



Modeling drivers of fintech adoption in Sub-Saharan Africa using machine learning

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Abstract

This study explores the socio-demographic, financial, and technological determinants of FinTech adoption across 36 Sub-Saharan African countries utilizing micro-level data from the 2021 World Bank Global Findex survey. We employ a hybrid methodological framework integrating traditional econometric models (Logit and Probit) with supervised machine learning algorithms (Random Forest, Gradient Boosting, and XGBoost) to enhance predictive accuracy.

Our findings show that formal account ownership and access to technology, particularly mobile phone ownership and internet connectivity, are the strongest drivers of FinTech adoption. Digital transactions are closely linked to formal financial infrastructure, while mobile money extends financial access to unbanked and rural populations. Income, education, employment, and regional disparities significantly influence adoption patterns. These results highlight the complementary role of formal banking and digital finance. The study recommends targeted policies focusing on rural digital infrastructure, integrated digital-banking strategies, and digital literacy programs. This research provides an empirical foundation for evidence-based policymaking to accelerate financial inclusion through FinTech in Sub-Saharan Africa.

Keywords FinTech adoption · Financial inclusion · Mobile money · Machine learning · Digital payments · Sub-Saharan Africa

1 Introduction

Globally, fintech is expanding abruptly, which has made financial actors rethink the value they can provide to the economic system (Sakarya & Aksu, 2021). Both at the macro and micro levels, FinTech development is producing significant benefits.

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By encouraging investment decisions through fundraising, FinTech has accelerated the growth of digital financial services, which has increased financial inclusion, decreased inequality, and stimulated the creation of new businesses at the micro-economic level (Abbasi et al., 2021; Croutzet & Dabbous, 2021). From a macro-economic standpoint, the absence of traditional banking institutions in rural areas has been increasingly mitigated by the proliferation of FinTech services. This digital transformation has expanded access to financial services, thereby enhancing banking efficiency, reducing poverty levels, and contributing to broader financial stability (Fung et al., 2020; Wang et al., 2021).

FinTech is a powerful force that can significantly influence the organization of the financial sector in Sub-Saharan Africa (SSA). It could alter the competitive environment of the financial industry in SSA, which is underdeveloped in comparison to other parts of the world (Maino et al., 2019a). For instance, the global expansion of mobile money services between 2001 and 2019 reveals notable regional disparities. Of the 289 services launched worldwide during this period, 144 were introduced in Sub-Saharan Africa (SSA), accounting for 49.6% of the total. In comparison, East Asia and the Pacific registered 17.9%, South Asia 12.7%, Latin America and the Caribbean 9.31%, the Middle East and North Africa 7.24%, and Europe and Central Asia only 3.10% (Nika, 2020). This disproportionate concentration highlights mobile money services as the predominant and most viable form of FinTech in the Sub-Saharan African context. These services extend beyond basic transactions, offering a comprehensive suite of functionalities including banking, currency exchange, and payment solutions, thereby profoundly altering the competitive dynamics of the region's financial industry.

FinTech has emerged as a promising tool for socio-economic development in Africa; however, its adoption remains relatively limited. According to Anakpo et al. (2024), although there has been substantial investment and growth in FinTech across Africa over the past decade, its adoption remains limited, with usage rates below 25%, in stark contrast to approximately 80% in more advanced economies. This is despite its considerable promise in promoting financial inclusion, improving education and public health, supporting gender equality, and enhancing agricultural development. Further, the study identified several determinants influencing the adoption of FinTech, including perceived value and usefulness, trust and perceived security risks, ease of use, economic benefits, social influence, individual self-efficacy, and employment expectations. Nevertheless, the sector continues to confront significant barriers such as underdeveloped infrastructure, weak regulatory systems, managerial inefficiencies, high entry costs, and competition from established financial institutions. This study investigates the key determinants influencing FinTech adoption in Sub-Saharan African countries. Consistent with established literature, mobile money account ownership is employed as the primary proxy for FinTech usage (Adeleke, 2024; Amoah et al., 2020). Additionally, the use of digital payments, capturing whether individuals have sent or received money through digital platforms, is incorporated as a secondary indicator.

