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# Artificial Intelligence Adoption and the Financial Performance of Commercial Banks in Kenya

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**Abstract**

Commercial banks in Kenya have invested heavily in artificial intelligence (AI), yet sector profitability has weakened, with average return on assets (ROA) falling from 3.3 percent in 2021 to 2.6 percent in 2024. This research investigated the effect of AI adoption on the financial performance of commercial banks in Kenya. Specifically, it examined the effects of AI-enabled customer service, machine learning credit scoring, robotic process automation and AI-driven fraud detection on financial performance, measured by ROA, as well as the mediating effect of operational efficiency and the moderating effect of bank size. A census of all 38 commercial banks licensed by the Central Bank of Kenya was undertaken, using data from audited annual reports and Central Bank of Kenya supervisory returns. Data were analysed using random effects panel regression with cluster-robust standard errors, the causal steps approach supplemented by the Sobel test, and moderated regression. AI-enabled customer service had a positive and significant effect on ROA ($\beta = 0.927$, $p = 0.003$). Machine learning credit scoring ($\beta = -0.046$, $p = 0.841$), robotic process automation ($\beta = -0.450$, $p = 0.098$) and AI-driven fraud detection ($\beta = 0.137$, $p = 0.459$) had no significant effects. AI-enabled customer service lowered the cost-to-income ratio ($\beta = -0.194$, $p < 0.001$), but operational efficiency did not significantly mediate its relationship with ROA (Sobel $z = 1.287$, $p = 0.198$). The interaction between AI adoption and bank size was not significant ($\beta = 0.154$, $p = 0.589$). The study concluded that the effect of AI adoption on bank performance is application-specific. Only customer-facing AI translated into higher profitability, while the credit scoring, process automation and fraud detection applications did not. Operational efficiency did not mediate, and bank size did not moderate, the connection between AI adoption and performance.

**Keywords:** *Artificial Intelligence, AI-enabled Customer Service, Machine Learning Credit Scoring, Robotic Process Automation, AI-driven Fraud Detection, Operational Efficiency, Bank Size, Return on Assets, Commercial Banks, Kenya.*

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## 1. Introduction

At its core, banking is a business built on information. Banks' role in the economy is to collect, process and react to information about the borrowers, depositors and markets in a more efficient way than individual depositors and investors (Adeniran et al., 2024; Basaran & Bagheri, 2020). The current technology transformation is perhaps the biggest change in this capability since banks computerized their operations; it moves technology from recording transactions to supporting and making decisions (Kalyani & Gupta, 2023). Today, learning algorithms are used to evaluate loan applications, virtual assistants are used to answer customer questions, software robots are used to complete routine back-office tasks and detection engines are used to monitor transactions in real-time (Konigstorfer & Thalmann, 2020). These are expected to reduce costs, improve decision-making and service, and increase bank profitability over time.

Globally, AI has moved from pilot programs to integration into banks' daily processes (Ashta & Herrmann, 2021), with estimates of up to one trillion USD in value added to the banking sector annually (McKinsey & Company, 2020). The real-world story is not so clear. Documented benefits are primarily cost savings, risk management and service quality and are only partially proven and rarely connected to audited profits (Konigstorfer & Thalmann, 2020). There are also slow returns to AI investment, which is linked to investment in complementary data, governance and skills, and is concentrated within larger firms (McElheran et al., 2024). This mirrors the productivity paradox observed in information technology and suggests that the link between AI and performance is mediated by other processes and depends on factors such as banking environments (Fares et al., 2023).

South Africa, Nigeria, Egypt and Kenya lead AI adoption in Africa's financial services sector (Arakpogun et al., 2021). Mobile money has produced rich alternative-data records that make machine learning credit scoring particularly useful (Mhlanga, 2020), although skills shortages, fragmented data systems, and evolving regulation hold adoption back. Kenya is therefore a useful setting for this question. Its 38 licensed commercial banks operate alongside one of the world's most advanced mobile money systems. Digital lending products use machine learning to assess millions of borrowers almost instantly; the largest banks offer virtual assistants on mobile, web, and social messaging platforms, and increasingly use robotic process automation and machine-learning fraud monitoring in reconciliation, onboarding, and anti-money-laundering work (Kenya Bankers Association, 2023). Industry bodies have identified AI as a strategic priority, and the Central Bank of Kenya has given greater supervisory attention to model risk, data protection and cyber resilience.

In this research, AI adoption is defined as a licensed commercial bank's observable use, in a given financial year, of AI applications in four areas: customer service, credit assessment, back-office processing and fraud control (Wamba-Taguimdje et al., 2020; Rahman et al., 2023). The construct is treated as multidimensional because the four applications differ in their costs, revenue links, and risks, so there is no reason to assume they affect performance in the same way (Shiyyab et al., 2023).

Across the study panel, a composite AI adoption index, calculated as the simple average of the four indicators, averaged about 0.60, meaning the typical bank-year observation involved using AI in two or three of the four areas. Fraud detection was the most widely adopted application and AI-enabled customer service the least. Adoption also varied across the sector's tiers. Large banks with strong balance sheets tended to adopt more applications, while smaller and

financially distressed banks adopted fewer. This pattern is consistent with the organisational context of the technology, organisation and environment framework, in which financial capacity shapes the uptake of innovation, and it provides the variation needed to test whether bank size moderates the effect of adoption.

AI-enabled customer service refers to the use of chatbots, virtual assistants, and intelligent self-service platforms, built on natural language processing, to handle client queries and transactions without staff involvement (Polireddi, 2024). It affects financial performance in two ways. First, it reduces the cost of serving each additional customer by replacing branch and call centre work with automated interaction. Second, it supports cross-selling and customer retention through round-the-clock availability and the capture of behavioural data, which helps to sustain non-interest income (Rahman et al., 2023). In Kenya, Equity Bank introduced its Equity Virtual Assistant on WhatsApp, Facebook Messenger and Telegram in 2022, allowing customers to open accounts, transfer funds and obtain statements through chat (Equity Group Holdings, 2022). Absa Bank Kenya and Kenya Commercial Bank have introduced similar tools.

Machine learning credit scoring entails the application of learning algorithms trained on transaction records, behavioural data and alternative data, such as mobile money flows and repayment histories, to estimate the likelihood of default and to automate lending decisions (Polireddi, 2024). By expanding the information available at the time of lending, algorithmic scoring reduces the adverse selection that leads lenders to ration credit, which is expected to increase lending volumes, lower processing costs and, when models are well designed, reduce credit losses (Rahman et al., 2023). Kenya is among the most developed markets for this application. Products such as M-Shwari, KCB M-Pesa, and Fuliza established the model, and by 2024 about 79 percent of commercial and microfinance banks offered digital credit products (Central Bank of Kenya, 2025b), despite rising non-performing loans and tighter monetary conditions.

