Assessing Students' Business studies Ability in Taraba State Schools: A Cognitive Diagnosis Model Approach

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Abstract
School students exhibit varying level of intellectual abilities in the classroom setting during instruction process due to variation in natural abilities of individual student. The purpose of this study is to determine the proportion of students that possesses specific skills in business studies. The study applied the DINO model of cognitive diagnosis models (CDMs), for measurement of business studies skills mastery. A sample of one thousand and fifty (1050) students' scores in Basic Education Certificate Examination (BECE) business studies for 2019/2020 academic session was randomly selected and used for the study. A Q-matrix showing various skills needed to answer the test items was constructed. The GDINA package version 2.7.8. in R programme version 3.6.2 via R-studio 1.2.5033 was employed to analyze the data. The result showed that students have not mastered any of the skills in business studies. Also, the guessing and slipping parameters showed that there is 26 percent chance of students endorsing the right response and a 47 percent possibility that students who have some of the skills required for an item endorsed the incorrect response. It was recommended that students should pay close attention to those skills combination in business studies that will help them earn a living after graduation.
Keywords: Business studies, cognitive diagnosis model, DINO, Q-matrix, guessing, slipping

Introduction

Every practicing teacher will believe that in the classroom setting, different student exhibit varying level of intellectual abilities. Consequent upon this variation in students' intellectual abilities, it becomes imperative that the classroom teacher takes his/her time to understand the degree of mastery of concepts properly grabbed by the students during and after instruction processes. The teacher by this method of noting the concept or skill mastery of students will help the teacher to plan for future lesson. In Nigeria, what is obtainable among classroom teachers is that after lesson delivery, which usually ends up in formative evaluation, teachers do not diagnose the concepts or skills mastery profile of the students. Anamezie and Nnadi (2019) noted that the common practice among the teachers is that corrections are given to the students at the end of evaluation as an antidote to concepts or skills mastery by all the students. They added that the teacher switches to the next topic in subsequent instruction with a vague knowledge of the degree of students' concepts attainment in the previous lesson. The implication of this kind of instructional strategy is that students with below average working memory will be placed at a disadvantaged position. So also, students with low or moderate working memory and who need extra time to be able to attain mastery of concepts will be abandoned with this type of instructional strategy. For proper balance between students with above and below average working memory, Mbajiorgu, Raid, and Ezeano, (2017) recommended that classroom condition should be arranged in such a way that it will avoid instructional bias and provide equal opportunities for students to learn regardless of their genetic or gender differences. As a result of teachers' inability to diagnose students' extent of skills or concepts mastery and using the result from such cognitive diagnosis constitutes a setback in instructional progress.

In order to take care of variation in students' abilities while investigating the students' cognitive structures, there are yet other educational psychometric measurement models that African educational psychometric measurement researchers and Nigerian psychometric researchers in particular seems to have ignored or perhaps have no idea of the information such models provide on test items and test takers alike as against the conventional item response theory (IRT) and classical test theory. These models are generally known called cognitive diagnostic models (CDMs). The CDMs serve as alternative to IRT models but provides more useful information using multiple fine-grained skills in solving problems rather than the usual latent proficiency continuum ordering of students.

Cognitive Diagnostic Models (CDM) is seen as probabilistic, confirmatory multidimensional latent variable models which have a simple or complex loading structure (Rupp & Templin, 2008). CDM probabilistic nature is seen in its expression of students' performance level in terms of separate attribute mastery of individual person in individual latent class (Lee & Sawaki, 2009). In the words of DiBello and Stout (2007), cognitive diagnostic models (CDMs), link observed item responses to categorical latent variables that are characterized by differing levels of attribute mastery which means that the latent trait in a CDM is categorical rather than continuous. Templin and Rupp, (2010); Rupp and Templin, (2008b) as cited in Rupp, Templin and Henson (2010) noted that the confirmatory multidimensional nature of CDMs is seen in the loading structure/Q-matrix which is complex to reflect within-item multidimensionality or simple to reflect between-item multidimensionality. It can also be seen that CDMs suits modelling of observable response variables with various scale types, combining latent predictor variable with series of linear effects can result in compensatory and/or non-compensatory ways for the prediction of observable item response thus providing multivariate attribute profiles for respondents' statistically derived classifications.

