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Artificial Intelligence Adoption and Procurement Performance of State Corporations in the Energy Sector, Kenya

Ericson M. Nyamamba*, Charles Ndeto
Department of Procurement and Logistics, Jomo Kenyatta University of Agriculture and Technology, Kenya
*Corresponding author email: nyamambaericson@gmail.com

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Abstract

The study examined the relationship between artificial intelligence adoption and the performance of state corporations in Kenya's energy sector. The specific objectives were to examine machine learning, computer vision, natural language processing, and expert systems. The study drew on institutional theory, the technology acceptance model, and RBV theory. This study employed a cross-sectional research design. The target population included 441 respondents from various departments, including users involved in procurement processes and other departmental functions in state corporations in Kenya's energy sector. The study used stratified sampling to obtain the sample. The data collected were analyzed using SPSS version 26. Data analysis included Descriptive statistics and regression analysis. The findings showed that the four independent variables jointly explained 82.8% of the variation in State Corporations' performance. The adjusted R-squared was 0.824, indicating that the model maintained substantial explanatory power after accounting for the number of predictors and sample size. The study found that adoption of natural language processing and expert systems had a positive and statistically significant relationship with organizational performance. Further, adoption of machine learning and computer vision had a positive but statistically insignificant relationship with the performance of State Corporations in the Energy Sector, Kenya. The study recommended that management invest in reliable, integrated procurement databases to support machine learning applications. Strengthen procurement personnel capacity through specialized training in data analytics and machine learning technologies. Management should invest in appropriate imaging technologies, automated scanning equipment and computer vision infrastructure. Integrate computer vision applications with inventory management and procurement information systems.

Keywords: *Artificial intelligence adoption, performance, machine learning, computer vision, natural language processing, expert systems.*

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1. Introduction

Procurement is the act of sourcing and purchasing goods, services, or raw materials for a business from vendors or suppliers. It includes every action involved in sourcing these goods or services, and an official procurement process helps purchasing teams request, approve, and track every purchase and control business spend. Regardless of size or industry, no business is entirely self-sufficient. Everyone relies on purchasing goods and services provided by third-party suppliers to maintain internal operations and/or manufacture products to sell (Blaney, 2025). Procurement involves not only deciding what to buy based on needs and budget, but also ensuring the company receives enough value from the purchase. We all do this ourselves. Any purchase you make depends on product quality, delivery time, the value you'll get, and many other factors (Blaney, 2025).

Global procurement is more than just buying goods and services from international suppliers. It's a complex, strategic process that involves sourcing, negotiating, and managing relationships across borders. At its core, global procurement aims to optimize a company's spending while accessing the best possible resources worldwide (Maliki, 2024). Governments worldwide spend approximately $13 trillion per year on public procurement. The goods and services provided are critical to delivering public services and infrastructure. Public procurement also promotes competition, innovation, and inclusive social and economic growth by providing a level playing field for suppliers. Unfortunately, public procurement is also one of a government's key risks for inefficiency, mismanagement and corruption (Open Data institute, 2024).

The global procurement market, estimated at $13 trillion annually according to research by the Open Contracting Partnership (OCP) and Spend Network, underscores the economic significance of this activity. 2 Notably, 77% of this market – more than $10tn, is spent by just 16 countries, with China leading at $4.2tn per annum, followed by the United States at $1.8tn. 14 other countries spend between $100bn and $1tn per annum. Disturbingly, the United Nations reports that approximately $1 trillion is paid in bribes and $2.6tn is lost to corruption each year. This enormous sum accounts for 5% of the global GDP. 3 A lack of transparency perpetuates this corruption, posing a significant obstacle to promoting competition, especially for small and medium-sized enterprises and underrepresented business enterprises. Good open procurement practices recommend that procurements are all open and openly published (Lindsey, 2024).

