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ASSESSING EDUCATION QUALITY IN MILITARY BASE SECONDARY SCHOOLS: A CANONICAL CORRELATION STUDY OF INPUTS AND OUTPUTS IN KADUNA STATE

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ABSTRACT

Education Quality (EQ) encompasses various factors influencing the effectiveness of an education system in achieving its learning objectives. This study assessed education quality in Military Base Secondary Schools (MBSS) in Kaduna State, Nigeria, using Canonical Correlation Analysis (CCA) on data from the 2020-2022 West Africa Senior Schools Certificate Examination (WASSCE). Factors analyzed included student performance in Mathematics, English Language, Chemistry, Physics, and Biology, and educational inputs such as student-teacher ratio (STR), average laboratory expenditure per student (AE), gender parity index for teachers (GPI), teachers' teaching experience (TTE), and ratio of military to civilian staff (RMCS). Descriptive statistics showed significant disparities, notably in RMCS (mean = 16.73, SD = 18.65). A weak negative correlation (-0.217) between STR and AE and a moderate positive correlation (0.358) between TTE and GPI were found. A strong positive correlation (0.964) between Mathematics and English Language performance was also identified. The study highlighted that a higher proportion of military staff negatively impacts student performance, emphasizing the need for balanced staffing policies. The predictive model underscored the significant role of RMCS in education quality in MBSS The study recommends that military authorities and educational policymakers address staffing disparities, Efforts should ensure balanced staffing, optimize resource allocation for laboratory expenses, promote gender balance among teachers, and prioritize recruiting experienced educators. Additionally, integrated teaching approaches should reinforce the positive correlation between English language proficiency and mathematics performance.

Keywords: Assessing**,** Education Quality, Military Base Secondary Schools, Canonical correlation analysis, Educational inputs, Student performance

INTRODUCTION

The importance of education in any country cannot be overstated, as it serves as a foundation for individual development, societal progress, and national prosperity. Education plays a fundamental role in influencing human capital, fostering economic growth, promoting social cohesion, and advancing technological innovation. In the context of Nigeria, where budgetary allocations to the education sector have varied over the years, education remains decisive for several reasons. Despite recent budgetary figures showing fluctuations, such as 6.7% in 2020, 5.6% in 2021, 5.4% in 2022 and 5.3% in 2023, education continues to be a vital investment for the nation's future (Ohaegbulem & Chijioke, 2023).

The fundamental role of education is the provision of skilled labour that drives economic growth. Additionally, to stand out and have a better chance at success in life, students must devote a significant amount of time to their studies in order to graduate with high academic standing (Tadese *et al*., 2022). Therefore, academic success is an accomplishment or output that demonstrates the degree to which a person has achieved particular objectives that were the focus of activities in instructional environments, such as primary school, college, and the university. Within the Nigerian context, as is the case with most other developing countries, accomplishment by a student is measured by the performance in both external and internal exams; exams that test the knowledge and subject areas the person has learnt.

The maximum level of student accomplishment that can be attained is related to a variety of educational inputs, such as those from families, peers, and institutions of higher learning. In essence, the quality of education relates different educational inputs to educational outputs. The degree to which pupils succeed intellectually and morally is a reflection of their accomplishments. When these accomplishments are quantifiable, they are typically assessed using specialized tests and exams, such as termly cognitive exams, external exams like the Senior School Certificate Examinations (SSCE), Unified Tertiary Matriculation Exams (UTME), and Scholastic Aptitude Tests (SAT), among others. Therefore, education quality (EQ) links diverse educational inputs to the highest possible level of student accomplishment (Tilley, 2023).

Education quality (EQ) encompasses various elements that define the effectiveness and efficiency of an education system in achieving desired learning outcomes. It includes the quality of teaching, curriculum, learning materials, infrastructure, and the overall learning environment. High-quality education is characterized by well-trained and motivated teachers, relevant curricula, well-maintained facilities, and a supportive learning environment fostering student engagement and success (Ole, 2013). Additionally, education quality is shown by improvements in student performance on standardized tests, higher graduation rates, and success in college or getting jobs (Alhussam *et al*., 2024). Effective teaching methodologies, teacher qualification, and student-teacher interactions, supported by systems ensuring continuous professional development, are vital components of education quality (Darling-Hammond, 2010). Furthermore, safe, inclusive, and resource-rich environments with sufficient infrastructure and access to learning materials contribute to education quality, promoting equity and inclusion (Rawal & Das, 2023).

Understanding EQ is therefore essential for effective resource allocation in school policy and long-term educational planning. This study focuses on the correlation between standard indicators of school outputs, such as students' performance in WASSCE and educational inputs (students-teacher ratio, average expenditure for laboratory as per science student, gender parity index for teachers, teachers' teaching experience and ratio of military to civilian staff), aiming to explain these connections. According to Worthington (2001), the output in assessing the EQ may be defined in terms of intermediate outcomes, such as student test scores, or education outcomes, such as employment rates or acceptance rates into higher education. The typical inputs in EQ include characteristics of the teaching and learning environment, such as student attendance, homework, expenditure on education, technology, teacher experience, certification, salary, students-teacher ratio, and parental education and income levels. Therefore, understanding the EQ provides understandings into improving student outcomes with minimal additional resources, highlighting the importance of prioritizing and adjusting educational inputs to achieve desired results (Buerkle *et al*., 2010)

Several studies have explored the dynamics of the quality of education across diverse contexts. Kwagena & Anthony (1991) used canonical regression and examined how community socioeconomic factors impact high school education quality in Michigan. Their findings show that socioeconomic factors positively influenced educational outcomes. However, they couldn't isolate the individual effects of these factors due to their strong correlation with school resources. The study also found that parents' education level is the most reliable indicator of overall socioeconomic status, without misrepresenting the role of education quality.

Olasunkanmi & Mabel (2012) conducted a study and analyzed the administrative and managerial aspects of both public and private secondary schools in Lagos State between 2006 and 2010. The authors examined input variables such as teachers, students, infrastructure, and curriculum, while output variables included students' academic performance in the Junior Secondary School Certificate Examination (JSSCE) and Senior Secondary School Certificate Examination (SSSCE). The study sampled 4,000 teachers and 400 principals selected through stratified random sampling from 200 public and 200 private junior and senior secondary schools. They employed the descriptive statistics and analysis of variance (ANOVA) to analyzed data. The findings revealed that public secondary schools had an advantage over private ones in terms of having quality professional teachers. However, the study found that insufficient teacher numbers limited their effectiveness. Furthermore, inadequacies such as fewer student seats, outdated classrooms, and overcrowded, noisy classrooms negatively impacted the academic performance of public secondary schools compared to private schools with better infrastructure.

