant), REGR factor score 2 for analysis 1, REGR factor score 1 for analysis 1

Table 16. Regression coefficients for inclusion instructional approach

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	3.050	.031		99.971	.000	2.989	3.111
	REGR factor score 1 for analysis 1	.512	.031	.729	16.685	.000	.451	.572
	REGR factor score 2 for analysis 1	.373	.031	.532	12.181	.000	.313	.434

Coefficients[a]

a. Dependent Variable: ASF13

The relationship between Inclusion approaches and diagnostic assessment was positive was and statistically significant (B_1 =.512, B_2 =.373, F= 213.375, P<0.001). The R-square value of .815 shows that the regression model explains about 82% of the variance. In other words, use of inclusion approaches in teaching predicts the same output as using diagnostic assessment with a predictive power of 82%.

7. DISCUSSION

Our study has revealed a direct relationship between diagnostic assessment and instructional strategies such as differentiated learning, scaffolding and inclusion. Scaffolding technique was the most effective predictor of diagnostic assessment; with a predictive power of 91%. The implication of this finding is that when teachers have enough training to scaffold their students, they are already achieving about 91% of the benefits from the use of diagnostic assessment which was not explicitly emphasized in Ghana's new Basic School Curriculum. This finding corroborates the study [12] which revealed a positive relationship between diagnostic and scaffolding strategies; where the predictive accuracy of the developed model was 95.5%.

In our study, differentiated learning approaches were the second most effective predictor of diagnostic assessment, with a predictive power of 87%; suggesting that 87% of the benefits from using diagnostic assessment are achieved with effective use differentiated approaches that are embedded in the curriculum. Inclusive assessment technique followed, predicting diagnostic assessment up to 82%. These other findings from our study are in tandem with the study [13] which revealed that diagnostic assessment models instructional strategies such as Inclusion, Scaffolding and differentiated learning.

8. CONCLUSION

Our study was aimed at determining the power with which scaffolding; differentiated learning and Inclusion instructional approaches predict diagnostic assessment. The results showed a direct relationship between diagnostic assessment and the instructional strategies such as scaffolding, differentiated learning and inclusion with predictive power of 91%, 87% and 82% respectively. These findings give strong support to Ghana's new Basic Education curriculum for indirectly providing for diagnostic assessment using scaffolding, differentiated learning and inclusion as instructional approaches.

9. 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.

10. IMPLICATION FOR FURTHER STUDY

Future studies could consider Factor Analysis in exploring the impact of Scaffolding techniques on students' academic achievement across subject areas to ascertain whether it produces same positive effects and convenience.

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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