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Data Preparation and Bootstrapping Analysis for Stakeholder Participation in School Management: Impact on Academic Achievement in Ugandan Public Secondary Schools

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ABSTRACT

Data preparation for stakeholder participation in school management aims to organize and structure data for analysing its impact on academic achievement in Ugandan public secondary schools. The process ensures a reliable dataset for bootstrapping analysis, thus enabling making of inferences on stakeholder participation's effects on academic achievement. This paper presents part of the findings from a larger study conducted in public secondary schools in Uganda. Specifically, the focus is on the preliminary analysis which is necessary for conducting the bootstrapping technique as a multivariate analysis. The findings indicate 5 discrete dimensions of participation in school management that influence learners' academic achievement in public secondary schools. Stakeholder participation in school management creates a collaborative and supportive ecosystem that positively influences the learner's academic achievement by addressing challenges, implementing effective strategies, and creating an environment that nurtures the intellectual and social development of learners. Through collaboration, stakeholders can foster a supportive environment that positively influences learners' academic achievement. Practical and theoretical implications, study limitations, and future research considerations are presented.

Keywords: Academic achievement, Bootstrapping, Factor Analysis, Stakeholder participation, School management

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1. Introduction

The article underscores the critical role of understanding variable relationships in enhancing multivariate models, which demand larger datasets and more intricate data handling compared to univariate analyses. Researchers face challenges such as missing data and outliers, requiring meticulous examination techniques to safeguard analysis validity—an "investment in multivariate insurance."(Hair et, al., 2018: Mertler, et, al., 2021: Hartmann, et. al., 2023). Neglecting this scrutiny heightens the risk of distorted results, potentially compromising the entire analysis (Chong, et, al., 2020). Diligent data management and quality assurance are pivotal for ensuring research data's integrity and suitability for analysis. The article emphasizes the importance of pre-emptive measures in identifying and rectifying potential analytical pitfalls before conducting analyses. It highlights the significant impact of avoiding even a single severe issue on researchers' perspectives, underlining the enduring value of rigorous data examination in producing accurate and reliable multivariate analysis outcomes (Wenfei & Floris, 2022). Overall, it stresses the necessity of meticulous data scrutiny to uphold the validity and credibility of research findings.

The study focuses on preparing for bootstrapping analysis, a multivariate technique, through robust empirical diagnostic measures and preliminary data examination. It emphasizes understanding the underlying data characteristics and relationships between variables. The study investigates stakeholders' participation in school management as the independent variable and academic achievement in public secondary schools as the dependent variable. It highlights emerging trends in school management, particularly the School-Based Management (SBM) model((Cheng, 2023).Deitje, et, al, (2018) opine that one of the key elements of SBM is participatory management. Collaborative decision-making involves various stakeholders employing a comprehensive approach to tackle the issues that schools encounter in shaping their strategic direction, ultimately aiming to achieve educational goals(Kadir, 2019). The study underscores the importance of strong cross-sectoral collaborations to support learners' educational journeys and address learning barriers. It advocates for a holistic approach that prioritizes learners' multifaceted needs, emphasizing the significance of stakeholder involvement in shaping effective school governance and accountability (Nishimura, 2017; Johnston & Xenakis, 2017). Overall, the study underscores the critical role of stakeholders in enhancing school effectiveness, quality, and the overall learning experience.

Although several studies indicate that stakeholders' participation has the potential to develop education concerning the quality of learning outcomes if well-established (Kieti, 2017; Moate, 2018, Nakiyaga, et, al., 2021; Guzman, 2022; Cheng, 2023), limited robust empirical research exists on prioritizing stakeholder participation in schools with consistent academic decline, notably in developing nations like Uganda. Discrepancies between stakeholder involvement in

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school management and educational outcomes are evident in persistently low academic achievements in public secondary schools. The national pattern of academic performance in Uganda Certificate of Education (UCE) exams from 2015 to 2018 shows a concerning decrease in attainment of at least division 3, essential for seamless progression to the next educational level raising questions about the role of stakeholder involvement in school management in addressing academic challenges. In 2015 the failure rate was 9.7% compared to 13.2% in 2016. In 2017 the failure rate was 14.2% while in 2018 the failure rate was 15.4% (UNEB, 2019). Could it be possible that the poor academic achievement among learners is attributed to the non-involvement of the stakeholders in the management of public secondary schools?