The importance of this research lies in its potential to inform evidence-based policy interventions that can accelerate financial inclusion across Sub-Saharan Africa, where over 300 million people remain unbanked despite the region's leadership in

mobile money innovation. The continent is home to 21 out of 50 economies around the world having account ownership rates lower than 60 percent (Klapper et al., 2025). Despite the rapid growth of FinTech in the region, significant gaps remain in understanding the complex interplay of factors that drive or hinder its adoption. Moreover, the region's unique socio-economic diversity, infrastructural challenges, and high reliance on mobile money necessitate a more distinctive analytical approach. Existing studies predominantly rely on linear econometric models, which may overlook nonlinear interactions and variable hierarchies critical to real-world decision-making.

This study addresses these gaps by leveraging machine learning techniques alongside traditional models to provide a more comprehensive understanding of FinTech adoption dynamics. Its relevance extends beyond academic contribution, as it offers policymakers and financial institutions actionable insights into how different population segments engage with digital financial services, thereby bridging the digital divide and promoting sustainable economic development in one of the world's most financially underserved regions. Furthermore, the comparative analysis of digital payments and mobile money usage reveals distinct adoption pathways, informing tailored interventions for underserved groups, including women, rural populations, and low-income households. The hybrid methodological approach employed presents a replicable framework for similar analyses in other developing economies, thereby contributing to the global understanding of technology adoption patterns in emerging markets.

The remainder of this study is structured as follows: Sect. 1 reviews the relevant literature, outlining both theoretical foundations and empirical findings related to FinTech adoption. Section 2 presents the data sources and methodological framework employed in the analysis. Section 3 reports the empirical results and provides a detailed interpretation of the findings. Finally, Sect. 4 offers concluding remarks and discusses policy implications and potential directions for future research.

2 Literature review

Mobile money services have emerged as a significant driver of financial technology (FinTech) adoption in Sub-Saharan Africa, serving as a gateway to broaden digital financial services. This literature review section aims to synthesize relevant studies to explore the factors affecting FinTech, conceptualized within a framework that incorporates mobile money adoption, income quintile, employment status, demographic factors, financial inclusion, and digital infrastructure.

2.1 Conceptualizing digital financial services use through technology adoption frameworks

Investigating how and why people adopt innovations and technology has inspired a great deal of work (Straub, 2009). The adoption of digital financial services is an illustration of the diffusion of innovations, a social process that disseminates

knowledge about a novel concept and has a substantial impact on the composition and operation of the social system, ultimately leading to important social repercussions. The innovation-development process in the financial services industry consists of five progressive stages: first, determining the need for new financial solutions; second, carrying out research and development; third, commercializing the innovations; fourth, actively encouraging their broad distribution; and fifth, seeing people use these digital financial services and seeing noteworthy results. This process highlights the transformative potential of digital financial services in empowering African citizens and changing the landscape of financial inclusion throughout the continent, reflecting the dynamic character of innovation diffusion (Rogers, 1987).

The Technology Acceptance Model (TAM) proposed by Davis (1989) provides a foundational framework for understanding the drivers of digital financial services adoption. As highlighted by Charness and Boot (2016), the constructs of perceived usefulness and perceived ease of use are critical determinants influencing individuals' engagement with digital financial technologies. Building on this, Venkatesh et al. (2003) introduced the Unified Theory of Acceptance and Use of Technology (UTAUT), which identifies multiple factors shaping adoption behavior. Social influence plays a pivotal role by affecting individuals through the opinions and behaviors of their social networks. Additionally, facilitating conditions, such as stable internet access, device compatibility, and intuitive interfaces, significantly enhance usability and acceptance. The perceived effort involved in learning and utilizing digital financial services also impacts adoption decisions; simpler and more accessible processes promote uptake, whereas complexity acts as a barrier. Performance expectancy further influences adoption, as users weigh anticipated benefits including convenience, efficiency, security, and improved financial management. Positive expectations increase the likelihood of adoption, while negative perceptions can deter it. Understanding these factors is vital for designing effective interventions to promote digital financial service adoption and to advance financial inclusion through digital channels (Sanga & Aziakpono, 2022).

