Impact of Artificial Intelligence on Procurement Management Performance

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Abstract

This study examined the impact of Artificial Intelligence (AI) on procurement management performance at the College of Business Education (CBE), Mbeya Campus, with a focus on transparency, accountability, and value for money. Employing a descriptive research design with a quantitative approach, data were collected from 40 purposively selected participants—including procurement officers, auditors, and accountants—through structured questionnaires. The study applied descriptive statistics, Pearson correlation, and multiple regression analyses to evaluate the influence of AI technologies such as Robotics, Process Automation, and Machine Learning on procurement outcomes. Findings revealed that all three AI technologies significantly and positively affect procurement performance. Machine Learning demonstrated the strongest impact, particularly enhancing transparency and value for money, followed by Process Automation and Robotics. High Cronbach's Alpha scores (≥0.8) confirmed the internal consistency of the instruments used, while data normality tests validated the use of parametric statistical techniques. The Pearson correlation coefficients showed strong and statistically significant relationships between AI tools and performance indicators, especially between Process Automation and Transparency ($r = 0.642$) and Machine Learning and Value for Money ($r = 0.612$). Regression results further supported Machine Learning as the most influential predictor of procurement performance ($\beta = 0.581$, $p = 0.001$). Despite positive perceptions of AI integration, performance indicators like accountability and transparency showed room for improvement, suggesting a gap between technological adoption and its effective utilization. The study recommends capacity building for procurement practitioners to optimize AI applications and improve procurement outcomes in public institutions.

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1.Introduction

Procurement management plays a critical role in ensuring that organizations acquire goods and services efficiently, transparently, and in alignment with strategic objectives (John, 2023). In public institutions, procurement processes directly affect service delivery, resource utilization, and institutional integrity (Ameyaw *et al.,* 2012). However, traditional procurement systems characterized by manual operations, human judgment, and paper-based documentation that often lead to inefficiencies, delays, and increased risks of fraud and corruption (Anchilla, 2023; Adam, 2024; Dimoso & Andrew, 2021). These limitations underscore the urgent need for more intelligent and reliable systems that ensure accountability, transparency, and value for money in public procurement (Eadie *et al.,* 2010; Kitole, 2025).

Artificial Intelligence (AI) has emerged as a transformative force capable of reshaping procurement management across sectors (Allal-Chérif & Maira, 2020; Bahameish *et al.*, 2023). By enabling machines to learn, reason, and make data-driven decisions, AI supports automation, supplier evaluation, risk management, compliance tracking, and predictive analytics (Guida *et al.*, 2023; Menezes *et al.,* 2023; Dekker & de Boer, 2020). Research shows that AI in procurement enhances performance by streamlining operations, reducing errors, and improving outcomes across both strategic and operational dimensions (Perifanis & Kitsios, 2023; Kitole & Shukla, 2024; Bolanle, 2024; Nida, 2025).

AI also directly influences the three pillars of procurement performance—transparency, accountability, and value for money. For transparency, AI tools offer real-time tracking, automated audit trails, and anomaly detection, significantly minimizing favoritism and information asymmetry (Khorana *et al.*, 2024; Thanasas *et al.*, 2025; Shukla & Tiwari, 2022). In terms of value for money, AI supports efficient supplier selection, optimized procurement cycles, and improved cost forecasting (Bozarth & Handfield, 2016; Ivanov & Dolgui, 2020; Wamba & Queiroz, 2022). For accountability, AI systems ensure traceability in decision making, reduce human discretion, and promote compliance with policies and procedures (OECD, 2021; Waditwar, 2024; Spreitzenbarth *et al.,* 2021).

Globally, the adoption of AI in public procurement is gaining momentum. In the Czech Republic, AI has been successfully integrated into government procurement to enhance efficiency and transparency (Basl & Doucek, 2019; Utouh & Kitole, 2024). In Africa, Kenya has adopted digital procurement systems through its Public Procurement Regulatory Authority, enabling AI-based monitoring and performance tracking (Hussein, 2014). Similarly, South Africa has utilized AI tools to combat corruption and assess supplier performance (Kitole & Utouh, 2023; Elhassan Gadour, 2024). These examples reflect a regional shift toward AI-driven procurement modernization.