Data preparation is the initial step in the analysis of quantitative data. It is essential for ensuring the quality, integrity, and suitability of the dataset for analysis (Hartmann, et. al., 2023). It sets the foundation for reliable statistical inferences and enhances the credibility of research findings (Naresh, 2020). This process certifies that quantitative data is clean and complete for use before performing any multivariate analysis (Chong, et, al., 2020). Data preparation for stakeholder participation in school management aims to organize and structure data for analysing its impact on academic achievement in Ugandan public secondary schools. The process ensures a reliable dataset for bootstrapping analysis, thus enabling to making of inferences on stakeholder participation's effects on academic achievement. Regrettably, this stage of analysis is rarely undertaken by researchers perhaps, because of the encumbrance associated with it (Hair et al, 2018). Neglecting this stage would often lead to poor quality of output and correctness of the type of analysis to be used. Effective data preparation ensures that the results of multivariate analysis are reliable, valid, and interpretable, ultimately contributing to robust and meaningful conclusions in research or decision-making processes. Through meticulous data preparation, the researchers can uncover insights into the relationship between stakeholder participation, school management practices, and the academic output of students in Ugandan public secondary schools. Using computer software, the researcher can identify hidden errors that were not possible to discover by mere proofreading (Mertler, et, al., 2021).

Firstly, data preparation determines how to handle missing data, whether through imputation or other methods, to avoid bias and maintain the completeness of the dataset(Hair, et, al., 2018). Secondly, is to check certain assumptions about the data. If the data violates these assumptions, corrective measures are taken (Osborne & Waters, 2019). These include transformations of variables to meet the assumptions such as; log transformations or normalization, to meet the requirements of the chosen analysis. Thirdly, identifying and addressing outliers is essential for the robustness of statistical analyses. Outliers can disproportionately influence results; hence data cleaning helps researchers decide whether to remove, transform, or retain them based on the context of the study (Costello & Osborne, 2019). Fourthly, addressing data issues early in the

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process saves time and resources in the long run. It prevents the need to backtrack during or after analysis and ensures a smoother progression from data collection to interpretation. More so, check for incorrect entries, typos, and inconsistencies in the database, unengaged responses (respondents that were not engaged)-similarly rating all questionnaire items)-yea-sayers (answering favorably to all questions) or nay-sayers (answering unfavorably to all questions response-style effects). Fifthly, to identify and understand the underlying structure or patterns in a set of observed variables through factor analysis (Beavers, et al., 2019). This aims to uncover the latent factors that contribute to the observed correlations among variables. The primary goal of factor analysis is to simplify the complexity of data by reducing a large number of variables to a smaller set of underlying factors, especially if the questionnaire used in data collection was generated from the literature reviewed.

Following meticulous data preparation and ensuring data readiness, the research advanced into a phase of multivariate analysis utilizing the robust bootstrapping technique. This technique is adopted when data violates the assumptions of normality of the distribution (Carl, 2018). It involves resampling with replacement to estimate the distribution of a dataset, helping in drawing inferences about the population concerning the impact of stakeholder participation in school management on academic achievement. The paper begins with an introduction, a review of the literature, and then presents the methodology that was followed in undertaking the study. It presents the key results, a discussion of findings, and policy implications. The paper ends with recommendations.

3. Methodology

Survey questionnaire data was generated to address managerial functions related to planning, budgeting, and coordinating academic activities. Simple random sampling was utilized to select these five schools that were stratified according to the five divisions of Kampala district. A sample frame was created for all potential participants, and a simple random proportionate sample of 217 participants was chosen based on the sample size determination formula proposed by Kothari (2004).

$$n = \frac{z^2.p.q.N}{e^2(N-1) + z^2.p.q}$$

Out of 198 surveys, 190 were suitable after excluding 8 incomplete ones. Preliminary analysis ensured data cleanliness and completeness, including demographic details, descriptive statistics, factor analysis, and normality tests. Missing data assessment preceded parametric tests, like bootstrapping, preparing for subsequent analysis.

