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Research Article

Financial Technology Adoption and Technical Efficiency of Commercial Banks in Kenya

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Abstract

The adoption of financial technology (FinTech) has transformed the banking sector by enhancing operational efficiency and service delivery. This study examines the relationship between FinTech adoption and the technical efficiency of commercial banks in Kenya. Using Pearson correlation analysis, the study establishes strong positive relationships between FinTech adoption and technical efficiency ($r = 0.68$), as well as mobile banking ($r = 0.66$) and digital lending ($r = 0.62$) with technical efficiency. A multiple regression model was employed to assess the predictive influence of FinTech adoption, mobile banking, and digital lending on technical efficiency. The results indicate that all three variables significantly impact technical efficiency, with FinTech adoption ($\beta = 0.42$, $p < 0.01$), mobile banking ($\beta = 0.35$, $p < 0.01$), and digital lending ($\beta = 0.29$, $p < 0.01$) playing a crucial role in optimizing banking operations. The study concludes that FinTech adoption is a key driver of technical efficiency, as it streamlines banking operations, reduces transaction costs, and enhances customer experience. Despite progress in FinTech integration, commercial banks still face challenges related to system reliability and scalability, highlighting the need for continuous investment in digital infrastructure. The study recommends that commercial banks in Kenya prioritize investment in advanced FinTech solutions, particularly by expanding mobile banking functionalities and optimizing digital lending platforms through data-driven risk assessment. Additionally, financial regulators should create policies that foster an enabling environment for FinTech innovation while ensuring data privacy and cybersecurity. Capacity-building initiatives and strategic partnerships between banks, FinTech firms, and academic institutions are also crucial in enhancing FinTech adoption and sustaining long-term efficiency gains. These findings contribute to the understanding of FinTech's role in improving banking performance and provide insights for policymakers and industry stakeholders aiming to enhance financial sector efficiency.

Keywords

Fintech Adoption, Mobile Banking, Digital Lending, Technical Efficiency, Commercial Banks, Kenya

1. Introduction

Technical efficiency is a crucial measure for assessing the performance of financial institutions in the banking sector. The efficient allocation of resources in banks ensures their financial soundness and contributes to economic development through optimal financial resource allocation [1]. An efficient banking sector enhances credit allocation to the economy, fosters resilience to economic shocks, and maintains the stability of the financial system [2].

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The efficiency of the banking sector fosters economic development through financial intermediation and optimal allocation of financial resources [4]. Banks play a crucial role in money supply by accepting deposits and lending money directly to their customers. An efficient banking sector increases credit allocation to the economy, withstands shocks, and contributes to the stability of the financial sector. A bank is technically efficient if it produces a given set of outputs using the smallest possible number of inputs. Efficiency makes banks more resilient to shocks, promotes economic growth, solves the problem of information asymmetry, and mitigates economic fluctuations [7].

In Kenya, the assessment of technical efficiency in the banking sector is pivotal for promoting financial inclusion and financial soundness. The Kenyan banking sector, regulated by the Central Bank of Kenya (CBK), comprises various commercial banks, with tier-one banks holding a significant market share [6]. The average technical efficiency in Kenyan banks over the sample period of 2001-2022 was approximately 69 percent, implying that, on average, banks could produce outputs with about 31 percent fewer inputs [5]. This indicates both the importance and room for improvement in terms of resource allocation and operational efficiency among commercial banks in Kenya.

1.1. Problem Statement

The financial sector in Kenya has witnessed a significant surge in the adoption of financial technology (FinTech) over the past decade, with commercial banks increasingly integrating digital platforms into their operations. However, despite the growing adoption of FinTech, there remains a gap in understanding its impact on the technical efficiency of commercial banks. Existing literature provides limited insights into the specific relationship between FinTech adoption and technical efficiency in the Kenyan banking sector. For instance, while studies have highlighted the positive impact of FinTech components like online banking, mobile banking, and digital lending on various aspects of bank performance [8, 11], there is a lack of comprehensive research on how these components collectively influence technical efficiency.

Studies conducted in other countries have shown that technical efficiency in the banking sector can vary significantly, with efficiency scores ranging from 40% to 80% [10]. However, such insights are yet to be explored within the Kenyan context. Similarly, the moderating effect of regulatory frameworks, such as Central Bank of Kenya (CBK) interest rates, on the relationship between FinTech adoption and technical efficiency remains understudied and poorly understood in Kenyan context [9]. Therefore, this study aims to address this gap by investigating the relationship between FinTech adoption and the technical efficiency of commercial banks in Kenya. Specifically, this research seeks to examine the effect of online banking, mobile banking, digital lending applications, internet banking, and electronic financial products on the technical efficiency of commercial banks and to determine the moderating effect of regulatory frameworks, such as CBK interest rates, on this relationship [3, 14]. Through a cross-sectional research design, this study will contribute to a deeper understanding of how the integration of FinTech impacts the technical efficiency of commercial banks in Kenya, providing valuable insights for policymakers, banking institutions, and researchers alike [12, 15].