Dilhani (2014) evaluated the Education Production Function (EPF) for G.C.E. ordinary Levels Students in Passara education zone, Sri Lanka, within the setting of the country's free education system. The author adopted CCA and the Cobb-Douglas type production function, and identified factors that influenced students' cognitive achievements. The research revealed that dedicating more time to self-directed learning positively correlates with cognitive achievements among students and excessive sleeping hours and a lack of educational resources at home are identified as factors that negatively impacted students' academic performance.

Nelson (2014) conducted a study and assessed the impact of school inputs on the quality of education in day secondary schools located in Kenya. The research was carried out across eighteen-day secondary schools situated in Kisumu County. The study employed the education production function framework to examine the input-output relationship. The author adopted the multiple and Stepwise regression analysis techniques and determine regression coefficients. The findings revealed that a one percent increase in instructional material supplied led to a 0.4827 percent enhancement in the performance of day secondary schools in the district, while a one percent increase in laboratory equipment expenditure resulted in a 0.2313 percent improvement in performance. Moreover, a one percent decrease in the teacher-pupil ratio was associated with a performance improvement of 0.3357 percent, and a one percent increase in the student average admission score was linked to a performance enhancement of 0.3650 percent. However, the qualifications and experience of both the head teacher and teachers were deemed statistically insignificant at the 0.05 confidence level in a two-tailed test.

In order to assess the extent of the relationship between educational inputs and output, Philothere (2016) conducted a study and investigated the relationship between educational inputs and output in public secondary schools in Nyamasheke and Nyarugenge districts of Rwanda, The research identified educational inputs available in the schools, assessed their correlation with educational output, determined the factors influencing educational output, and examined the strategies implemented by school administrators to improve educational outcomes. Lead by the Education Production Function theory, the study adopted a correlation research design. The author used the descriptive statistics and characterized the way the inputs were provided, while Pearson correlation (r) and regression analysis were used to analyze the implications of inputs for output. The research discovered insufficient provision of educational inputs. Among endogenous inputs, teacher qualifications, training, experience, availability of library and laboratory, and student-classroom ratio emerged as key predictors of student performance, explaining between 41% and 78% of performance variance. Moreover, prior performance and parental educational level were identified as key predictors of student performance among exogenous inputs, accounting for between 18% and 43% of performance variance. Financial inputs such as staff, boarding, and recurrent expenditure were also found to significantly predict student performance, explaining between 44% and 62% of school mean performance.

Jeremiah & George (2018) also utilized the Canonical Correlation Analysis (CCA) technique and established the relationship between the school characteristics and performance in Science, Technology, Engineering, and Mathematics (STEM) education in Kenya. The study found that school factors significantly influenced the level of performance in STEM education and that subjects like Mathematics and Physics had the greatest influence on the level of performance in STEM education. The study also revealed that factors like the percentage of students who had grades C+ or above and the percentage of students who took Biology and Physics had a significant impact on how well students performed in STEM courses.

Otoibhi & Ubani (2020) investigated the pattern of inputs and outputs of the educational system over a period of seven (7) years and looked at how educational input impacted the output of students in three (3) senatorial districts of public secondary schools in Edo State. The research was focused on the performance of pupils who took the junior and senior secondary school certificate exams, as well as the new intake of junior secondary school admissions into JSS1. The total number of pupils admitted into each of the public schools from the three senatorial districts was the subject of the authors' data analysis, which they utilized to determine the

Pearson's Product-Moment correlation. The findings discovered a connection between input and output, and that the number of students in a class had an impact on how well students performed in both internal and external examinations. The authors, however, restricted their research to simply looking at the impact of the input (number of students admitted per class with respect to teachers available) on students' performance.

Research on educational outcomes in MBSS has garnered attention due to the distinct environment and characteristics of these institutions. Studies such as those conducted by Khan & Al-Zubaidy (2017) and Hooker (2011) have delved into the impact of the military environment on student behavior, discipline, and academic performance. Khan & Al-Zubaidy research focused on the relationship between students' performance and various influencing factors, such as academic aptitude, military or physical training, and time allocated to Training Need Analysis (TNA) modules. The study utilized a multiple regression model to predict students' performance, incorporated independent variables such as aptitude test scores, time spent in physical training, and time dedicated to TNA modules. The results suggested that at least one of the predictor variables contributed significantly to predicting students' performance which indicated the model's effectiveness in moderately predicting attrition in engineering programs. Additionally, the study highlighted that structured engineering and TNA course loads at military academies, minimized the impact of specific discipline choices compared to civilian institutions. The early identification of students at academic risk is emphasized as a valuable tool for designing mentoring strategies early in the admission process.

On the other hand, Hooker explored the impact of military service on the well-being and academic performance of fourth-grade students, considered the challenges posed by deployments and separations of active-duty military personnel from their families. The study compares the emotional well-being, academic achievement, attendance rates, and social skills of fourth-grade military students with those of their nonmilitary counterparts. By analyzing Terra Nova Normal Curve Equivalence Scores in reading, language, and math, attendance rates, and social skills ratings from report cards, the author assessed differences between the two groups. The author adopted Analysis of Variance (ANOVA) and chi-square for the analysis carried out in the research. These studies shed light on the multifaceted influences within these institutions, highlighting the importance of understanding the interplay between military culture and educational outcomes.

Despite these efforts, there remains a gap in the literature regarding comprehensive analyses of factors influencing educational outcomes in MBSS using advanced statistical methods such as CCA. This gap presents an opportunity for future research to employ rigorous statistical techniques to systematically examine the education quality in MBSS.

MATERIALS AND METHODS

The data used in this research was obtained from MBSS, including the Nigerian Military School (NMS) Zaria, Command Secondary School Kaduna South, Command Secondary School Ribadu Cantonment, and Command Day Secondary School Jaji Cantonment on students' performance in five subjects (Mathematics, English Language, Chemistry, Physics and Biology) in West Africa Senior Schools Certificate Examination (WASSCE) from 2020 to 2022 and the schools inputs (students-teacher-ratio, average expenditure for the laboratory per science student, gender parity index for teachers, teachers' teaching experience and ratio of military to civilian staff) within each of the MBSS. This data, considered secondary, was not directly collected by the researcher but rather obtained from existing sources.