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3.1Assessing Missing Data

Addressing missing data is crucial for valid multivariate analysis, as it influences research outcomes significantly Hair et al. (2018, pp. 41-69). Researchers meticulously reviewed the submitted questionnaires and analyzed the patterns, and relationships inherent in the missing data to rectify issues.

Step 1: Determined the type of missing data.

Initial SPSS analysis checked for missing data. Instances were attributed to procedural factors like incomplete questionnaires and data entry errors (Craig, 2022).

Step 2: Determine the extent of the missing data.

The researcher analyzed missing data patterns to determine their impact on study outcomes. Using a tabulation method, results were assessed for the prevalence across variables and cases to identify both the extent and any noteworthy concentration of missing data. Results, showed a negligible proportion (less than 5%), minimizing the influence on result generalizability. This was in line with Craig (2022).

Step 3: Diagnose the randomness of the missing data.

Data was assessed for severity and randomness of missing data patterns across all variables, contrasting them with the anticipated pattern for a random missing data process, employing a test for randomness, Missing Completely at Random (MCAR) (Hair et al., 2018; Craig, 2022).

Step 4: Select the imputation method using only valid data.

The complete Case Approach (LISTWISE) imputation method for Likert scale variables was chosen due to strong inter-variable relationships and low missing data (Hair et al., 2018; Craig, 2022).

Step 5: Assessment of Outliers

Outliers were identified via a univariate approach using a 95% confidence interval rule. Items removed were falling beyond ±2 standard deviations. This ensured data integrity for subsequent analysis (Hair et al., 2018; Roderick & Donald, 2019).

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4. Results and Discussion

4.1: Descriptive statistics.

Demographic characteristics are presented in Table 1.

Table 1. Cross-tabulation showing the demographic characteristics of respondents, (n =190)

Sex (F/ (%)		Highest level of Education Attainment
Male	**Female**	
0(0)	6 (100)	Diploma
105 (78.4)	40 (27.6)	Bachelors
29 (74.4)	10 (25.6)	Masters
		Teaching experience
20 (80)	5 (20)	6-10yrs
7 (23.3)	23 (76.7)	11-15yrs
107 (79.3)	28 (20.7)	>16yrs

Source: Field Data (2020)

Table 1 illustrates participant demographics, revealing gender disparities in education and teaching experience. Male respondents105(78.4%) predominantly held bachelor's degrees and 29(74.4%) had advanced their education to a master's level, while only 10(25.6%) of females had done so. With teaching experience, of over 16 years,107(79.3%) were male, contrasting with females 40(27.6%) who had lower educational attainment and shorter teaching tenures 28(20.7%). These differences may stem from persistent educational inequalities, especially in developing nations. Despite this, participants' high education levels suggest their ability to provide valuable insights into stakeholder participation in school management. Teaching experience, a crucial variable, reflects participants' potential to contribute to decision-making processes impacting educational quality, consistent with prior research emphasizing its significance (Rice, 2010; Irvine, 2019). Overall, the findings imply that participants possess the knowledge and experience necessary to inform efforts aimed at enhancing academic achievement through collaborative school management practices.

4.2 Preparation of data for Multivariate Analysis.

Thorough initial data screening and treatment, emphasized by Hair et al., (2018) and Roderick & Donald, (2019), are vital for effective multivariate analysis. This involves reducing original data into composites with high inter-correlation and developing new labels for each group of variables. The analytical phase encompassed an examination of both independent and dependent variables, employing Exploratory Factor Analysis, Reliability Analysis, and Inferential Statistics.

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Principal Components Analysis (PCA) was used for scrutiny, evaluating the three discrete dimensions of stakeholder participation based on the SBM model. The dimensions included; School Improvement Planning(SIP), budgeting processes, and coordinating the academic activities alongside the dependent variable learners' academic achievement.

4.2.1Data Reduction using Exploratory Factor Analysis

Exploratory Factor Analysis (EFA) is applied especially if items in a questionnaire are generated as a result of the literature reviewed. This analysis condenses complex interconnections among items within a variable into concise factors, capturing underlying dimensions in the dataset (Hair et al., 2010; Cavana&Sekeran, 2001). Three key decisions guided data reduction.