In America, improving procurement efficiency involves streamlining processes, reducing costs, and optimizing resource allocation through strategies like digitalization, data analysis, and fostering strong supplier relationships. Procurement in the United States is subject to the federal procurement statutes as implemented by the FAR and, where applicable, agency FAR (Federal Acquisition Regulation) supplements and other agency guidance. In negotiated procurements, an agency may publish pre-solicitation notices that provide a generalized description of the scope of the acquisition and that allow the agency to advise potential tenderers regarding their potential to be viable competitors. An agency may also limit the number of proposals eligible for award by establishing a "competitive range" composed of the most highly rated tenderers. Establishing a "competitive range" after an initial evaluation is the most common type of "short-listing" that occurs in federal procurement (McCullough, 2025).

In Africa, procurement functions are in for a challenging period as they grapple with inflation, geopolitical disruption, and global supply chain constraints. Soaring external spend is putting significant pressure on many companies' profit margins. After a prolonged period of low inflation and relatively easy access to goods and raw materials, many businesses-globally and in Africa-may find themselves ill-prepared for these challenges. Procurement organizations have mobilized to manage and optimize external spend, but too many have not exercised the necessary muscles recently, leaving their companies behind the global curve in adopting digital tools to drive procurement efficiency. Moreover, for the foreseeable future, procurement functions are likely to find it difficult to obtain the goods they need at historical cost (Laurent Sarda, and Marco Ziegler, 2022).

In Kenya, the public procurement system, while aiming for efficiency and value for money, faces challenges including corruption, lack of transparency, and inefficient processes, leading to potential losses and hindered service delivery. The implementation of e-GP system in Kenya has numerous benefits for both the government and suppliers. By digitizing procurement processes, the government can improve efficiency, transparency, and accountability while fostering a healthy competitive environment among suppliers. Moreover, e-GP system can improve supplier relationships and provide enhanced data analytics capabilities, leading to better-informed procurement decisions and ultimately better value for taxpayers' money (The National treasury, 2023).

1.1 Problem Statement

AI can add value to procurement and supply teams by enabling better decisions through analytics and data-driven insights. It can process vast amounts of data, helping teams uncover cost savings or opportunities they might otherwise miss. Despite the increasing adoption of AI technologies in various sectors, public procurement in Kenyan State corporations still faces challenges such as lack of transparency, poor supplier selection, inefficient resource allocation, supply disruption cases and contract management issues. AI can automate procurement tasks to improve productivity and reduce administrative burden, freeing procurement staff to focus on more strategic activities. AI can help cut the time it takes to complete basic procurement tasks by up to 80%, according to a 2023 KPMG study. The same research concludes that well over 50% of procurement labor can be automated to help increase efficiency and reduce cost. One commercial property developer reportedly uses AI to collect procurement data 92% faster compared to manual methods (Jackley, 2025). Despite the wealth of information generated, a critical examination reveals that these contributions, though substantial, have not adequately addressed the central issue. AI adoption in the public sector is largely driven by technical performance, but little is known about its effect on procurement performance. This gap highlights the need for a more focused and comprehensive investigation.

1.2 Research Objectives

1. To determine the relationship between machine learning adoption and the performance of state corporations in the energy sector in Kenya.
2. To examine the relationship between computer vision adoption and performance of energy sector state corporations in Kenya.
3. To establish the relationship between natural language processing adoption and the performance of energy sector state corporations in Kenya.

4. To assess the relationship between expert systems adoption and performance of energy sector state corporations in Kenya.

2. Literature Review

2.1 Theoretical Review

2.1.1 Technology Acceptance Model

Fred Davis developed the Technology Acceptance Model in 1986 as an adaptation of the Theory of Reasoned Action (TRA). It was specifically designed to model users' acceptance of information systems and technologies. TAM builds upon the TRA by incorporating two key constructs: perceived usefulness and perceived ease of use. The Technology Acceptance Model is a widely used framework that explains how users come to accept and use new technologies. It suggests that perceived usefulness and perceived ease of use are key factors influencing an individual's decision to adopt a technology (Malatji, 2020).