Robotic process automation (RPA) uses configurable software robots to carry out high-volume, rule-based tasks across existing systems, such as customer onboarding, payment processing, reconciliations, regulatory reporting and know-your-customer checks. It is treated here as part of AI adoption because banks increasingly combine it with machine learning and document recognition tools within the same automation programmes (Polireddi, 2024; Wamba-Taguimdje et al., 2020). RPA works mainly through operational efficiency, by reducing manual steps, processing time and errors, so its expected effect is a lower cost-to-income ratio rather than higher revenue. Since it must be integrated with core banking systems and requires significant upfront spending, its uptake has been uneven, with larger banks more able to fund multi-year automation programmes than smaller and distressed banks.

AI-driven fraud detection refers to the utilization of supervised and unsupervised learning, including anomaly detection, to monitor transactions and the behaviour of customers and staff in order to identify and stop fraud as it happens (Polireddi, 2024). Its value lies mainly in avoiding losses and in reducing regulatory, reputational and insurance risks, rather than in generating revenue, and because banks often buy such systems from vendors, they are less likely than customer-facing tools to give a lasting advantage (Shiyyab et al., 2023). In Kenya, a worsening fraud environment has driven deployment. Fraud cases in the banking sector rose from 173 in 2023 to 353 in 2024, while losses increased from about KES 412 million to about

KES 1.5 billion, mainly through mobile banking, card fraud and identity theft (Central Bank of Kenya, 2025b).

Operational efficiency is the mediating variable because the main theoretical thesis in the AI literature is that technology's impact on success is mediated primarily through its effect on the firm's cost structure (Wamba-Taguimdje et al., 2020). Manual tasks are automated, algorithmic decisions speed up processes, and intelligent monitoring minimizes losses. These changes should be designed to improve operating-cost efficiency in generating income before increasing profits (Spring et al., 2022). Operational efficiency was measured by the cost-to-income ratio, the standard supervisory measure, where a lower ratio implies greater efficiency. Treating efficiency as a mediator separates the total effect of AI adoption into an indirect part that works through efficiency and a direct part that works through other channels, such as revenue growth and better risk selection. Evidence of this kind is largely missing from Kenyan studies.

Bank size is treated as the moderating variable because AI is expected to show strong economies of scale. Building and governing models is costly, but applying them to an additional transaction cost very little, so banks can recover fixed costs in data infrastructure, skilled staff and model risk management across a large base of assets and customers (McElheran et al., 2024). Complementary resources, like proprietary data, larger technology budgets and specialised staff, are additional resources that large banks control and can convert standard technology into capabilities that are harder for rivals to duplicate (Barney, 1991). The Kenyan sector is highly tiered, with a few large banks holding most of its assets and profits (Central Bank of Kenya, 2024). Bank size was measured as the natural logarithm of total assets (Kirimi et al., 2022).

Financial performance was measured using ROA, the main profitability indicator the Central Bank of Kenya uses to supervise banks, which also avoids differences in leverage between banks. Accounting-based measures were preferred to market-based measures because only a few banks are listed on the NSE in Kenya, and market-based measures would have significantly reduced the number of banks to be studied. Table 1 shows the sector's ROA from 2019 to 2024.

**Table 1: Return on Assets of the Kenyan Banking Sector, 2019 to 2024**

| Year | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 |
|---|---|---|---|---|---|---|
| Return on assets (%) | 2.9 | 1.9 | 3.3 | 3.0 | 2.8 | 2.6 |

Source: Central Bank of Kenya, Bank Supervision Annual Reports (2019 to 2024); Kenya Bankers Association (2024).

Table 1 shows that the sector's profitability has generally weakened since a short-lived recovery in 2021. ROA fell sharply from 2.9 percent in 2019 to 1.9 percent in 2020, reflecting the COVID-19 pandemic, then recovered to a peak of 3.3 percent in 2021. The recovery was not sustained, and ROA declined in each following year to 2.6 percent in 2024. The downward trend since 2022 indicates that banks are under increasing pressure to earn profits on their investments.

### 1.1 Problem Statement

In principle, commercial banks in Kenya should be gaining considerably from their investment in AI (Konigstorfer & Thalmann, 2020). The sector has invested heavily and consistently in digital capabilities. Machine learning models support digital credit products that serve millions of borrowers, while the largest banks, and increasingly mid-sized banks, have deployed virtual assistants, robotic process automation and intelligent fraud monitoring. Both innovation theory and evidence from developed markets suggest that this investment should lower cost-to-income ratios, reduce credit and fraud losses, and increase, or at least maintain, profitability across the sector (Mu et al., 2026).

In contrast, sector ROA declined from 3.0 percent in 2022 to 2.6 percent in 2024, a 13.3 percent decline (Table 1), despite increased AI investment. There are concerns about banks' sustainability regarding profitability and a need to identify which AI uses, and in what shape and form, are enhancing bank performance. Without these examples, banks may invest in technology that is not economically viable, and regulators have no basis to inform policy on banking investments in AI.

The empirical literature also shows contextual, conceptual, methodological and theoretical gaps. Mu et al. (2026) used panel data on 430 Chinese banks and found that AI adoption raised profitability through cost and mobile banking channels, but the Chinese setting differs from Kenya's thinner data infrastructure, creating a contextual gap. Kamau and Kihara (2020) employed survey data to demonstrate a favourable link between mobile banking and profitability in Kenya, but mobile banking differs from AI, creating a conceptual gap. Muthuuri and Kihara (2025) used a cross-sectional design to show that machine learning improved the efficiency of credit analysis in tier two Kenyan banks, but they tested only direct effects, creating a methodological gap, and did not ground adoption in an integrated theoretical framework, creating a theoretical gap.

This research addresses these gaps by covering all 38 licensed commercial banks in Kenya across the three tiers from 2020 to 2024, yielding 190 bank-year observations drawn from audited reports and Central Bank of Kenya supervisory data rather than survey responses. AI adoption is broken down into four dimensions, namely AI-enabled customer service, machine learning credit scoring, robotic process automation and AI-driven fraud detection, and financial performance is measured by ROA. Beyond direct effects, the study tests operational efficiency as a mediator using the causal steps method and the Sobel test, and bank size as a moderator using moderated regression, within a framework anchored on the technology, organisation and environment framework.

### 1.2 Objectives of the Study

The general objective of the research was to investigate the effect of artificial intelligence adoption on the financial performance of commercial banks in Kenya. The research was directed by the following specific objectives:

i. To assess the effect of artificial intelligence-enabled customer service on the financial performance of commercial banks in Kenya.

ii. To ascertain the effect of machine learning credit scoring on the financial performance of commercial banks in Kenya.

iii. To establish the effect of robotic process automation on the financial performance of commercial banks in Kenya.

iv. To examine the effect of artificial intelligence-driven fraud detection on the financial performance of commercial banks in Kenya.

v. To determine the mediating effect of operational efficiency on the relationship between artificial intelligence adoption and the financial performance of commercial banks in Kenya.

vi. To establish the moderating effect of bank size on the connection between artificial intelligence adoption and the financial performance of commercial banks in Kenya.

