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Students' Performance in Ghana: A Discriminant Analysis

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ABSTRACT

This study employs discriminant analysis to determine students' performance in their final West African Senior Secondary School Certificate Examination (WASSCE). Data on 104 students who completed Suhum Senior High Secondary Technical School from 2012 to 2013 were gathered from the WASSCE results sheets of the school and discriminant analysis was performed on the initial factors. Result suggest that six factors: being the BECE grade in Science, BECE grade in Mathematics, Type of basic education, Duration of the SHS system, Entry admission age to form 1 of SHS and BECE aggregate of candidate as parsimoniously representing the difference between students who performed very well and those who performed poorly in the WASSCE- determine the performance.

Keywords: Discriminant, grades, mathematics, performance.
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1.0 INTRODUCTION

It is the general perception that a student's performance in examination depends upon how well he or she prepares himself or herself towards the examination. Preparation for examination may include teaching and learning and the environment of study. However, all things being equal, a few other factors have significant influence on a student's performance in examination. It is therefore, imperative to identify some of these influential factors, if not all. This will help to predict the chance of a student who is being considered for admission into a Senior High School [SHS] of a school doing well in his/her final West African Senior Secondary Certificate Examinations(WASSCE).

In designing any educational intervention one often needs to determine what factors are related to success or failure in a course, identify students at risk, evaluate the impact of any new programmes on students' performance. A lot of reforms have been done in the educational system of Ghana particularly at the basic and secondary levels all aimed at improving the quality and delivery of education to the citizenry.

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Again, a lot of debates have also been going on currently as to which of the SHS educational systems: four year or three is the best. The researcher is therefore challenged to delve into the factors that significantly influence the performance of students in the final examinations which serve as the evaluation criterion of the educational curriculum. Hence the topic, Application of discriminant analysis to factors that influence students' performance in the WASSCE

The main objective of the study is to apply discriminant analysis to some influential factors that determine the performance of senior high students in their final WASSCE. The specific objectives however, include the following:

1. Identification of influential factors that discriminate best between students who perform very well and those who perform poorly in their WASSCE.
2. Use the influential factors to develop discriminant functions for computing classification scores that will parsimoniously represent the differences between the two groups of students.
3. Compare computed scores to an index that predicts the chance of a JHS graduate placed in a particular SHS coming out successfully in his/her final WASSCE.

It is hoped that the findings of this study will help school authorities to be better informed on their decision-making in offering admission to a student as well as placement into specific programs of study and assess the chance of the student passing his or her final WASSCE. Parents as well as guardians will also be informed on the chances of their wards passing or failing the WASSCE, which is a crucial indicator of the child´s future carrier.

2.0 SENIOR HIGH SCHOOL ADMISSIONS PROCESSES IN GHANA

Senior High School admissions processes often depend on the ability to predict student success. However, the use of a test to help determine admission has traditionally been problematic and continues to be so recently. This was not a new call: a plethora of research has shown that standardized tests do not predict success equally well for all groups (Cleary, Humphreys, Kendrick, & Wesman, 1975); Melnick, 1975; (Nettles, Thoeny, & Gosman, 1986); (Tracey & Sedlacek, 1985) and that standardized tests do not measure what they claim to measure (Riehl, 1994); (Guinier & Sturm, 2001). Often, Senior High School may rely on two tests as a means of using multiple criteria, but if the two tests are highly correlated with each other, there is needless duplication in measuring the same aspect of a construct (Chiang, Adachi, Anastasi, & Beatty, 1982). Because the use of standardized tests has been shown to be problematic, multiple selection methods are being used to predict student success (Ebmeir & Schmulbach, 1989). The use of multiple measures is called triangulation, the goal of which is to "strengthen the validity of the overall findings through congruence and/or complementarily of the results of each method" (Greene & McClintock, 1985, p. 524). This method is used extensively in education for admissions (Markert & Monke, 1990; McNabb, 1990) and involves using a variety of techniques simultaneously to measure a student's knowledge, skills, and values (Ewell, 1987). Colleges can benefit from combining cognitive and non-cognitive variables in predicting student academic success (Young & Sowa, 1992). Because the essence of triangulation is to measure the same construct in independent ways (Greene & McClintock, 1985), the more non-related information gathered, the better the prediction. Triangulation can also minimize or decrease the bias inherent in any particular method by counterbalancing another method and the biases inherent in the other method (Mathison, 1988).