1. ***Calculating the Input Data***

To achieve the Correlation Matrix, the researcher grouped variables through R-factor analysis and calculated input data to achieve the objective. Key variables SIP, budgeting process, coordinating academic activities, and academic achievement were identified, reflecting hypothesized underlying factors. The validated variables were then used to evaluate outcomes practically. Adhering to EFA sample size requirements (exceeding 100 with a 10:1 ratio of tested items to variables), the researcher ensured the 190 tested items and 4 variables met the criterion, yielding a 48:1 ratio, surpassing the threshold for conducting FA (Hair et al., 2018).

2. ***Assumptions for Factor Analysis***

The essential prerequisites for performing Factor Analysis (FA) are primarily conceptual rather than statistical (Kyriazos, 2018). Within the framework of FA, paramount attention is directed toward the nature and constitution of the variables under consideration. Conceptually, it is posited that there must exist an inherent structure within the chosen set of variables. Additionally, an assumption is made that the sample is homogenous concerning the underlying factor structure.

The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity were computed to ensure Factor Analysis (FA) applicability. Higher KMO values near 1.0 suggest consolidated correlation patterns, crucial for reliable factors (Dziuban& Shirkey, 1974). Bartlett's Test assessed variances across samples, indicating significant correlations between variables, supporting FA suitability (Hadi et al., 2016). Calculated values for both tests, detailed in Table 3, affirmed the factorability of the correlation matrix, validating relationships among investigated variables (Dziuban & Shirkey, 1974; Hadi et al., 2016). Bartlett's Test demonstrated statistical significance for both independent and dependent variables at $p < 0.05$ and $p < 0.001$, respectively.

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Table 3 shows the KMO and Bartlett Test results of the variables.

KMO and Bartlett's Test Result Variables	Kaiser-Meyer-Olkin of sampling adequacy	Barlett's test of Sphericity approx Chi-square	df	Sig.
Planning	0.638	1164.40	91	0.001
Budgeting	0.723	964.46	66	0.001
Coordinating	0.652	1417.64	91	0.000
Academic achievement	0.600	2901.48	703	0.000

Source: Field Data (2020)

The VARIMAX approach was utilized for orthogonal factor rotation to optimize variance summation within the factor matrix. A loading significance threshold of 0.40 was established for interpretation. Conversely, items with loadings below 0.4 or those demonstrating cross-loading tendencies were excluded from subsequent analysis (Hair, et, al., 2018; Craig, 2022).Five distinct, unidimensional factors, devoid of cross-loading items, elucidated 81% of the overall variance and were retained for further analysis, aligning with institutional objectives and managerial functions(Onyango, 2018).These factors encompass performance indicators, school culture, budgeting process, monitoring, and evaluation. Standardized loadings (ranging between 0.43 and 0.85) were significant ($p < 0.05$), with only twenty-one items demonstrating loadings <0.70. This analysis, detailed in Table 4

TABLE 4 shows items and loadings of the 5-factor (independent variables) specified model

Item	loading
Performance indicator	
Performance indicators are realistic	0.850
Performance indicators are attached to each target	0.824
Performance indicators are achievable	0.816
Learners actively participate in decision-making that improves their academic achievement.	0.666
Standards of achievement are attached for each measurable indicator.	0.485
The academic targets to be achieved are well documented.	0.438
School Culture Predictor	
All stakeholders actively participate in developing goals that improve academic achievement	0.764
A culture of shared responsibility among stakeholders to improve academic achievement.	0.724
Stakeholders are given the responsibility to achieve the goals of the school	0.724
There is mutual support from the stakeholders to improve academic	0.720