2.2 Mobile money adoption and fintech engagement

The adoption of mobile money services has been a significant contributor to the development and growth of financial technology in Africa, particularly in regions where formal financial institutions are inefficient. Tiony (2024) argues that mobile money acts as a catalyst, enabling users to access a broader range of FinTech services, thereby enhancing financial inclusion and economic growth. This indicates that mobile money facilitates the transition from cash-based transactions to digital platforms, which is crucial in areas lacking traditional banking infrastructure. Furthermore, the findings of Senyo et al. (2022) support this view, showing that mobile money usage significantly correlates with increased access to FinTech services, particularly among populations previously excluded from banking. Similarly, reports from the African mobile economy sectors highlight that mobile money serves as a pathway to FinTech adoption by reducing barriers to entry and laying the foundation

for more advanced financial services (GSMA, 2021). Moreover, mobile money implementation fuels engagement with digital financial applications, as it familiarizes users with digital transactions and builds trust in digital platforms (Munyegeza & Matsumoto, 2016; Suri & Jack, 2016).

2.3 Socio-economic factors influencing fintech adoption

The adoption of financial technology (FinTech) is influenced by a diverse range of socioeconomic factors. The income level plays a substantial role, with higher-income individuals exhibiting greater propensity for FinTech adoption. This correlation is primarily attributed to enhanced financial literacy and greater affordability. As Demirguc-Kunt et al. (2018) observe, higher earners are more likely to possess the necessary smartphones and mobile devices essential for accessing FinTech services. Furthermore, individuals with higher incomes typically demonstrate stronger financial literacy, enabling them to effectively navigate and trust digital financial platforms (Lusardi & Mitchell, 2014).

Employment status also emerges as a significant determinant. Employed individuals are more inclined to utilize FinTech services due to their consistent income streams and regular financial activities. Ozili (2018) notes that stable revenue sources facilitate engagement with digital finance, as employed individuals frequently seek efficient methods for managing their finances.

A notable disparity in FinTech adoption exists between urban and rural areas, with urban residents demonstrating higher rates of engagement with digital financial services. This trend is largely attributable to the more robust digital infrastructure prevalent in urban regions, encompassing reliable internet connectivity and extensive mobile networks, both of which are critical for FinTech utilization. Study by Wu and Peng (2024) underscore that inadequate digital infrastructure significantly impedes the uptake of FinTech adoption in rural areas. Reinforcing the importance of infrastructure, Jie et al. (2024) further demonstrate that digitalization elements, such as the availability of digital infrastructure, are crucial in bridging the income gap between urban and rural populations. Consistent with these findings in their examination of household survey data from transition countries, Beck and Brown (2011) found that households in metropolitan areas, along with those possessing higher incomes and wealth, are more likely to utilize banking services and their digital platforms. This suggests that individuals with relatively higher incomes in urban settings are more predisposed to adopt digital financial systems, partly because the associated transaction fees are negligible to them, whereas for lower-income individuals in rural areas, such fees can be substantial, thereby diminishing their motivation to engage with digital finance platforms.

2.4 Financial inclusion and digital infrastructure

The financial sector in Sub-Saharan Africa (SSA) is undergoing a profound structural transformation driven by the rapid emergence and proliferation of Financial Technology (FinTech). This technological revolution introduces innovative solutions

that are fundamentally altering the competitive landscape of the continent's financial industry. Specifically, FinTech is challenging the established dominance of traditional banking institutions by democratizing access to various financial services (Maino et al., 2019b). This paradigm shift holds significant potential for fostering greater financial inclusion, bridging the historical divide between previously underserved populations and the financial elite, and ultimately driving economic development across the region. While FinTech obviously expands financial access, evidence remains mixed on its net impact, whether disruptive or complementary, on traditional financial inclusion. Consequently, optimizing financial inclusion in Sub-Saharan Africa necessitates those traditional financial institutions strategically integrate FinTech innovations, fostering a more robust and inclusive financial ecosystem (Kamara & Yu, 2024).

The drivers of FinTech growth in Sub-Saharan Africa vary significantly with the prevailing innovation model. In East African nations, where financial service innovation is predominantly driven by mobile technology, the widespread use of mobile money, mobile banking, and e-wallet services, often accessible via basic phones without the need for continuous internet connectivity, has emerged as the primary catalyst for financial inclusion. Conversely, in countries characterized by bank-led digital financial innovation, the reach and impact of FinTech are more closely correlated with advanced cellular network coverage, specifically LTE, rather than older GSM or UMTS technologies (Mothobi & Kebotsamang, 2024).