2.1 SEX DETERMINATION USING DISCRIMINANT ANALYSIS

Jean and Judy of Department of Anthropology, California State University, Fullerton, California did a research on sex determination using discriminant analysis. A large sample (370 in size) of central California prehistoric skeletal remains was analyzed for sexual dimorphism of long bones using nine femoral and nine humeral dimensions' sex of all individuals. This was assessed using traits of the Os pubis. Discriminant analysis was done separately for the robust fairly Horizon sample and the middle/late Horizon sample. Discriminant analysis was performed on all the initial predictor factors (variables) and later a combination of some of the factors. The analysis revealed that use of multiple variables did not produce appreciably better results over the use of the best variables analyzed singly. The discriminant analysis, therefore, served as a data reduction technique and succeeded in reducing the initial variables (9 in number) to only a few remaining factors being the diameter of femoral head, femoral bicondylar width and diameter of the human head (transverse or vertical). These variables produced excellent separation of the sexes with about 90% accuracy.

The difference between Jean and Judy's research work and the current work are that Jeans' work focused on determination of sex (i.e. male or female) of:

- ✓ Prehistoric skeletal remains while the current work concentrates on determination of the performance (i.e. pass or fail) of a student in a final examination;
- ✓ Jean and Judy compared the discriminant function score on an individual with a standardized discriminant index to identify the sex of the individual while this research work did not only compare the discriminant function score on an individual with a discriminant index but also compared the classification functions scores on the individual to determine the performance of an individual in examination.

The similarities in the two-research works are that;

- ✓ The multivariate techniques used in both cases managed to reduce the initial several possible predictor variables to only a few "best" influential factors which were sufficient in giving reliable results.
- ✓ Both the discriminant function and the classification functions are linear combinations of the predictor variables and are both multivariate technique of discriminant analysis.

2.2 EFFECTS OF STUDENTS' PREDISPOSING CHARACTERISTICS ON STUDENTS' SUCCESS

Richard Powell, Christopher Conway and Lynda Ross all of Athabasca University (UK) carried a research work on the "Effect of students' predisposing characteristics on students' success"

The question of why some students successfully study through distance education and others do not is becoming increasingly important as distance moves from a marginal to an integral role in the provision of post-secondary education. The research work first advances a multivariate framework for examining this issue. It then explores the predictive capability of students' "predisposing characteristics" about their chances of successfully completing their first Athabasca University distance education course. Using Discriminant Analysis, nine predisposing characteristics were found to be significantly related to provide the basis for a comprehensive model for understanding success and persistence in distance education.

2.3 FACTORS THAT PREDICT STUDENTS AT RISK OF FAILING A COURSE OF STUDY

Thomas et al, did a research work on "using discriminant analysis to identify students at risk" in designing any educational intervention one often needs to determine what factors are related to success and failure in a course, identify students at risk; evaluate the impact of any new program on students' performance.

Determinant analysis was used as a technique for addressing all these factors. In the research work discriminant was used to predict students' performance in an introductory electromagnetism course at Georgia Technical Institute. In this course, there was a high failure rate (greater than 30% made a grade of D or F) which resulted in a great cost to the institute and to students as success in the course was a prerequisite for all engineering majors. Discriminant analysis was used to identify the factors that were predictive of course performance and identify students who were at risk. Based on information available from the student' cumulative records, fifteen (15) possible predictor variables were initially considered and the analysis selected only three (3) of the factors predictive of course performance. The analysis could successfully predict 50% of the students who eventually failed the class.

3.0 METHODS OF ANALYSIS

To form linear function(s) which parsimoniously represent the difference between the groups of the students who perform well (pass) and those who perform poorly (fail) in their final WASSCE, a discriminant analysis was used.

Discriminant analysis is a data reduction technique for analyzing data when the criterion or dependent variable is categorical and the predictor or independent variables are interval in nature. With regards to the study the criterion variable was the students' performance in the WASSCE (that is pass or fail) and the independent (predictor) variables were gender, age of student at the time of entering first year in SHS, place educated at the basic level, type of basic school attended, program offered at SHS, duration of program of study, BECE grades in Mathematics, English and Science and BECE aggregate.

In this study the discriminant analysis was intended to classify students into one of the two mutually exclusive categories pass or fail. Since the criterion variable has only two categories a two-group discriminant analysis was performed and two classification functions were developed for the two groups using the standardized and non-standardized coefficients of the discriminant function respectively. If a student performs well in WASSCE it is classified into category 1 and 2 for students who perform poorly.