CDMs as psychometric models, can equally serve as another good mean of evaluating students' good or bad performances. These models give specific details in form of score outlines which give room for effective measurement of student's learning and progress, designing a more refined instruction, and possibly intervention to deal with discrete and category needs. This is at deviance to the unidimensional item response models (IRMs) whose primary aim is to scale and rank students on a hidden (latent)competency sequence. Thus, the general scores made available by IRMs contain no needed detail to assist in scheming selected instruction and desired remedy. Cognitive Diagnosis Models provide details on the proficiency position of testees of a group of separate interrelated characteristics. Proficiency position of a test taker is demonstrated either in the forms of possibilities for individual test takers who are proficient in respective and distinct skill required to answer items of a test successfully or in forms of a trajectory of 1/0s showing proficiency and non-proficiency as well. An examination or test that requires five different skills, as in this study, a student who has proficiency in the first and fourth traits (attributes) but do not have in the second, third and last traits (attributes), could be allocated the trajectory (1,0,0,1,0) or (.81, .27, .32, .76, .23), where probabilities below.5 and 0s show non-mastery, and probabilities above .5 and 1s show mastery. For instance, to calculate the annual depreciation value of an asset bought for N3000 which is used for 3 years and has a residual value of N600, a student will require the knowledge of (a) "methods of calculating depreciation" (b) "cost price" (c) "residual value" (d) "subtracting residual value from cost price" and (e) "dividing the result of difference between (b) and (c) by expected useful life". So, if a student correctly responds 800, we may conclude that he or she possesses all five capacities. On the other hand, if a student responds, say 600, we will conclude that he or she possesses only the third attribute and does not possess other attributes to be able to respond to the item. The beauty of CDMs is that they are a category of separate or hidden variable models, meaning that one can trace the answer a respondent gives to an item to show that he possesses the fundamental traits of the area embodied by the item. The intention of Cognitive Diagnostic Assessment (CDA) approach promotes appraisal for learning and the learning process in contrast to appraisal of learning outcome by providing information which a teacher needs to effect changes in his teaching and learning in classroom (Jang, 2008).

One advantage of CDM models is most apparent in situations where a need for diagnostic feedback is given to individual respondent or respondents, and criterion-referenced interpretations of multiple proficiencies are most needed (Rupp, 2007). He further explained that individual learner's strengths and weaknesses in a target area of learning and instruction can be identified through the formative diagnostic information provided by CDMs. In Business studies learning, formative diagnosis helps to overhaul educational approaches, assess educational methods, and ensure necessary steps are taken to fix students' weaknesses accordingly. Contrasted with the combined test scores which supported one-dimensional scaling, a diagnostic assessment gives a comprehensive estimate about the present situation of data and learners' skills (Jang, 2008) so that teachers and their students can take necessary measures to fix their limitations in various aspects of business studies skill. Cognitive diagnostic models are broadly classified into three groups namely: compensatory, non-compensatory and general CDMs. Finch and French (2019) explained that, compensatory models allow for a non-zero chances of a correct response for individuals who have mastered some, but not all of the concepts assessed while the non-compensatory models are based on an assumption that for an examinee to answer correctly to an item, such examinee must have mastered every attribute measured by the item. The general CDM, Ravand and Robitzsch (2015) explained that general CDM allow for both compensatory and non-compensatory relationships within a single test. For the purpose of this paper, the researcher used one of the compensatory models known as DINO.

Deterministic input noisy orgate model (DINO), is one of the compensatory CDM developed by (Templin& Henson, 2006) which is analogous to the DINO model which is non-compensatory in nature. The assumption underlying this model is that if one of the attributes is lacking, it can be compensated by another attribute. That is, proficiency, in at least one trait, can make up for deficiencies in all the other measured traits. Slip and guess parameters are gauged at the item level just like DINO. By using the rule of disjunctive condensation, if at least one measured trait is present, gives room for a high chance of an item being endorsed (Rupp et al., 2010).

To build DINO model formula, three basic components are required. First, a latent response variable (ω_{ic}) defining item i for respondent in latent class c, the deterministic input. So, the latent response variable can be represented mathematically as

$$\omega_{ic} = 1 - \prod_{a=1}^{A} (1 - \alpha_{ca})q_{ia},$$

In this formula, the contribution of individual attribute is condensed and summarized in the latent response variable.

