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Artificial Intelligence Technologies and Process Efficiency in the Banking Industry: A Case Study of Selected Commercial Banks in Kenya

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Abstract

Banks are increasingly integrating Artificial Intelligence (AI) technologies in their processes and systems to streamline operations, reduce manual effort, and enhance accuracy in transactions. While AI is expected to improve key process efficiency metrics, such as transaction turnaround time, decision-making speed, process error rate, and overall process cost, the actual impact of AI on these specific performance indicators remains underexplored in Kenya's banking industry. Thus, this research examined the impact of AI technologies on process efficiency in selected commercial banks in Kenya. The study applied the technology acceptance model, the resource-based view, and the diffusion of innovation theory. The key independent variables: machine learning, robotic process automation, natural language processing, and predictive analytics, were analyzed in relation to process efficiency. The target population comprised the 38 commercial banks in Kenya. The sampling frame was Equity Bank, KCB, Cooperative Bank, NCBA, and Standard Chartered Bank branches in Nairobi County. The unit of analysis encompassed the banks' branch managers and IT managers, selected via purposive sampling. The sample size was 192 participants. Data was collected using closed-ended questionnaires, with a pilot study involving 19 participants to ensure the validity and reliability of the instruments. Statistical analysis was conducted using SPSS, and findings were presented in tables. Ethical standards were adhered to throughout the study. The findings showed that machine learning, robotic process automation, natural language processing, and predictive analytics impacted process efficiency in varying magnitudes. All the four regression coefficients were statistically significant at $p<0.05$. Robotic process automation had the most significant impact on process efficiency while predictive analytics had the least significant impact. The results of the correlation analysis showed a positive, statistically significant, and strong correlation between each of the four independent variables and process efficiency. The study concluded that AI technologies significantly impacted process efficiency in the selected commercial banks in Kenya. The findings underscored the importance of incentivizing the investment in AI technologies in Kenya's banking industry. Future studies could explore associations underpinning other AI technologies and process efficiency metrics.

Keywords: Process efficiency, artificial intelligence, machine learning, robotic process automation, natural language processing, predictive analytics

1. Introduction

AI technologies refer to tools, algorithms, and systems derived from artificial intelligence, which are applied to perform and automate complex functions (Gyau et al., 2024). These technologies vary in complexity and scope but share a common goal: to increase efficiency, reduce human error, and enhance decision-making capabilities. In the banking sector, the adoption of AI tools has been gaining momentum, particularly in areas related to customer service, fraud detection, risk assessment, and operational efficiency (Mishra, 2025). Among the most commonly, used AI tools in banking are Machine Learning (ML), Robotic Process

Automation (RPA), Natural Language Processing (NLP), and Predictive Analytics. ML is a subset of AI that involves training algorithms to learn from data and improve performance without being explicitly programmed (Sarker, 2021). In banking, ML is widely applied in credit scoring, transaction monitoring, fraud detection, and personalized product offerings. For example, ML algorithms can quickly analyze customer data to assess loan eligibility, detect anomalies in financial transactions, or forecast future customer behavior (Pattnaik et al., 2024). RPA refers to the use of software robots or "bots" to automate repetitive and rule-based tasks traditionally performed by humans. In commercial banks, RPA is commonly used to streamline operations such as data entry, customer onboarding, compliance checks, and report generation (Papa, 2022). This not only accelerates task completion but also reduces operational costs and minimizes the risk of human error. NLP is an AI technique that enables machines to understand, interpret, and generate human language. In the banking sector, NLP is employed in chatbots, virtual assistants, automated email responses, and the analysis of customer feedback (Du et al., 2025). These applications improve customer engagement and support by enabling real-time, conversational interactions between banks and clients. Lastly, predictive analytics combines AI, statistics, and data mining to analyze current and historical data to make informed predictions about future events. In banking, predictive analytics is used to forecast loan defaults, assess credit risks, anticipate customer needs, and optimize marketing campaigns (Broby, 2022). By providing insights into likely outcomes, this tool allows banks to act proactively and improve strategic decision-making.

Process efficiency refers to the effectiveness with which an organization uses its resources, such as time, labor, and technology, to achieve desired outcomes with minimal waste or delay. It has become a strategic imperative for banks across the world in today's fast-paced and digitally driven global economy (Mbecca, 2022). In business operations, especially within service industries like banking, process efficiency is essential for maintaining competitiveness, improving customer satisfaction, and reducing operational costs. Efficient processes streamline workflows, minimize redundancies, and ensure that tasks are completed accurately and quickly (Ghertescu et al., 2024). Process efficiency in the banking sector today heavily relies on the integration of Artificial Intelligence (AI) technologies in the banks' processes and operations. Key indicators of process efficiency in the banking industry include the cost-to-income ratio, return on assets (ROA), loan processing time, and customer turnaround time (Itumo, 2013). According to Mwaura, Yaanga & Ruto (2018), process efficiency also includes metrics, such as transaction turnaround time, error rate reduction, the number of customers served per day, and improvements in service speed following IT adoption. Thei integration of AI technologies into banking systems holds the potential to enhance process efficiency by improving speed, accuracy, consistency, and scalability in service delivery. As Kenyan commercial banks continue to invest in digital transformation, it is crucial to assess the specific impact these AI technologies have on process efficiency.