In Tanzania, digital transformation efforts are underway. The National e-Procurement System (NeST) incorporates automation, robotics, and blockchain for real-time procurement oversight (Mwanjisi, 2022). AI tools are being considered to further improve the detection of procurement irregularities and support decision-making across public institutions (Ngowi & Moshi, 2021; Makongoro, 2023). Nevertheless, empirical studies on the real-world impact of AI on procurement outcomes especially in developing countries are limited (Tasheva & Ivanov, 2021; Collins *et al.*, 2021; Guida *et al.*, 2025).

As such, this study investigates the influence of Artificial Intelligence on procurement management performance at the College of Business Education (CBE) in Mbeya, Tanzania. It focuses on how AI affects transparency, accountability, and value for money within procurement systems. The findings are expected to provide practical insights for public institutions seeking to optimize their procurement strategies through technology adoption, while contributing to the growing body of knowledge on AI in public sector governance.

2. Review of Related Literature

Artificial Intelligence (AI) has played a transformative role in enhancing transparency in procurement management. Transparency, as a principle of effective procurement, promotes fairness and openness throughout procurement processes, making procedures more visible and reducing opportunities for favoritism and corruption (Mwanjisi, 2022). The integration of AI into procurement has significantly enhanced transparency, particularly in areas such as tender advertisement, bid evaluation, supplier monitoring, and contract management (Makongoro, 2023). AI systems allow for all procurement activities to be digitally recorded and stored, thereby improving auditability and traceability (Thanasas *et al.,* 2025). This reduces the likelihood of unsound procurement decisions, as every transaction can be traced and reviewed (Elhassan Gadour, 2024). Furthermore, AI-powered analytics and machine learning tools detect patterns and anomalies such as repeated contract awards to the same vendor helping to identify potential fraud or irregularities (Hussein, 2014).

The ability of AI to process large volumes of data through natural language processing has further enhanced transparency in procurement systems. These tools can analyze complex procurement documents to identify compliance issues and overlooked terms, thereby mitigating risks that manual systems might miss (Khorana *et al.,* 2024). AI also supports real-time data sharing and improves public access to procurement information, such as supplier lists, procurement schedules, and tender award decisions. This level of openness enables external monitoring and encourages accountability among procurement officials (Thanasas *et al.,* 2025). However, a significant challenge remains in the absence of standardized tools and indicators for measuring AI's impact on procurement transparency, particularly in Sub-Saharan Africa. The region continues to be underrepresented in empirical assessments, and the practical implementation of AI tools often lacks rigorous evaluation.

In addition to transparency, AI has shown great potential in enhancing value for money (VfM) in procurement. Value for money involves achieving the best possible outcome by balancing efficiency, economy, and effectiveness in the use of resources (Perifanis & Kitsios, 2023). AI contributes to VfM by reducing waste, enabling strategic sourcing, and improving decision-making processes. Through AI-driven supplier evaluations, market trend predictions, and risk assessments, organizations can identify reliable suppliers that offer high-quality goods and services at competitive prices (Guida *et al.,* 2023; Adam, 2024). Machine learning algorithms further assist in accurate demand forecasting, which reduces overstocking, shortens procurement lead times, and optimizes inventory turnover. This ensures that procurement activities are aligned with actual organizational needs, minimizing unnecessary expenditure and storage costs (Collins *et al.*, 2021).

AI also plays a crucial role in strengthening accountability within procurement systems. Accountability, both at the organizational and individual level, is the obligation to be answerable for decisions and actions taken during procurement processes (Anchilla, 2023). With AI technologies that document every step in the procurement lifecycle, from requisition to contract execution, it becomes easier to track who is responsible for specific decisions (John, 2023). The traceability offered by AI platforms obliges procurement practitioners to act diligently, as their actions are subject to scrutiny. Analytics provided by AI tools offer clear data on pricing, supplier selection, and contract awards, which reinforce both internal and external accountability (Guida *et al.,* 2023). Nevertheless, a growing concern exists regarding the lack of transparency in how AI systems themselves reach decisions. This "black box" nature of AI can limit oversight, potentially undermining human accountability and raising ethical and regulatory questions.