The other two components are the slipping and guessing parameters of the model which are stochastic elements that lead to the noise in the or-gate.

$g_i = P(X_{ic} = 1 \mid \omega_{ic} = 0)$ (the probability of providing a score of 1 when required attribute is absent

$s_i = P(X_{ic} = 0 \mid \omega_{ic} = 1)$ (the probability of providing a score of 0 when the required attribute is present

Therefore, the DINO model for responding positively is the combination of the slipping and the guessing parameters, latent response variable written as

$$\pi_{ic} = P(X_{ic} = 1 \mid \omega_{ic}) = (1 - s_i)^{\omega ic} g^{1-\omega ic}$$

Where, P is the probability, πic is the chance (probability) of correct response for item i in latent class c,X_{ic} is the observed response for item i in latent class c, ω_{ic} is the latent response variable for latent class c on item i, $(1 - s_i)$ is the chance (probability) of not slipping for item i, and g_i is probability of guessing for item i.

Currently, Nigeria operates 1- 6 – 3 – 3 – 4 system of education that is, 1-year Pre-primary education, 6 years of primary schooling, 3 years for junior secondary education, 3 years of SSE and 4 years university (FRN, 2014). At the end of the first three (3) years of lower secondary school, an examination known as Basic Education Certificate Examination (BECE) shall be taken by the students to determine if they are qualified to move to the upper secondary school. Business studies is one of the subjects that students take in BECE. Business studies is very important in building a strong base for anyone seeking for advanced specialised training and further study in business areas such as management, communication technology, international business, marketing, accounting, entrepreneurship, finance, etc (Briggs, 2019). Several studies on CDMs focused mostly on English language or Mathematics and few studies were conducted using business studies as a subject. This study, therefore, uses DINO model for calibration and diagnosis of business studies skills of junior secondary school students looking at the importance of business studies in making student self-reliance and contributing to gross domestic product of a nation.

Objectives of study

The objectives of this study were to:

(i) determine the fraction of students possessing specific skills inbusiness studies.

(ii) determine the fraction of students possessing specific combination of skills in business studies.

(iii)determine the slipping with guessing parameters of the business studies test items.

Research question

1. What fraction of students possessed a specific skill in business studies?
2. What fraction of students possessed a specific combination of skills in business studies?
3. What are the guessing parameters of the business studies test items?

Methodology

The population of the present study include the entire students that took the BECE in 2019 and a sample of 1050 Junior secondary school (JSS) three (3) students who took the Basic Education Certificate Examination (BECE) in 2019 were randomly selected. The BECE is usually in three parts, short answers, essays and 50 multiple choice questions. In this study, the researcher used multiple-choice items that were scored dichotomously. A Q-matrix was constructed. Bandalos (2018) described the Q-matrix as the DCM equivalent of the factor loading matrix in factor analysis in that it specifies how latent traits are associated with observed responses. The entries within the Q-matrix are denoted by qia, where qia = 0 if item i does not measure attribute a and qia = 1 if it does. Probabilities of 0.5 and above indicate mastery of the attribute while probabilities below 0.5 denote non-mastery of the attribute. Ravand and Robitsch (2015) noted that CDMs can be used in two ways: it could either be used for (i) backfitting (post-hoc analysis) of existing non-diagnostic tests to get more substantial detail or (ii) developing several new items or task from the beginning for the purpose of diagnosis. This study therefore uses the retrofitting approach to extract information about students from non-diagnostic test. Since this study is that of retrofitting, no detailed task performance for cognitive diagnosis was obtainable and intrinsically, the researcher got two experienced Business Studies teachers to deliberate on the feasible attributes the test measured. They specified a group of 5 fundamental attributes of the business studies test, that is; Book-keeping, Commerce, Office Practice, Typing and Shorthand. Then two other Business Studies teachers with over ten years of Business Studies teaching experience were interrogated separately to specify the attributes which individual 50Business Studies items measured. The information collected with the ultimate Q-matrix (Table 1), were analyzed using GDINA package version2.7.8 in R software 3.6.2 version via R-studio 1.2.5033 version.