1.2 Statement of the problem

The contemporary financial landscape is rapidly evolving, and commercial banks are under increasing pressure to improve process efficiency, reduce costs, and enhance customer experience in order to remain competitive and compliant with dynamic regulatory requirements (CBK, 2021). Traditional banking processes that are often characterized by manual operations, lengthy turnaround times, and susceptibility to human error are proving inadequate in meeting the demands of modern banking. As a result, many banks globally are turning to AItechniques and technologies such as Machine Learning (ML), Robotic Process Automation (RPA), Natural Language Processing (NLP), and Predictive Analytics (PA) to automate and optimize their processes (Marouf & Ibrahim, 2021; Jordan & Mitchell, 2015). In Kenya, leading commercial banks such as Equity Bank, KCB, and NCBA have already begun integrating AI technologies to enhance service delivery, risk assessment, and decision-making (Gitau & Omwenga, 2020). While AI is expected to enhance key operational metrics, such as transaction turnaround time, decision-making speed, process error rate, and overall process cost, there is limited information on the actual impact of AI technologies on performance metrics in the local banking context (Gikunda & Mwirigi, 2021). Besides, many commercial banks in Kenya still experience operational inefficiencies that raise questions about the effectiveness of these AI technologies in achieving the desired outcomes; e.g., long transaction turnaround times, delays in decision-making, high error rates in data processing, and persistent operational costs continue to challenge banks even after AI implementation (Wainaina, 2022; CBK, 2021). This discrepancy points to a critical gap between AI adoption and measurable process efficiency. Moreover, most existing research on AI's impact tends to focus on global or developed market contexts, where infrastructure, regulatory frameworks, and digital maturity are significantly more advanced (PwC, 2020; McKinsey & Company, 2021). There is need for a context-specific study to evaluate the actual impact of AI technologies on several dimensions of process efficiency in Kenya's banking sector. Therefore, this study seeks to bridge this knowledge gap by examining the impact of AI technologies on process efficiency in selected commercial banks in Kenya.

1.3 Objectives of the Study

i. To determine the impact of machine learning on process efficiency in selected commercial banks in Kenya.
ii. To determine the impact of robotic process automation on process efficiency in selected commercial banks in Kenya.
iii. To determine the impact of natural language processing on process efficiency in selected commercial banks in Kenya.
iv. To determine the impact of predictive analytics on process efficiency in selected commercial banks in Kenya.

2. Review of Literature

2.1 Theoretical Review

Technology Acceptance Model

The technology acceptance model (TAM) was proposed by Fred Davis in 1986 to explain how perceived usefulness and perceived ease of use underpin the adoption and utilization of innovations by individuals or organizations. Perceived usefulness refers to the extent to which entities believe that a certain technology will improve the quality of performance outcomes (Kabir et al., 2022). Perceived ease of use is the extent to which users believe that utilization of a particular technology will not consume much effort or resources (Alsyouf et al., 2023). The theory was pertinent to this study as it guided the understanding of the extent to which commercial banks perceived AI technologies as useful, user-friendly, and compatible with existing workflows.

The Resource-Based View Theory

Jay Barney put forward the Resource-based View (RBV) theory in 1991 to pinpoint the place of strategic resources in a firm's competitiveness. The resources that make a firm competitive are only those that are valuable, rare, inimitable, and non-substitutable. A firm that creates a proper blend of resources can significantly improve its performance and competitiveness (Samole, 2014). AI technologies are considered as strategic resources, and the banks' abilities to integrate AI into their operations and systems can be seen as unique internal strengths that improves process efficiency (Ali &Aysan, 2025). This study used the RBV to explain why some commercial banks derive more efficiency benefits from AI technologies than others, based on their capacity to acquire, develop and deploy AI technologies more effectively.

The Diffusion of Innovation Theory

Everest Rodgers introduced the Diffusion of Innovation (DOI) theory in 1962 to explain the reason and speed, at which technologies develop, evolve and gain momentum in a particular system. DOI proposes five adopter categories, which affect the spread of innovations, depending on the category that has the majority of entities. The first category includes innovators who want to be the first to try out the technology. The second category includes early adopters who are the opinion leaders. The third category is the early majority who want to see evidence that the technology works before adopting it. The fourth category is the later majority who will only adopt the technology after it has been tried by the majority; and the fifth majority comprise the laggards who are very conservative (Kaiser et al., 2025). This study used DOI to assess the commercial banks' levels of digital maturity and readiness to invest in AI technologies.

2.2 Empirical Review

Machine Learning and Process Efficiency

Buchanan & Wright (2021) studied the impact of ML on UK financial services. The researchers adopted a qualitative research approach and collected secondary data from publications in the UK financial services sector. The study found that the use of machine learning in the UK's banking and financial services sector grew notably after the COVID-19 pandemic, alongside the rise of mobile money, digital currencies, and cashless payment systems. The results further showed that adoption of ML significantly improved operational efficiency in the UK financial services sector, as banks were able to handle the increased volume of customer inquiries. The speed and volume of processed loan applications also significantly increased because of integration of ML in the financial services sector. This study presents a contextual gap since it focused on the UK financial services sector while the present study focused on selected commercial banks in Kenya.

Similarly, Pattnaik, Ray, and Raman (2024) explored how AI and ML are applied within the financial services industry. The researchers used a bibliometric review approach and analyzed 1045 articles published in an array of journals, and identified 177 unique terms in the articles. The findings showed that the financial services industry had experienced significant transformations following the adoption of ML and AI. Notably, the study did not focus on any particular context and did not evaluate the impact of ML in the financial services industry. This study used a correlational design to examine how ML influences process efficiency in selected commercial banks in Kenya.

Furthermore, Frank & Lebron (2024) examined the effect of ML on operational efficiency of Nigerian banks. The researchers used a descriptive survey design and a qualitative research approach. The study relied on secondary data collected from publications in Nigeria's financial services and banking sectors. The findings suggested that ML had significantly improved operational efficiency of the banks by reducing costs, speeding transactions, improving the quality of customer service, and improving accuracy. There is both a methodological and contextual gap in the study. The current study adopted a quantitative approach and collected primary data via questionnaires from employees of selected commercial banks in Kenya.

Finally, Mbeca (2022) investigated how AI influences competitive advantage in the Kenyan banking sector, with a focus on Absa Bank. The research adopted a causal study design, and a quantitative approach on the impacts of AI on competitive advantage. The study targeted all the 42 ABSA branches in Nairobi. The research sample was 171 participants encompassing branch managers, IT managers and operational managers of the banks, who were selected via stratified random sampling. The findings indicated a significant and positive correlation between ML and competitive advantage. There is a contextual and conceptual gap in the study. The current study focused on several commercial banks and used process efficiency as the dependent variable.