Despite the recognized contributions of AI to procurement performance—particularly in enhancing transparency, value for money, and accountability—its implementation in developing economies remains uneven. Sub-Saharan Africa, including countries like Tanzania, has begun adopting AI-driven procurement systems, but gaps remain in evaluating their effectiveness and adapting them to local contexts. The lack of standardized metrics, limited technological infrastructure, and insufficient technical expertise hinder the full realization of AI's benefits. Therefore, more empirical research and policy guidance are needed to assess how AI tools can be optimally utilized to improve procurement outcomes in these settings.

Theoretical Model: Technology Acceptance Model (TAM)

Technology Acceptance Model developed by Davis in 1986 guided this study. The model has been to a large extent used to predict and explain adoption and use of technology in numerous contexts. The model explains that, actual technology usage is determined by Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). Perceived ease of use is the degree in which a person believes that the system usage would be effortless and thus could contribute to performance whereas perceived usefulness is an extent that a person believes on using respective system to enhance job performance. TAM presents that, perceived usefulness and perceived ease of use have influence on intention and attitude of users towards adoption of technology which thereof impact actual use of systems as well as system performance. TAM is ideal for this study since it provides a mechanism of exploring the means by which AI influence procurement processes for attaining required performance. On further note, how procurement practitioners and decision makers perceive artificial intelligence influences its adoption and use and thus contribute in attaining value for money, transparency and accountability.

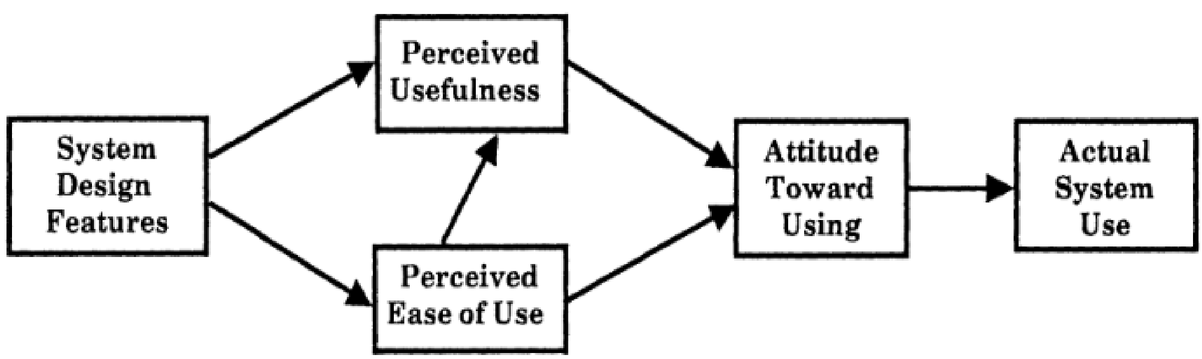

Figure 1: Technological Acceptance Model (TAM)
Source: Davis (1986)

Therefore, the use of TAM to underpin this study provided a practical and logical framework that examined the relationship between adoption of AI in procurement and attitude of procurement practitioners with esteemed influence on performance through transparency, accountability and value for money.

Conceptual Framework

The conceptual model presents the relationship established between artificial intelligence on procurement management performance. Artificial intelligence is described by robotics, machine learning and process automation whereas procurement management performance is described by accountability, transparency and value for money. Perceived ease of use and perceived usefulness tend to influence the procurement management performance.