The data constitutes two main variables: educational input and output variables. The input variables (X_i) included students-to-teacher ratio, average expenditure for the laboratory per science student, gender parity index for teachers, teachers' teaching experience and ratio of military to civilian staff, while the output variables (Y_i) included: pass rate in five (5) subjects (Mathematics, English Language, Chemistry, Physics and Biology) in WASSCE from 2020 to 2022.The primary aim of this research is to study the relationship between $X_i$and Y_i.

Description of Variables

The breakdown and descriptions of the variables used in this study are outlined below:

***Education Input Variables* (X_1 to X_5):**

X_1: Students-to-teacher ratio (STR)
X_2: Average expenditure for the laboratory per science student (AE)
X_3: Gender parity index for teachers (GPI)
X_4: Teachers' teaching experience (TTE)
X_5: Ratio of military to civilian staff (RMCS)

***Performance of Students in WASSCE Subjects* (Y_1 to Y_5):**

Y_1: Percentage passes in Mathematics
Y_2: Percentage passes in English
Y_3: Percentage passes in Chemistry
Y_4: Percentage passes in Physics
Y_5: Percentage passes in Biology

The set of variables for the Education Input Variables (X_1 to X_5) included factors that influenced the educational environment in MBSS. Firstly, X_1, the students to teacher ratio, signifies the extent of individualized attention students may receive. X_2, the average expenditure for the laboratory per science student, reflected the resources allocated to practical learning experiences, essential for understanding scientific concepts. X_3, the gender parity index for teachers, highlighted gender representation among educators, which may influence role modeling and diversity in teaching styles. X_4, teachers' teaching experience, reflected the level of expertise and educational skill among teachers, influenced instructional quality. Finally, X_5, the ratio of military to civilian staff, speaks to the unique context of military schools, impacting the culture and disciplinary approach within the institutions. On the other hand, the set of variables (Y_1 to Y_5) represents the performance of students in various subjects of the West African Senior School Certificate Examination (WASSCE) and served as a comprehensive measure of academic achievement.

Correlation Matrix, Variance Inflation Factor (VIF) and Tolerance for the Test of Multicollinearity

Multicollinearity refers to the presence of high correlations among predictor variables in a regression analysis, which can lead to unreliable estimates of the regression coefficients. Detecting multicollinearity is decisive as it can affect the interpretation and stability of the regression model. Several methods can be employed to test for multicollinearity, this includes:

1 ***Correlation Matrix***: One of the ways to detect multicollinearity is by examining the correlation matrix among predictor variables. High correlations (typically above 0.7 or 0.8) indicate potential multicollinearity issues (Agyekum *et al*, 2023). Visual inspection or statistical measures such as Pearson correlation coefficients (r) given by (1) can be used for this purpose.

$$r = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2 \times \sum_{i=1}^{n}(Y_i - \overline{Y})^2}} \quad (1)$$

where

X_i and Y_i represent individual data points

$\overline{X}_i$ and $\overline{Y}_i$represent the mean of the values of variables X and, respectively.

2 ***Variance Inflation Factor (VIF):*** VIF quantifies the extent of multicollinearity by assessing how much the variance of an estimated regression coefficient is increased due to multicollinearity. A VIF value greater than 10 suggests multicollinearity (Bayman & Dexter, 2021). VIF is calculated for each predictor variable in the regression model and is given by:

$$VIF_j = \frac{1}{1 - R_j^2} \quad (2)$$

Where R_i^2 is value of coefficient of determination (ranging from 0 to 1) of the regression model with predictor variable *j* as the dependent variable and all other predictor variables as independent variables. Each R_i^2 value is calculated by regressing the predictor variable *j* on all other predictor variables in the model, and then squaring the resulting multiple correlation coefficient. This process is repeated for each predictor variable in the model to obtain the VIF for each predictor.

3 ***Tolerance***: Tolerance is the reciprocal of VIF and measures the proportion of variance in a predictor variable that is not explained by other predictor variables. A tolerance value less than 0.1 indicate multicollinearity (Kyriazos & Poga, 2023).

Canonical Correlation Analysis (CCA)

Canonical Correlation Analysis (CCA), is a standard tool of multivariate statistical analysis for the detection and quantification of relationships between two sets of variables. This study describes the covariance structure or correlation structure between **X** and **Y** random vectors by expressing them in fewer linear combinations. A joint covariance analysis of the two variables yields the canonical correlation vectors. Tests are provided on how to determine the significance of the identified relationship.CCA is a generalization of the concept of regression analysis, but rather than being a relationship between one variable Y and a group of variables $X_i, X_2, \ldots, X_q$, the canonical correlation measures the relationship between a group of independent variables $X_i, X_2, \ldots, X_q$ and another group of dependent variables $Y_i, Y_2, \ldots, Y_p$ **(**Karatas & Cinaroglu, 2024).

Development of Canonical Correlation

Canonical correlation vectors are found by a joint covariance analysis of the two variables $\underset{(p\times 1)}{\boldsymbol{X}}$ and $\underset{(q\times 1)}{\boldsymbol{Y}}$. assuming $p \le q$ with associated variance/covariance matrices: $\underset{(p\times p)}{\sum_{XX}}, \underset{(q\times q)}{\sum_{YY}}, \underset{(p\times q)}{\sum_{XY}}$ and $\underset{(q\times p)}{\sum_{YX}}$.

where it is assumed that $\sum_{XX} > 0$ and $\sum_{YY} > 0$and when there is no linear relationship between **X** and **Y**, then $\sum_{XX} > 0$. The basic idea of CCA is to find linear combinations describing a possible link between **X** and **Y** known as canonical variates. The linear combinations are:

$$\boldsymbol{U} = \boldsymbol{\alpha}'\boldsymbol{X} \quad (3)$$

and

$$\boldsymbol{V} = \boldsymbol{\beta}'\boldsymbol{Y} \quad (4)$$

where α and β are two constant vectors of element p and q respectively. The canonical variates are expressed as

$$U = \alpha' X = (\alpha_1, \alpha_2, \ldots, \alpha_q)\begin{pmatrix} X_1 \\ X_2 \\ \vdots \\ X_q \end{pmatrix} = \alpha_1 X_1 + \alpha_2 X_2 + \ldots + \alpha_q X_q \quad (5)$$

and

$$V = \beta' Y = (\beta_1, \beta_2, \ldots, \beta_p)\begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_p \end{pmatrix} = \beta_1 Y_1 + \beta_2 Y_2 + \ldots + \beta_p Y_p \quad (6)$$

The coefficients in the linear combinations are called canonical weights.