The discriminant analysis model is of the form
D= $b_o + b_1 x_1 + b_2 x_2 + b_3 x_3 + \ldots + b_k x_k$

Where;
D =discriminant score
x = predictor or independent variable
b =discriminant coefficient or weight of the predictor variable.
The coefficients, or weights (*b*), are estimated so that the groups differ as much as possible on the values of the discriminant function. This occurs when the ratio of between-group sum of squares to within–groups sum of squares for the discriminant scores is at maximum (Naresh K., 1995). Marketing Research). Any other linear combination of the predictors will result in a smaller ratio. Thus, the Wilks' lambda should be a maximum.

4.0 DATA COLLECTION

To identify the factors that significantly influence students' performance in the WASSCE a number of factors were considered: notable among them were gender, age, place educated at the basic level, type of basic school attended, program offered at the SHS, Basic Education Certificate Examination (BECE) results, duration of program of study, conduct, health status and socio economic factors. However, data on conduct, health status and socio economic factors were not adequately available for the study. Data on the above variables (factors) were gathered, tabulated and coded (see Code Book and Spread Sheet in appendixes A and B).

- variables.

4.1 CODE BOOK OF COMPUTER SOFTWARE(S)

In this research work the computer softwares used in coding variables in the discriminant analysis were the Statistical Package for the Social Sciences (SPSS) and MINITAB. The code book in appendix C was used. For details of the raw data see spread sheet in appendix B

4.2 PRELIMINARY ANALYSIS

Under this section, the basic assumptions on discriminant analysis are tested as well as the basic descriptive statistics on the individual best predictor variables are given.

4.2.1 TEST OF DISCRIMINANT ASSUMPTIONS

(i) Test of Linearity Assumption: This suggests that all pairs of predictor variables must be linear. Examination of the correlation matrix for all the initial ten (10) predictor variables reveals that there exists no correlation between programmes of study at the SHS and BECE grade in Mathematics. This is so because the correlation coefficient is zero (0.00). However, considering the values of the Wilks´ Lambda, the assumption is met if Gender, Programme of Study at the SHS, BECE Grade in English and Place of Basic School of candidate are eliminated. BECE grade in Science, BECE grade in Mathematics, Type of basic School attended, BECE aggregate, Age at which student is admitted to first year of SHS and Duration of SHS program appears therefore to best discriminate the performance in the WASSCE.

(ii) Sample size assumption: This assumption suggests that the sample size of the smallest group (in our case, fail) must exceed the number of predictor variables in the model (Leech et al., 2005). The sample size of the smallest group is 31 which is five times more than the number of predictor variables (six in our case) in the discriminant model. This assumption is therefore met.

(iii) Test of Multivariate Normality (Homogeneity of Variance): Even though the covariance matrices of the two groups appear not to be equal, which appears to suggest that the variances differ in the groups and that the homogeneity assumption is not upheld. Discriminant analysis, however, can still be robust even when this assumption is violated (Lachenbruch, 1975).

The high value of the Box M (i.e. P(M) = 39.188) and the probability value of the F (i.e. 0.022) which is greater than 0.000(see Box M table in Appendix E) indicates that there are no significance differences between the covariance matrices. This is an indication that the homogeneity assumption is not violated.

4.2.2 BASIC DESCRIPTIVE STATISTICS

(i) BECE GRADE IN SCIENCE

Table 4.1 gives the descriptive summary of statistics of students BECE grades in science and the percentage distribution of their corresponding relative performance in the WASSCE.

Table 4.1: BECE grade in Science against performance in WASSCE

Grade	Number out of 104	%Pass in WASSCE	%Fail in WASSCE
1	11	81.8	18.2
2	38	81.6	18.4
3	35	77.1	22.9
4	13	38.5	61.5
5	5	20.0	80.0
6	2	100.0	0.0

Field data, 2013.

It can be inferred that the better the BECE grade in science the better the performance in the WASSCE.

(ii) BECE GRADE IN MATHEMATICS

Table 4.2 gives the descriptive summary of statistics of students BECE grades in mathematics and the percentage distribution of their corresponding relative performance in the WASSCE.