3 Data and methodology

3.1 Study area

This study focuses on 36 countries in Sub-Saharan Africa (SSA), a region that is characterized by a diverse range of socio-economic, political, and environmental contexts. Geographically, SSA comprises nations located south of the Sahara Desert, spanning West, East, Central, and Southern Africa. The selection of countries is based exclusively on the availability of relevant data.

3.2 Data source

This study utilizes data from the World Bank's 2021 Global Findex Database to examine the factors influencing the adoption of FinTech in Sub-Saharan Africa using machine learning methods. The comprehensive database provides nationally representative data on financial inclusion and digital financial services, based on surveys conducted in 120 economies with over 125,000 adults aged 15 and above.

The analysis focuses on 36 low- and middle-income countries in Sub-Saharan Africa, excluding Angola, Burundi, the Central African Republic, Rwanda, Somalia, and Sudan due to data unavailability. The final sample includes 35,533 individuals, capturing information on digital financial service usage, technological access, and socio-demographic characteristics.

3.3 Research questions and hypotheses

This study is guided by the following research questions and hypotheses:

3.4 Research questions:

1. What are the key socio-demographic, financial, and technological determinants of FinTech adoption in Sub-Saharan Africa?
2. How do the drivers of digital payment usage differ from those of mobile money adoption?
3. Can machine learning models provide superior predictive accuracy compared to traditional econometric approaches in identifying FinTech adoption patterns?

3.5 Research hypotheses:

Based on the Technology Acceptance Model (TAM), UTAUT, and existing literature, we formulate the following hypotheses:

***Hypothesis 1** Formal account ownership positively influences both digital payment and mobile money adoption, with a stronger effect on digital payments.*

***Hypothesis 2** Mobile phone ownership and internet access significantly increase the likelihood of FinTech adoption.*

***Hypothesis 3** Higher income, educational attainment, and employment status are positively associated with FinTech adoption.*

***Hypothesis 4** Urban residence and male gender are associated with higher adoption rates, reflecting persistent digital divides.*

***Hypothesis 5** Machine learning models outperform traditional econometric methods in predicting FinTech adoption patterns.*

These hypotheses are empirically tested using binary choice models and supervised machine learning classifiers.

3.6 Methodology

This study aims to investigate the determinants of FinTech adoption in Sub-Saharan Africa using machine learning approaches. The main objective is to identify factors that may influence an individual's decision to adopt FinTech services, as represented by a binary dependent variable indicating whether the person made or received a digital payment and whether the person owns a mobile money account or not. Each model is estimated independently, using the same vector of socio-demographic, economic, and technological explanatory variables to maintain a consistent comparative

analysis. Logit and Probit models work as the baseline model, presenting interpretable odds ratios and insights into statistically significant predictors due to their role as generalized linear models. This traditional method offers a clear overview for comprehending the strength and direction of individual predictor effects.

Logit regression:

$$\begin{aligned} \text{logit}(\text{DigitalTransac}) = & \beta_0 + \beta_1 \text{FormalAccount} + \beta_2 \text{MobileOwner} + \beta_3 \text{InternetAccess} \\ & + \beta_4 \text{Education} + \beta_5 \text{Income} + \beta_6 \text{Employment} \\ & + \beta_7 \text{Age} + \beta_8 \text{Gender} + \beta_9 \text{Region} + \varepsilon \end{aligned} \quad (1)$$

$$\begin{aligned} \text{logit}(\text{MobileMoney}) = & \beta_0 + \beta_1 \text{FormalAccount} + \beta_2 \text{MobileOwner} \\ & + \beta_3 \text{InternetAccess} + \beta_4 \text{Education} + \beta_5 \text{Income} \\ & + \beta_6 \text{Employment} + \beta_7 \text{Age} + \beta_8 \text{Gender} + \beta_9 \text{Region} + \varepsilon \end{aligned} \quad (2)$$