Taking a sample of n size (***p + q***) – vectors on the two sets of the variables $X = [X_i, X_2, \ldots, X_q]$ and$Y = [Y_i, Y_2, \ldots, Y_p]$, the mean vector is given by $\binom{\overline{X}}{\overline{\overline{Y}}}$, the covariance and correlation matrices are given by equation (7) and (8) respectively.

$$\boldsymbol{S} = \begin{pmatrix} \boldsymbol{S}_{XX} & \boldsymbol{S}_{Xy} \\ \boldsymbol{S}_{yX} & \boldsymbol{S}_{yy} \end{pmatrix} = \begin{pmatrix} \boldsymbol{S}_{XX} & \boldsymbol{S}_{Xy} \\ \boldsymbol{S}'_{xy} & \boldsymbol{S}_{yy} \end{pmatrix} \quad (7)$$

$$\boldsymbol{R} = \begin{pmatrix} \boldsymbol{R}_{XX} & \boldsymbol{R}_{Xy} \\ \boldsymbol{R}_{yX} & \boldsymbol{R}_{yy} \end{pmatrix} = \begin{pmatrix} \boldsymbol{R}_{XX} & \boldsymbol{R}_{Xy} \\ \boldsymbol{R}'_{yX} & \boldsymbol{R}_{yy} \end{pmatrix} \quad (8)$$

Pairs of Canonical Variate

Pairs of canonical variates refer to the sets of linear combinations derived from canonical correlation analysis (CCA). In CCA, the goal is to find linear combinations of variables (canonical variates) within **X** and **Y** in such a way that the correlation between the canonical variates is maximized. For each canonical correlation obtained in CCA, there is a corresponding pair of canonical variates – one from the set **X** and another from the set **Y**. These pairs represent the directions in the respective variable spaces that maximize the correlation between the two sets. Canonical variates are similar to new variables that capture the shared information or covariance between the original sets of variables. Given that the number of variables **X** and **Y** is *q* and *p* respectively, the maximum number of pairs is *k = min(p,q).* Pairs of variates are chosen in such a way that each pair exhibits a high degree of correlation. The first variate pair is given by(U_1^*, V_1^*).

Canonical Correlation Coefficients

The canonical correlation coefficients test for the existence of overall relationships between two sets of variables **X** and **Y**. The canonical correlation coefficient for the *i*th pair of variates between equations (5) and (6) is given by equation (9)

$$\rho_i^* = \mathrm{cov}(\boldsymbol{U}, \boldsymbol{V}) = \frac{\boldsymbol{\alpha}' \sum_{xy} \boldsymbol{\beta}}{\sqrt{\boldsymbol{\alpha}' \sum_{xx} \alpha} \times \sqrt{\boldsymbol{\beta}' \sum_{yy} \boldsymbol{\beta}}} \quad (9)$$

CCA creates an equation connecting the **X** and **Y** variables that optimizes the canonical correlation coefficient between the pair of variates.

The correlation matrix and its partition is expressed as:

$$R = \begin{pmatrix} R_{xx} & \vdots & R_{xy} \\ R_{yx} & \vdots & R_{yy} \end{pmatrix} \quad (10)$$

where

$R_{xx}$is the covariance matrix of the independent variables (Set **X**)

$R_{yy}$is the corresponding covariance matrix of the dependent variables (Set **Y**)

$R_{xy}$is the covariance matrix between the independent and dependent variables

$R_{yx}$is the covariance matrix between the dependent and independent variables

The Eigenvector and Eigenvalues

The eigenvalues represent the canonical correlation coefficients. For a given CCA with *r* canonical variables, there are *r* canonical correlation coefficients denoted by $\lambda_1, \lambda_2, \ldots, \lambda_r$. These eigenvalues indicate the strength of association between the two sets **X** and **Y**. The larger the eigenvalue, the stronger the association.

On the other hand, eigenvectors represent the canonical vectors associated with each canonical correlation. For each eigenvalue $\boldsymbol{\lambda}_i$, there is a corresponding pair of canonical vectors, one from each set of variables (**X** and **Y**).

The canonical vectors are used to form the canonical variates. The eigenvalues are obtained by solving the generalized eigenvalue problem:

$$|R_x - \lambda I| = 0 \quad (11)$$

And

$$\left|R_y - \lambda I\right| = 0 \quad (12)$$

where

$$\boldsymbol{R_x = R_{xx}^{-1} R_{xy} R_{yy}^{-1} R_{yx}} \quad (13)$$

$$R_x = R_{yy}^{-1} R_{yx} R_{xx}^{-1} R_{xy} \quad (14)$$

and $\lambda$is the eigenvalue. Detailed information on mathematics associated to inversion problem of equation (20) can be found in Tasi'u et al., (2020).

It is very important to note that the square root of the largest eigenvector of matrix $R_x$corresponds to the Pearson's correlation coefficient between the two sets of variables.

The Canonical Weights

The canonical weight measures the amount of contribution each variable makes to a variate. Raw correlation coefficients are sensitive to scaling and are therefore not appropriate for interpretation (Bolton *et al,* 2023).

Standardized Coefficients

The standardized coefficients are obtained by multiplying α_i and β_i by the standard deviations of the corresponding variables to remove the effect of scaling.

$$c_i = D_x \alpha_i,\ d_i = D_y \beta_i \quad (15)$$

where: $D_X = diag(\sum_{XX})$, and $D_Y = diag(\sum_{YY})$

The eigenvectors of the matrices of equations (13) and (14) give the sample estimates $\hat{c}_i$ and $\hat{d}_i$ respectively. The coefficients in $X_i$represent the amount of contribution made by each of X_i to $X^*{}_i$and the coefficients in d_i represent the amount of variation contributed by each of Y_i (Alvin, 2002).

Canonical Loadings and Canonical Cross Loadings

Canonical loadings are the correlations between the variables and variates within the same group. CCA generates multiple dimensions of relationships between variates. Each relationship is independent of the others.

The loadings for the **X** - set are given by

$R_{xx}\hat{c}_i$

and the loadings for **Y** - set are given by

$R_{yy}\hat{d}_i$

On the other hand, Canonical cross loadings are correlations between the variables and variates within the different groups. In other words, it is the correlation between the independent variables and the dependent variate or the correlation between the dependent variables and the independent variate. This measure is obtained by multiplying canonical loadings with canonical correlation coefficients.