Robotic Process Automation and Process Efficiency

Villar & Khan (2021) studied the application and impact of RPA in the banking industry. The researchers adopted a case study design, and used Deutsche Bank, Germany as the study area. Primary data was collected via interviews from the bank's executives. The findings indicated that RPA had improved the bank's operational efficiency. This research focused on selected commercial banks in Kenya, and measured the impact of RPA on process efficiency.

In addition, Alassuli (2025) examined how RPA influences the efficiency of internal audit operations in selected commercial banks in Jordan. The study adopted a descriptive survey approach and targeted 12 commercial banks' employees who were directly involved in processes that utilized RPA. The sample size was 480 workers who were selected via systematic random sampling. The researcher administered questionnaires via Google Forms. Statistical analyses found that RPA significantly enhanced internal audit operations by reducing human errors, minimizing the cost of operations, improving real-time risk management, and easing work processes. The current study focused on selected commercial banks in Kenya.

Furthermore, Mohamed (2023) probed the impact of RPA adoption on productivity in the Egyptian banking sector. The researcher utilized case study approach and used Misr Bank. The sample size was 380 employees drawn from various departments of the bank. Stratified random sampling was applied, and the demographic characteristics of the respondents analyzed. Questionnaires were issued to the participants. The results showed that RPA adoption improved productivity at the bank, by reducing errors and speeding up transactions. The present study focused on Kenya's banking sector, and used process efficiency as the dependent variable.

Lastly, Iyamu & Mlambo (2023) examined the adoption of RPA in a South African bank, pseudo-named Misuzulu bank. 12 employees of the bank were issued with semi-structured questionnaires to complete and return. The study identified five factors that hindered the adoption of RPA in the bank: systems integration, modern IT solutions, business requirements, implementation and usage, and the functions of RPA. While RPA was yet to be fully mainstreamed in the bank, the results showed that addressing those prohibitive factors would improve adoption. Contextual, conceptual and methodological gaps emerged. The current study adopted a correlational design, focused on Kenya's commercial banks, and measured the impact of RPA on process efficiency.

Natural Language Processing and Process Efficiency

Gurung and Parajuli (2024) investigated how chatbots affect operational efficiency in Nepal's banking sector. The study embraced a quantitative methodology and collected data via questionnaires from 400 participants working in the Nepalese banking sector. The study concluded that adopting chatbots in Nepal's banking sector greatly improved customer satisfaction, operational efficiency, and the overall banking experience. The analysis further revealed that when chatbots effectively meet customer expectations, satisfaction levels increase, underscoring the importance of aligning chatbot capabilities with customer needs. The current study tackled the impact of NLP on process efficiency in selected commercial banks in Kenya.

Similarly, Boukhelifa & Merabet (2024) examined role of NLP in automating regulatory compliance and legal risk management in 17 Algerian banks. The researchers used an experimental design. The results showed that NLP utilization significantly improved accuracy in the extraction of regulatory requirements, and precision in detection of compliance violations. Overall, the NLP framework showed significant improvements of traditional rule-based systems. There is a contextual and methodological gap in the study. The present study used a correlational research design to determine the impact of NLP on process efficiency in selected commercial banks in Kenya.

Additionally, Adejuwon & Unesiri (2024) studied the impact of NLP on financial performance of Deposit Money Banks (DMBs) in Nigeria. The researchers relied on secondary data of 27 DMB banks for the years ranging from 2015 to 2023. Nonprobability and convenience sampling techniques were used. The data was interpreted using thematic content analysis. The findings showed that the adoption of NLP positively affected the financial performance of the DMB Banks, although the results were not statistically significant. The current study sought to provide a clearer picture by evaluating the impact of NLP on process efficiency of selected commercial banks in Kenya.

Lastly, Edibo, Dibua & Edokobi (2025) studied the role of AI technologies in the optimization of business processes in sampled Nigerian banks. The study utilized a descriptive research approach, targeting 1,399 personnel. 311 respondents were selected using the Taro Yamane sampling formula. A structured questionnaire was used for data instrumentation. The findings revealed that AI tools have a significant and positive impact on enhancing operational efficiency in commercial banks. A contextual gap emerged in the study, which was covered in the current research.

Predictive Analytics and Process Efficiency

Broby (2022) studied the use of predictive analytics in finance. The researcher used multiple search engines to conduct a broad literature review of 187 papers. A major finding was that in the financial sector, predictive analytics is commonly understood as the process of detecting irregularities and making forecasts with computational models based on collected and processed data. These methods are becoming more integrated into information systems (IS), which strengthens

management's capacity to anticipate future trends and make informed decisions. The present study specifically focused on the impact of predictive analytics on process efficiency in Kenya's commercial banks.
Similarly, Aro (2024) examined the use of predictive analytics in financial management, with a particular focus on risk management and enhancing decision-making. The study relied on secondary data by highlighting case studies of several firms that had utilized predictive analytics to improve risk mitigation and financial performance. The findings showed that the effective integration of predictive analytics in financial management significantly improves risk assessment, decision-making capabilities and overall financial performance. It is noteworthy that the study did not show the impact of predictive analytics on a specific dependent variable in the banking sector. Therefore, this study demonstrated how predictive analytics influences process efficiency in Kenya's commercial banks.
Furthermore, Ekundayo et al. (2024) investigated the use of predictive analytics in cyber threat intelligence within the FinTech sector, drawing on machine learning and big data. The researcher used a descriptive research design to describe characteristics, trends, or relationships found in existing data or literature. The results highlighted the critical role of automating incident response processes with the help of sophisticated machine learning models to minimize reaction time and limit disruptions to operations. Evidently, the impact of predictive analytics on process efficiency was not known, hence the current study.