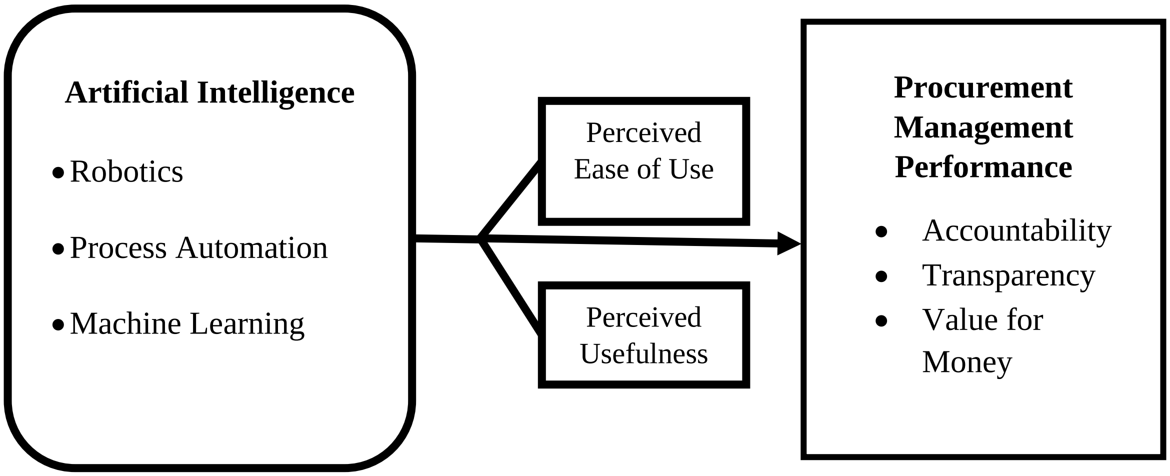

Figure 2: Conceptual framework
Source: Reviewed literatures (2023)

3.Methodology

This study was conducted at the College of Business Education (CBE) in Mbeya, Tanzania, with the aim of assessing the impact of Artificial Intelligence on procurement management performance, focusing specifically on transparency, accountability, and value for money. A total of 40 respondents participated in the study, selected through purposive sampling. This sampling technique was chosen to ensure that only individuals with relevant knowledge and experience in procurement processes were included. The participants comprised procurement officers, accountants, internal auditors, and other staff members directly involved in procurement activities at the institution. The selection of CBE Mbeya was strategic due to its growing interest in incorporating technology into its procurement functions, making it a suitable setting for the investigation.

Data collection was carried out using structured questionnaires, which were designed to gather both quantitative and qualitative information related to the study variables. The questionnaire included closed-ended questions to facilitate measurable responses, as well as a few open-ended questions to allow respondents to express detailed views and experiences regarding the use of AI in procurement. This method was chosen for its ability to ensure consistency across responses and support effective comparison and analysis. Prior to administration, the questionnaire was reviewed for clarity and relevance. Participation was voluntary, and respondents were assured of the confidentiality of their responses. The data collected was analyzed using descriptive statistics for quantitative data and thematic analysis for qualitative inputs to draw meaningful conclusions about the influence of AI on procurement performance at CBE Mbeya.

Results

Reliability Test of Variables

The reliability of the research instrument was assessed using Cronbach's Alpha, which measures internal consistency to determine how closely related a set of items are as a group. A Cronbach's Alpha value of 0.7 or higher is generally considered acceptable, while values above 0.8 indicate good reliability, and those above 0.9 reflect excellent internal consistency. The results presented in Table 1 show that all variables in this study met or exceeded the acceptable threshold, indicating that the questionnaire used to collect data was reliable and suitable for further statistical analysis.

Among the technological components of Artificial Intelligence examined in this study, Machine Learning exhibited the highest reliability score with a Cronbach's Alpha of 0.911, reflecting excellent consistency in how the related questionnaire items measured this construct. Process Automation followed with a strong reliability score of 0.865, and Robotics demonstrated a reliability coefficient of 0.812. These results suggest that the items used to assess different AI technologies were coherent and consistently captured respondents' understanding and perceptions of these systems in the context of procurement at CBE Mbeya.

In terms of procurement performance indicators, Transparency yielded the highest Cronbach's Alpha value at 0.968, suggesting extremely high internal consistency among the items used to measure this construct. This finding reinforces the importance and clarity of transparency-related items in the questionnaire. Value for Money and Accountability also demonstrated strong reliability scores of 0.844 and 0.814 respectively, confirming that the questions effectively captured how AI impacts these dimensions of procurement performance. Overall, the high reliability coefficients across all variables confirm that the instrument used was both dependable and consistent, making the findings of the study robust and credible.