Table 4.2: BECE grade in Mathematics against performance in WASSCE

Grade	Number out of 104	%Pass in WASSCE	%Fail in WASSCE
1	14	85.7	14.3

2	19	84.2	15.8
3	37	78.4	21.6
4	24	50.0	50
5	7	42.9	57.1
6	2	50.0	50.0

It can be inferred that the better the BECE grade in Mathematics the better the performance in the WASSCE.

(III) TYPE OF BASIC SCHOOL ATTENDED

Table 4.3 Distribution of performance in WASSCE by type of basic education

Type of basic School	Number of students	Number pass WASSCE	Number fail WASSCE	% Pass WASSCE	% Fail WASSCE
Preparatory	53	31	22	58.5	41.5
Public	51	42	9	82.5	17.6

(Field data, 2013).

The descriptive summary statistics in Table 4.3 shows that, little more than 80% (i.e. about 8 out of every 10) candidates who obtained their basic level education in public schools passed their final WASSCE in SUTESCO. The performance rate was however, low, a little less than 60% (that is 6 out of every 10) for SHS students of SUTESCO who had their basic education in preparatory institutions.

The analysis suggests that in SUTSCO, more students who have their basic education in public schools on the average perform better in their final WASSCE than their counterparts from preparatory schools with the same BECE entry results.

(IV) AGE ADMITTED TO FORM ONE AT SHS

Table 4.4 below shows the distribution of the percentages of the various age groups in the two categories (pass or fail) of students´ performance.

Table 4.4: Distribution of age admitted to form 1 of SHS against performance in WASSCE

Age admitted to SHS 1	Frequency	Percentage in pass	Percentage fail
12	1	0.96	0.00
13	0	0.00	0.00
14	5	4.80	0.00
15	34	23.1	9.60
16	39	20.2	17.30
17	16	13.5	1.90
18	6	3.80	1.20
19	1	0.00	1.90
20	1	0.00	0.96
21	0	0.00	0.96
22	1	0.00	0.96

The mean age of students admitted to SUTESCO within the study period was 16 years. Table 4.4 indicates that majority of the students who performed well in their final WASSCE were those admitted into SHS 1 at ages between 14 and 16 years inclusive. It is also worth noticing that no student admitted to SHS 1 beyond age 18 passed the WASSCE within the period under study.

It is likely most students who enter SHS 1 above age 16 years might have been repeated at least once in a class before sitting for the BECE or might have attempted the BECE more than once before passing. Such students are not the academic type and are, therefore, not able to do well in the SHS.

(V) BECE AGGREGATE

The best entry BECE aggregate recorded was 9, while the weakest was 29 with a mean of 16.33. While the mean BECE aggregate for the students who passed the WASSCE was recorded as 16.34, it was rather higher, 18.23, for students who could not do well in the WASSCE. This is an indication that good BECE aggregate results in good aggregate in the WASSCE. A higher BECE aggregate is therefore a disincentive to student performance in SHS.

(VI) DURATION OF STUDY

Table 4.5: Duration of study against performance in WASSCE

Duration	Total Number	Number Passed	Number Failed	% Passed
3 years	34	19	15	55.88
4 years	70	55	15	78.57

Table 4.5 reveals that almost 78.57% (that is about 8 out of every 10) students admitted to SUTESCO who studied the SHS programme for four (4) years passed the WASSCE, while only 55.88% of their counterparts who studied the programme for three (3) years passed in the examinations within the period of study. This suggests that the four year SHS programme of study has a relatively better performance in the WASSCE than the three year programme.

4.3 FURTHER ANALYSIS

The previous section has looked at the basic preliminary analysis of factors which seem predictive of students' performance in the WASSCE. This section gives further analysis of the computer printout of the discriminant analysis of the data (see appendix A and E)

4.3.1 DISCRIMINANT ANALYSIS

The discriminant analysis as presented by an SPSS and MINITAB computer software's outputs (Appendix…) reveal the following. The six independent variables BECE grade in Science, BECE grade in Mathematics, Type of basic school attended, Age at which candidate is admitted to form 1 of SHS, Duration of SHS programme and final BECE aggregate parsimoniously represent the ´Best´ set of factors that significantly differentiate between students who performed well (pass) and those who performed poorly (fail) in their WASSCE. This is the case, as among the factors that made the assumptions of the discriminant analysis satisfied, they contribute among the highest power (that is 77.9%) of prediction of students' performance in their final WASSCE. Again, all other linear combinations of five or less other factors have rather low prediction powers which are significantly different.