### 1.3 Research Hypotheses

The study tested the following null hypotheses:

$H_{01}$: Artificial intelligence-enabled customer service has insignificant effect on the financial performance of commercial banks in Kenya.

$H_{02}$: Machine learning credit scoring has insignificant effect on the financial performance of commercial banks in Kenya.

$H_{03}$: Robotic process automation has insignificant effect on the financial performance of commercial banks in Kenya.

$H_{04}$: Artificial intelligence-driven fraud detection has insignificant effect on the financial performance of commercial banks in Kenya.

$H_{05}$: Operational efficiency has insignificant mediating effect on the connection between artificial intelligence adoption and the financial performance of commercial banks in Kenya.

$H_{06}$: Bank size has no significant moderating effect on the connection between artificial intelligence adoption and the financial performance of commercial banks in Kenya.

## 2. Literature Review

### 2.1 Theoretical Review

#### 2.1.1 Technology-Organisation-Environment Framework

The study was anchored on the Technology-Organisation-Environment framework (Tornatzky & Fleischer, 1990). The framework proposes that three related contexts shape a firm's adoption of a technological innovation. Technological context: the technology's features and expected benefits; organizational context: the firm's size, resources, and management; environmental context: competition, customers, and regulation. For this study, the framework is appropriate for three reasons. Firstly, it is an organisational decision regarding the adoption of AI in banking, which allows for the use of several dimensions of the independent variable. Secondly, the framework can be applied to an independent variable with multiple dimensions. Thirdly, the organisational context of the framework is appropriate for treating bank size as a moderating variable. This framework has been criticized as more of a classification scheme than a comprehensive causal theory, so the study was conducted alongside theories that more directly explain technology's value-creation role.

### 2.1.2 Diffusion of Innovation Theory

Diffusion of Innovation theory (Rogers, 2003) explains how an innovation spreads among potential adopters based on its comparative benefit, compatibility, intricacy, testability, and visibility. The theory supports the study's independent variable because it explains why AI adoption varies in Kenyan banks. It also supports the study's central hypothesis that innovations spread because early adopters benefit from them through relative advantage; in the banking sector, this includes reduced costs, improved risk selection, and enhanced service. The principal drawback of this theory is its optimism about adoption, as it makes few claims about implementations that do not bring benefits. To address this, the research focused on the effects of AI on performance as a question to be answered, not a conclusion reached by the theory.

### 2.1.3 Technology Acceptance Model

The Technology Acceptance Model (TAM) (Davis, 1989) suggests that the use of technology is influenced by the perceived usefulness and ease of use. The model is relevant because customer-facing and credit-scoring applications require acceptance by two groups to be beneficial. Before the cost of interacting with them decreases, customers need to shift to chatbots and self-service options, and employees need to believe in and act on algorithmic decisions before scoring and monitoring systems alter real-life decisions. The model was constructed to account for individual technology use, not firm-level outcomes, and has been criticized for this reason. Therefore, it was used in a supporting capacity to clarify that acceptance, not deployment, determines whether these applications affect performance.

### 2.1.4 Resource-Based View

The Resource-Based View (Barney, 1991) argues that lasting superior performance comes from resources that are valuable, rare and difficult to imitate. AI systems are increasingly bought off the shelf, so what is scarce is the combination of proprietary data, skilled staff and governance capability that surrounds them, and this combination tends to be concentrated in larger banks. The theory has been criticized as being circular and static. This study aims to address these concerns by measuring bank size and operational efficiency separately and testing their respective roles over a five-year panel data period. The four theories together give the foundation to the mediating role of operational efficiency and the moderating role of bank size presented in the conceptual framework of Figure 1.

## 2.2 Empirical Review

### 2.2.1 AI-enabled Customer Service and Financial Performance

Konigstorfer and Thalmann (2020) reviewed AI applications in commercial banks to identify where the technology is used and the challenges its implementation raises. Through an extensive literature review, they conclude that AI is helping banks lower their lending losses, ensure payment security, automate compliance and better target customers, but they also note that there are issues of transparency, privacy and user acceptance on the horizon. The review relied on secondary information primarily from developed markets and did not consider any advantages reported to be associated with the profitability of audited operations. In markets with more robust data infrastructure than Kenya's, Rao, Panjwani and Srivastava (2026) observed favorable and substantial effects of AI on the financial success of banks in the GCC region, such as ROA. In this research, the level of AI-enabled customer service is measured

from disclosures by all 38 licensed banks in Kenya, and its impact is estimated on audited performance.

### 2.2.2 Machine Learning Credit Scoring and Financial Performance

Mwesigwa et al. (2026) studied how algorithmic credit scoring is practised within Kenya's digital lending sector. Through nine months of ethnographic research, including observations of four start-up lenders and interviews with financial and policy actors, they found that practitioners assemble alternative data through technical and legal workarounds and negotiate model performance through both technical and political means. Scoring outcomes were therefore shaped as much by regulation and institutional relationships as by model accuracy. The study offers rich contextual insight, but its findings cannot be generalised and it measured no bank-level financial outcomes. This research fills this gap by estimating the effect of machine learning credit scoring on the audited profitability of all commercial banks in Kenya.

### 2.2.3 Robotic Process Automation and Financial Performance

Mamede et al. (2023) examined whether automation improves banking performance when processes are redesigned before automation. Using a design science research approach, they developed and demonstrated a lean method for robotic process automation and found that RPA delivers far less than it's potential when poorly designed processes are automated as they are, with benefits appearing mainly as shorter processing times and fewer errors. Chibole and Ondara (2025) similarly found that RPA improved process efficiency among selected commercial banks in Kenya. Both studies relied on process-level measures and did not extend to audited bank profitability. The present study examines this relationship directly by estimating RPA's effect on Kenyan banks' financial performance.

### 2.2.4 AI-driven Fraud Detection and Financial Performance

Al-Hashedi and Magalingam (2021) reviewed research published between 2009 and 2019 on using data mining techniques to detect financial fraud, classifying studies by technique, fraud type and field of research. They found that supervised machine learning techniques consistently improve the accuracy of credit, insurance, and financial statement fraud detection. However, the reviewed studies assessed models based on statistics, not profitability, and found few models that link improved detection to increased bank profitability, and none that include Kenyan banks. This research bridges this gap by estimating the impact of a disclosure-based measure of AI power fraud detection on Kenyan banks' audited performance.

### 2.2.5 Operational Efficiency, AI Adoption and Financial Performance

Elmahdy et al. (2025) examined the connection between financial technology, operational efficiency, and profitability among Egyptian banks, testing operational efficiency as a mediator and bank size as a moderator. They applied the two-step system generalised method of moments using financial data from 16 banks between 2015 and 2022 and discovered that there is a substantial adverse connection between financial technology and profitability, which is in line with the productivity paradox. Their independent variable was financial technology in general, however, not AI, and so the mediating mechanism was not tied to any intelligent capabilities. The current research further develops this test by segmenting AI adoption into four dimensions and using the causal steps approach and the Sobel test.