The Technology Acceptance Model offers a helpful framework for understanding how Nairobi City County's state companies want to implement e-payments as part of their e-procurement strategy. According to TAM, people are more likely to adopt and use these technologies if they believe they are useful and easy to use. Procurement personnel will likely adopt e-payments once they see how they can streamline financial transactions, reduce human error, and speed up processing. Future performance results will be shaped by attitudes toward technology, as seen in rising adoption that improves procurement operations' efficiency.

2.1.2 Resource-Based View

The RBV developed as a complement to the industrial organization (IO) view, with Bain (1968) and Porter (1979, 1980, and 1985) among its main proponents. In the company's resource-based (RBV) perspective, intangible knowledge-based assets serve as a source of competitive advantage as they tend to be unique to the company, hard to copy, and culturally integrated. Resources are regarded as strategic in the RBV and are a source of competitive advantage if they provide economic value, are distinctive (uncommon), are hard to copy (inimitable) and have organizational assistance (Chungu, 2022).

In many different but overlapping methods, strategic resources have been categorized. While some classified these as physical, natural, and capital, others added categories of technological and reputational resources and some proposed proprietary (or tangible) rather than knowledge-based (or intangible) resources. While concrete resources allow a company to carry out its business processes, it is the intangible, knowledge-based resources that are more likely to serve as sources of competitive advantage because they enable businesses to integrate precious, rare and inimitable practices into their fabric and have organizational support (Beamish, 2021). This theory is important to this study because it recognizes AI as a key internal resource that can position the company above its competitors, helping it gain a competitive edge in the market.

2.1.3 Institutional Theory

DiMaggio and Powell proposed this hypothesis in 1983. Institutional theory aims to explain why organizations act similarly, as they pointed out. This theory distinguishes three institutional pillars: normative, cultural, and regulatory. In order to ensure compliance, the regulatory pillar places a strong emphasis on using laws, regulations, and penalties as enforcement tools (Hoefer, 2022).The normative pillar, which serves as the foundation for

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compliance, outlines the standards and actions that must be followed, as well as the values (desired or preferred) that must be upheld and societal obligations. Lastly, the cultural-cognitive pillar is based on shared perceptions, symbols, and ideas that support mutual understanding. Institutional theory is particularly relevant to public administration because it provides a framework for understanding the complex interactions among government agencies, policies, and societal outcomes. By examining the institutional context in which public administration operates, researchers and practitioners can gain insights into the factors that shape policy implementation, organizational behavior, and service delivery (Borges, 2021).

Institutional theory is criticized primarily for being too rigid, which makes it difficult to understand the dynamics of institutional change; for failing to adequately understand the role of power in institutions; for simplifying more complex social processes by emphasizing conformity to other norms at the expense of people's and groups' agency to challenge or reform institutions; and for providing an explanation that is frequently too general, losing sight of its own central ideas and possibly overlooking subtleties in some situations. Institutional theory fits this study because it explains the adoption of AI as an organizational policy that all stakeholders must follow.

2.2 Conceptual Framework

A conceptual framework synthesizes interrelated components and variables that help solve a real-world problem (DeMarco, 2020).