The cross loadings for X - set are given by

$R_{xx}\hat{c}_i\hat{\rho}_i^*$

and the cross loadings for Y - set are given by

$R_{yy}\hat{d}_i\hat{\rho}_i^*$

Canonical Variate Scores

The canonical variate scores of X - set and Y - set of variables from the i^{th}canonical variate pair (U_i^*, V_i^*) are Uc_i and Vc_i respectively where $U$and V are vectors of predictors and response variables respectively. The scores of U_i^* can be used to predict V_i^*. This predicted value is obtained from the regression analysis of V_i^* on U_i^*. The predicted V_i^* is given by:

$$\widehat{\boldsymbol{V}}_1^* = \rho_i(U_i^* - \hat{c}_i'\bar{U}_i) + \hat{d}_i'\bar{V} \quad (16)$$

Tests of independence between X - set and Y - set

In order to perform CCA, the very first thing to determine is if two groups of variables are dependent. We wish to test the null hypothesis that the canonical coefficients corresponding to each variable are all equal to zero. This is comparable to the null hypothesis that the X – set is independent of the Y – set. (Alvin, 2002). The test statistic is Wilk's lambda Λ.

Wilk's lambda Λ is given by:

$$\Lambda(p, n-1-q, q) = \prod_{k}^{i=1}(1-\lambda_i) = \frac{|S_{yy}^{-1}S_{yx}S_{xx}^{-1}S_{xy}|}{|S_{yy}|} \quad (17)$$

where k = *min* (*p*, *q*) and $P_i = \sum_{i=1}^{s}\lambda_i$is the i^{th}eigenvalue of $S_{yy}^{-1}S_{yx}S_{xx}^{-1}S_{xy}$.

If the values of these statistics are too large, the *p*-value is small. This indicates rejection of the null hypothesis

H_o:$\sum xy = 0$

and can conclude that the **X** – set and the **Y** – set are dependent. Also, the above null hypothesis is comparable to testing the null hypothesis that all variate pairs are not correlated,

H_o:$\rho_1^* = \rho_2^* = \ldots = \rho_p^*$

For a large *n*, the statisticΛ in equation (17) follows a Chi-square distribution with *pq* degrees of freedom, where:

$$\chi^2 = -[(n-1) - \tfrac{1}{2}(p+q+1)]\, ln\, \Lambda \quad (18)$$

We reject H_o if $\chi^2 \geq \chi_\alpha^2$ and hence perform CCA. Again, the F–distribution of the equation is given by (19)

$$F = \frac{1-\lambda^{\frac{1}{t}}}{\lambda^{\frac{1}{t}}}\frac{df_2}{df_1} \quad (19)$$

with degrees of freedom df_2anddf_1 (Alvin 2002)

where $df_1 = pq$,$df_2 = wt - \frac{1}{2}pq + 1$,

$w = n - \frac{1}{2}(p+q+3)$, $t = \sqrt{\frac{p^2q^2-4}{p^2+q^2-5}}$

We reject H_0 if $F > F_\alpha$.

There are other test statistics for the hypothesis H_o: $\sum xy = 0$ such as Pillai's Trace Criterion, Hotelling-Lawley Trace Criterion and Roy's Greatest Root Criterion. Detailed information on the test statistics can be found in Alvin, 2002.

Tests of significance of the ithvariate

If the test in (17) based on all k canonical correlations reject H_0, we are not sure if the canonical correlations of the remaining are significant (Alvin, 2002). To test the significance of the remaining we used equation (20) judged by Wilk's lambda λ as well.

$$\lambda_2 = \prod_{i=2}^{k}(1-\lambda) \quad (20)$$

If the null hypothesis in equation (20) is rejected, we conclude that at least $\rho_2^*$is significantly not equal to zero. We proceed in this style, testing each ρ_i^*one at a time, until a test fails to reject the null hypothesis (Alvin, 2002).

The chi-square and F – distribution corresponding to (20) are given in (21) and (19) respectively.

$$\chi_i{}^2 = -\left[n - \frac{1}{2}(p+q+3)\right] ln\,\lambda_i \quad (21)$$

with $(p-k+1)(q-k+1)$ degrees of freedom.

where in (19):

$$df_1 = (p-k+1)(q-k+1), df_2 = wt - \frac{1}{2}[(p-k+1)(q-k+1)] + 1, w = n - \frac{1}{2}(p+q+3),$$

$$t = \sqrt{\frac{(p-k+1)^2(q-k+1)^2 - 4}{(p-k+1)^2 + (q-k+1)^2 - 5}}$$

RESULTS AND DISCUSSION

Descriptive Statistics

Table 1: Descriptive Statistics of Predictor and Response Variables in MBSS

Variables	Range	Minimum	Maximum	Mean	Std. Deviation
Predictor Variables					
STR	0.195	0.107	0.301	0.19485	0.064797
AE	0.00021	0.00004	0.00024	0.0000783	0.00005989
GPI	0.963	0.020	0.983	0.73572	0.269133
TTE	0.008	0.010	0.018	0.01466	0.002981
RMCS	69.114	2.315	71.429	16.73116	18.654385
Response Variables					
Y_1	93.450	5.620	99.070	81.21583	26.540589
Y_2	91.670	8.330	100.000	81.16167	25.333306
Y_3	38.570	60.580	99.150	83.51833	15.085489
Y_4	24.040	75.960	100.000	89.46583	8.636645
Y_5	43.540	56.460	100.000	91.38000	12.065110

Table 1 provided an overview of educational inputs and student performance in MBSS for assessing education quality. STR ranges from 0.107 to 0.301 with a mean of 0.19485 and a standard deviation of 0.064797, indicating variability in class sizes. AE ranges from 0.00004 to 0.00024 with a mean of 0.0000783 and a standard deviation of 0.00005989, reflecting financial differences for science students. GPI ranges from 0.020 to 0.983 with a mean of 0.73572 and a standard deviation of 0.269133, suggesting gender parity differences. TTE ranges from 0.010 to 0.018 years with a mean of 0.01466 and a standard deviation of 0.002981, indicating consistent teacher experience levels. RMCS ranges from 2.315 to 71.429 with a mean of 16.73116 and a standard deviation of 18.654385, indicating significant differences in military to civilian staff ratios. The response variables reflect student performance in five (5) subjects of the West Africa Senior School Certificate Examination (WASSCE). Mathematics (Y_1) ranges from 5.620 to 99.070 with a mean of 81.21583 and a standard deviation of 26.540589. English (Y_2) ranges from 8.330 to 100.000 with a mean of 81.16167 and a standard deviation of 25.333306. Chemistry (Y_3) ranges from 60.580 to 99.150 with a mean of 83.51833 and a standard deviation of 15.085489. Physics (Y_4) ranges from 75.960 to 100.000 with a mean of 89.46583 and a standard deviation of 8.636645. Biology (Y_5) ranges from 56.460 to 100.000 with a mean of 91.38000 and a standard deviation of 12.065110. These statistics reveal that Physics and Biology show consistently high performance, while Mathematics and English exhibited greater variability in student outcomes.