3. Research Methods

This study used a correlational research design. As Creswell & Creswell (2018) affirm, correlational design shows whether a relationship exists between variables and brings out its strength, and direction, whether positive or negative. The target population of the study was the 38 commercial banks in Kenya (Cytonn Investments, 2023). The sampling frame of the study comprised of Equity Bank, KCB, Co-operative Bank, Standard Chartered Bank, and NCBA Bank, selected because of their known utilization of AI technologies. The five commercial banks have 185 branches operating in Nairobi County. The unit of analysis was the branch managers and information technology managers of every Nairobi branch of the five selected commercial banks. The sampling size was 192 participants, who were selected via purposive sampling technique. The data was collected via a closed-ended questionnaire. The questionnaire was split into six distinct sections. Section A detailed the respondents' basic demographic information; Section B addressed survey inquiries on machine learning; Section C had survey items on robotic process automation; Section D focused on natural language processing; Section E detailed survey inquiries on predictive analytics, and Section F contained inquiries on process efficiency. A five-point Likert scale standardized the participants' responses, in which case 1= strongly disagree, 2= disagree, 3= partially agree, 4= agree, and 5=strongly agree. Cronbach's Alpha was employed to gauge the questionnaire's consistency as a data collection tool. The threshold of this was 0.7 and any values less than 0.7 were revised or removed. Values greater than 0.7 showed more agreement among the survey questions thus deemed to be acceptable reliability. The reliability test results are presented in table 1 below:

Table 1: Cronbach's Alpha for the questionnaire

Variable	No. of items	Cronbach's Alpha	Remark
Machine learning	5	0.759320	Reliable
Robotic process automation	5	0.832630	Reliable
Machine learning	5	0.720989	Reliable
Predictive analytics	5	0.749372	Reliable
Process efficiency	5	0.734131	Reliable
Total reliability for the questionnaire	25	0.764127	Reliable

Source: Pilot Test Data (2025)

The modified survey questionnaire attained a total reliability of 0.764127, thereby meeting the reliability threshold. Besides, all the five variables met the reliability threshold. According to Bujang et al. (2018), a research instrument's survey items ar reliable if they achieve a Cronbach's alpha value of 0.7 or higher. Therefore, this study adopted the modified questionnaire, having met the reliability threshold.

The means, standard deviations, and aggregate means of the participants' responses as measured by the Likert scale were calculated and presented in tables. The relationships governing the independent and dependent variables were shown using the regression model below:

$Y = \beta o + \beta 1X1 + \beta 2X2 + \beta 3X3 + \beta 4X4 + \varepsilon$

Where Y = Process Efficiency
XI= Machine Learning
X2 = Robotic Process Automation
X3 = Natural Language Processing
X4 = Predictive Analytics
βo = constant

Ɛ =random error term
The current study's regression results were interpreted at a 5% significance level.

4 Research Findings

4.1 Baseline Information

124 out of 192 participants returned the questionnaires, representing a response rate of 65 percent, which is adequate, consistent Mugenda and Mugenda (2003). The average respondents' age was 42 years, suggesting that most of the respondents were in advanced stages of their careers and were conversant with the survey items of the current research. All (100%) of the respondents possessed at least a Bachelor's degree and had the capacity to share information on the effect of AI technologies on process efficiency. Lastly, more than 95% of the sampled participants had work experiences of at least six years and therefore understood the impact of AI technologies on process efficiency in their banks.

4.2 Descriptive Statistics

Machine Learning and Process Efficiency

This study used five survey entries to assess the impact of machine learning on process efficiency of the selected commercial banks. The results are presented in Table 2 below.

Table 2: Machine Learning and Process Efficiency

STATEMENT	Mean	Standard Deviation
Machine learning techniques are used to automate decision-making processes at the bank	4.11	.7201
Machine learning techniques have made fraud detection processes at the bank easier and seamless	4.02	.7524
Accuracy of credit scoring models have improved due to utilization of machine learning techniques	3.92	.7096
Machine learning techniques have improved efficiency in the bank's loan approval systems	4.05	.7212
Machine learning techniques have improved overall process efficiency in the bank	4.23	.7355
Aggregate	4.09	.7317

Source: Field Data 2025

The aggregate mean affirms the participants' agreement that machine learning techniques are utilized in commercial banks, and that they have positively impacted markers of process efficiency in those banks ($\bar{x}$=4.09, D=.7317). This is because the respondents agreed that machine learning techniques are used to automate decision-making processes at the banks ($\bar{x}$=4.11, D=.7201). Additionally, the participants agreed that Machine learning techniques have made fraud detection processes at the bank easier and seamless ($\bar{x}$=4.02, D=.7524). Furthermore, the respondents marked as slightly true, the statement that accuracy of credit scoring models have improved due to utilization of machine learning techniques ($\bar{x}$=3.92, D=.7096). Lastly, the participants scored as agree, the statement that ML techniques have improved efficiency in the bank's loan approval systems ($\bar{x}$=4.05, D=.7212).

Robotic Process Automation and Process Efficiency

This study used five survey entries to assess the impact of robotic process automation on process efficiency of the selected commercial banks. The results are presented in Table 3 below

Table 3: Robotic Process Automation and Process Efficiency

STATEMENT	Mean	Standard Deviation
1. The utilization of robotic process automation techniques has reduced manual processing at the bank	4.02	.7907
2. Robotic process automation has led to faster transaction processing	4.06	.8922
3. Integration of robotic process automation in the bank's process has automated customer onboarding processes	4.45	.7938
4. Robotic process automation has imroved back-office automation	4.05	.7944
5. Adoption of robotic process automation has improved overall process efficiency at the bank	4.77	.7816
Aggregate	4.31	.7694

Source: Field Data 2025

According to the aggregate mean, it was agreeable that RPA techniques were implemented in the selected commercial banks, and they had considerable impacts on indicators of process efficiency ($\bar{x}$=4.31, 7694). This is because the participants agreed that the utilization of robotic process automation techniques has reduced manual processing at the bank ($\bar{x}$=4.02, D=.7907), and that robotic process automation has led to faster transaction processing ($\bar{x}$=4.06, D=.8922). The participants also agreed with the statement that integration of robotic process automation in the bank's process has automated customer onboarding processes ($\bar{x}$=4.45, D=.7938). Lastly, the study's respondents agreed with the statement that RPA techniques significantly improved overall process efficiency in the selected banks ($\bar{x}$=4.77, D=.7816).