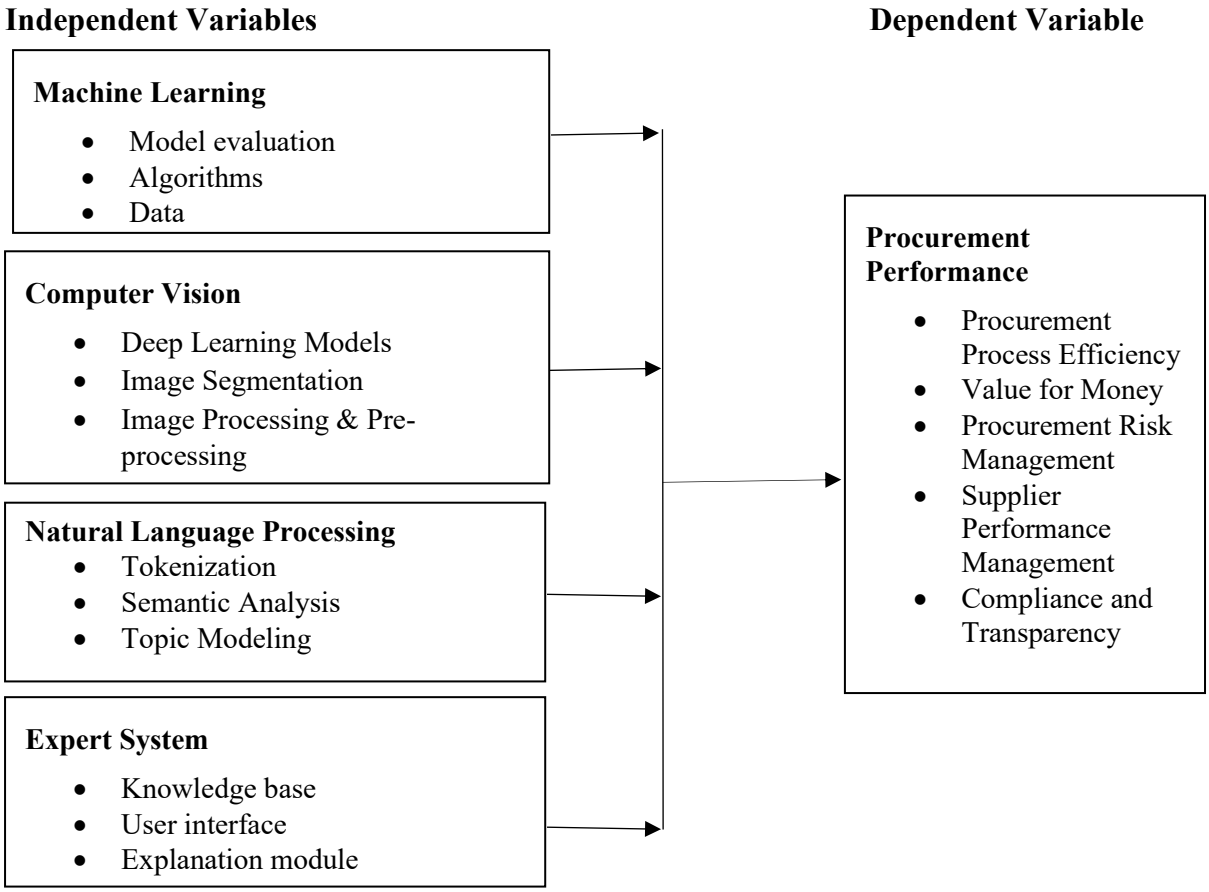


Figure 1: Conceptual framework

2.3 Empirical Review

A study by Vahermo (2023) examined the current advantages and challenges of using machine learning in purchasing and procurement procedures. In addition to a theoretical analysis of procurement and machine learning based on current industry and academic resources, the study conducted empirical research by interviewing eight participants from a single firm. The interviews aimed to identify inefficiencies in current procurement procedures, pinpoint tasks where information systems could help, and evaluate machine learning's ability to address these problems. In domains like pricing, cost analysis, and material need forecasts, participants saw significant promise for machine learning. Nevertheless, the study also identified important challenges, including low data quality, overwhelming data volumes, and data traceability issues. Unreliable forecasting and poor levels of process automation were further issues. The results indicate that machine learning has promising applications that could greatly improve purchasing and procurement activities, despite these obstacles.

Villegas-Ch, Maldonado Navarro and Sanchez-Viteri (2024), in their study titled *Optimization of Inventory Management through Computer Vision and Machine Learning Technologies*, examined the application of computer vision and machine learning technologies in improving warehouse inventory management. The study developed and evaluated a computer vision platform that utilized convolutional neural networks to recognize and classify products from real-time images. The findings established that the system reduced inventory counting time by 45%, improved stock efficiency by 50% and increased inventory accuracy by 9%. Additionally, overcounting errors declined by 67%, while undercounting errors declined by 85%. The study demonstrated that computer vision enhances inventory accuracy, minimizes manual intervention and improves operational efficiency. These findings provide empirical support for applying computer vision to improve inventory management and procurement performance.