Table 1: Reliability Results

Variable	Cronbach's Alpha
Robotics	0.812
Process Automation	0.865
Machine Learning	0.911
Accountability	0.814
Transparency	0.968
Value for Money	0.844

Source: Field data (2024)

Data Normality

Table 2 presents the results of the data normality test using skewness, kurtosis, and the adjusted chi-square (adj_chi2) values. The individual *Pr (Skewness)* and *Pr (Kurtosis)* columns test whether the data distribution for each variable deviates significantly from a normal distribution based on asymmetry and peakedness, respectively. For all variables—Robotics, Process Automation, Machine Learning, Accountability, Transparency, and Value for Money—the p-values for both skewness and kurtosis are below 0.05. This suggests that, when considered independently, both skewness and kurtosis indicate potential deviations from a perfectly normal distribution for each variable.

Table 2: Data Normality Results

Variable	Pr (Skewness)	Pr (Kurtosis)	adj_chi2 (2)	Prob> chi2
Robotics	0.000	0.001	28.220	0.501
Process Automation	0.002	0.001	31.590	0.712
Machine Learning	0.000	0.000	27.128	0.132
Accountability	0.000	0.001	33.790	0.601
Transparency	0.000	0.002	29.490	0.082
Value for Money	0.001	0.000	30.105	0.386

Source: Field data (2024)

However, the *adj_chi2* column, which represents the joint test of skewness and kurtosis (also known as the Doornik-Hansen or D'Agostino test, depending on the software), provides a more holistic assessment. The corresponding *Prob > chi2* values (p-values) indicate whether the combined skewness and kurtosis significantly deviate from a normal distribution. For this test, a p-value greater than 0.05 suggests that the data does **not** significantly deviate from normality, meaning the assumption of normality is met. In this case, all six variables show *Prob > chi2* values above 0.05, ranging from 0.082 (Transparency) to 0.712 (Process Automation). This means that, despite skewness or kurtosis being significant on their own, the overall distribution for each variable can still be considered approximately normal when the combined measure is used.

This outcome supports the suitability of applying parametric statistical analyses to the dataset, as the assumption of normality is sufficiently met based on the joint skewness-kurtosis test. It implies that the responses for all constructs—including AI-related technologies and procurement performance measures—follow a roughly normal distribution. This enhances the reliability of inferential statistical methods used later in the study, such as correlation, regression, or ANOVA, by confirming that the data is well-aligned with the assumptions required for these techniques. Thus, the results from Table 2 provide confidence in the statistical validity of subsequent analyses conducted in the study.

Pearson Correlation

Table 3 presents the Pearson correlation coefficients that measure the strength and direction of linear relationships between Artificial Intelligence (AI) technologies—namely Robotics, Process

Automation, and Machine Learning—and procurement performance indicators: Accountability, Transparency, and Value for Money (VfM). Correlation coefficients range from -1 to +1, where values closer to +1 indicate a strong positive correlation, values near 0 suggest no correlation, and values closer to -1 indicate a strong negative relationship. The significance (Sig. 2-tailed) values determine whether the correlation is statistically significant, with values below 0.05 generally considered significant. Starting with Robotics, the results show moderate positive correlations with all three performance indicators: Accountability (r = 0.312), Transparency (r = 0.212), and Value for Money (r = 0.420). While the correlation with Transparency is relatively weaker, the relationship with Value for Money is more noticeable and suggests that the use of robotics may enhance cost-effectiveness and efficiency in procurement processes. Importantly, the correlations involving Robotics and Transparency as well as Value for Money are statistically significant, indicating that these relationships are unlikely due to chance.