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achievement.	
Parents/guardians check on the academic progress of the learners.	0.638
Parents actively participate in decision-making that improves academic achievement	0.602
Budgeting Process	
Resource allocation and mobilization is based on academic inventory	0.860
An established system of monitoring and evaluation of the implementation of the budget is in place.	0.779
Monitoring and evaluation of the budgeting process are jointly done by the stakeholders.	0.736
Stakeholders use the accounted and audited reports as a basis to adjust resource allocations	0.715
Stakeholders are aware that regular academic inventory is used as a basis for resource allocation.	0.711
Stakeholders participate in joint decision-making on resource allocation and mobilization	0.635
Academic inventory is communicated to the stakeholders for resource allocation and mobilization.	0.546
There are accounting and auditing systems that drive the effective use of resources.	0.539
Monitoring	
There are monitoring systems to check on the implementation of academic interventions	0.826
There are academic interventions to improve the learners' academic achievement.	0.820
Reports on the implementation of the intervention are periodically generated	0.803
I am held accountable for the learner's performance.	0.695
Recommendations at points of action to improve performance are made.	0.681
The reports on the implementation of the intervention are jointly shared with all school stakeholders	0.639
The majority of stakeholders visit the school to ensure quality performance is achieved.	0.586
It is good practice to involve external stakeholders to improve the quality of academic performance.	0.49
Evaluation	
The stakeholders use these reports to inform decision-making on the intervention	0.765
A formative evaluation of the intervention is done against performance indicators.	0.753
A summative evaluation of the intervention is done against the performance indicators.	0.681
There are tools with indicators used to monitor the intervention implementation.	0.612

Source: Field Data (2020)

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The factor analysis conducted on the dependent variable yielded a unidimensional factor encompassing thirteen (13) items, with loadings ranging from 0.440 to 0.839, as delineated in Table 5.

Table 5: Rotated component matrix

Academic Achievement	**Factor loadings 1**
Adequate exercises are given to the learners.	0.839
Performance targets are realistic.	0.810
Performance targets are achievable.	0.789
Parents/guardians regularly check on their children's academic progress	0.779
Timely feedback is given after the assessment of learners' performance.	0.747
Action points for academic improvement are made.	0.736
Parents/guardians participate in joint decision-making toward academic improvement.	0.726
I check regularly on the notes written by the learners.	0.672
Parents/guardians participate in allocating financial resources that influence academic achievement.	0.662
Parents/guardians assist their children with school work whenever possible.	0.592
Performance targets are set by the school administration.	0.526
Adequate equipment and learning materials are provided at school.	0.472
Learners are held accountable for their performance.	0.440

Construct validity was performed to confirm the data consistency across measurements (Clark & Watson, 2019). Cronbach's Alpha evaluated internal consistency and inter-correlation among variables (Hair et al., 2018). Cronbach's alpha exceeding .60 is considered satisfactory, as detailed in Table 6.

Table 6 shows Cronbach Alpha for extracted variables.

The Reliability Coefficient for the Extracted Variables	**Cronbach alpha**	**Number of items after elimination**
Performance Indicator	0.802	6
School Culture	0.778	6
Budgeting	0.847	8
Monitoring	0.858	8
Evaluation	0.706	4
Academic achievement	0.809	13

Source: Field Data (2020)

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Upon completion of the exploratory factor analysis on items characterizing both the independent and dependent variables, the data was tested to confirm whether it was normally distributed before performing the multivariate analysis (Monroe, et al., 2022.).

4.3 Tests of Normality

Normality tests, including the Shapiro-Wilk test, were conducted using SPSS version 20.0 to validate data distribution assumptions. A significance level of $p < 0.05$ was set, with results presented in Table 7. The hypotheses tested were: H^0 - Data is not normally distributed; H^1 - Data is normally distributed (Gissane, 2015; Wesolowski & Thompson, 2018; González-Estrada &Cosmes, 2019).

Table7: Tests of Normality

	Kolmogorov-Smirnov[a]			**Shapiro-Wilk**		
	Statistic	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
A-achievement	.168	190	.000	.923	190	.000
Performance in	.127	190	.000	.971	190	.001
Culture	.156	190	.000	.947	190	.000
Budgeting	.126	190	.000	.936	190	.000
Monitoring	.188	190	.000	.903	190	.000
Evaluation	.201	190	.000	914	190	.000

Note: Achievement (Academic Achievement).

Table 7 shows non-significant differences ($p < 0.05$), indicating non-normal data, hindering hypothesis testing. Remedial measures included Mahalanobis D2 to detect outliers ($p < 0.001$), transformation techniques (e.g., "Lg10," square root), were applied but data failed to comply and bootstrap technique for regression analysis was adopted due to non-normality (Hair et al., 2018; Rousselet et al., 2023).