Kumar and Agrawal (2024), in their study titled *A Quality-Based Sustainable Supply Chain Architecture for Perishable Products Using Image Processing in the Era of Industry 4.0*, examined image processing and machine learning to improve quality-based supply chain management. The study proposed an integrated architecture that uses image processing techniques to assess and classify product quality. The findings demonstrated how visual data could support decisions relating to procurement, pricing, storage and transportation. The study highlighted the importance of image-based product assessment in supporting informed supply chain decisions. These findings are relevant to procurement performance because computer vision can facilitate objective product inspection, minimize the acceptance of substandard supplies and improve quality assurance during goods receipt.

A study by Lawson (2022) explores how NLP affects trust and Customer Relationship Management, offering a comprehensive framework that fills important research gaps. Few empirical studies have examined the practical uses of NLP across sectors, even though it is extensively discussed across disciplines. By examining how traditional consumer engagement methods often lead to misunderstandings and higher language-processing costs, our study fills this gap. The study presents methods designed to reduce human error and promote multi-level trust in customer interactions. By separating positive and negative opinions of NLP tools using sentiment polarity analysis, the study assesses how NLP might improve CRM systems using a sentiment analysis-driven literature review. The authors offer a comprehensive paradigm that links CRM and trust to the three pillars of artificial intelligence: machine learning, deep

learning, and natural language processing. Hadoop systems and data warehouses are examples of data infrastructure components that enable this paradigm. The paper ends with theoretical and practical suggestions and urges more research to use statistical techniques to validate the framework empirically.

3. Methodology

This study employed a cross-sectional research design. The target population included 441 respondents from various departments, including users involved in procurement processes and other departmental functions in state corporations in Kenya's energy sector. The study used stratified sampling to determine the sample size. Primary data was the main source of the study's data, which was collected using questionnaires. The study conducted pilot testing to establish the data collection instrument's reliability and validity. The data collected were analyzed using SPSS version 26. Descriptive statistics summarized and organized the dataset characteristics, presented as means and standard deviations. Regression analysis was used to establish relationships between the study variables.

4. Results and Discussion

4.1 Descriptive Analysis of Variables

4.1.1 Machine learning

Table 1 summarizes the findings.

Table 1: Descriptive analysis for Machine learning

Statement	Mean	Std. Dev
ML reduces human errors in procurement performance.	3.77	1.007
ML supports data-driven inventory management decisions.	4.23	1.039
ML tools are integrated into the procurement process for efficiency.	4.35	0.944
ML helps predict future procurement needs.	3.82	1.024
ML identifies potential supply chain disruptions.	3.92	1.045
ML systems are transparent and explainable for compliance.	3.75	0.996
The organization invests in ML technologies for procurement improvement	4.25	1.100
Aggregate Score (Overall Perception)	**4.01**	**1.022**

On average, values across all indicators were 4.01 (SD = 1.022), suggesting a generally favorable perception of machine learning's role in procurement processes. These findings were in tandem with those of (Vahermo, 2023) investigated the present advantages and difficulties of using machine learning in purchasing and procurement procedures. In addition to a theoretical analysis of procurement and machine learning based on current industry and academic resources, the study conducted empirical research by interviewing eight participants from a single firm. The results indicate that machine learning has interesting applications that might greatly improve purchasing and procurement activities, despite these obstacles.

4.1.2 Computer Vision

The table below shows the results for risk management responses.