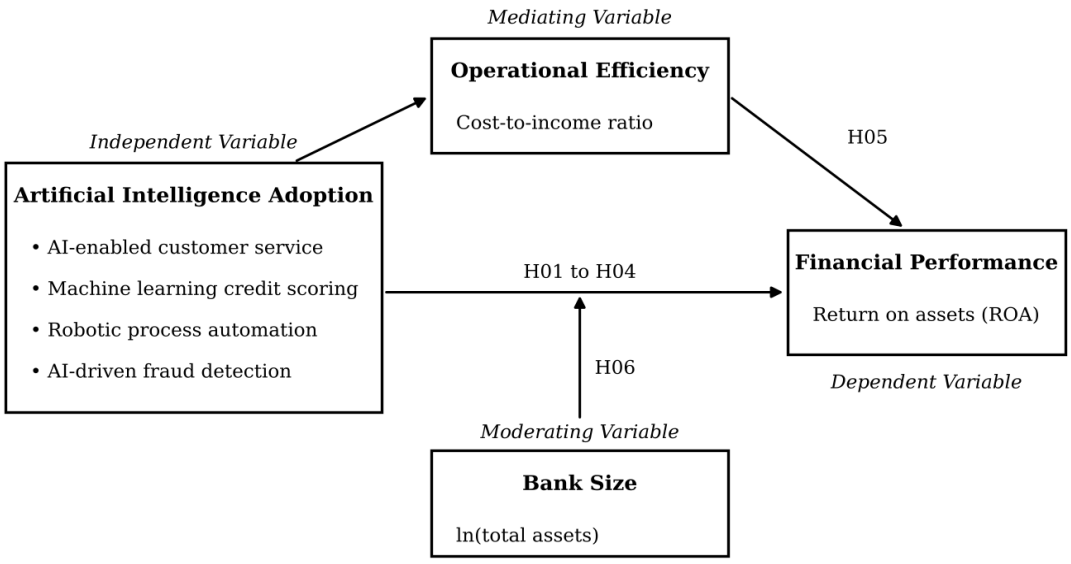
### 2.2.6 Bank Size, AI Adoption and Financial Performance

Kirimi et al. (2022) examined whether bank size moderates the connection between financial soundness and the financial success of commercial banks in Kenya. Using panel data on 39 banks from 2009 to 2018, they suggested that bank size adversely moderated the effect of financial soundness on both net interest margin and ROA, but had no moderating effect on return on equity. Chhaidar et al. (2023), by contrast, found that larger European banks gained more from financial technology investment than smaller ones. Neither study examined AI adoption, and the Kenyan evidence ends before the sector's rapid investment in AI. The present study applies the same moderating logic to AI adoption using data from 2020 to 2024.

## 2.3 Conceptual Framework

Figure 1 displays the conceptual framework. AI adoption, made up of four dimensions, is the independent variable and financial performance, measured by ROA, is the dependent variable. The four dimensions are expected to affect ROA directly ($H_{01}$ to $H_{04}$) and indirectly through operational efficiency ($H_{05}$), while bank size is expected to change the strength of the connection between AI adoption and ROA ($H_{06}$).

**Figure 1: Conceptual Framework**




## 3. Methodology

### 3.1 Research Design, Population and Data

The research used a positivist philosophy and an explanatory, longitudinal panel design to test six null hypotheses derived from the TOE framework and supporting theories. The intended audience was the 38 commercial banks licensed by the CBK during the study period. Given the small, finite population, the study adopted a census, yielding a balanced panel of 38 banks observed from 2020 to 2024, or 190 bank-year observations. Microfinance banks, mortgage finance companies and representative offices of foreign banks were excluded because their business models and disclosure requirements differ from those of commercial banks.

Secondary data were collected with a structured data collection sheet from audited annual and integrated reports, investor presentations, CBK Bank Supervision Annual Reports and Kenya Bankers Association publications (CBK, 2024; Kenya Bankers Association, 2024). Each AI dimension was coded one where a bank disclosed operational use of the application in a given year and zero otherwise. This disclosure-based approach, used in panel research on AI and bank performance (Shiyyab et al., 2023), avoids the perception-based Likert measures common in Kenyan studies, which cannot be matched to audited accounts (Mbeca, 2022). The scoring guide was reviewed by experts, piloted and cross-checked by a second rater, with inter-rater agreement above 90 percent, and 10 percent of the data were entered twice and compared. Table 2 summarises how the variables were measured.

Validity was ensured through expert review, grounding in theory and comparison with observable indicators. The supervisor and other academics in the field assessed content validity, while the literature and standard definitions of financial measures supported construct validity. Criterion validity was assessed by comparing the AI adoption scores with observable indicators of digital maturity, such as the availability of mobile and digital banking channels. Reliability was strengthened by relying on audited financial statements and regulatory publications, piloting the scoring guide with more than one rater, and conducting test-retest and inter-rater checks.

**Table 2: Operationalisation and Measurement of Variables**

| Variable | Type | Indicator | Measurement |
|---|---|---|---|
| AI-enabled customer service | Independent | Chatbot or virtual assistant deployment; queries resolved digitally | 1=adopted; 0=not adopted |
| Machine learning credit scoring | Independent | Machine learning underwriting; digital credit assessment | 1=adopted; 0=not adopted |
| Robotic process automation | Independent | Automated back-office processes across banking operations | 1=adopted; 0=not adopted |
| AI-driven fraud detection | Independent | Real-time transaction monitoring; machine learning anti-fraud and AML systems | 1=adopted; 0=not adopted |
| Operational efficiency | Mediating | Cost-to-income ratio | Operating expenses ÷ operating income × 100 |
| Bank size | Moderating | Total assets | Natural logarithm of total assets |
| Financial performance | Dependent | Return on assets | Profit after tax ÷ total assets × 100 |