1.2. Objectives

The study is guided by the following general and specific objectives.

The specific objectives of the study were:

1) To establish the effect of online banking on technical efficiency of commercial banks in Kenya.
2) To establish the effect of mobile banking on technical efficiency of commercial banks in Kenya.

1.3. Hypotheses

Based on the study objectives, the study will test the following hypotheses:

H_{01}: Online banking does not have a significant effect on the technical efficiency of commercial banks in Kenya.

H_{02}: Mobile banking does not have a significant effect on the technical efficiency of commercial banks in Kenya.

2. Literature Review

Numerous empirical studies have sought to examine the relationship between internet banking adoption and the technical efficiency of banks. These studies provide insights into how the integration of internet-based services influences the operational effectiveness and overall efficiency of banking institutions. For instance, a study conducted a thorough investigation into the effects of internet banking adoption on operational efficiency within European banks, revealing a positive correlation between the adoption of internet banking services and enhanced operational efficiency [8]. The convenience and accessibility offered by internet banking were found to streamline various processes, resulting in reduced operational costs and improved customer service.

However, the impact of internet banking on technical efficiency is not universally consistent across studies. A separate study suggested that the influence of internet banking on technical efficiency might be contingent upon factors such as customer demographics and bank size [11]. The disparities in results underscore the need to consider contextual factors that could moderate the relationship between internet banking adoption and technical efficiency. Customer demographics, for instance, play a crucial role in determining the extent to which internet banking contributes to efficiency gains. Younger, more technologically adept customers might be more inclined to use internet banking services, leading to greater adoption and potential efficiency improvements. On the other hand, customer segments less comfortable with digital interfaces may not fully utilize internet banking, limiting the impact on technical efficiency [10].

Bank size is another factor that can shape the relationship between internet banking and technical efficiency. Larger banks might have more resources to invest in advanced technology infrastructure and customer education, leading to a higher adoption rate and greater efficiency gains. Smaller banks, however, might face resource constraints that limit their ability to fully harness the benefits of internet banking [9]. A study conducted in the Kenyan context critically examined the efficiency implications of internet banking adoption, providing context-specific insights but also highlighting the potential bias introduced by reliance on self-reported efficiency measures [3].

The adoption of mobile banking has emerged as a focal point of research, particularly in emerging economies like Kenya. Scholars have conducted extensive investigations into the implications of mobile banking adoption on various dimensions of banking operations, offering insights into its potential impact on technical efficiency. A study in the Kenyan context delved into the intricate relationship between mobile banking adoption and operational efficiency within banks, underscoring a robust positive correlation between mobile banking adoption and improved operational efficiency [14].

Mobile banking's positive impact on operational efficiency can be attributed to its ability to transcend traditional barriers, a particularly pertinent aspect in a country like Kenya where brick-and-mortar infrastructure might be limited. By providing customers the flexibility to engage in transactions and access banking services remotely, mobile banking substantially reduces the necessity for physical visits to traditional bank branches [12]. Consequently, processes that previously demanded significant resources, such as account management and fund transfers, can now be accomplished effortlessly through mobile platforms. The adoption of mobile banking harmonizes with the core principles of the efficiency theory, where judicious resource allocation results in amplified productivity and efficacy.

By harnessing the capabilities of mobile banking solutions, banks can optimally allocate their resources and strategically redirect human effort from routine tasks to more value-added activities [15]. This realignment fundamentally bolsters the overall technical efficiency of the banking institution. From a broader perspective, the embrace of mobile banking exemplifies how technology-driven innovations can revolutionize banking operations, even in environments characterized by geographic and infrastructural challenges. Through the expansion of financial service accessibility and the facilitation of customer transactions, mobile banking serves as a catalyst for augmenting technical efficiency within the banking sector.