Correlations

Table 2: Correlations within Education Input (Set X)

	STR	AE	GPI	TTE	RMCS
STR	1				
AE	-0.217	1			
GPI	0.089	-0.584*	1		
TTE	0.338	0.214	0.358	1	
RMCS	-0.328	0.017	-0.173	-0.507	1

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Table 2 outlined the relationships between predictor variables (education inputs) within the MBSS. The results in the table revealed that there is a weak negative correlation (-0.217) between STR and AE. This suggests that as the student-to-teacher ratio increases, there is a slight decrease in laboratory spending per student, although this relationship is statistically not significant. Similarly, there is a moderate negative correlation (-0.584) between GPI and AE. This implies that higher gender parity among teachers tends to accord for lower laboratory expenditures per science student. On the other hand, the correlation between TTE and GPI is 0.358, indicating a moderate positive correlation. This suggests that schools with more gender-balanced staff also tend to have more experienced teachers.

Table 3: Correlations within Students' Performance in WASSCE (Set Y)

	Y_1	Y_2	Y_3	Y_4	Y_5
Y_1	1				
Y_2	.964**	1			
Y_3	.646*	.647*	1		
Y_4	0.460	0.447	.740**	1	
Y_5	.928**	.981**	.626*	0.428	1

**. Correlation is significant at the 0.01 level (2-tailed).*. Correlation is significant at the 0.05 level (2-tailed).

Table 3 shows the correlation for students' performance in the WASSCE (set Y). The result revealed that there is strong positive correlation (0.964) between performance in English (Y_2) and Mathematics (Y_1). This strong positive correlation suggests that students who perform well in Mathematics also tend to perform well in English. Similarly, there is a positive correlation between the performance of students in Biology and other subjects. Furthermore, there is a significant relationship among Chemistry (Y_3), Physics (Y_4), and other subjects.

Table 4: Correlations between Education Input (Set X) and Students' Performance in WASSCE (Set Y)

	Y_1	Y_2	Y_3	Y_4	Y_5
STR	0.390	0.380	0.378	.659*	0.290
AE	-0.021	0.030	-0.544	-0.543	0.004
GPI	0.209	0.205	0.210	0.161	0.196
TTE	0.452	0.555	0.095	0.256	0.500
RMCS	-0.958**	-0.971**	-0.686*	-0.415	-0.946**

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Table 4 shows the correlation between education inputs and students' performance in the WASSCE from 2020 to 2022 and offered explanation into the relationships between various education inputs and students' performance. The results show that student-to-teacher ratio (STR) correlate with all subjects, with the highest correlation being with Physics (Y_4) at 0.659*, which is statistically significant at the 0.05 level, suggesting that smaller class sizes may benefit students' performance in Physics. AE correlate negatively and near-zero with student performance with notable negative correlations with Chemistry (Y_3) at -0.544 and Physics (Y_4) at -0.543, indicating inefficiencies in resource allocation. The gender parity index for teachers (GPI) shows weak positive correlations with all subjects, none of which are statistically significant, suggesting that gender balance among teachers has a minor direct impact on students' academic performance in MBSS. Teachers' teaching experience (TTE) displayed generally positive correlations with student performance, with the highest being with English (Y_2) at 0.555, indicating that more experienced teachers may positively influence academic outcomes. The ratio of military to civilian staff (RMCS) shows strong negative correlations with student performance in all subjects, with significant negative correlations for Mathematics (Y_1) at -0.958**, English (Y_2) at -0.971**, and Biology (Y_5) at -0.946**, indicating that a higher proportion of military staff is associated with lower student performance, suggesting a need for more balanced staffing policies to improve educational outcomes.

Test of Multicollinearity

Multicollinearity test provide evidence when independent variables are highly correlated such that it may pose challenges in discerning the unique effects of education inputs on student performance. Variance inflation factor (VIF) analysis identified problematic levels of multicollinearity, and safeguarded against inflated coefficients and mistaken interpretations in regression models. Addressing multicollinearity ensures the accuracy and reliability of regression analysis findings.

Table 5: Results of Multicollinearity Test

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	96.796	17.372		5.572	0.001		
	STR	71.792	46.489	0.175	1.544	0.173	0.661	1.513
	AE	100413.698	70850.984	0.227	1.417	0.206	0.333	3.001
	GPI	23.796	15.589	0.241	1.526	0.178	0.341	2.934
	TTE	-2147.085	1391.071	-0.241	-1.543	0.174	0.349	2.867
	RMCS	-1.402	0.157	-0.985	-8.919	0.000	0.698	1.433

In Table 5, the Variance Inflation Factor (VIF) values provided insight into the extent of multicollinearity among the predictor variables. Generally, a VIF value exceeding 10 is considered problematic and indicates high multicollinearity, suggesting that the variance of the estimated regression coefficients is inflated due to correlations among the predictors (Kyriazos & Poga, 2023). Conversely, a Tolerance value close to 1 indicates low multicollinearity, implying that each predictor variable provides unique information to the model without redundancy. The results in table 5, shows that the VIF values for the predictor variables (STR, AE, GPI, TTE, and RMCS) are relatively low, ranging from 1.433 to 3.001, indicating that multicollinearity is not a significant concern in the model. Additionally, the Tolerance values are close to 1, further supporting the absence of multicollinearity. This suggests that each predictor variable contributes unique information to the model without being overly influenced by correlations with other predictors.

Test of Significance

Multivariate tests of significance are typically conducted in SPSS when you have more than one dependent variable. These tests help determine whether there are statistically significant differences among the groups or conditions in your study.