### 3.2 Empirical Models

In all models, subscript *i* denotes the bank and *t* the year. Following the Hausman test, we used the random effects estimator, so each model includes a bank-specific random effect ($u_i$), shown in Equation 1 and omitted thereafter for brevity. The direct effects ($H_{01}$ to $H_{04}$) were tested with Equation 1, which includes the cost-to-income ratio and bank size as controls:

$$ROA_{it} = \beta_0 + \beta_1 CS_{it} + \beta_2 MLCS_{it} + \beta_3 RPA_{it} + \beta_4 FD_{it} + \beta_5 CTI_{it} + \beta_6 BS_{it} + u_i + \varepsilon_{it} \quad (1)$$

where ROA is return on assets, CS is AI-enabled customer service, MLCS is machine learning credit scoring, RPA is robotic process automation, FD is AI-driven fraud detection, CTI is the cost-to-income ratio, BS is bank size and ε is the error term. The mediating effect of operational efficiency ($H_{05}$) was tested with the causal steps approach of Baron and Kenny (1986). Step 1 regresses the mediator on the AI dimensions (path *a*), Step 2 regresses ROA on the AI dimensions (total effect, path *c*), and Step 3 adds the mediator (direct effect, path *c′*, and path *b*):

$$CTI_{it} = \beta_0 + \beta_1 CS_{it} + \beta_2 MLCS_{it} + \beta_3 RPA_{it} + \beta_4 FD_{it} + \varepsilon_{it} \quad (2)$$

$$ROA_{it} = \beta_0 + \beta_1 CS_{it} + \beta_2 MLCS_{it} + \beta_3 RPA_{it} + \beta_4 FD_{it} + \varepsilon_{it} \quad (3)$$

$$ROA_{it} = \beta_0 + \beta_1 CS_{it} + \beta_2 MLCS_{it} + \beta_3 RPA_{it} + \beta_4 FD_{it} + \beta_5 CTI_{it} + \varepsilon_{it} \quad (4)$$

Mediation requires significant *a* and *b* paths. It is full when *c′* becomes insignificant once CTI is included, and partial when *c′* remains significant but smaller than *c*. The indirect effect (*a* × *b*) was tested with the Sobel (1982) statistic, where $s_a$ and $s_b$ are the standard errors of *a* and *b*, and $|z| > 1.96$ indicates significance:

$$z = (a \times b) / \sqrt{(b^2 s_a^2 + a^2 s_b^2)} \quad (5)$$

The moderating effect of bank size ($H_{06}$) was tested by moderated regression (Aiken & West, 1991), using a composite AI adoption index equal to the mean of the four indicators, which ranges from 0 (no applications adopted) to 1 (all four adopted):

$$AI_{it} = (CS_{it} + MLCS_{it} + RPA_{it} + FD_{it}) / 4 \quad (6)$$

$$ROA_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 BS_{it} + \beta_3 (AI_{it} \times BS_{it}) + \varepsilon_{it} \quad (7)$$

$H_{06}$ was rejected because $\beta_3$ was significant at the 5 percent level, with its sign showing whether bank size strengthens or weakens the relationship.

### 3.3 Data Analysis

Data were analysed in Stata. After descriptive statistics, the data were tested for normality (Jarque-Bera and skewness-kurtosis tests), multicollinearity (variance inflation factors), heteroskedasticity (Modified Wald and Breusch-Pagan tests), autocorrelation (Wooldridge test) and model specification (Ramsey RESET and Hausman tests) (Baltagi, 2021; Hair et al., 2019). All models were estimated with standard errors clustered at the bank level, and all hypotheses were tested at the 5 percent significance level (Wooldridge, 2010).

## 4. Results and Discussion

### 4.1 Descriptive Statistics

**Table 3: Descriptive Statistics of Study Variables**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| ROA (%) | 190 | 1.105 | 2.197 | −5.22 | 9.30 |
| AI-enabled customer service | 190 | 0.395 | 0.490 | 0 | 1 |
| Machine learning credit scoring | 190 | 0.663 | 0.474 | 0 | 1 |
| Robotic process automation | 190 | 0.511 | 0.501 | 0 | 1 |
| AI-driven fraud detection | 190 | 0.826 | 0.380 | 0 | 1 |
| Cost-to-income ratio (%) | 190 | 154.853 | 781.159 | 20.30 | 10,509.92 |
| Bank size (ln total assets) | 190 | 24.926 | 1.414 | 21.917 | 28.076 |

Source: Research findings (2026).

Table 3 shows considerable variation in commercial banks' financial performance from 2020 to 2024. ROA averaged 1.105 percent, meaning banks earned about KES 1.10 in profit for every KES 100 of total assets. The standard deviation of 2.197 percent is almost twice the mean, showing that profitability was widely spread around the average. ROA ranged from −5.22 percent to 9.30 percent, so while some bank-year observations recorded losses, others earned relatively high returns. This spread confirms that ROA varies enough to examine AI adoption's effect on financial performance.

AI adoption also differed considerably across banks. AI-driven fraud detection had the highest mean of 0.826, indicating adoption in about 82.6 percent of the 190 bank-year observations. It was followed by machine learning credit scoring at 0.663, robotic process automation at 0.511 and AI-enabled customer service at 0.395. The high uptake of fraud detection aligns with banks' priority of managing security and operational risks, while the lower uptake of AI-enabled customer service suggests customer-facing applications were still spreading across the sector. The standard deviations, ranging from 0.380 to 0.501, show meaningful variation in adoption, which is needed to estimate each application's effect on ROA.

The cost-to-income ratio averaged 154.853 percent and ranged from 20.30 to 10,509.92 percent. The extreme maximum reflects loss-making banks whose operating costs far exceeded income, and explains why the mean exceeds 100 percent. Bank size was more evenly distributed, with a mean of 24.926 and a variation of 1.414. In the regressions, the cost-to-income ratio was entered as a ratio (CTI divided by 100) so that its coefficient is on a scale comparable to the other variables.

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### 4.2 Diagnostic Tests

**Table 4: Summary of Diagnostic Test Results for the ROA Model**

| Test | Statistic | p-value | Decision |
|---|---|---|---|
| Jarque-Bera (normality) | $\chi^2 = 73.73$ | 0.000 | Residuals not normal |
| Skewness-kurtosis (normality) | $\chi^2 = 19.35$ | 0.000 | Residuals not normal |
| Variance inflation factors | Mean VIF = 2.14; max = 3.25 | n/a | No serious multicollinearity |
| Modified Wald (heteroskedasticity) | $\chi^2(38) = 15{,}513.77$ | 0.000 | Groupwise heteroskedasticity |
| Breusch-Pagan/Cook-Weisberg | $\chi^2(1) = 3.72$ | 0.054 | Borderline; not rejected |
| Wooldridge (autocorrelation) | $F(1, 37) = 13.307$ | 0.001 | First-order autocorrelation |
| Ramsey RESET (specification) | $F(3, 180) = 2.92$ | 0.035 | Some misspecification |
| Hausman (FE vs RE) | $\chi^2(6) = 8.33$ | 0.215 | Random effects preferred |

As Table 4 shows, the residuals were not normally distributed, likely because of the extreme observations noted above, but with 190 observations, inference can rely on the asymptotic properties of the estimators. Variance inflation factors were well below 10 and the highest pairwise correlation (0.748, between AI-enabled customer service and robotic process automation) was below 0.8, so multicollinearity was not a concern. The Modified Wald and Wooldridge tests showed heteroskedasticity across banks and first-order autocorrelation, so we clustered standard errors at the bank level. The RESET test suggested some functional-form misspecification, consistent with the extreme cost-to-income ratios, and this is noted as a limitation. The Hausman test favoured the random effects estimator.