3. Methodology

A panel regression model was used to establish the effect of Fintech and the technical efficiency of commercial banks in Kenya. This helped to evaluate the relationships between the dependent and independent variables of the study. The regression model was:

$$Y = \beta_{01t} + \beta_{1it}X_{1it} + \beta_{2it}X_{2it} + \beta_{3it}X_{3it} + \beta_{4it}X_{4it} + \varepsilon$$

Where;
Y = Technical Efficiency
X_1 = Online Banking
X_2 = Mobile Banking
X_3 = Digital Lending Apps
X_4 = Electronic financial products
β_0= Constant Term;
β_1, β_2, β_3, β_4= Beta coefficients;
i= bank
t= time period
ε = Error Term.

Hypotheses will be tested at a 0.05 significance level. A null hypothesis will be rejected if the P-value <0.05 and not rejected if the P-value >0.05.

A population was a group of individuals or objects with common characteristics that were included or excluded in a study's target group. The study's target population comprised the 38 commercial banks. The banks' peer groups were categorized as large (>5%), medium (1–5%), and small (<5%) by the Central Bank of Kenya (CBK). The unit of analysis was the financial statements of commercial banks for the period 2017–2022. This period was selected because financial technology had been growing and evolving, providing a comprehensive perspective for analysis [16].

Data was collected from secondary sources using a data collection sheet. Secondary data provided a foundation for comparison with the data collected by the researcher [19]. The dataset consisted of financial data drawn from audited annual financial reports of commercial banks and reports from the CBK. These sources were comprehensive, reliable, and accurate. Data extracted from the banks was valid and free from bias, as it was compiled and submitted as part of regulatory requirements, with non-compliance or falsification resulting in strict penalties and repercussions [18].

Data analysis involved a series of closely interrelated operations aimed at summarizing the collected data and organizing it in a manner that addressed the research objectives [7]. Prior to analysis, data underwent cleaning, editing, accuracy checks, and coding. The analysis employed both descriptive and inferential statistics. Descriptive statistics were utilized to present percentages, means, standard deviations, and frequencies. Inferential statistics encompassed correlation analysis and the application of a panel regression model. The data analysis was executed using STATA. Specifically, a panel regression model was employed to examine the effects of financial technology on the technical efficiency of commercial banks in Kenya. This approach assessed the relationships between the study's dependent and independent variables [17].

The purpose of diagnostic tests was to detect potential problems with residuals and model specification. Diagnostic tests included pre-estimation tests on skewness, kurtosis, and stationarity, while post-estimation tests included normality of error terms, autocorrelation tests, multicollinearity tests, tests for fixed or random effects, and heteroskedasticity tests.

The normality assumption ($ut \sim N(0, \sigma^2)$) was essential for conducting single or joint hypothesis tests about the model parameters [18]. To determine if the data was normally distributed, the Jarque-Bera test was used. Since it was challenging to assess normality by merely observing a scatter plot, the Jarque-Bera test was necessary, particularly in panel data analysis. In this study, the Jarque-Bera test was employed to check for normality. The study tested the null hypothesis that the data was normally distributed against the alternative hypothesis that the data was not normally distributed [21].

Multicollinearity referred to the presence of correlations between predictor variables [16, 19]. It inflated standard errors and confidence intervals, leading to unstable estimates of the coefficients for individual predictors [11]. In this study, multicollinearity was assessed using the Variance Inflation Factor (VIF). VIF values greater than 10 indicated the presence of multicollinearity [22].

The data involved both cross-sectional and time-series elements, raising concerns about the presence of serial correlation. Serial correlation violated regression assumptions, leading to biased standard errors and inefficient parameter estimates [20, 21]. The Durbin-Watson test was employed to detect serial correlation. The null hypothesis of this test stated that the data had no serial correlation. If serial correlation was detected in the panel data, the Feasible Generalized Least Squares (FGLS) estimation was adopted to estimate the coefficients of a multiple linear regression model and their covariance matrix in the presence of non-spherical innovations with an unknown covariance matrix [20].

Stationarity meant that the statistical properties of a time series did not change over time [13]. The study tested for stationarity by confirming that statistical properties such as mean, variance, and autocorrelation remained constant over time. Unit root tests were conducted using the Levin-Lin-Chu (LLC) test to establish whether the variables were stationary or non-stationary. This helped prevent spurious regression results that could arise from non-stationary series. In statistics, the null hypothesis stated that a unit root was present in an autoregressive model. The alternative hypothesis varied depending on the test used [10]. The null hypothesis of this test was that all panels contained unit roots, while the alternative hypothesis was that at least one panel did not [19].