Probit regression:

$$\begin{aligned} \text{probit}(\text{DigitalTransac}) = & \beta_0 + \beta_1 \text{FormalAccount} + \beta_2 \text{MobileOwner} \\ & + \beta_3 \text{InternetAccess} + \beta_4 \text{Education} \\ & + \beta_5 \text{Income} + \beta_6 \text{Employment} + \beta_7 \text{Age} \\ & + \beta_8 \text{Gender} + \beta_9 \text{Region} + \varepsilon \end{aligned} \quad (3)$$

$$\begin{aligned} \text{probit}(\text{MobileMoney}) = & \beta_0 + \beta_1 \text{FormalAccount} + \beta_2 \text{MobileOwner} \\ & + \beta_3 \text{InternetAccess} + \beta_4 \text{Education} \\ & + \beta_5 \text{Income} + \beta_6 \text{Employment} + \beta_7 \text{Age} \\ & + \beta_8 \text{Gender} + \beta_9 \text{Region} + \varepsilon \end{aligned} \quad (4)$$

Beyond the baseline, a set of machine learning models is estimated to capture the complex and nonlinear relationship between the response and predictors. Decision Trees (DT), while susceptible to overfitting, offer an interpretable hierarchical structure of decision rules, which is further improved by combination of methods such as Extra Trees (ET) and Random Forest (RF). By combining predictions from several trees, these collective approaches increase accuracy and decrease variation. Extra Trees bring more unpredictability for quicker training and lower variance. Although they necessitate careful hyperparameter adjustment, Gradient Boosting (GB) and its improved variant, Extreme Gradient Boosting (XGBoost), offer excellent prediction accuracy by concentrating on hard-to-predict observations and building trees sequentially to repair earlier errors. By modifying the weights of incorrectly identified observations, AdaBoost (AB) also combines weak learners and works well on datasets that are complex. Finally, K-Nearest Neighbors (KNN) classifies based on proximity to existing data points, while Support Vector Machine (SVM) excels in high-dimensional spaces by identifying optimal separating hyperplanes. Both methods offer clear advantages in capturing non-linear patterns, though they have different computational considerations for large datasets.

3.7 Descriptive analysis and binary choice models

3.7.1 Model evaluation metrics

To evaluate how well the machine learning models used in this work performed, several evaluation metrics were applied. The model's overall accuracy, precision, recall, and resilience to class imbalances are just a few of the indicators that provide light on its efficacy. We outline the primary metrics utilized in this study below:

3.7.2 Accuracy

The accuracy metric, which counts the percentage of correctly categorized cases among all observations, is calculated as follows:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

In this case, False Positives (FP) stands for wrong positive predictions, False Negatives (FN) for incorrect negative predictions, True Positives (TP) for correctly predicted positive occurrences, and True Negatives (TN) for correctly anticipated negative instances. Despite its widespread use, accuracy might not be the best statistic for unbalanced datasets. Fortunately, class response of variable in this study was nearly balanced.

3.7.3 Precision

Precision, also known as Positive Predictive Value (PPV), is the fraction of accurately predicted positive cases among all instances categorized as positive:

$$Precision = \frac{TP}{(TP + FP)}$$

The higher the precision score, the fewer false positives there are, and hence the better the model. As a result, the precision metric is especially relevant in situations where minimizing erroneous positive predictions is critical.

3.7.4 Recall

Recall, also known as Sensitivity or True Positive Rate (TPR), is an important evaluation parameter in classification tasks, particularly when the primary goal is to identify as many positive cases as feasible. It is calculated as the ratio of true positives to the sum of true positives and false negatives to determine the proportion of genuine positive cases accurately classified by a model.

$$Recall = \frac{TP}{(TP + FN)}$$

A high percentage of false negatives results from a model that has a low recall (nearly 0), which means it is missing many real positive cases. In situations where missing positives might have major repercussions, a high recall (near to 1) indicates that the model accurately detects most positive cases.