### 4.3 Effect of AI Adoption on Financial Performance

**Table 5: Random Effects Regression Results for the ROA Model**

| Variable | Coefficient | Robust SE | z | P > \|z\| | 95% CI |
|---|---|---|---|---|---|
| AI-enabled customer service | 0.9270 | 0.3089 | 3.00 | 0.003 | 0.3215 to 1.5325 |
| Machine learning credit scoring | −0.0457 | 0.2281 | −0.20 | 0.841 | −0.4928 to 0.4014 |
| Robotic process automation | −0.4504 | 0.2721 | −1.66 | 0.098 | −0.9837 to 0.0829 |
| AI-driven fraud detection | 0.1369 | 0.1851 | 0.74 | 0.459 | −0.2258 to 0.4996 |
| Constant | −21.7522 | 4.3062 | −5.05 | 0.000 | −30.1921 to −13.3122 |

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The model was jointly significant (Wald $\chi^2(6) = 48.11$, $p = 0.000$) and explained 42.67 percent of the overall variation in ROA and 54.17 percent of the variation between banks. The rho of 0.4635 shows that about 46 percent of the unexplained variance is bank-specific, supporting a panel estimator over pooled OLS.

AI-enabled customer service had a favorable and substantial effect on ROA (β=0.9270, z=3.00, p=0.003): banks that adopted chatbots and virtual assistants recorded an ROA about 0.93 percentage points higher than non-adopters, holding other factors constant. Machine learning credit scoring (β=−0.0457, p=0.841) and AI-driven fraud detection (β=0.1369, p=0.459) had no significant effect. Robotic process automation had a negative coefficient (β=−0.4504, p=0.098) that was significant only at the 10 percent level. Bank size had a favorable and substantial effect on ROA (β=0.9080, z=5.19, p=0.000). $H_{01}$ was therefore rejected, while $H_{02}$, $H_{03}$ and $H_{04}$ were not rejected. The fitted model is:

$$ROA = -21.7522 + 0.9270CS - 0.0457MLCS - 0.4504RPA + 0.1369FD + 0.0028CTI + 0.9080BS \quad (8)$$

### 4.4 Mediating Effect of Operational Efficiency

**Table 6: Mediating Effect of Operational Efficiency (Causal Steps and Sobel Test)**

| Variable | Step 1: CTI (path a) | | Step 2: ROA (path c) | | Step 3: ROA (paths c′, b) | |
|---|---|---|---|---|---|---|
| | β | p | β | p | β | p |
| AI-enabled customer service | −0.1944 | 0.000 | 1.2466 | 0.000 | 1.2397 | 0.000 |
| Machine learning credit scoring | −0.0771 | 0.155 | 0.1489 | 0.515 | 0.1483 | 0.519 |
| Robotic process automation | −0.0263 | 0.631 | −0.3748 | 0.208 | −0.3765 | 0.207 |
| AI-driven fraud detection | −4.6994 | 0.254 | 0.2854 | 0.145 | 0.2810 | 0.151 |
| Cost-to-income ratio (path b) | | | | | −0.00475 | 0.167 |
| Constant | 5.5729 | 0.176 | 0.4694 | 0.075 | 0.4844 | 0.068 |

Table 6 reports the three mediation steps. In Step 1, AI-enabled customer service significantly lowered the cost-to-income ratio (β = -0.1944, p = 0.000) by about 19.4 percentage points relative to non-adopters, while the other dimensions had no significant effect; the large coefficient for fraud detection reflects the extreme cost-to-income ratios of a distressed non-adopter. In Step 2, AI-enabled customer service had a substantial total effect on ROA (β = 1.2466, p = 0.000), larger than in Table 5 because this model does not control for bank size. In Step 3, the cost-to-income ratio had an insignificant effect on ROA (β = -0.00475, p = 0.167), and the coefficient of AI-enabled client service barely changed, from 1.2466 to 1.2397.

The Sobel test was applied to AI-enabled client service, the only dimension significant in both path *a* and path *c*. The indirect effect (a × b = 0.000923, Sobel SE = 0.000718) was not significant (z = 1.287, p = 0.198), so $H_{05}$ was not rejected. Although AI-enabled customer

service lowered costs relative to income, this efficiency gain did not translate into profitability, and its effect on ROA is direct rather than mediated.

### 4.5 Moderating Effect of Bank Size

**Table 7: Moderating Effect of Bank Size on the Relationship between AI Adoption and ROA**

| Variable | Coefficient | Robust SE | z | P > \|z\| | 95% CI |
|---|---|---|---|---|---|
| AI adoption index | −3.4304 | 7.1318 | −0.48 | 0.631 | −17.4084 to 10.5476 |
| Bank size | 0.8324 | 0.2678 | 3.11 | 0.002 | 0.3075 to 1.3573 |
| AI index × bank size | 0.1544 | 0.2862 | 0.54 | 0.589 | −0.4064 to 0.7153 |
| Constant | −19.9384 | 6.6175 | −3.01 | 0.003 | −32.9085 to −6.9683 |

Source: Research findings (2026).

The moderation model was jointly significant (Wald $\chi^2(3) = 38.43$, p=0.000). Bank size had a favorable and substantial effect on ROA (β=0.8324, p=0.002), but the interaction between the AI index and bank size was not significant (β=0.1544, p=0.589), and its confidence interval includes zero. The AI index coefficient (β=−3.4304, p=0.631) represents the effect of adoption at a bank size of zero, far outside the observed range, and should not be read as the general effect of AI adoption. $H_{06}$ was therefore not rejected: the effect of AI adoption on ROA did not differ significantly between larger and smaller banks.

### 4.6 Summary of Hypothesis Testing

Table 8 summarises the results of the six null hypothesis tests.

**Table 8: Summary of Hypothesis Testing**

| Hypothesis | Test statistic | p-value | Decision |
|---|---|---|---|
| $H_{01}$: AI-enabled customer service has insignificant effect on financial performance | β = 0.9270 | 0.003 | Rejected |
| $H_{02}$: Machine learning credit scoring has insignificant effect on financial performance | β = −0.0457 | 0.841 | Not rejected |
| $H_{03}$: Robotic process automation has insignificant effect on financial performance | β = −0.4504 | 0.098 | Not rejected |
| $H_{04}$: AI-driven fraud detection has insignificant effect on financial performance | β = 0.1369 | 0.459 | Not rejected |
| $H_{05}$: Operational efficiency has insignificant mediating effect | Sobel z = 1.287 | 0.198 | Not rejected |
| $H_{06}$: Bank size has insignificant moderating effect | $\beta_3$ = 0.1544 | 0.589 | Not rejected |

### 4.7 Discussion

The main finding is that the profitability benefits of AI in Kenyan banking are not evenly distributed across applications. Between 2020 and 2024, AI-enabled customer service had a strong and significant link with ROA, while the other three applications did not. This helps to explain the problem set out in Section 1.1: sector profitability declined as AI investment grew because much of that investment lies in applications whose benefits have not yet appeared in audited results, or have been offset by implementation and governance costs. The customer service result is congruent with Rao et al. (2026), who found that AI adoption raised the ROA of GCC banks, and with Fares et al. (2023), who reported that the financial benefits of AI in banking are concentrated in customer-facing uses.