4.4 Regression using Bootstrap Technique

The regression bootstrapping method was applied to analyze the study population, allowing inference despite potential biases and outliers. It repeatedly resamples from observed data to approximate the statistic distribution, beneficial when data don't meet traditional method assumptions. This method aims to assess the linear association between independent and dependent variables (Rousselet et al., 2023; Gimenez-Nadal et al., 2019).

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4.4.1 Regression Analysis Results on Performance Indicators and Academic Achievement

H_0^1= There is no statistically significant relationship between the performance indicators and academic achievement in the enhancement of learners' academic achievement in government-aided secondary schools in the Kampala district.A statistical examination using an F-test was conducted to establish whether the model was significant. Results are presented in Table 8.

Table8: ANOVA

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.290	1	2.937	11.750	.001[b]
	Residual	36.644	188	.195		
	Total	38.934	189			

a. Dependent Variable: Achievement

a. Predictors: (Constant), Per performance indicator

Table 8 displays the significance test outcomes for the model's predictive capacity regarding the dependent variable. The regression model was significant ($F=11.750$, $df=1,188$, $p<0.05$), affirming the performance indicator's ability to predict academic achievement. The null hypothesis was rejected, confirming a significant positive influence of the performance indicator on academic achievement. The determination of the regression equation involved a simple linear regression at a Bias Corrected Accelerated (BCA) 95% confidence level, with bootstrap coefficients detailed in Table 9 below;

Table 9 shows the bootstrap coefficient for Performance Indicators and Academic Achievement.

Bootstrap for Coefficients

Model		B	Bootstrap				
			Bias	Std. Error	Sig. (2-tailed)	BCa 95% Confidence Interval	
						Lower	Upper
1	(Constant)	3.237	.004	.194	.001	2.844	3.602
	Performance and	.148	-.002	.051	.005	.040	.259

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples.

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The BCA method confirms data significance, with the confidence interval for the intercept (0.040, 0.259) excluding zero. Each unit rise in performance indicators correlates with a 0.148 increase in academic achievement, affirming a significant relationship between the two.

4.4.2 Regression Analysis Results on School Culture and Academic Achievement

H_0^2 = There is no statistically significant relationship between the school culture and academic achievement in the enhancement of learners' academic achievement in government-aided secondary schools in the Kampala district. To test the hypothesis, a statistical examination using an F-test was conducted, and the results are presented in Table 10that there is no statistically significant relationship between the school culture and academic achievement, an F-test was done as shown in Table 10.

Table 10: ANOVA

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.214	1	2.214	11.337	.001[b]
	Residual	36.720	188	.195		
	Total	38.934	189			

a. Dependent Variable: Academic Achievement

a. Predictors: (Constant), culture

Table 10 assesses the model's significance in predicting the dependent variable. The regression model proved significant, with $F(1, 188) = 11.337$, $p < 0.05$, supporting the prediction of academic achievement by school culture. Rejecting the null hypothesis, the F-test ($p < 0.05$) implies school culture effectively predicts academic achievement.

Table 11. Bootstrap Coefficient for School Culture and Academic Achievement

Bootstrap for Coefficients

Model		B	Bootstrap				
			Bias	Std. Error	Sig. (2-tailed)	BCa 95% Confidence Interval	
						Lower	Upper
1	(Constant)	3.053	-.010	.320	.001	2.463	3.684
	culture	.203	.003	.079	.009	.040	.367

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

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Using Bias Corrected Accelerated (BCA), we assert the data's significance with 95% confidence as the interval (0.040 to 0.367) excludes zero. A 1-unit enhancement in school culture predicts a 0.203 increase in academic achievement, indicating a significant correlation.

4.4.3 Regression Analysis Results on Budgeting Process and Academic Achievement

H_0^3 = There is no statistically significant relationship between the budgeting process and academic achievement in the enhancement of learners' academic achievement in government-aided secondary schools in Kampala district. To test the hypothesis a statistical examination using an F-test was conducted, and the results are presented in Table12.