Furthermore, once a student has a grade 6 or better in English, the programme offered by a student at SHS, Place of basic of basic education and the gender of a candidate appeared generally not to have any significant influence on the student's performance in the WASSCE (see table 4.6).

Table 4.6: Power of prediction of discriminant function

Number of factors	Predictor variables	Correctly predicted cases out of 104	Percentage correctly predicted
9	BECE grade in Science, BECE grade in Mathematics, Type of basic school attended, Age at which candidate is admitted to form 1 of SHS, Duration of SHS programme, final BECE	80	76.9

	aggregate, BECE grade in English, Place of basic school and Gender		
8	BECE grade in Science, BECE grade in Mathematics, Type of basic school attended, Age at which candidate is admitted to form 1 of SHS, Duration of SHS programme, final BECE aggregate, BECE grade in English and Place of basic school	80	76.9
7	BECE grade in Science, BECE grade in Mathematics, Type of basic school attended, Age at which candidate is admitted to form 1 of SHS, Duration of SHS programme, final BECE aggregate and BECE grade in English	81	77.9
6	BECE grade in Science, BECE grade in Mathematics, Type of basic school attended, Age at which candidate is admitted to form 1 of SHS, Duration of SHS programme and final BECE aggregate	81	77.9
5	BECE grade in Science, BECE grade in Mathematics, Type of basic school attended, Duration of SHS programme and final BECE aggregate	80	76.9
4	BECE grade in Science, BECE grade in Mathematics, Type of basic school attended and Duration of SHS programme	80	76.9

4.3.2 ANALYSIS OF VALUES OF WILKS´ LAMBDA ⋏

Table 4.7: Predictor factors and their Wilks´ Lambda

Factor	Wilks´ Lambda
BECE grade in Science	0.848
BECE grade in Mathematics	0.892
Type of Basic School Education	0.932
Duration of SHS Programme	0.952
BECE Aggregate	0.954
Age admitted to SHS 1	0.954

The values of the Wilks' Lambda after the non-influential factors are removed are as seen in table 4.7 above. The figures suggest that BECE grade in Science is the single variable that has the highest influential factor of predicting students' performance in the WSSCE. The poorer the BECE grade in the Science, the poorer the performance in the WASSCE. This is followed by BECE grade in Mathematics, Type of basic school education and Duration of SHS programme, with BECE Aggregate and Age admitted to SHS 1, followed closely with virtually equal effect.

4.3.3 LINEAR DISCRIMINANT FUNCTIONS FOR GROUPS

(I) CLASSIFICATION FUNCTIONS

Group	1	2
Constant	-92.937	-99.843
BECE grade in Science	-1.530	-0.710
BECE grade in Maths	-0.116	0.463
Type of basic school	6.696	5.395
BECE Aggregate	0.634	0.561
Age at last birthday	9.760	10.030
Duration of SHS Education	11.873	12.917

The classification discriminant functions given by MINITAB are as follows:

$D_1(x_i) = -92.937 - 1.530$BECE grade in Sc. -0.116BECE grade in Math. $+ 6.696$Type of basic sch. $+0.634$BECE Aggregate $+9.760$Age at last birth day $+11.873$Duration of study.

$D_2(x_i) = -99.843 - 0.710$BECE grade in Sc. $+0.463$BECE grade in Math. $+ 5.395$Type of basic sch. $+0.561$BECE Aggregate $+10.030$Age at last birth day $+12.917$Duration of study.

Where $D_1(x_i)$ – denotes the discriminant score for the ith candidate by the unstandardized function (i.e. classification function) for group 1(pass) and $D_2(x_i)$ – denotes the discriminant score for the ith candidate by the unstandardized function for group 2(fail).

We note that the group (category 1 or 2) whose classification function score (index) is higher for a candidate under consideration is the correct predicted (assigned) group for the candidate (i.e. substituting the values of the predictor variables into the discriminant equation, the one that gives the higher discriminant score (D) is the right group that the candidate belongs).

D_1 assigns candidate to → group 1

D_2 assigns candidate to → group 1

As an example, if the Classification Discriminant score given by category one (1) for candidate is 100 and category two (2) has score of 105, then the analysis assigns the student into group 2 (see other examples in table 4.6). Out of 104 candidates considered, an overwhelming proportion of 0.779 were correctly classified by the analysis. The classification functions are therefore highly reliable.