The result for machine learning credit scoring is notable given the central place of digital lending in discussions of AI in Kenyan banking. It shares this insight with Sherstiuk (2026), who noted that improvements in the predictive performance of machine learning credit scoring don't automatically translate into better operational efficiency or financial results. Improvements in scoring accuracy could be offset by an increase in low-margin loans or governance and multiple-borrowing issues, as Mwesigwa et al. (2026) found in Kenya's digital credit market, which may reduce returns that improved scoring should provide. Furthermore, the benefits of credit risk may be realized over the full course of the loan, which can be more than five years, especially during an era of increasing NPLs.

The same applies to the outcome for robotic process automation. Staff-cost savings, especially where automation displaces manual reconciliation and onboarding activities, should, in principle, reach the income statement fairly soon. In this study, the RPA coefficient was adverse and substantial only at the 10 percent level, and RPA did not significantly affect the cost-to-income ratio. This contrasts with Chibole and Ondara (2025), who identified process gains in Kenyan banks as a result of RPA, implying that process gains are not necessarily an immediate improvement in ROA. This aligns with Fares et al. (2023), who noted that most literature and evidence on the financial gains of RPA comes from vendor case studies, and with Mamede et al. (2023), who found that RPA projects achieve far less than anticipated when processes are not first optimized.

The outcome of AI-powered fraud detection should be interpreted in light of the growing fraud landscape mentioned in Section 1. Attacks on Kenyan banks via mobile and machine-learning monitoring have become standard practice, not a competitive edge, while card and internal channels are increasingly subject to fraud attempts. Because this technology is adopted in more than four out of five bank-year observations, it is hard to link it to differences in performance between banks, as few non-adopters remain to compare with. This is a limitation of the measure used in this study, not evidence that fraud detection has no financial value, and a measure of deployment depth would better capture its effect.

Bank size had a strong and consistent favorable effect on ROA. Larger banks earned higher returns regardless of their level of AI adoption, a finding consistent with Nyabaga and Wepukhulu (2020), who found a substantial favorable effect of bank size on the ROA of listed Kenyan banks, and with the resource-based view, which explains the pattern through the proprietary data, technical skills and governance capacity that scale makes affordable (Barney, 1991). However, bank size did not affect the returns banks earned from AI adoption. The wider literature on this question is mixed: Chhaidar et al. (2023) found a positive size moderation and

Kirimi et al. (2022) a negative one, while Elmahdy et al. (2025) found, as in this study, that bank size did not substantially influence the association.

Finally, the absence of mediation challenges the common view that AI improves performance mainly by cutting costs (Wamba et al., 2020). In line with the productivity paradox reported by Elmahdy et al. (2025) for Egyptian banks, the benefit of AI-enabled customer service appears to work through revenue channels, such as wider reach and stronger customer relationships, rather than through lower costs. This result should be read with caution, because extreme cost-to-income ratios among distressed banks weaken the ratio as an efficiency measure.

## 5. Conclusion

The research concluded that AI adoption does not necessarily translate into uniform financial performance across applications for commercial banks in Kenya. The results indicate that commercial banks in Kenya do not necessarily improve financial performance when they adopt AI across applications. AI in customer service shows gains in profitability, as it is the only application significantly correlated. During the study period, machine learning credit scoring, RPA, and AI-based fraud detection showed no statistically significant benefits in ROA. While AI-powered customer service reduced the cost-to-income ratio, the favorable impact on profitability is not necessarily realized when you streamline your operations, which is why it is more likely to be experienced from revenue channels. Increased size directly improved bank profitability but did not change the returns banks gained from AI adoption.

## 6. Recommendations

### 6.1 Recommendations for Practice

Commercial banks should invest in and build AI-driven customer service applications, as evidence shows a favorable impact on profitability. Banks need to enhance the capabilities of virtual assistants and self-service options, and leverage customer information from these tools to build a better cross-selling and retention proposition. Banks should more carefully monitor the costs and benefits of each application to avoid further capital investment in machine learning credit scoring and AI fraud detection. Such tracking should evaluate metrics such as loan loss, processing time, and fraud avoided to determine each investment's value.

Before banks automate their processes, they should review and streamline them to ensure that they optimise their process. Given the strong correlation between bank size and profitability, smaller entities should consider whether the cost of AI systems can be amortized over enough transactions to offset the expense. If volumes are small, they might want to try cloud-based or shared solutions, partner with tech vendors, and/or prioritize applications with the highest potential ROI (return on investment), such as AI-powered customer service.

### 6.2 Recommendations for Policy

CBK should complete and publish risk-based guidance on the governance of AI models in banking, including data quality, explainability and accountability, and model validation. It should also require banks to report the costs and benefits of AI with greater granularity in their prudential returns and annual reports, enabling the regulator, investors, and researchers to better evaluate the benefits of AI investments. More transparent disclosure would also reduce future reliance on voluntary, uneven disclosure.

Policymakers should also explore shared digital infrastructure or industry utilities, for example in fraud monitoring and credit data, that would allow smaller banks to access the benefits of AI currently concentrated among larger institutions. These could lower the "adoption costs" of smaller banks, increase competition in the banking system, and make the adoption process more cost-effective. Furthermore, collaboration between the CBK and the Office of the Data Protection Commissioner is required to ensure that alternative data are used in machine learning credit scoring in ways that do not compromise borrowers' rights while promoting responsible innovation.

### 6.3 Suggestions for Further Research

Future studies should test other possible mediators of the connection between AI adoption and financial success, such as staff productivity, loan portfolio quality or the volume of digital transactions, since the cost-to-income ratio did not carry the effect in this study. Researchers should also extend the panel beyond 2024, because five years may be too short to capture benefits that emerge over a full technology investment cycle. Measures of adoption depth, such as the share of loans scored by machine learning or the number of processes automated, should replace simple presence indicators. Finally, dynamic panel or instrumental variable methods would strengthen causal inference, since banks do not adopt AI at random, and similar studies could be conducted for microfinance banks and banks in other African countries.

### References

Adeniran, I. A., Efunniyi, C. P., Osundare, O. S., & Abhulimen, A. O. (2024). Integrating business intelligence and predictive analytics in banking: A framework for optimizing financial decision-making. Finance & Accounting Research Journal, 6(8), 1517–1530.

Aiken, L. S., & West, S. G. (1991). Multiple regression: Testing and interpreting interactions. Sage.