Natural Language Processing and Process Efficiency

This study used five survey entries to assess the impact of natural language processing on process efficiency of the selected commercial banks. The results are presented in table 4 below;

Table 4: Natural Language Processing and Process Efficiency

STATEMENT	Mean	Standard Deviation
1.Utilization of AI powered chatbots has increased the volume of customer queries handled	4.81	.7447
2. The introduction of voice-based banking has made transaction processing faster	4.00	.8235
3. The adoption of natural language processing techniques has improved the quality of customer service	3.88	.7628
4. Email sorting and categorization is now faster because of natural language processing techniques at the bank	4.04	.8133
5. Natural language processing techniques have improved overall process efficiency at the bank	4.09	.7887
Aggregate	4.23	.7776

Source: Field Data 2025

According to the aggregate mean, the participants agree that natural language processing techniques are utilized in the commercial banks, and affect process efficiency ($\bar{x}$=4.23, D=.7776). This was because the participants agree that utilization of AI powered chatbots has increased the volume of customer queries handled ($\bar{x}$=4.81, D=.7447). Moreover, the respondents agreed with the statement that the introduction of voice-based banking has made transaction processing faster ($\bar{x}$=4.00, D=.8235). Additionally, the participants slightly agreed with the statement that the adoption of natural language processing techniques has improved the quality of customer service ($\bar{x}$=3.88, D=.7628). Lastly, the participants agreed with the statement that email sorting and categorization is now faster because of natural language processing techniques at the bank ($\bar{x}$=4.04, D=.8133).

Predictive Analytics and Process Efficiency

This study used five survey entries to assess the impact of predictive analytics on process efficiency of the selected commercial banks. The results are presented in Table 5 as follows;

Table 5: Predictive Analytics and Process Efficiency

STATEMENT	Mean	Standard Deviation
1. The utilization of predictive analytics has improved accuracy in the prediction of customer behaviors, preferences and trends	4.51	.6536
2.The use of predictive analytics has augmented the bank's cross-selling and up-selling strategies	4.07	.7743
3. Early warning systems have enabled the bank to assess, mitigate and manage risks more effectively	4.23	.7248
4. Predictive analytics have improved accuracy in revenue forecasting at the bank	4.78	.7180
5. Predictive analytics have improved overall process efficiency at the bank	4.06	.8042
Aggregate	4.44	.7461

Source: Field Data 2025

According to the aggregate mean, the participants agreed that predictive analytics were used at their banks, and that they affected various measures of process efficiency ($\bar{x}$=4.44, D=.7461). This is because the respondents agreed with the statement that the utilization of predictive analytics has improved accuracy in the prediction of customer behaviors, preferences and trends ($\bar{x}$=4.51, D=.6536). The participants also agreed that early warning systems have enabled the bank to assess, mitigate and manage risks more effectively ($\bar{x}$=4.23, D=.7248). Also marked as true was the statement that predictive analytics has improved accuracy in revenue forecasting at the bank ($\bar{x}$=4.78, D=.7180), which enabled the management to make sound financial decisions. Lastly, the respondents agreed that predictive analytics have improved accuracy in revenue forecasting at the bank ($\bar{x}$=4.06, D=.8042).

Process Efficiency of the Commercial Banks

Process efficiency is a powerful metric that gauges the effectiveness with which an organization uses its resources, such as time, labor, and technology, to achieve desired outcomes with minimal waste or delay. This study measured process efficiency by transaction turnaround time, decision-making speed, process error rate, and process cost. The researcher used the four survey entries to assess the impact of AI technologies on process efficiency of the selected commercial banks. The findings are presented in Table 6 as follows;

Table 6: Process Efficiency

STATEMENT	Mean	Standard Deviation
1.AI technologies have improved transaction turnaround time at the bank	4.03	.6113
2. AI technologies have made decision-making at the bank faster	4.24	.6756
3. The adoption of AI tool has reduced the process error rate at the bank	4.09	.6508
4.Process costs have decreased following the integration of AI technologies in the bank's processes	3.95	.6901
Aggregate	4.08	.6722

Source: Field Data 2025

According to the aggregate mean, the participants agree that the adoption of AI technologies has improved process efficiency in the selected commercial banks ($\bar{x}$=4.08, D=.6722). This is because the respondents scored as true, the statement that AI technologies have improved transaction turnaround time at the bank ($\bar{x}$=4.03, D=.6113). The respondents also agreed with the statement that AI technologies have made decision-making processes at the banks faster ($\bar{x}$=4.24, D=.6756). The participants of this study also agreed with the statement that the adoption of AI tool has reduced the process error rate at the bank ($\bar{x}$=4.09, D=.6508). Lastly, the participants slightly agreed with the statement that process costs have decreased following the integration of AI technologies in the bank's processes ($\bar{x}$=3.95, D=.6901).

4.3 Inferential Statistics

The investigator conducted inferential analysis to make predictions about the data collected. This included Pearson's correlation analysis and regression analysis.

Pearson's correlation analysis results

Pearson's correlation analysis was done to assess the strength and direction of the relationship between each independent variable and the dependent variable at $p<0.05$. The analysis is summarized in table 4.6 as follows:
Pearson's correlation analysis results are summarized in table 7.

Table 7: Correlation Analysis Results

		Job Performance
Process Efficiency	Pearson correlation Sig(2-tailed)	1
	N	124
Machine learning techniques	Pearson correlation Sig(2-tailed)	.7516* .0000
	N	206
Robotic process automation	Pearson correlation Sig(2-tailed)	.6824* .0000
	N	124
Natural language processing	Pearson correlation Sig(2-tailed)	.8056* 0.0000
	N	124
Predictive analytics	Pearson correlation Sig(2-tailed)	.7442* 0.0000
	N	124

The results of the correlation analysis show a positive, statistically significant, and strong correlation (0.7516x) between machine learning and process efficiency at 0.05 level of significance. Furthermore, the current study found significant, positive, and strong correlation (0.6824x) between robotic process automation and process efficiency at 0.05 level of significance. In addition, the correlation analysis found a positive, significant and strong correlation (0.8056x) between natural language processing and process efficiency. Lastly, the correlation analysis showed show that there was a positive, significant and strong correlation (0.7442x) between predictive analytics and process efficiency at 0.05 level of significance.