Table 6: Test of Significance Results for Dependent Variables

Test Name	Value	Approx. F	Hypoth. DF	Error DF	Sig. of F
Pillais	2.9274	1.69491	25	30	0.084
Hotellings	702.15963	11.23455	25	2	0.085
Wilks	0.00002	6.68613	25	8.93	0.003
Roys	0.99854				

Table 6 shows the results of several tests of significance (Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root) for the dependent variables. Pillai's Trace has a value of 2.9274 and an approximate F-statistic of 1.69491, with a significance level of 0.084 (> 0.05). These values suggest that there is relationship between the variables, but they do not meet the standard threshold for statistical significance of 0.05. Similarly, Hotelling's Trace, with a value of 702.1596 and an F-statistic of 11.23455, suggests a possible association but also falls short of conventional significance standards, with a significance level of 0.085, requiring cautious interpretation. However, Wilks' Lambda showing a statistically significant correlation between education inputs and student performance, with a value of 0.00002 and an F-statistic of 6.68613 at significance level of 0.003 (< 0.05).

Table 7: Test of Five Canonical Correlations (Cancor) of MBSS Data

Variates (k)	Wilks Statistic	F	Num D.F.	Denom D.F.	Sig.
1 to 5	0.000	6.686	25.000	8.932	0.003
2 to 5	0.011	2.100	16.000	9.803	0.120
3 to 5	0.148	1.308	9.000	9.886	0.340
4 to 5	0.818	0.263	4.000	10.000	0.895
5 to 5	1.000	0.002	1.000	6.000	0.969

Table 7 presents the results of the test of five Cancor for the MBSS data. The Wilks Statistic measures the amount of variance unaccounted for by the Cancor. The results show that only the first canonical correlation (k = 1 to 5) is statistically significant with Wilks Statistic of 0.000 and a p-value of 0.003 (< 0.05). This suggests that there is a significant relationship between the sets of variables represented by Variates 1 to 5.Therefore, CCA provided only one canonical roots or dimension that described the linear relationships between education inputs and students' performance in WASSCE within MBSS.

Eigenvalues and Canonical Correlations

Table 8: Eigenvalues and Canonical Correlations

Canonical Correlation	Variates				
	1	2	3	4	5
Coefficient	0.99927	0.96351	0.90495	0.42579	0.01642
Eigenvalue	0.99854	0.92835	0.81894	0.18129	0.00027

The analysis shown in Table 8 yielded five Cancor, with the first correlation showing a notably strong relationship (0.99927) between the predictor variables and the response variables. However, the subsequent correlations exhibited decreasing magnitudes. Eigenvalues associated with each correlation indicated that the first Cancor explains the majority of the variance in the dependent set of variables. Therefore, there is a strong degree of linear relationship between the education inputs and the pass rates in the five subjects in WASSCE from 2020 to 2022.

Canonical Weights

Table 9: Raw and Standardized Canonical Weights

Variables	Variate 1	
	Raw Canonical Weights	Standardized Canonical Weight
Predictor Variables		
STR	0.140	0.009
AE	-8306.914	-0.498
GPI	-1.664	-0.448
TTE	156.510	0.467
RMCS	0.059	1.103
Response Variables		

Y_1	-0.030	-0.788
Y_2	0.001	0.017
Y_3	-0.018	-0.276
Y_4	0.061	0.524
Y_5	-0.019	-0.234

The variables inherently had varied scales. Standardized coefficients were used to facilitate a direct comparison of the relative importance of each variable within its respective set, which distinguished the magnitude and direction of their impact on the Cancor. Standard canonical coefficients do not reflect the differences in scaling and are hence used in the canonical function to calculate the canonical variate scores. The standardized canonical correlation coefficients in table 9 can be used to create the standardized canonical variates for the response variables as follows.
For the first canonical variate pair, we have;

$$\hat{U}_1^* = 0.009\text{STR} - 0.498\text{AE} - 0.448GPI + 0.467\text{TTE} + 1.103\text{RMCS}$$

$$\hat{V}^*{}_1 = -0.788Y_1 + 0.017Y_2 - 0.276Y_3 + 0.524Y_4 - 0.234Y_5 \quad (22)$$

Among the education input variables, RMCS has the largest impact (1.103), highlighting the importance of staffing composition in military-base schools. On the other hand, coefficients on student performance show how each subject (Y_1 through Y_5) affected the canonical variate. The results indicated that there is an inverse relationship between Mathematics performance and the canonical variate. Notably, Mathematics (Y_1) exhibited the highest negative coefficient (-0.788), highlighting the sensitivity of Mathematics to the quality of education input.

Canonical Loadings and Canonical Cross Loadings

Canonical loadings represent the correlations between the original variables and their respective canonical variates while Canonical cross-loadings extend the concept of canonical loadings to variables from the opposite set. They measure the correlation between variables from one set and the canonical variates derived from the other set. Table 10 presented the canonical loadings and cross loadings for this research; it provided better understanding of the contributions of individual variables to the canonical variates and assessed the cross-set relationships that contributed to the overall correlation between education inputs and students' performance in the five (5) subjects of WASSCE.

Table 10: Canonical Loadings and Canonical Cross Loadings

Variables	Variate X	Variate Y
	1	**1**
Predictor Set		
STR	-0.127	**-0.127**
AE	-0.118	**-0.118**
GPI	-0.180	**-0.180**
TTE	-0.356	**-0.356**
RMCS	0.932	**0.931**
Response Set		
Y_1	**-0.925**	-0.926
Y_2	**-0.915**	-0.916
Y_3	**-0.532**	-0.533
Y_4	**-0.134**	-0.134
Y_5	**-0.897**	-0.897

In table 10, variables with higher absolute loadings have a more considerable impact on determining the canonical variates. In Variate **X** - 1, ratio of civilian teachers to military teachers (RMCS) has a loading of 0.932, suggesting its high significant impact to the first canonical variate. In Variate **Y** - 1, the students' performance rate in Y_1 (Mathematics) to Y_5 (Biology) have a negative influence on determining Variate 1.