Al-Hashedi, K. G., & Magalingam, P. (2021). Financial fraud detection applying data mining techniques: A comprehensive review from 2009 to 2019. Computer Science Review, 40, Article 100402. https://doi.org/10.1016/j.cosrev.2021.100402

Arakpogun, E. O., Elsahn, Z., Olan, F., & Elsahn, F. (2021). Artificial intelligence in Africa: Challenges and opportunities. In A. Hamdan, A. E. Hassanien, A. Razzaque, & B. Alareeni (Eds.), The fourth industrial revolution: Implementation of artificial intelligence for growing business success (pp. 375–388). Springer. https://doi.org/10.1007/978-3-030-62796-6_22

Ashta, A., & Herrmann, H. (2021). Artificial intelligence and fintech: An overview of opportunities and risks for banking, investments, and microfinance. Strategic Change, 30(3), 211–222. https://doi.org/10.1002/jsc.2404

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. https://doi.org/10.1177/014920639101700108

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of Personality and Social Psychology, 51(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

Basaran, B., & Bagheri, M. (2020). The relevance of "trust and confidence" in financial markets to the information production role of banks. European Journal of Risk Regulation, 11(3), 650–666.

Chhaidar, A., Abdelhedi, M., & Abdelkafi, I. (2023). The effect of financial technology investment level on European banks' profitability. Journal of the Knowledge Economy, 14, 2959–2981. https://doi.org/10.1007/s13132-022-00992-1

Chibole, A. N., & Ondara, B. (2025). Artificial intelligence technologies and process efficiency in the banking industry: A case study of selected commercial banks in Kenya. African Journal of Commercial Studies, 6(5), 130–144. https://doi.org/10.59413/ajocs/v6.i5.12

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

Elmahdy, A. H. A. M., Abdelkader, M. T. K. M., & Shaker, M. A. M. (2025). Bridging the nexus between fintech, operational efficiency and banks profitability: The moderating role of bank size. Future Business Journal, 11, Article 62. https://doi.org/10.1186/s43093-025-00478-x

Fares, O. H., Butt, I., & Lee, S. H. M. (2023). Utilization of artificial intelligence in the banking sector: A systematic literature review. Journal of Financial Services Marketing, 28, 835–852. https://doi.org/10.1057/s41264-022-00176-7

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8th ed.). Cengage Learning.

Kalyani, S., & Gupta, N. (2023). Is artificial intelligence and machine learning changing the ways of banking: A systematic literature review and meta-analysis. Discover Artificial Intelligence, 3(1), Article 41.

Kamau, P., & Kihara, E. (2020). The impact of mobile banking on the financial performance of commercial banks in Kenya. International Journal of Economics, Commerce and Management, 8(9), 87–101.

Kirimi, P. N., Kariuki, S. N., & Ocharo, K. N. (2022). Moderating effect of bank size on the relationship between financial soundness and financial performance. African Journal of Economic and Management Studies, 13(1), 62–75. https://doi.org/10.1108/AJEMS-07-2021-0316

Konigstorfer, F., & Thalmann, S. (2020). Applications of artificial intelligence in commercial banks: A research agenda for behavioral finance. Journal of Behavioral and Experimental Finance, 27, Article 100352. https://doi.org/10.1016/j.jbef.2020.100352

Mamede, H. S., Goncalves Martins, C. M., & Mira da Silva, M. (2023). A lean approach to robotic process automation in banking. Heliyon, 9(7), Article e18041. https://doi.org/10.1016/j.heliyon.2023.e18041

Mbeca, V. N. (2022). Effect of artificial intelligence on competitive advantage in the Kenyan banking industry: A case of Absa Bank Kenya [Unpublished master's thesis]. United States International University-Africa.

McElheran, K., Li, J. F., Brynjolfsson, E., Kroff, Z., Dinlersoz, E., Foster, L., & Zolas, N. (2024). AI adoption in America: Who, what, and where. Journal of Economics & Management Strategy, 33(2), 375–415. https://doi.org/10.1111/jems.12576

Mhlanga, D. (2020). Industry 4.0 in finance: The impact of artificial intelligence (AI) on digital financial inclusion. International Journal of Financial Studies, 8(3), Article 45. https://doi.org/10.3390/ijfs8030045

Mu, Y., Liu, Z., & Wang, J. (2026). Does artificial intelligence enhance bank profitability? Evidence from China. Finance Research Letters, 90, Article 109366. https://doi.org/10.1016/j.frl.2025.109366

Muthuuri, C., & Kihara, A. (2025). Machine learning adoption and its effect on efficiency of credit analysis in Tier II commercial banks in Kenya. International Journal of Finance, 10(8), 70–89. https://doi.org/10.47941/ijf.3357

Mwesigwa, D., Jackson, S. J., & Csikszentmihalyi, C. (2026). Risk, data, alignment: Making credit scoring work in Kenya. In Proceedings of the 2026 CHI Conference on Human Factors in Computing Systems (CHI '26). Association for Computing Machinery. https://doi.org/10.1145/3772318.3790924

Nyabaga, R. M., & Wepukhulu, J. M. (2020). Effect of firm characteristics on financial performance of listed commercial banks in Kenya. International Journal of Economics and Financial Issues, 10(3), 255–262. https://doi.org/10.32479/ijefi.9692

Polireddi, N. S. A. (2024). An effective role of artificial intelligence and machine learning in the banking sector. Measurement: Sensors, 33, Article 101135.

Rahman, M., Ming, T. H., Baigh, T. A., & Sarker, M. (2023). Adoption of artificial intelligence in banking services: An empirical analysis. International Journal of Emerging Markets, 18(10), 4270–4300. https://doi.org/10.1108/IJOEM-06-2020-0724

Rao, P., Panjwani, K., & Srivastava, N. (2026). Effect of artificial intelligence on the financial performance of GCC banks. Journal of Digital Economy, 5, 214–225. https://doi.org/10.1016/j.jdec.2026.05.004

Shiyyab, F. S., Alzoubi, A. B., Obidat, Q. M., & Alshurafat, H. (2023). The impact of artificial intelligence disclosure on financial performance. International Journal of Financial Studies, 11(3), Article 115. https://doi.org/10.3390/ijfs11030115

Sobel, M. E. (1982). Asymptotic confidence intervals for indirect effects in structural equation models. Sociological Methodology, 13, 290–312. https://doi.org/10.2307/270723

Spring, M., Faulconbridge, J., & Sarwar, A. (2022). How information technology automates and augments processes: Insights from artificial-intelligence-based systems in professional service operations. Journal of Operations Management, 68(6–7), 592–618. https://doi.org/10.1002/joom.1215

Tornatzky, L. G., & Fleischer, M. (1990). The processes of technological innovation. Lexington Books.

Wamba-Taguimdje, S. L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: The business

value of AI-based transformation projects. Business Process Management Journal, 26(7), 1893–1924. https://doi.org/10.1108/BPMJ-10-2019-0411

Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data (2nd ed.). MIT Press.