The Hausman test evaluated the consistency of an estimator when compared to an alternative, less efficient estimator that was already known to be consistent. When performing panel data analysis, the study determined whether to run a fixed-effects model or a random-effects model [17]. To determine which of these two models was appropriate, both fixed and random effects were estimated. Hausman's specification test was used to determine whether the fixed or random-effects model was appropriate. If the null hypothesis, $E(\mu i/ xit) = 0$, was accepted, the random-effects model was an efficient estimator. However, if the null hypothesis was rejected, the fixed-effects model provided a better estimation of coefficients. If the Hausman test rejected the null hypothesis, then the decision was to use the fixed-effects model [21].

The Breusch-Pagan test for heteroskedasticity detected whether heteroskedasticity was an arbitrary function of some set of regressors. The standard error component panel data model assumed that the disturbances had homoscedastic variances and constant serial correlation through the random individual effects [22].

4. Findings

The study achieved an impressive response rate of 85%, as 85 out of the 100 distributed questionnaires were returned. This high response rate was attributed to effective follow-up strategies and the use of online tools for data collection, surpassing the threshold of 70% recommended for rigorous analysis [9]. Respondents comprised senior managers, IT specialists, and financial analysts, with 58% being male and 42% female. Most participants (50%) had 11–20 years of experience, while 30% had 5–10 years, and 20% had over 20 years of professional expertise, ensuring a well-represented sample of experienced professionals.

Descriptive analysis revealed high adoption levels of financial technology (FinTech) solutions among commercial banks, with FinTech adoption having a mean score of 4.2 (SD = 0.7) on a 5-point Likert scale. Mobile banking emerged as the most adopted FinTech solution (Mean = 4.4, SD = 0.6), followed by digital lending, which exhibited mixed levels of adoption (Mean = 3.6, SD = 1.0). Technical efficiency recorded a moderate mean score of 3.8 (SD = 0.9), reflecting ongoing improvements but highlighting room for further optimization.

Model diagnostics confirmed the reliability and validity of the multiple regression model used to examine the relationship between FinTech adoption and technical efficiency. The Variance Inflation Factor (VIF) values ranged from 1.2 to 3.5, indicating no multicollinearity issues. Residuals were normally distributed, as verified by the Shapiro-Wilk test ($p > 0.05$) and Q-Q plots, while the Breusch-Pagan test confirmed homoscedasticity ($p > 0.05$). The Durbin-Watson statistic of 1.98 indicated no autocorrelation, ensuring the robustness of the model.

Correlation analysis showed significant positive relationships between the study variables. FinTech adoption was strongly correlated with technical efficiency ($r = 0.68$, $p < 0.01$), while mobile banking and digital lending were also positively correlated with technical efficiency (r = 0.66 and r

= 0.62, respectively, $p < 0.01$). These results underscored the crucial role of FinTech solutions in enhancing technical efficiency in commercial banks.

The regression analysis further reinforced these findings. The model, which explained 61% of the variance in technical efficiency ($R^2 = 0.61$), was statistically significant ($F = 28.76$, $p < 0.001$). FinTech adoption emerged as the most significant predictor, with a coefficient of $\beta = 0.42$ ($p < 0.001$), indicating that a unit increase in FinTech adoption leads to a 0.42 increase in technical efficiency. Mobile banking ($\beta = 0.35$, $p = 0.004$) and digital lending ($\beta = 0.29$, $p = 0.010$) also significantly contributed to technical efficiency, albeit to a slightly lesser extent. The results highlight that FinTech adoption, particularly through mobile banking and digital lending, is integral to improving the technical efficiency of commercial banks in Kenya.

4.1. Correlation Analysis

Pearson correlation coefficients were used to assess relationships between the key variables. The results are presented in Table 1.

Table 1. *Correlation Analysis.*

Variable	FinTech Adoption	Mobile Banking	Digital Lending	Technical Efficiency
FinTech Adoption	1	0.72**	0.64**	0.68**
Mobile Banking	0.72**	1	0.59**	0.66**
Digital Lending	0.64**	0.59**	1	0.62**
Technical Efficiency	0.68**	0.66**	0.62**	1

Strong positive correlations were observed between FinTech adoption and technical efficiency ($r = 0.68$), as well as mobile banking and technical efficiency ($r = 0.66$).

4.2. Diagnostic Tests

4.2.1. Normality Test

The Jarque-Bera test was used to assess whether the residuals followed a normal distribution. The test yielded a Jarque-Bera statistic of 3.21 with a p-value of 0.201, indicating that the residuals were normally distributed at the 5% significance level. Thus, the null hypothesis that the residuals were normally distributed was not rejected.

4.2.2. Multicollinearity Test

Multicollinearity among predictor variables was assessed using the Variance Inflation Factor (VIF). The VIF values ranged between 1.8 and 3.5, which were well below the threshold of 10, suggesting that multicollinearity was not a concern in the model.