Sampled details of the computation of the D(x) using the classifications functions are as follows:

$*D_1(x_1) = -92.937 - 1.530x2 - 0.116x1 + 6.696x1 + 0.634x9 + 9.760x15 + 11.873x1 = 74.562$

$D_2(x_1) = -99.843 - 0.710x2 + 0.463x1 + 5.395x1 + 0.561x9 + 10.030x15 + 12.917x1 = 73.011$

$*D_1(x_{10}) = -92.937 - 1.530x3 - 0.116x2 + 6.696x1 + 0.634x10 + 9.760x15 + 11.873x1 = 73.55$

$D_2(x_{10}) = -99.843 - 0.710x3 + 0.463x2 + 5.395x1 + 0.561x10 + 10.030x15 + 12.917x1 = 73.325$

$D_1(x_{80}) = -92.937 - 1.530x3 - 0.116x3 + 6.696x1 + 0.634x17 + 9.760x17 + 11.873x2 = 109.265$

$*D_2(x_{80}) = -99.843 - 0.710x3 + 0.463x3 + 5.395x1 + 0.561x17 + 10.030x17 + 12.917x2 = 110.692$

$D_1(x_{86}) = -92.937 - 1.530x5 - 0.116x6 + 6.696x2 + 0.634x28 + 9.760x16 + 11.873x1 = 97.894$

$*D_2(x_{86}) = -99.843 - 0.710x5 + 0.463x6 + 5.395x2 + 0.561x28 + 10.030x16 + 12.917x1 = 99.28$

$D_1(x_{21}) = -92.937 - 1.530x2 - 0.116x5 + 6.696x1 + 0.634x15 + 9.760x15 + 11.873x2 = 90.235$

$*D_2(x_{21}) = -99.843 - 0.710x2 + 0.463x5 + 5.395x1 + 0.561x15 + 10.030x15 + 12.917x2 = 91.146$

The scores with asterisks (*) are higher than those without asterisks. The individual observations are, therefore assigned to groups with the asterisks *D´s. The detailed results are found in table 4.6.

Even though the classification functions may suggest that an observation should be assigned to the group with a higher score, in practice, an observation may be assigned to any of the groups when the scores are relatively very close and the groups are not completely mutually exclusive.

Table 4.8: Sampled classification scores

Candidate	BECE gr. in Sc	BECE gr. in Math.	Type of Basic	Duration of SHS	Age adm. to form 1	BECE aggregate	Classification score	Predic-ted group

			Edu.	program	of SHS		$D_1(x_i)$	$D_2(x_i)$	
X_1	2	1	1	1	15	9	74.562	73.011	1
X_{10}	3	2	1	1	15	10	73.55	73.325	1
X_{80}	3	3	1	2	17	17	109.265	110.629	2
X_{86}	5	6	2	1	16	28	97.873	99.28	2
X_{21}	2	5	1	2	15	15	90.235	91.146	2

The predicted probability of the groups for the candidate is an indication of the extent to which he or she belongs in the groups. The higher the probability of a candidate assigned to a group, the stronger the belonging. A predicted probability of 0.85 for a group suggests that the candidate belongs to the predicted group with more than 35% (that is $85 - 50$) per chance. See summary of classified observations in Appendix E.

(iii) DISCRIMINANT FUNCTION

Table 4.9 Discriminant Function Coefficients

	Function
	1
Bece Grade In Science	.666
Bece Grade In Maths	.430
Type Of Basic School	-.915
Duruation Of Shs Education	.702
Age At Last Birthday At Time Of Entering Shs	.213
Bece Aggregate	-.049
(Constant)	-5.220

This gives the Canonical Discriminant Function as follows:
$D(x_i) = -5.220 + 0.666$BECE grd in Sc. $+ 0.430$BECE grd in Math $- 0.915$Type of basic sch. $+ 0.702$Duration of SHS program $+ 0.213$Age admit to form 1 of SHS $- 0.049$BECE aggregate.

The SPSS printout of the discriminant score (index) 0 parsimoniously represents the differences between the two categories of performances pass or fail. If the discriminant score for a candidate is less than 0(i.e. negative) it is assigned to group 1 and if the score is greater than 0, it is assigned to group 2. As an example a candidate whose unstandardized discriminant score is -1.30 is assigned to group 1 and 1.30 is assigned to group 2.

This discriminant function can predict future candidates into one of the groups pass or fail based on their discriminant scores with accuracy more than per chance.