3.7.5 F1-Score

The F1-score is a model metric for evaluating the performance of a classification model. It is very handy when dealing with skewed datasets. The harmonic mean of precision and recall balances the trade-off between these two measurements by providing a single value that accounts for both aspects of model performance. The binary observations in survey datasets are usually skewed, and the situations in this study are no exception. As a result, this metric is useful for model performance evaluation.

$$F1 - Score = \frac{2 \times (Precision \times Recall)}{(Precision + Recall)}$$

3.8 Receiver operating characteristic—area under the curve (ROC-AUC)

The ROC-AUC score is a useful indicator for determining the model's ability to distinguish between positive and negative classes. The Area Under the Curve (AUC) is a scalar statistic that represents the model's overall performance. It computes the area under the ROC curve for values from 0 to 1. An AUC of 1 implies perfect performance, where the model correctly classifies all positive and negative samples. In contrast, an AUC of 0.5 suggests that the model is unable to discriminate between classes, performing no better than random guessing. AUC values between 0.7 and 0.9 are considered good; however, values between 0.5 and 0.7 indicate that the model's performance is comparable to random guessing.

$$ROC - AUC = \int_0^1 TPRd(FPR)$$

The True Positive Rate (TPR) is displayed against the False Positive Rate (FPR). A higher ROC-AUC score indicates an improved model discriminating between the two classes.

$$TPR = \frac{TruePositives}{TruePositives + FalseNegatives}$$

$$FPR = \frac{FalsePositives}{FalsePositives + TrueNegatives}$$

3.9 Matthews correlation coefficient (MCC)

Matthews Correlation Coefficient (MCC) is a reliable evaluation statistic that accounts for all four components of the confusion matrix: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Unlike other performance metrics, which can be distorted in the presence of imbalanced datasets, MCC provides a fair assessment of a model's predictive potential by considering both positive and negative classifications. This makes it especially useful for testing models in imbalanced classification issues, where traditional metrics such as accuracy, precision, and recall might be misleading.

MCC is calculated using the formula:

$$MCC = \frac{[(TP \times TN) - (FP \times FN)]}{\sqrt{[(TP + FP) \times (TP + FN) \times (TN + FP) \times (TN + FN)]}}$$

3.10 Cohen's Kappa (κ)

Cohen's Kappa (κ) is a statistical indicator that assesses agreement amongst raters or classifiers, accounting for chance. It is particularly useful in classification problems involving class imbalances because it provides a more reliable assessment of model performance than simple accuracy. Cohen's Kappa is commonly used in fields such as medical diagnosis, sentiment analysis, and inter-annotator agreement in research. Cohen's Kappa is calculated as follows:

$$\kappa = \frac{(p_o - p_e)}{(1 - p_e)}$$

where p_o represents the actual agreement and p_e is the predicted agreement by chance. The value of κ ranges from -1 to $+1$. A κ value of $+1$ implies complete agreement between the model's predictions and actual values, whereas a κ value of 0 indicates no better than random chance. Higher κ values indicate higher model performance, as predictions line more closely with ground truth labels.

3.11 Geometric Mean (G-Mean)

Geometric Mean (G-Mean) assesses the balance of sensitivity (recall) and specificity, making it particularly useful for imbalanced datasets. It is computed as:

$$G - Mean = \sqrt{(Sensitivity \times Specificity)}$$

G-Mean confirms that the model works well across both classes, avoiding the majority class from dominating performance metrics. A high G-Mean value indicates that a model correctly classifies positive and negative examples, making it a useful indicator for evaluating classifiers in cases of class imbalance.

Table 1 Description of the variables. Source: Global Findex database

Variables	Definition
FinTech	
Made or received a digital payment	The dummy variable is coded as 1 if the individual made or received any digital payment, 0 otherwise
Ownership of a mobile money account	The dummy variable is coded as 1 if the individual owns a mobile money account, 0 otherwise
Financial inclusion	
Formal account ownership	The dummy variable is coded as 1 if the individual owns an account at a financial institution, 0 otherwise
Technology access	
Mobile phone ownership	The dummy variable is coded as 1 if the individual owns a mobile phone, 0 otherwise
Internet access	The dummy variable is coded as 1 if the individual has internet access, 0 otherwise
Socio-demographic factors	
Education – primary school or less	The dummy variable is coded as 1 if the individual has completed primary school or less, 0 otherwise
Education – Secondary school	The dummy variable is coded as 1 if the individual has completed secondary school, 0 otherwise
Education – tertiary education or more	The dummy variable is coded as 1 if the individual has completed tertiary education or more, 0 otherwise
Income quintile 1 – Poorest 20%	The dummy variable is coded as 1 if the individual is in the poorest quintile, 0 otherwise
Income quintile 1 – Second 20%	The dummy variable is coded as 1 if the individual is in the second quintile, 0 otherwise
Income quintile 1 – Middle 20%	The dummy variable is coded as 1 if the individual is in the middle quintile, 0 otherwise
Income quintile 1 – Fourth 20%	The dummy variable is coded as 1 if the individual is in the fourth quintile, 0 otherwise
Income quintile 1 – Richest 20%	The dummy variable is coded as 1 if the individual is in the richest quintile, 0 otherwise
Employment	The dummy variable is coded as 1 if the individual is in the workforce, 0 otherwise
Age	Age of the individual
Age squared	Square of the age of the individual
Gender	The dummy variable is coded as 1 if the individual is a female, 0 otherwise
Region	The dummy variable is coded as 1 if the individual lives in a rural area, 0 otherwise