Table 2: Descriptive analysis for Computer Vision

Statement	Mean	Std. Dev
Computer vision reduces delays in delivery and distribution.	4.35	1.010
Computer vision improves real-time inventory tracking.	3.90	0.828
Computer vision enables automated stock counting and reporting	3.94	0.842
Computer vision improves the accuracy of product quality inspection	4.15	1.083
Computer vision enhances visibility across the supply chain.	3.86	0.916
Computer vision reduces wastage and losses in inventory handling	3.97	0.923
Computer vision identifies anomalies in supply chain operations.	3.74	1.264
Computer vision provides real-time data for better decision-making	4.85	0.359
Overall Perception	**4.09**	**0.89**

The overall aggregate mean score of 4.09 and standard deviation of 0.89 suggest a high level of agreement among respondents regarding the contribution of computer vision to procurement performance. The findings align well with Cannas et al. (2024), in their study titled Artificial Intelligence in Supply Chain and Operations Management: A Multiple Case Study Research, which investigated how artificial intelligence applications support supply chain and operations management. The researchers adopted a multiple-case study design involving six companies and 17 AI implementation cases, using semi-structured interviews to collect data. The findings established that AI applications contributed to reduced operational costs and lead times, improved service delivery, quality, safety and sustainability. Of particular relevance to computer vision, the study identified visual inspection applications used in manufacturing quality control. These applications enabled automated assessment of product quality and reduced dependence on repetitive manual inspections. The study shows how computer vision-supported inspection can strengthen quality assurance and operational efficiency, key components of procurement performance.

4.1.3 Natural Language Processing

Table 3 summarizes the descriptive results.

Table 3: Descriptive analysis for Natural language processing

Statement	Mean	Std. Dev
NLP improves accuracy in document analysis and data extraction	4.26	0.967
NLP improves communication between the organization and suppliers	3.89	0.926
NLP enhances efficiency in contract management.	3.97	0.926
NLP improves forecasting and planning through data analysis	3.90	0.894
NLP helps detect risks in procurement contracts and communications	4.23	1.028
NLP enhances monitoring of supplier compliance	4.84	0.370
NLP reduces human bias in procurement decisions	4.85	0.354
Aggregate Score (Overall Perception)	**4.28**	**0.780**

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The aggregate mean score of 4.28 and standard deviation of 0.780 indicate strong agreement among respondents regarding NLP's contribution to procurement processes. The range for this matrix was 4.00, while the minimum and maximum values were 1.00 and 5.00, respectively. These findings suggest that natural language processing can strengthen transparency, accuracy, accountability and efficiency in procurement operations within state corporations in Kenya's energy sector.

4.1.4 Expert Systems

The results are shown in Table 4 below:

Table 4: Descriptive Statistics for Expert Systems

Statement	Mean	Std. Dev
Expert systems assist in evaluating procurement alternatives.	4.33	1.013
Expert systems help in predicting future procurement results	4.02	0.881
Expert systems support data-driven decision-making.	4.04	0.899
Expert systems improve supplier selection decisions.	4.26	0.944
Expert systems improve risk assessment in procurement processes	3.89	0.878
Expert systems provide transparent and explainable decisions.	4.83	0.469
Expert systems reduce procurement cycle time	4.74	0.552
Aggregate Score (Overall Perception)	**4.30**	**0.81**

The standard deviations ranged from 0.469 to 1.013, indicating varying levels of dispersion in respondents' opinions. The relatively low standard deviations for transparency and explainability (0.469) and reduction of procurement cycle time (0.552) suggest strong consensus among respondents. Conversely, the higher standard deviation for evaluating procurement alternatives (1.013) indicates relatively greater variation in respondents' perceptions.

4.1.5 Procurement Performance of State Corporations in the Energy Sector, Kenya

Table 5 provides descriptive data for the performance indicators.