Table 3: Pearson Correlation Results

Variables	Pearson Correlation	Robotics (R)	Process Automation (PA)	Machine Learning (ML)	Accountability (A)	Transparency (T)	Value for Money (VfM)
R	Correlation Coefficient	1	0.512	0.722	0.312	0.212	0.420
	Sig. (2-tailed)						
PA	Correlation Coefficient		1	0.111	0.530	0.642	0.651
	Sig. (2-tailed)						
ML	Correlation Coefficient	0.481	0.932	1	0.544	0.653	0.612
	Sig. (2-tailed)						
A	Correlation Coefficient	0.462	0.330	0.412	1	0.612	0.301
	Sig. (2-tailed)	0.000				0.000	0.006
T	Correlation Coefficient	0.785	0.732	0.612	0.742	1	0.659
	Sig. (2-tailed)	0.000			0.000		0.001
VfM	Correlation Coefficient	0.431	0.612	0.612	0.510	0.659	1
	Sig. (2-tailed)	0.001			0.016	0.002	

Source: Field data (2024)

Process Automation demonstrates a stronger and more consistent influence on procurement performance indicators. It shows a moderate to strong positive correlation with Accountability (r = 0.530), Transparency (r = 0.642), and Value for Money (r = 0.651). These findings suggest that automation technologies significantly enhance openness, traceability, and financial efficiency in procurement processes. The statistically significant correlations imply that organizations integrating automation tools into procurement can expect measurable improvements in accountability and outcomes that reflect value for money. Machine Learning exhibits particularly strong correlations across the board, especially with Transparency (r = 0.653) and Value for Money (r = 0.612), alongside a moderate correlation with Accountability (r = 0.544). The strength of these relationships, all of which are statistically significant, suggests that machine learning not only helps in identifying patterns and improving procurement decision-making but also plays a key role in enhancing performance outcomes. Notably, the correlation between Machine Learning and Process Automation (r = 0.932) is extremely high, indicating a close interplay between these technologies. This may reflect their often-complementary nature in AI applications, where machine learning algorithms operate through or enhance automated systems.

Overall, these correlation results suggest that all three AI technologies positively influence procurement performance dimensions. Transparency shows the strongest and most consistent relationship with all AI tools, highlighting it as the most impacted performance variable. Value for Money follows closely, particularly in connection with Machine Learning and Process Automation. Accountability, while still significantly correlated, appears slightly less influenced. These insights collectively reinforce the potential of AI integration to drive meaningful improvements in procurement outcomes, supporting both operational and strategic procurement goals.

Descriptive Statistics

Table 4 presents the descriptive statistics of the key variables analyzed in this study, providing insight into the general tendencies and variability in the respondents' views. The mean values indicate the average level of agreement or perception toward each variable, while the standard deviation (Std. Dev.) measures how much the responses varied from the mean. The minimum (Min) and maximum (Max) values show the range of responses given by participants, offering a clearer picture of the distribution across the scale.

From the results, Robotics scored the highest mean value at 4.29 (on a presumed 5-point scale), with a low standard deviation of 0.401, indicating that most respondents agreed or strongly agreed with positive statements regarding the role of robotics in procurement. Process Automation and Machine Learning followed with mean scores of 3.85 and 3.64 respectively, also suggesting relatively favorable perceptions, though slightly lower than Robotics. These results imply that respondents generally acknowledge the relevance and presence of AI technologies in procurement processes at CBE Mbeya, particularly robotics, which appears to be the most positively rated AI component.

Table 4: Descriptive Statistics Results

Variable	Mean	Std. Dev.	Min	Max
Robotics	4.29	0.401	3.14	4.86
Process Automation	3.85	0.411	2.71	4.57
Machine Learning	3.64	0.421	2.71	4.86
Accountability	1.706	0.558	1	2.8
Transparency	1.109	0.902	1	3
Value for Money	1.564	0.844	1	2.7

Source: Field data (2024)

On the performance side, the mean scores for Accountability (1.706), Transparency (1.109), and Value for Money (1.564) were much lower, suggesting that despite the integration of AI technologies, the perceived improvement in procurement performance remains limited. These variables likely used a reverse or binary scale (e.g., Yes/No or 1–3 Likert type), with lower mean values possibly indicating agreement with positive statements. However, the standard deviations for Transparency (0.902) and Value for Money (0.844) were relatively high, showing greater variability in perceptions. This suggests that while some respondents may recognize improvements in procurement outcomes due to AI, others may still be skeptical or have not experienced the benefits uniformly. These findings highlight a potential gap between the existence of AI tools and their tangible impact on procurement performance, pointing to the need for deeper implementation or more effective utilization.