Table 12: ANOVA

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.360	1	5.360	30.013	.000[b]
	Residual	33.574	188	.179		
	Total	38.934	189			

a. Dependent Variable: Academic Achievement

a. Predictors: (Constant), Budgeting

Table 12 showcases test results for predicting the dependent variable. The regression model proved significant F (1,188) = 30.013, $p < 0.05$), refuting the hypothesis that the budgeting process inadequately predicts academic achievement. Consequently, we infer a positive and significant impact of budgeting on academic achievement, affirmed by bootstrap coefficient analysis in Table 13.

Table 13 shows the Bootstrap coefficient for budgeting and Academic Achievement

Bootstrap for Coefficients

Model		B	Bootstrap				
			Bias	Std. Error	Sig. (2-tailed)	BCA 95% Confidence Interval	
						Lower	Upper
1	(Constant)	2.948	.009	.221	.001	2.494	3.338
	Budgeting	.228	.005	.056	.001	.122	.353

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

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The analysis utilizing the Bias-Corrected and Accelerated (BCA) method confirms, with 95% confidence, the statistical significance of the data. With each unit increase in the budgeting process, a corresponding 0.228 increase in academic achievement is anticipated, suggesting a significant correlation between the two.

4.4.4 Regression Analysis Results on Monitoring and Academic Achievement

H_0^4= There is no statistically significant relationship between monitoring academic activities and the enhancement of learners' academic achievement in government-aided secondary schools in Kampala district. A simple linear regression was performed at BCA 95% confidence level. To test the hypothesis that there is no statistically significant relationship between monitoring academic activities and academic achievement, an F-test was done as shown in Table 14

Table14: ANOVA

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.807	1	.807	3.977	.048[b]
	Residual	38.128	188	.203		
	Total	38.934	189			

a. Dependent Variable: Achievement

b. Predictors: (Constant), monitoring

Table 14 displays the results of the significance test for the predictive model of the dependent variable. The regression model exhibited statistical significance $F(1,188) = 3.977$, $p < 0.05$), supporting its predictive capability. However, based on the results, the F-test monitoring academic activities was not a significant predictor of academic achievement.

4.4.5 Regression Analysis Results on Evaluation and Academic Achievement

H_0^5= There is no statistically significant relationship between the evaluation of the academic activities and academic achievement in the enhancement of the learners' academic achievement in government-aided secondary schools in Kampala district. To test the hypothesis that there is no statistically significant relationship between the evaluation of academic activities and academic achievement, an F-test was done as shown in Table 15

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Table 15: ANOVA

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.878	1	5.878	33.341	.000b
	Residual	33.056	188	.176		
	Total	38.934	189			

a. Dependent Variable: Achievement

a. Predictors: (Constant), Evaluation

Table 15 assesses the model's significance in predicting the dependent variable. The regression model was statistically significant F (1, 188) = 33.431, $p < 0.05$), indicating its effectiveness in predicting the criterion variable. The inclusion of evaluation in the model significantly predicted academic achievement, rejecting the null hypothesis. To ascertain the regression equation, bootstrap coefficients were computed, as detailed in Table 16 below

Table16: Bootstrap for Coefficients

Bootstrap for Coefficients

Model		B	Bootstrap				
			Bias	Std. Error	Sig. (2-tailed)	BCa 95% Confidence Interval	
						Lower	Upper
1	(Constant)	2.820	-.003	.214	.001	2.342	3.211
	Evaluation	.256	.001	.055	.001	.156	.372

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

The BCA bootstrapping analysis of the intercept's confidence interval affirms the statistical significance of the data at 95% confidence. With bounds (0.156 and 0.372) not crossing zero, each unit increase in evaluation correlates with a 0.256 rise in academic achievement, indicating a significant relationship.