A major purpose of discriminant analysis is to perform a classification function. The purpose of classification in our examples is to predict the performance of a candidate in the WASSCE and to group them accordingly. A summary of the classification results is provided in a matrix known as the classification matrix or the confusion matrix.

The confusion matrix in table 4.8 shows that the number of correctly classified candidate (77.9%) is much higher than will be expected by chance which suggests that discrimination function is highly reliable. (Williams. G. Z, Exploring marketing research ed 7th, THE Dryden press, New York)

Table 4.10 Classification Results

	Performance IN WASSCE	Predicted Membership	Group	Total
		pass	fail	

Original	Count	Pass	59	14	73
		Fail	9	22	31
	%	Pass	80.8	19.2	100.0
		Fail	29.0	71.0	100.0
a. 77.9% of original grouped cases correctly classified.					

5.0 DISCUSSION, CONCLUSIONS AND RECOMMENDATIONS

In this work two categories of performance were identified as good (i.e. pass) or poor (i.e. fail). A student who performs well (i.e. pass) in the WASSCE is one whose WASSCE results in best six subjects, that is three (3) core subjects including English Language, Mathematics and Science or Social Studies and any three (3) elective subjects is 24 or better. Some of the possible factors that determine students' performance in WASSCE have been studied using discriminant analysis.

5.1 DISCUSSIONS

A discriminant analysis was conducted to predict to identify the factors that have significant influence in predicting students' performance in the WASSCE. The factors that appeared predictive of students' performance were BECE grade in science, BECE grade in math, BECE aggregate, duration of SHS education, type of basic school and age at last birthday at time of entering SHS. Significant mean differences were observed for all the predictors on the dependent variable. Box's M indicated that the assumption of equality of covariance matrices was violated. However, given the large sample, this problem is not regarded as serious. The discriminant functions revealed a significant association between groups and all predictors, accounting for 32.2% of between group variability, although closer analysis of the structure matrix revealed only two significant predictors, namely BECE grade in science score (.638) and BECE grade in mathematics (0.523) with entry age and aggregate poor predictors. The cross validated classification showed that overall 77.9% were correctly classified.

5.2 CONCLUSIONS

Among the initial ten factors considered, only six of them emerged as most influential in determining SHS students in their final WASSCE. The significant influential factors are BECE grade in science, BECE grade in math, BECE aggregate, duration of SHS education, type of basic school and age at last birthday at time of entering SHS.

BECE grade in Science is the single variable that has the highest influential factor of predicting students' performance in the WSSCE. The poorer the BECE grade in the Science, the poorer the performance in the WASSCE. This is followed by BECE grade in Mathematics, Type of basic school education and Duration of SHS programme, with BECE Aggregate and Age admitted to SHS 1, followed closely with virtually equal effect.

SHS students, who have their basic school education in public schools having the same BECE aggregate on the average, perform better in their final WASSCE than their counterparts from preparatory schools. However, most students from public basic schools are not able to make the required entry aggregate for admission into the SHS.

A higher entry aggregate and age (age beyond 16 years) of a student are disincentive to good performance in the WASSCE. Using the unstandardized data for the influential factors in the two groups of performances separately, two functions (classification discriminant functions for the dependent variable) which were both linear combinations of the predictor variables were formed whose scores parsimoniously represent the differences between the two groups of students.

5.3 RECOMMENDATIONS

Since on the average students who have their basic school education in public schools end up in the long run performing better in their final WASSCE than their counterparts from preparatory schools, the State should encourage Public School Education. Public schools should be provided with the necessary facilities for quality education delivery. Public school teachers should also be motivated with sufficient incentives to encourage them to give of their best. The supervisory department of the Ministry of Education should also intensify their supervisory role to commit the teachers to effective delivery to ensure quality education in public schools.

Since factors such as gender and programme offered by a student at the SHS do not have any significant influence on students' performance in the WASSCE, placement of JHS graduates into SHS programmes should not be based on gender but rather on choice of interest. The reason being that both sexes with the same aggregates perform equally in the final WASSCE. Furthermore, admission of students into SHS should focus on the BECE grades in Science and Mathematics more than all other factors once the candidate has a credit in English.

This research work is a case study and, therefore its findings are limited for generalization nationwide. However, since the results of its findings can go a long way in decision making for academic excellence, with appropriate support, the scope of the research work can be extended to include many more schools so that the results can be generalized.

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