Effects of the Artificial intelligence on the procurement management performances

Table 5 presents the results of a multiple regression analysis conducted to examine the extent to which different components of Artificial Intelligence—namely Robotics, Process Automation, and Machine Learning—predict procurement management performance. The unstandardized coefficients (B) show the expected change in the dependent variable (procurement performance) for each unit increase in the predictor variable, holding all else constant. The standardized coefficients (Beta) allow for the comparison of the relative importance of each predictor by eliminating unit differences. The t-values and significance levels (Sig.) assess whether the relationships observed are statistically meaningful.

Table 5: Multiple Regression Result on effects of AI on procurement management performances

	Unstandardized Coefficients		Standardized Coefficients		
Coefficients	**B**	**Std. Error**	**Beta**	**t**	**Sig**
(Constant)	0.404	0.015		3.210	0.000
Robotics	0.456	0.030	0.185	4.275	0.027
Processing Automation	0.414	0.093	0.220	3.377	0.034
Machine Learning	0.556	0.024	0.581	5.265	0.001

a Dependent Variable: Procurement Performance

The constant (intercept) value of 0.404 indicates the predicted base level of procurement performance when all AI components are held at zero. Among the predictors, Machine Learning has the highest standardized beta coefficient ($\beta = 0.581$) and is statistically significant at $p = 0.001$, suggesting it is the strongest and most influential predictor of procurement performance. This means that improvements in Machine Learning tools—such as predictive analytics, intelligent data processing, and decision support—are most likely to lead to noticeable improvements in procurement outcomes at CBE Mbeya.

Robotics and Process Automation also show positive and statistically significant effects on procurement performance, with standardized beta values of 0.185 and 0.220, and p-values of 0.027 and 0.034 respectively. Although their influence is moderate compared to Machine Learning, these results still indicate that the integration of robotics (e.g., for repetitive task execution) and automation (e.g., auto-generation of procurement documents and workflow management) positively contributes to procurement efficiency, transparency, and accountability. In summary, all three AI components significantly and positively impact procurement management performance, with Machine Learning having the most substantial effect. These findings emphasize the importance of strengthening AI systems to achieve improved procurement outcomes within public institutions.

4.Discussion

The findings of this study confirm the significant and positive role that Artificial Intelligence (AI) plays in enhancing procurement management performance, specifically in the areas of transparency, accountability, and value for money. These results align with the growing body of literature emphasizing the transformative capacity of AI in public sector operations. As shown in the regression analysis, machine learning emerged as the most influential AI component, contributing significantly to procurement performance. This supports Guida *et al.* (2023), who observed that machine learning allows for improved forecasting, supplier evaluation, and fraud detection, which are crucial to effective procurement management. The integration of such tools not only boosts efficiency but also helps reduce human bias and error in decision-making.

Transparency, one of the key variables assessed in the study, was found to be highly influenced by AI tools, especially machine learning and process automation. The correlation and regression results indicated strong associations between these technologies and transparent procurement practices. These findings are consistent with the work of Thanasas *et al.* (2025), who assert that AI enhances auditability and regulatory compliance through real-time data tracking, automated reporting, and predictive alerts. Similarly, Khorana *et al.* (2024) highlight the importance of e-GP systems and AI in ensuring open access to procurement information, which empowers oversight bodies and the public to monitor processes and outcomes effectively. In this context, AI fosters trust and accountability by minimizing the likelihood of data manipulation and favoritism.

The study also revealed that AI significantly contributes to accountability in procurement by making actions traceable and decisions data-driven. This is particularly relevant in public institutions where accountability is a cornerstone of ethical governance. As discussed by Adam (2024), accountability in public procurement demands that officials be answerable for how decisions are made and resources are utilized. AI systems, by keeping detailed records of procurement activities and enabling audit trails, hold procurement personnel responsible for their choices. However, it is worth noting the caution raised by Collins *et al.* (2021), who argue that while AI improves internal accountability, the complexity and opacity of some AI systems may limit external scrutiny, leading to a potential "black box" issue that could undermine transparency if not properly addressed.