4.2.3. Serial Correlation Test

The Durbin-Watson test was conducted to check for autocorrelation in the residuals. The test yielded a Durbin-Watson statistic of 1.98, which was within the acceptable range (1.5 to 2.5), indicating no significant autocorrelation in the data.

4.2.4. Heteroskedasticity Test

The Breusch-Pagan test was employed to examine whether the error terms exhibited heteroskedasticity. The test produced a Chi-square statistic of 2.76 with a p-value of 0.096, suggesting that heteroskedasticity was not present in the model.

4.2.5. Stationarity Test

To ensure that the data was stationary, the Levin-Lin-Chu (LLC) unit root test was conducted. The test yielded a test statistic of -4.32 with a p-value of 0.001, rejecting the null hypothesis of unit roots and confirming that the data was stationary.

4.2.6. Model Selection: Fixed vs. Random Effects

The Hausman test was conducted to determine whether a fixed-effects or random-effects model was more appropriate. The test yielded a Chi-square statistic of 6.78 with a p-value of 0.034, leading to the rejection of the null hypothesis. This indicated that the fixed-effects model was the better fit for the data.

5. Inferential Analysis

The study modeled the influence of FinTech adoption (X1), mobile banking (X2), and digital lending (X3) on technical efficiency (Y). The results are presented in Table 2.

$$Y=\beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3+\epsilon$$

Table 2. Inferential Analysis.

Predictor	Coefficient (β)	Std. Error	t-value	p-value
Constant	1.25	0.45	2.78	0.007**
FinTech Adoption	0.42	0.10	4.20	0.000**
Mobile Banking	0.35	0.12	2.92	0.004**
Digital Lending	0.29	0.11	2.64	0.010**

6. Conclusions

The study concluded that the adoption of financial technology (FinTech) solutions significantly enhances the technical efficiency of commercial banks in Kenya. High adoption rates of mobile banking and digital lending demonstrate their pivotal role in streamlining banking operations, reducing transaction costs, and improving service delivery. The strong positive correlation between FinTech adoption and technical efficiency underscores the transformative impact of digital solutions in addressing operational inefficiencies and meeting customer demands. Furthermore, the findings highlight that while commercial banks have made notable progress in integrating FinTech into their processes, there remains room for further optimization, particularly in leveraging emerging technologies to address challenges such as system reliability and scalability.

The diagnostic tests validated the robustness of the regression model, confirming the significance of FinTech solutions in predicting technical efficiency. The study's results emphasize the importance of a comprehensive approach to FinTech adoption, focusing on strategies that integrate multiple digital tools. Moreover, the findings suggest that while mobile banking has reached a mature stage of adoption, opportunities exist to enhance digital lending and other innovative solutions to achieve sustained technical efficiency gains. The study provides evidence that effective FinTech adoption can serve as a catalyst for improving banking performance and maintaining competitiveness in a rapidly evolving financial landscape.

7. Recommendations

Based on the findings, commercial banks in Kenya should prioritize investment in advanced FinTech solutions to further enhance technical efficiency. Specifically, banks should focus on expanding mobile banking functionalities to include personalized services and real-time analytics, which can significantly improve customer experience and operational effectiveness. Digital lending platforms should be optimized to enhance loan approval processes, reduce default rates through data-driven risk assessments, and increase financial inclusion. Furthermore, banks should invest in robust IT infrastructure to address issues related to system reliability and scalability, ensuring seamless service delivery during periods of high demand.

The government and financial regulators should also play a proactive role in fostering an enabling environment for FinTech adoption. Policies and incentives that encourage innovation and reduce barriers to technology adoption are critical. Regulatory frameworks should support data privacy and cybersecurity while enabling flexibility for FinTech startups to collaborate with banks. Additionally, capacity-building initiatives, such as training programs for bank employees, are essential to equip staff with the skills needed to implement and manage FinTech solutions effectively. Lastly, fostering partnerships between commercial banks, FinTech firms, and academic institutions can accelerate the development and integration of innovative solutions, driving sustained efficiency and growth in the banking sector.

Abbreviations

FinTech	Financial Technology
CBK	Central Bank of Kenya
KBA	Kenya Bankers Association
KYC	Know Your Customer
USSD	Unstructured Supplementary Service Data
DEA	Data Envelopment Analysis
VIF	Variance Inflation Factors
FGLS	Feasible Generalized Least Squares
LLC	Levi Lechun

Conflicts of Interest

The authors declare no conflicts of interest.

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