Proportion of Variance Explained

Table 11: Proportion of Variance Explained

Canonical Variable	Set 1 by Self	Set 1 by Set 2	Set 2 by Self	Set 2 by Set 1
1	0.212	0.211	0.560	0.560
2	0.220	0.204	0.036	0.034
3	0.221	0.181	0.355	0.291
4	0.090	0.016	0.020	0.004
5	0.257	0.000	0.028	0.000

*Set 1 = **X** and Set 2 = **Y***

Table 11 provided the proportion of variance explained for each canonical variable in assessing the relationship between education inputs (Set 1: X) and student performance (Set 2: Y). The first column, "Set 1 by Self," shows that the first canonical variable explains 21.2% of the variance in Set 1, while the second explains 22.0%. The "Set 1 by Set 2" column indicates that the first canonical variable in Set 2 explains 21.1% of the variance in Set 1, demonstrating a strong relationship, with the second canonical variable in Set 2 explaining 20.4%. The "Set 2 by Self" column reveals that the first canonical variable explains 56.0% of the variance in Set 2, and the "Set 2 by Set 1" column shows that the first canonical variable in Set 1 explains 56.0% of the variance in Set 2, further indicating a strong relationship. The results highlighted that the first canonical variate pair has the highest explanatory power for both sets. Hence, it is the most significant in capturing the relationship between education inputs and student performance.

Summary of Results for the CCA

The results of the analysis can be summarized as follows:

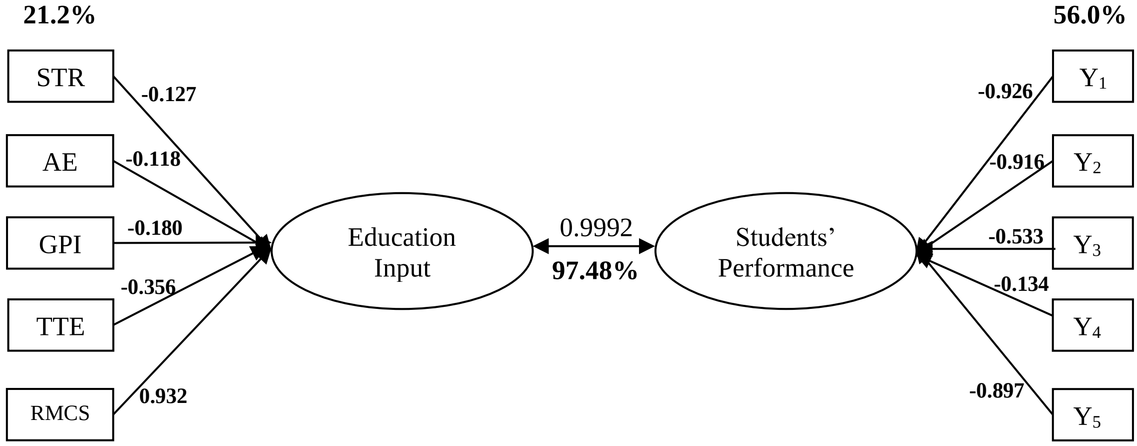

Figure 1: First canonical correlation between Education Input and Students' Performance

Figure 1 illustrates the first canonical correlation between predictor variables (STR, AE, …, RMCS) and the response variables (Y_1, Y_2, …, Y_5). There is a strong and positive correlation (of 0.9992) between education inputs and students' performance. It accounted for about 97.48%of the variance between the canonical variates. The total variances explained by the predictor and response variables are 22.6% and 9.5% respectively.

Prediction

The sets of variate scores obtained in equation (22) can be used to examine the relationship between education inputs and the pass rate of students in subject of WASSCE. The score $\hat{U}_1^*$ (Education input) can be used to predict a value of the score $\hat{V}_1^*$ (Students' performance in WASSCE). The predicted value of the students' performance given$\hat{U}_1^*$is as follows:

$$\hat{V}_1^{**} = \sqrt{\rho_1}\left(\hat{\boldsymbol{U}}_1^* - \boldsymbol{c'}_1\bar{\boldsymbol{X}}\right) + \boldsymbol{d'}_1\bar{\boldsymbol{Y}} \qquad (23)$$

Kanti, e*t al* (1995)

where:

$\hat{V}_1^{**}$ is the predictor

$\rho_1 = 0.9992$

$\hat{U}_1^* = 0.009\text{STR} - 0.498\text{AE} - 0.448GPI + 0.467\text{TTE} + 1.103\text{RMCS}$

$\boldsymbol{c'}_1$= (0.009, - 0.498, -0.448, 0.467, 1.103)

$\boldsymbol{d}'_1$ = (-0.788, 0.017, -0.276, 0.524, -0.234)

$$\bar{\boldsymbol{X}} = \begin{pmatrix} \overline{STR} \\ \overline{AE} \\ \overline{GPI} \\ \overline{TTE} \\ \overline{RMCS} \end{pmatrix} = \begin{pmatrix} 0.19485 \\ 0.0000783 \\ 0.73572 \\ 0.01466 \\ 16.73116 \end{pmatrix} \text{and}$$

$$\bar{\boldsymbol{Y}} = \begin{pmatrix} \overline{Y_1} \\ \overline{Y_2} \\ \overline{Y_3} \\ \overline{Y_4} \\ \overline{Y_5} \end{pmatrix} = \begin{pmatrix} 81.21583 \\ 81.16167 \\ 83.51833 \\ 89.46583 \\ 91.38 \end{pmatrix}$$

Hence,

$\hat{V}_1^{**}$ =0.9992(0.009STR – 0.498AE – 0.448GPI + 0.467TTE + 1.103RMCS – 18.1334273) – 60.17221

$\hat{V}_1^{**}$ =0.00899STR – 0.4976AE – 0.4476GPI + 0.4666TTE + 1.10216RMCS – 78.2911 (24)

Equation (24) provided the predictive model to forecast student performance based on educational inputs and show that STR, AE, GPI, TTE and RMCS collectively influenced student performance. The variable that contributed most is the RMCS (with coefficient of 1.103). Hence, a higher ratio of military to civilian staff significantly will increase students' performance. The constant (-78.2911) represents the intercept or baseline value of students' performance when all predictor variables are zero.

CONCLUSION

In conclusion, the research findings highlighted the multifaceted dynamics that influenced Education Quality (EQ) within MBSS. The military-to-civilian staff ratio varies greatly throughout MBSS, indicating a variety in staffing compositions. There are issues with resource allocation as seen by the reported negative association between the student-to-teacher ratio and the amount of money spent on laboratory as per science student. On the other hand, the positive relationship between teachers' teaching experience levels and gender balance suggests a favorable interaction between these variables. Furthermore, the strong correlation between performance in Mathematics and English Language proficiency underscores the interrelation of academic outcomes. However, in order to maximize educational achievements, balanced staffing practices are required, as evidenced by the correlation found between higher proportions of military personnel and lower student performance. Importantly, the predictive model emphasizes the essential role of staffing composition, with RMCS identified as the most influential factor.

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