5. Discussion and Policy Implications

The study aimed to analyze the extent of stakeholders' participation in school management to enhance the learners' academic achievement in public secondary schools in Uganda. Due to the limited empirical validation of stakeholder participation measures, this research provides

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valuable insights into reliable dimensions for measuring and subsequently monitoring, managing, and enhancing stakeholder participation. The validation process involved a large sample and employed both exploratory factor analysis and bootstrapping techniques. The results revealed five distinct dimensions of solutions, supporting the notion that effective school management is complex (Delavallade, et al. 2019; Cheng, 2023). The study's overall findings indicate that inclusive participation of key stakeholders in managerial functions, such as planning, budgeting, and coordination of school interventions, contributes to the improvement of learners' academic achievement, outcomes, and job competencies for the future 21st century. This inclusive approach also positively impacts service delivery, ultimately leading to high-quality educational outcomes. The study further identifies variables through which key stakeholders can exert influence on the enhancement of academic achievement in public secondary schools. Stakeholder participation in school management creates a collaborative and supportive ecosystem that positively influences the learner's academic achievement by addressing challenges, implementing effective strategies, and creating an environment that nurtures the intellectual and social development of learners. Through collaboration, stakeholders can foster a supportive environment that positively influences learners' academic achievement.

The Predictive correlation research design adopted for multivariate analysis may haveintroduced bias into the participants' feedback process. This design aimed to predict the strength and direction of relationships among variables and interpret the findings. However, it did not delve deeply into analyzing the causes behind observed patterns in the data. Cause-and-effect relationships were not the focus of this observational research type, which solely examines the extent of relationships and the distribution of variables. In this approach, variables are not manipulated but rather identified and studied as they naturally occur.

To eliminate this impact, further research can bed one to investigate the level of participation of stakeholders in school administration, aiming to improve academic performance among learners. This could be achieved through a Comparative descriptive research design, specifically comparing public and private secondary schools in Uganda. It's essential to note that the results remain applicable solely to the study and within the specific context of public secondary schools. The author asserts that these outcomes can be replicated in analogous settings of public secondary schools in other regions.

The conclusions align with Jensen and Meckling's Agency theory (1976), asserting that managers (Agents) primarily act in their self-interest, displaying a self-centred approach that may neglect stakeholders' concerns. Consequently, leaving managers (Agents) without oversight, insight, and foresight makes it unrealistic to expect them to prioritize the interests and aspirations of stakeholders. The Agency theory underscores the importance of establishing a robust governance framework that precisely outlines the authority and sufficient powers not only to

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guide but also to oversee management. This is essential for achieving the interests and desires of stakeholders. The assertion that the participation of stakeholders in school improvement planning, budgeting processes, and coordination of academic activities contributes to enhanced learners' academic achievement and outcomes is supported by empirical literature(Marchessault, 2016; Oyier&Odundo, 2017; Cheng, 2023)

To substantiate this viewpoint, Oyier and Odundo (2017) highlighted the significance of joint participation in decision-making for sufficient budget allocations, as it accountability and transparency in governance operations. It's important to highlight that there was no discernible evidence indicating a statistically significant impact of stakeholders' involvement in coordinating academic activities. However, there was a noticeable inclination for stakeholders to actively engage in monitoring academic activities, encompassing aspects such as (1) overseeing systems to assess the implementation of academic interventions, (2) devising academic strategies to enhance students' academic achievement, (3) periodically creating performance reports, (4) establishing action points for enhancements, (5) conducting joint periodic meetings to discuss the implementation of interventions, (6) stakeholders undertaking academic visits to ensure the delivery of quality services, and (7) involving external stakeholders to enhance the overall academic performance in the school.

Surprisingly, the assessment of academic activities exhibited a statistically significant correlation with the improvement of learners' academic performance. Existing research indicates that overseeing and assessing these activities can positively impact the delivery of educational services (Ferdaus, 2018; Cheng, 2023). This underscores the importance of involving stakeholders in the evaluation of instructional processes to effectively achieve educational objectives. Onyango (2018) and Mayanja (2020) argued that participatory monitoring and evaluation are crucial for ensuring that an institution attains its intended targets and goals. Participatory monitoring and evaluation entail actively engaging all relevant stakeholders in institution-related activities or interventions, sharing control over the process's content and results, and participating in corrective actions (World Bank, 2013)

6. Conclusion

The claim that the extent of stakeholders' participation in school management enhanced the learners' academic achievement guided the study. The involvement of stakeholders in school management was envisioned through activities such as school improvement planning, budgeting processes, and coordinating academic activities. While the study's scope is limited, its findings aim to enhance the understanding of effective participation, involving all crucial stakeholders influencing or impacted by the institution's interests to achieve desired academic objectives.

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