Table 1: Q-matrix for the Business Studies test

Items	BK	CO	OP	TP	SH	Items	BK	CO	OP	TP	SH
1	0	0	0	1	0	26	0	1	0	1	1
2	1	0	0	0	1	27	0	1	0	1	1
3	0	1	0	0	1	28	0	0	1	0	0
4	0	0	1	0	0	29	1	0	1	0	0
5	1	0	1	1	0	30	1	0	0	0	1
6	0	1	0	0	1	31	0	0	0	1	1
7	0	1	0	0	1	32	0	1	0	1	0
8	0	0	1	1	0	33	1	0	0	0	0
9	1	0	1	0	0	34	0	0	1	0	0
10	0	0	1	0	0	35	0	1	0	0	0
11	0	0	0	1	1	36	0	1	0	1	1
12	0	1	0	1	1	37	0	1	0	1	0
13	1	0	0	0	1	38	0	0	1	0	1
14	0	0	1	0	0	39	1	0	1	0	0
15	1	0	0	0	0	40	1	0	0	0	1
16	0	1	0	0	1	41	0	0	0	1	0
17	0	1	0	1	0	42	0	1	0	1	1
18	0	0	1	0	0	43	1	0	0	0	1
19	1	0	0	0	1	44	0	0	1	0	1
20	1	0	0	0	1	45	0	1	0	0	0
21	0	0	0	1	1	46	0	1	0	1	0
22	0	1	0	1	0	47	0	1	0	1	0
23	1	0	0	0	1	48	0	0	1	0	1
24	0	0	1	0	0	49	1	0	1	0	1
25	0	1	0	1	0	50	1	0	0	0	1

(Business Studies skills)

BK= Bookkeeping, CO= Commerce; OP= Office practice; TP= Typing; SH= Shorthand

RESULTS

Outcomes of the study were presented on table based on the research questions raised by the researcher below.

Research question 1: What fraction of students possessed a specific skill in Business Studies?

Table 2: Fraction of students in Business Studies skills

	Skill probabilities
Bookkeeping	0.45
Commerce	0.47
Office practice	0.23
Typing	0.23
Shorthand	0.00

Table 2 shows the distribution of students' mastery of different skills, Commerce, 47 % of the test takers, followed by Bookkeeping 45%, Typing and Office practice mastered by 23% each while no student mastered shorthand. Therefore, Bookkeeping and Commerce were the fairly difficult skills while Typing, Office practice and Shorthand were the most difficult attributes. On the whole, no skill was mastered since no skill probability was up to 0.5.

Research question 2: What fraction of students possessed a specific combination of skills in Business Studies?

Table 3: Fraction of students' skill combination

Latent class	Attribute profile	Class probability	Class expected frequency
1	00000	0.3	315
…	…	…	…
…	…	…	…
6	00001	0.25	257.27
…	…	…	…
11	01100	0.228	239
19	11001	0.227	238.70
31	01111	0	0
32	11111	0	0

Table 3 shows a portion of the output generated based on students' attribute combination. In this study, students were classified into 32 latent classes, that is 2^5. In column two of table 3, the plausible skill profiles for all the 32 latent classes are displayed. In column three of Table 3, the skill profile of α_1= [00000] had a class probability of 0.3 which is the highest class probability in all. This represent approximately 30% of the respondents, (about 315 respondents) who belonged to the first class and therefore do not have any of the five skills in Business Studies. Skill profile of α_6 = [00001] had class probability of .25 representing 25% of the respondents (about 257 respondents) had only one (1) out of the five skills. Skill profile α_{11}= [01100] shows that 0.227 or approximately 22.8% of the students (about 239 students) have a combination of at least two (2) skills. For at least three skills combination, Table 3 shows that 22.7% (about 239 students) were found to have three skills combination. For skill profile α_{31} and α_{32} shows that no student had a combination of up to four or five skills respectively.

Research question 3: What are the slipping with guessing parameters of the business studies test items?

Table 4: The guessing with slipping parameters of the Business Studies test items

Items	Guessing	Slipping	Items	Guessing	Slipping
1	0.2419	0.7581	26	0.1064	0.3000
2	0.0001	0.2404	27	0.6177	0.3800
3	0.0001	0.5527	28	0.3790	0.6210
4	0.0001	0.0001	29	0.7541	0.0001
5	0.0791	0.7209	30	0.3980	0.0001
6	0.0001	0.7152	31	0.0141	0.6019
7	0.0001	0.0001	32	0.8495	0.1505
8	0.0001	0.4314	33	0.0188	0.0001
9	0.2657	0.7343	34	0.3276	0.6724
10	0.3884	0.3965	35	0.4190	0.5810
11	0.6190	0.3810	36	0.0022	0.7619
12	0.6086	0.3914	37	0.0082	0.7154
13	0.3199	0.5850	38	0.0001	0.1760
14	0.2615	0.6263	39	0.6200	0.3800
15	0.3705	0.6295	40	0.0001	0.7550
16	0.2342	0.6827	41	0.0001	0.0001
17	0.3981	0.6019	42	0.1066	0.3029