Regression Analysis

Machine learning techniques, robotic process automation, natural language processing, and predictive analytics were each regressed against process efficiency. Table 8 below shows a model summary of the regression analysis for the present study;

Table 8: Regression Analysis Results

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square change	F Change	Df1	Df2	Sig. F Change
1	.825(a)	.527	.602	.45405	.527	1.085	4	124	.0000

Table 8 above shows a coefficient determination R=.527, which is equivalent to 52.7 % (p>0.05). This implies that machine learning techniques, robotic process automation, natural language processing, and predictive analytics jointly impact job performance by 52.7%. The p-value of .000 is less than 0.05, indicating significance at 95% level of confidence. The regression coefficients are presented in table 9 below:

Table 9: Regression Coefficients

Model	Unstandardized coefficients			Standardized coefficients		
	B	p	Std. Error	Beta	T	Sig.
1. Constant	0.442	0.00	0.135		1.246	0.000
ML	0.119	0.03	0.029	0.064	2.243	0.011
RPA	0.124	0.04	0.034	0.079	1.802	0.027
NLP	0.144	0.01	0.042	0.057	1.651	0.025
PA	0.141	0.03	0.033	0.046	1.643	0.036

The regression equation was as follows;
$Y= \beta o + \beta 1X1 + \beta 2X2 + \beta 3X3 + \beta 4X4 + \varepsilon$
Where Y = Process Efficiency
XI = Machine Learning
X2 = Robotic Process Automation
X3 = Natural Language Processing
X4 = Predictive Analytics
βo = constant
ε =random error term
Substituting with the above figures, the regression model is as follows:
$Y= 0.442 + 0.064X1+0.079X2+0.057X3+0.046X4+ 0.135$

From the regression equation above, it is evident that all the four variables affected performance but in different magnitudes. All the four regression coefficients were statistically significant at p<0.05, indicating that machine learning techniques, robotic process automation, natural language processing, and predictive analytics significantly affected process efficiency. RPA had the greatest impact on process efficiency at 0.079 units, suggesting that a change in 1 unit of RPA led to a change in process efficiency by 0.079 units. Moreover, the regression coefficient of 0.064 suggests that, a change in 1 unit of ML techniques led to a change in process efficiency by 0.064 units. Similarly, the regression coefficient of 0.057 suggests that a change in 1 unit of NLP led to a change in process efficiency by 0.057 units. The results are significant at p<0.05, showing that the effect of NLP on process efficiency was not due to chance. Lastly, the regression coefficient of 0.046 suggests that a change in 1 unit of predictive analytics led to a change in process efficiency by 0.046 units. Since the results are significant, it follows that there is a real relationship between predictive analytics and process efficiency at the banks.

4.4 Discussion

Machine Learning and Process Efficiency

The aggregate mean affirms the participants' agreement that machine learning techniques are utilized in commercial banks, and that they have positively impacted markers of process efficiency in those banks ($\bar{x}$=4.09, D=.7317). This is because the respondents agreed that machine learning techniques are used to automate decision-making processes at the banks ($\bar{x}$=4.11, D=.7201). In banking, ML is widely applied in credit scoring, transaction monitoring, fraud detection, and

personalized product offerings. The findings mirror those of an earlier study by Wright (2021) who showed that the application of ML in the banking industry had significantly increased during the COVID-19 pandemic, and enabled commercial banks to automate their decision-making processes. Additionally, the participants agreed that Machine learning techniques have made fraud detection processes at the bank easier and seamless ($\bar{x}$=4.02, D=.7524). The integration of ML algorithms in banks' processes and systems streamlined fraud detection processes. This concurs with Mbecca (2022) who showed that the adoption of ML in banks improved eased fraud detection processes, which enabled commercial banks to minimize financia losses. The study further showed that improved fraud detection helped commercial banks to gain competitive edge over those that did not utilize ML techniques.
Furthermore, the respondents marked as slightly true, the statement that accuracy of credit scoring models have improved due to utilization of machine learning techniques ($\bar{x}$=3.92, D=.7096). This suggests that commercial banks utilize ML techniques to develop credit-scoring models, which have improved their accuracy to a certain extent. This was consistent with Frank & Lebron (2024) who showed that ML had significantly improved operational efficiency of the banks by reducing costs, speeding transactions, improving the qulality of customer service, and improving accuracy in credit scoring. Lastly, the participants scored as agree, the statement that ML techniques have improved efficiency in the bank's loan approval systems ($\bar{x}$=4.05, D=.7212). The participants contended that ML techniques have enabled commercial banks to approve loans faster, and without requiring customers to visit the bank premises physically. This agrees with an earlier study by Wright (2021) who showed that the speed and volume of processed loan applications significantly increased because of integration of ML in the financial services sector.
The results of the correlation analysis show a positive, statistically significant, and strong correlation (0.7516x) between machine learning and process efficiency at 0.05 level of significance. The results agree with an earlier study by Frank & Lebron. (2024) which showed that showed that ML significantly improved operational efficiency of the banks by reducing costs, speeding transactions, improving the qulality of customer service, and improving accuracy.
Lastly, the regression coefficient of 0.064 suggests that, a change in 1 unit of ML techniques led to a change in process efficiency by 0.064 units. The findings underscore the importance of automated decision-making, fraud detection systems, AI-powered credit scoring models and loan approval systems in enhancing process efficiency (Pattnaik, Ray & Raman, 2024).