Table 5: Descriptive analysis for Procurement Performance of State Corporations in the Energy Sector, Kenya

Statement	Mean	Std. Dev
The organization consistently achieves its operational targets	3.97	0.837
Internal processes are regularly reviewed to improve efficiency	4.24	0.971
The organization consistently achieves its established strategic objectives.	3.88	0.883
The organization demonstrates accountability in the use of public resources.	4.09	1.097
The organization has the capacity to sustain its operations in the long term	4.83	0.374
The organization has improved productivity in its core operations.	4.83	0.457
The organization has successfully implemented its strategic plans.	4.77	0.495
Aggregate Score (Overall Perception)	**4.37**	**0.730**

The findings indicate that state corporations in Kenya's energy sector generally demonstrate a high level of organizational performance, as reflected in the aggregate mean score of 4.37 and a standard deviation of 0.730. This suggests that respondents generally agreed that their organizations perform well in achieving operational efficiency, strategic objectives, accountability, productivity and sustainability. The relatively low aggregate standard deviation further indicates considerable consistency in respondents' perceptions of organizational performance.

4.2 Multiple Linear Regression

4.2.1 Model summary

This Model Summary table presents the overall fit of the multiple regression model predicting PERFMG using CRMS, SRMGS, RISKM, and SOURCS as predictors.

Table 6: Model Summary

Model	R	Rsquare	Adjusted R Square	Std.Error of the Estimate
1	.910a	.828	.824	.20016

a. Predictors: (Constant), EXPS, NULP, MLearn, COMV

The model summary presents the results of a multiple regression analysis examining the relationship between the independent variables (EXPS, NULP, MLearn and COMV) and the dependent variable, organizational performance of State Corporations in the Energy Sector, Kenya. The results indicate a correlation coefficient (R) of 0.910, suggesting a very strong positive relationship between the combined independent variables and organizational performance. The coefficient of determination (R-square) is 0.828, indicating that the four independent variables jointly explain 82.8% of the variation in the performance of State Corporations in the Energy Sector, Kenya. This implies that the model has substantial explanatory power in predicting organizational performance.

The adjusted R Square is 0.824, meaning that after adjusting for the number of predictors included in the regression model and the sample size, the independent variables explain approximately 82.4% of the variations in organizational performance. The small difference between R Square (0.828) and Adjusted R Square (0.824) suggests the model is stable and that including the four predictors does not substantially inflate its explanatory power. Furthermore, the standard error of the estimate is 0.20016, indicating that the observed organizational performance values deviate from the values predicted by the regression model by approximately 0.20016 units. This suggests a relatively small prediction error, although its practical significance depends on the dependent variable's measurement scale.

4.2.2 ANOVA tests

Table 7 shows the results.

Table 7: ANOVA

Model		Sum of squares	Df	Mean Square	F	Sig
1.	**Regression**	34.747	4	8.687	216.827	.000[b]
	Residue	7.211	180	.040		
	Total	41.958	184			

a. Dependent Variable: PERF
b. Predictors: (Constant), EXPS, NULP, MLearn, COMV

The Analysis of Variance (ANOVA) results establish whether the multiple regression model examining the relationship between EXPS, NULP, MLearn and COMV and the performance of State Corporations in the Energy Sector, Kenya (PERF) is statistically significant.

The results indicate an F-statistic of 216.827 with 4 and 180 degrees of freedom, respectively, and a significance level of $p = 0.000$ ($p < 0.001$). This demonstrates that the overall regression model is statistically significant at the 5% level and reliable. The F-statistic of 216.827 indicates that the variation in organizational performance explained by the regression model is substantially greater than the unexplained variation. Consequently, the four independent variables jointly have a statistically significant relationship with the performance of State Corporations in Kenya's energy sector.

4.2.3 Coefficients Table (Regression Model)

Table 8 shows the p-value results.

Table 8: Regression Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	T	Sig
	B	Std Error	Beta		
1(Constant)	1.335	.149		8.980	.000
MLearn	.085	.048	.153	1.788	.075
COMV	.059	.069	.088	0.856	.393
NULP	.433	.079	.523	5.516	.000
EXPS	.140	.065	.174	2.152	.033

a. Dependent Variable: PERF

The results indicate that MLearn has a positive but statistically insignificant relationship with the performance of State Corporations in the Energy Sector, Kenya ($B = 0.085$, $\beta = 0.153$, $t = 1.788$, $p = 0.075$). This implies that a unit increase in MLearn is associated with a 0.085-unit increase in organizational performance, holding other variables constant. However, since the p-value of 0.075 exceeds the 0.05 significance threshold, the relationship is not statistically significant. Therefore, MLearn does not independently provide sufficient statistical evidence of an effect on organizational performance at the 5% significance level.