18	0.0260	0.0001	43	0.0001	0.6294
19	0.3152	0.6848	44	0.7724	0.2276
20	0.3249	0.6677	45	0.7477	0.0001
21	0.5276	0.4724	46	0.4973	0.2806
22	0.0002	0.5745	47	0.0001	0.7306
23	0.4657	0.5343	48	0.3000	0.7000
24	0.1714	0.8286	49	0.0001	0.7152
25	0.3276	0.6724	50	0.0001	0.7596
Mean				0.2577	0.4665

Table 4 presents guess and slip parameters of each item. As the results showed, the lowest guessing coefficients are for items 2, 3,4,6,7,8,38,40,41 and 45 with values of 0.0001 and values 0.8495 was the highest guessing coefficients for item 32. Items 4,7,18,29,30,41 and 45 have lowest slip value with equal values of 0.0001each and item 24 had the highest slip coefficient with values of 0.8286. Table 4 also showed that the slipping and guessing parameters averaged .47 and .26 respectively. The mean guessing parameter signifies that there is a 26 percent possibility that students, having no necessary skills for an item, will still choose the correct response and similarly the average slipping parameter is an indication that there is still a 47 percent possibility that students who claimed to have little of the skills will still choose the incorrect response.

DISCUSSION

Students exhibit varying levels in responding correctly to items of the test. Shorthand is the most difficult skill of the students since no one got any of the items of the skill correctly. The reason might be that there is carelessness on the part of the students. It might also be that the teachers of this subject do not possess the shorthand skill to teach it to the students. Office practice and typing seems to be difficult for the students as few proportions of the students could attempt the items correctly. Although a reasonable proportion of the students could attempt items on bookkeeping and commerce, it is not enough to conclude on students' mastery of the skills. This finding is consistent with Simon (2017) finding that students have only acquired marketing (commerce) and accounting (bookkeeping) skills to enable them to be self-reliant upon graduation. Students have poor skill combination to excel in business studies at the junior secondary school. This may be attributed to teachers because some teachers are selective in teaching some topics (Briggs, 2019). Where a teacher finds a topic difficult, the teacher may move to the next topic. The implication of this is the poor performance of students in final examinations. The study also agrees with Ahmed (2015) that Business Studies teachers were unable to motivate students to study the subject because they do not teach the subject properly.

The entire fifty items according to research question three showed that the guessing and slipping parameters are normal. The result suggested that the test items were capable of measuring the students' proficiency in Business Studies. For guess parameter, the coefficients showed that student who do not have the required skills may still respond correctly to the questions.On Slip,finding showed that most of the items had low slip value indicating the possibility that students might still answer the questions incorrectly, despite having the skills necessary to endorse the question. According to Rupp et al. (2010), items whose slipping and guessing probabilities are low gives the best information about test items.The current study showed that the originally non-diagnostic assessment test, the response data, and the DINO model so postulated yielded small guessing and slipping parameters which is an indication of a good fit among them. This result affirms the studies of Afzali et al. 2016 and Wafa, Hussaini, and Pazhman, (2020) that only three attributes were mastered by the students explaining the mathematical performance of first grade high school students using DINO model. The study also supports Rahimi, et al. (2018) that most of the attributes were not mastered.

CONCLUSION/RECOMMENDATION

This study's result showed that students do not have shorthand skill at all and also find bookkeeping, commerce, typing and office practice skills very difficult. There is poor combination of business studies skills among the students. Result also showed that guessing and slipping parameters were low indicating that students who were not having the necessary skills guessed the items while students who had the skills for the items slipped off due to carelessness and lack of concentration. It is recommended that:

1. Students should pay more attention to all the skills needed in Business Studies.
2. Students should also pay close attention to those skills combination in Business Studies that will help them to earn a living after graduation.
3. Students should read and understand every item properly before endorsing the item.

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