Natural Language Processing and Process Efficiency

According to the aggregate mean, the participants agree that natural language processing techniques are utilized in the commercial banks, and affect process efficiency ($\bar{x}$=4.23, D=.7776). This was because the participants agree that utilization of AI powered chatbots has increased the volume of customer queries handled ($\bar{x}$=4.81, D=.7447). Unlike the traditional customer care procedures that are slow and require human-human interactions, AI powered chatbots are faster and enable customers to receive feedback on real time bases. This was also true for Boukhelifa & Merabet (2024) who found that NLP helps organizations to extract insights, automate communication, and improve decision-making by analyzing large volumes of unstructured text data. The technology plays a key role in making interactions between humans and machines more natural and intuitive, hence increasing the volume of customer queries handled. Moreover, the respondents agreed with the statement that the introduction of voice-based banking has made transaction processing faster ($\bar{x}$=4.00, D=.8235). This indicates that largely, the number of customers served in the commercial banks increased following the adoption of NLP techniques. This agrees with an earlier study by Gurung & Parajuli (2024) which concluded that the adoption and effectiveness of chatbots in the Nepalese banking sector significantly enhanced customer satisfaction, operational efficiency, and the overall banking experience.
Additionally, the participants slightly agreed with the statement that the adoption of natural language processing techniques has improved the quality of customer service ($\bar{x}$=3.88, D=.7628). This suggests that the selected commercial banks reported higher customer satisfaction levels following the adoption of natural language processing techniques. This concurs with a study by Adejuwon & Unesiri (2024) which found a positive correlation between NLP techniques and customer satisfaction outcomes in the banking sector. Lastly, the participants agreed with the statement that email sorting and categorization is now faster because of natural language processing techniques at the bank ($\bar{x}$=4.04, D=.8133). The managers posited that banks were able to sort and categorize customer emails with improved ease, thereby allowing the dispatch of bulk emails. This concurs with Edibo, Dibua & Edokobi (2025) who showed that natural language processing techniques enabled commercial banks to communicate with more customers with reduced difficulty.
In addition, the correlation analysis found a positive, significant and strong correlation (0.8056x) between natural language processing and process efficiency. This shows that NLP techniques were strong predictors of process efficiency in the selected commercial banks. The current study agrees with Boukhelifa & Merabet (2024) who found positive, statistically significant and strong correlations between NLP and process efficiency.
Lastly, the regression coefficient of 0.057 suggests that a change in 1 unit of NLP led to a change in process efficiency by 0.057 units. The results are significant at $p<0.05$, showing that the effect of NLP on process efficiency was not due to chance. This study agrees with Gurung & Parajuli (2024) who found that NLP significantly process efficiency.

Robotic Process Automation and Process Efficiency

According to the aggregate mean, it was agreeable that RPA techniques were implemented in the selected commercial banks, and they had considerable impacts on indicators of process efficiency ($\bar{x}$=4.31, 7694). This is because the participants agreed that the utilization of robotic process automation techniques has reduced manual processing at the bank ($\bar{x}$=4.02, D=.7907), and that robotic process automation has led to faster transaction processing ($\bar{x}$=4.06, D=.8922). This mirrors the findings of Alassuli (2025) who showed that the adoption of RPA significantly enhanced internal audit operations by reducing human errors, minimizing the cost of operations, and easing work processes. Robotic processes replaced most of the manual processes at the banks, thereby increasing the overall speed of transactions. The participants also agreed with the statement that integration of robotic process automation in the bank's process has automated customer onboarding processes ($\bar{x}$=4.45, D=.7938). This concurs with the participants' responses in the study by Villar & Khan (2021) who affirmed that robotic processes automated customer onboarding processes at Deutsche bank, which significantly increased the bank's clientele. RPA techniques made it possible for customers to easily submit their KYC documents and open new accounts with the selected commercial banks. Lastly, the study's respondents agreed with the statement that RPA techniques significantly improved overall process efficiency in the selected banks ($\bar{x}$=4.77, D=.7816). The responses indicate that the RPA techniques positively affected various indicators of process efficiency in the selected commercial banks. This confirms the findings of Iyamu & Munyambo (2023), that the automation of tedious and time-consuming processes helps firms to improve operational efficiency, minimize errors, reduce costs, and allow workers ample time to focus on higher-value tasks that require human judgment and creativity.

Furthermore, the current study found significant, positive, and strong correlation (0.6824x) between robotic process automation and process efficiency at 0.05 level of significance. This was also true for Mbecca (2022) who found a significant, positive, and strong correlation between robotic process automation and process efficiency. In addition, the correlation analysis found a positive, significant and strong correlation (0.8056x) between natural language processing and process efficiency.

Lastly, RPA had the greatest impact on process efficiency at 0.079 units, suggesting that a change in 1 unit of RPA led to a change in process efficiency by 0.079 units. The results show that the adoption of RPA techniques by commercial banks reduced manual transactions, increased speed of transaction processing, and automated many of the banks' processes, which had the most significant impact on process turnaround time, process error rate, process costs and decision-making speed. The findings align with those of an earlier study by Mbecca (2022) which showed that RPA techniques significantly improved process efficiency in the banking sector by enhancing accuracy and speed of processes.

Predictive Analytics and Process Efficiency

According to the aggregate mean, the participants agreed that predictive analytics were used at their banks, and that they affected various measures of process efficiency ($\bar{x}$=4.44, D=.7461). This is because the respondents agreed with the statement that the utilization of predictive analytics has improved accuracy in the prediction of customer behaviors, preferences and trends ($\bar{x}$=4.51, D=.6536). Commercial banks relied on AI-powered predictive models to forecast trends in customer behaviours, and develop strategies that mirror customer expectations. This was also true for Broby (2022) who showed that banks used predictive analytics to make forecasts using computational models based on collected and processed data, thereby strengthening the management's capacity to anticipate future trends and make informed decisions. The participants also agreed that early warning systems have enabled the bank to assess, mitigate and manage risks more effectively ($\bar{x}$=4.23, D=.7248). This confirms the findings of earlier research by Aro (2024) which showed that the effective integration of predictive analytics in financial management significantly improved risk assessment, decision-making capabilities and overall financial performance. Also marked as true was the statement that predictive analytics has improved accuracy in revenue forecasting at the bank ($\bar{x}$=4.78, D=.7180), which enabled the management to make sound financial decisions. Lastly, the respondents agreed that predictive analytics have improved accuracy in revenue forecasting at the bank ($\bar{x}$=4.06, D=.8042). The findings suggest that using predictive analytics improved different indicators of process efficiency. This concurs with Ekundayo et al. (2024) who showed that predictive analytics positively correlates with various performance outcomes, including cybersecurity and risk assessment.