COMV also demonstrates a positive but statistically insignificant relationship with organizational performance (B = 0.059, β = 0.088, t = 0.856, p = 0.393). This suggests that a unit increase in COMV is associated with a 0.059-unit increase in organizational performance, holding other variables constant. However, the p-value of 0.393 is greater than 0.05, indicating that the relationship is not statistically significant. This implies that COMV does not independently make a statistically significant contribution to explaining organizational performance within the estimated regression model.

On the other hand, NULP has a positive and statistically significant relationship with organizational performance (B = 0.433, β = 0.523, t = 5.516, p less than 0.001). This indicates that a unit increase in NULP is associated with a 0.433-unit increase in organizational performance, holding other variables constant. The standardized coefficient (β = 0.523) further demonstrates that NULP has the strongest relative contribution among the four independent variables. This suggests that improvements in NULP are particularly important in explaining variations in the performance of State Corporations in the Energy Sector, Kenya.

Similarly, EXPS demonstrates a positive and statistically significant relationship with organizational performance (B = 0.140, β = 0.174, t = 2.152, p = 0.033). This implies that a unit increase in EXPS is associated with a 0.140-unit increase in organizational performance, holding other variables constant. Since the p-value of 0.033 is below 0.05, the relationship is statistically significant. The findings suggest that EXPS makes a meaningful independent contribution to explaining organizational performance.

5. Conclusion

The study concludes that machine learning adoption has a positive but statistically insignificant relationship with the performance of State Corporations in Kenya's energy sector. Although respondents generally recognized the usefulness of machine learning in forecasting, inventory management, procurement planning and identifying supply chain disruptions, the regression results did not establish a statistically significant independent relationship.

The study concludes that computer vision adoption has a positive but statistically insignificant relationship with organizational performance. Although computer vision was positively perceived in relation to inventory monitoring, quality inspection, stock counting and operational visibility, its independent contribution was not statistically significant.

The study concludes that natural language processing has a positive and statistically significant relationship with the performance of State corporations in the Energy Sector. Natural language processing emerged as the strongest predictor among the four AI technologies examined. Its ability to facilitate automated document analysis, contract processing, supplier communication, information extraction and compliance monitoring makes it an important technology for enhancing procurement performance.

The study concludes that expert systems have a positive and statistically significant relationship with the performance of State Corporations in Kenya's energy sector.

The findings demonstrate that expert systems provide important decision-support capabilities that can strengthen procurement planning, supplier evaluation, risk assessment and the consistency of procurement decisions. The study therefore concludes that expert systems are valuable technological resources for improving organizational performance.

6. Recommendations

Management should invest in reliable, integrated procurement databases to support machine learning applications. Strengthen procurement personnel capacity through specialized training in data analytics and machine learning technologies.

Management should invest in appropriate imaging technologies, automated scanning equipment and computer vision infrastructure. Integrate computer vision applications with inventory management and procurement information systems.

State Corporations in the Energy Sector, Kenya, should prioritize the strategic implementation of these technologies in procurement activities. The study recommends that State Corporations in the Energy Sector, Kenya, invest in natural language processing technologies to automate the analysis of procurement documents, tender documents, and supplier contracts. Procurement departments integrate NLP applications into contract management systems to improve the identification of contractual obligations, risks and compliance requirements.

State Corporations in the Energy Sector, Kenya should strengthen the use of expert systems in procurement decision-making. The study recommends that State Corporations in the Energy Sector, Kenya develop and implement expert systems with comprehensive knowledge bases covering procurement policies, procedures, regulations and organizational requirements.

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