Value for money, another performance indicator examined, was also positively associated with AI adoption. Technologies such as robotics and automation streamline procurement processes, reduce lead times, and support strategic sourcing—all of which contribute to better utilization of resources. These findings echo those of Perifanis and Kitsios (2023), who highlight that AI helps organizations align procurement with strategic goals while controlling costs and maximizing outcomes. In line with this, Waditwar (2024) emphasizes that AI enables more accurate supplier selection, minimizes procurement cycle times, and enhances quality assurance—all of which are critical in achieving value for money. However, as the descriptive statistics indicated, there is still variability in perceptions regarding the extent to which value for money is consistently realized, which may suggest uneven implementation or limited access to advanced AI tools.

The results also align with regional insights from Africa, where the potential of AI in public procurement has been increasingly recognized. Makongoro (2023) and Elhassan Gadour (2024) both point out that AI has the capacity to reduce corruption, promote transparency, and improve efficiency in public procurement across African nations. Tanzania, in particular, has made strides with systems like NeST, as noted by Ngowi and Moshi (2021), which integrate AI-driven functions such as real-time monitoring and automated compliance checks. However, the study highlights that while these technologies are promising, their full potential remains underutilized due to infrastructural, regulatory, and knowledge-related constraints. Addressing these gaps is vital to ensuring the scalability and sustainability of AI in procurement systems.

Therefore, this study confirms that Artificial Intelligence significantly enhances procurement performance at CBE Mbeya, particularly in strengthening transparency, accountability, and value for money. These findings are consistent with a growing body of academic and policy literature advocating for digital transformation in procurement. While the results are promising, they also point to the need for continuous investment in AI infrastructure, capacity building, and policy development to fully harness the benefits of these technologies. Future research should consider expanding the sample and incorporating longitudinal data to explore the long-term effects of AI adoption in procurement across various public institutions in Tanzania and beyond.

5.Conclusion

This study set out to examine the impact of Artificial Intelligence (AI) on procurement management performance at the College of Business Education (CBE) in Mbeya, with a focus on three key dimensions: transparency, accountability, and value for money. The findings clearly indicate that AI technologies—particularly machine learning, robotics, and process automation—positively influence procurement performance. Machine learning emerged as the most impactful, providing powerful data analytics and decision-support tools that enhance procurement planning, reduce fraud risks, and promote efficient resource use. Overall, the integration of AI has contributed to greater visibility, control, and traceability in procurement processes at CBE, reinforcing its potential to transform public procurement practices more broadly.

However, the study also uncovered areas requiring further attention. While AI's role in enhancing transparency and accountability was well-supported, the relatively lower mean scores in these variables from the descriptive statistics suggest that the perceived impact is not uniform across all respondents. This disparity may be attributed to differences in user familiarity with AI systems, limitations in infrastructure, or the partial adoption of AI tools. Furthermore, concerns about the complexity and opacity of AI-driven decisions—often referred to as the "black box" effect—raise questions about the transparency of the technologies themselves, even as they are used to make procurement more transparent. This calls for not only technological improvements but also user training and the establishment of clear guidelines on the use and oversight of AI systems in procurement.

Based on these findings, it is recommended that CBE and other public institutions investing in AI for procurement continue to expand their digital infrastructure, ensuring that AI tools are fully integrated and accessible across all departments. Training programs should be implemented to equip procurement staff with the knowledge and skills required to effectively utilize these tools. In addition, AI systems should be designed and managed in ways that allow for transparency in how decisions are made, including the documentation of algorithms and audit trails that can be reviewed by oversight bodies and stakeholders. Regular evaluation of AI performance should also be conducted to identify gaps and ensure alignment with procurement goals.

Lastly, policymakers and regulatory bodies should support the development of national standards and ethical guidelines for the use of AI in procurement. These frameworks should emphasize fairness, inclusiveness, and data protection, while also promoting innovation and continuous learning. Collaborative efforts between public institutions, academia, and technology providers can foster a more enabling environment for the responsible use of AI in procurement. Ultimately, as AI continues to reshape the procurement landscape, its success will depend not only on the tools themselves but also on the people, policies, and systems that guide their implementation and use.

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