Additionally, the correlation analysis showed show that there was a positive, significant and strong correlation (0.7442x) between predictive analytics and process efficiency at 0.05 level of significance. The study agrees with the findings of Broby (2022), which showed a positive, significant and strong correlation between predictive analytics and measures of process efficiency in commercial banks.

Lastly, the regression coefficient of 0.046 suggests that a change in 1 unit of predictive analytics led to a change in process efficiency by 0.046 units. Since the results are significant, it follows that there is a real relationship between predictive analytics and process efficiency at the banks. This study also agrees with earlier research by Mbecca (2022) who showed that predictive analytics significantly affected process efficiency. It is important to note that of the four variables, predictive analytics had the least impact on process efficiency. This was probably because commercial banks do not utilize predictive analytics in their day-to-day processes except when making periodical forecasts and trends analyses.

5 Conclusion and Recommendation

5.1 Conclusion

The first objective of the study was to determine the impact of machine learning on process efficiency in selected commercial banks in Kenya. The first hypothesis of the study was that machine learning has no impact on process efficiency in the selected commercial banks in Kenya. The results showed that machine learning significantly affected process efficiency in the selected commercial banks. The relationship was statistically significant (p=0.011). The current study rejected the null hypothesis and concluded that machine learning significantly impacts process efficiency in commercial banks in Kenya. The utilization of machine learning techniques reduced transaction turnaround time, improved decision-making speed, reduced process error rates, and enhanced cost savings.

The second objective of this research was to find out the impact of robotic process automation on process efficiency in selected commercial banks in Kenya. The null hypothesis was that robotic process automation has no impact on process efficiency in selected commercial banks in Kenya. The study reveals a positive and statistically significant relationship between robotic process automation and process efficiency in the selected commercial banks (p=0.027). Thus, the study rejects the null hypothesis and concludes that robotic process automation had a positive and significant impact on process efficiency of selected commercial banks in Kenya. The significant relationship was mediated by the benefits of robotic process automation, which included; reduced manual processing at the bank, faster transaction processing, automated customer onboarding processes, and improved back-office automation.

The third objective was to determine the impact of natural language processing on process efficiency in selected commercial banks in Kenya. The null hypothesis was that natural language processing had no impact on process efficiency in the selected commercial banks. The analysis showed a positive and statistically significant association between natural language processing and process efficiency in the commercial banks selected (p=0.025). Therefore, the study rejects the null hypothesis and concludes that natural language processing positively and significantly impacted process efficiency in selected commercial banks in Kenya. The utilization of natural language processing technologies enabled banks to handle larger volumes of customer queries, process transactions faster, improve the quality of customer service, and speed up the sorting and categorization of emails.

The fourth objective of this research was to find out the impact of predictive analytics on process efficiency in selected commercial banks in Kenya. The null hypothesis was that predictive analytics has no impact on process efficiency in selected commercial banks in Kenya. The study reveals a positive and statistically significant relationship between predictive analytics and process efficiency in the selected commercial banks (p=0.036). Thus, the study rejects the null hypothesis and concludes that predictive analytics had a positive and significant impact on process efficiency of selected commercial banks in Kenya. The significant relationship was influenced by the benefits of predictive analytics, which included; improved accuracy in the prediction of customer behaviors, preferences and trends, streamlined cross-selling and up-selling strategies, improved risk detection and mitigation, and improved accuracy in revenue forecasting at the bank.

5.2 Recommendations

Policy Recommendation

The government of Kenya through the National Assembly could implement laws that will incentivize the adoption of AI technologies by commercial banks in Kenya. This recommendation is anchored on the current study's finding of a significant, positive, and strong correlation between the four AI technologies studied and process efficiency in the selected commercial banks. The current study noted that some commercial banks are yet to adopt AI technologies in their processes. Thus, the government could also provide the appropriate technical support and training in AI technology for startups in the banking industry to bolster the level of awareness and adoption of AI technology.

Recommendation for Practice

The branch managers, IT managers and operations managers of commercial banks in Kenya could expedite the integration of AI technologies in their processes. This would enable the banks to improve efficiency in transaction processing, reduce errors, enhance process accuracy, improve risk detection, improve accuracy in trend analysis, and enhance overall process efficiency. This recommendation is based on the current study's illustration that AI technnologies significantly impact process efficiency in the selected commercial banks in Kenya. The five banks are a microcosm of Kenya's banking sector, and could inspire other commercial banks to integrate AI technologies in their processes.

Secondly, branch managers, IT managers and operations managers of commercial banks in Kenya could prioritize robotic process automation as they integrate AI technologies in their processes. This recommendation is informed by the finding that 1 unit change in robotic process automation causes a corresponding improvement in process efficiency by 0.079 units. In other words, robotic process automation had the most significant impact on process efficiency in this study. Adopting robotic process automation can significantly transform the commercial banks' day-to-day processes and yield greater process efficiency outcomes.

5.3 Limitations and Future Research Direction

The conceptual framework of this study has extended the knowledge on the direct impact of AI technologies and process efficiency of commercial banks in Kenya. The findings suggest that there is a significant and positive correlation between AI technologies and process efficiency. Future studies could go beyond this study's conceptual framework to consider other AI technologies. Future researcher could also consider other metrics when measuring process efficiency.

Declaration of Competing Interests

The authors declare that they are not aware of any competing financial interests or personal relationships that may have influenced the work described in this document.

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Ethical considerations

The article followed all ethical standards appropriate for this kind of research.

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