4 Results analysis and discussion

4.1 Descriptive analysis

Table 1 shows descriptive statistics examining the bivariate relationships between the two key measures of FinTech adoption, digital transactions and mobile money

accounts, and a vector of socio-demographic, economic, and technological factors in Sub-Saharan Africa. All Pearson's Chi-square tests yield statistically significant results ($p < 0.001$), confirming that the observed relationships reflect meaningful underlying patterns rather than random associations.

Access to formal financial services stands out as a critical driver of FinTech adoption. For digital transactions, individuals without a financial account show substantially lower adoption rates of 28.16% compared to a remarkable 86.86% among those with an account ($\chi^2 = 11,392.89$, $p < 0.001$). Similarly, for mobile money accounts, the adoption rate is also 28.16% among those without formal accounts versus 51.53% for account holders ($\chi^2 = 1,941.79$, $p < 0.001$). This pattern underscores the complementary rather than substitutive relationship between traditional and digital financial services as formal financial inclusion appears to serve as a gateway to digital financial engagement.

Technological access demonstrates a significant association with FinTech adoption. Mobile phone ownership increases the likelihood of using digital transactions (60.28% among owners vs. 16.83% among non-owners; $\chi^2 = 4,918.76$, $p < 0.001$) and mobile money accounts reaching 45.12% among owners compared to only 10.54% among non-owners ($\chi^2 = 3,350.73$, $p < 0.001$). Internet connectivity strengthens this effect even further, with 72.86% of connected individuals using digital transactions compared to just 32.96% of those without access to internet ($\chi^2 = 5,508.14$, $p < 0.001$). For mobile money accounts, the rates are 54.76% versus 23.63% ($\chi^2 = 3,612.45$, $p < 0.001$). These findings highlight the crucial role of digital infrastructure as a central facilitator of FinTech engagement, implying that technological inclusion is a necessary condition for meaningful participation in digital financial ecosystems.

Socioeconomic characteristics show strong associations with both types of FinTech adoption. Income shows a clear positive slope. While the digital transaction usage rises steadily from 33.99% in the lowest income quintile to 64.95% in the highest ($\chi^2 = 1,740.35$, $p < 0.001$), mobile money account ownership increases from 23.87% to 48.73% ($\chi^2 = 1,201.95$, $p < 0.001$). This pattern highlights the pivotal role of economic capacity and financial autonomy in facilitating FinTech engagement. Employment status further differentiates users from non-users. Individuals in the workforce show higher adoption rates for both digital transactions (55.68% vs. 35.91%; $\chi^2 = 1,163.60$, $p < 0.001$) and mobile money accounts (41.88% vs. 24.76%; $\chi^2 = 938.48$, $p < 0.001$) compared to those outside the labor force. This discrepancy likely reflects greater economic engagement, increased interaction with formal financial systems, and an increased necessity for digital financial tools in income-generating activities. Educational attainment also shows a positive correlation. For digital transactions, adoption rates increase dramatically from 31.11% among those with primary education to 62.69% for secondary education and 87.98% for tertiary education ($\chi^2 = 4,570.08$, $p < 0.001$). Mobile money account ownership follows a similar path, accounting 22.56% for primary, 47.09% for secondary, and 61.47% for tertiary education ($\chi^2 = 2,719.96$, $p < 0.001$). These findings suggest that knowledge, skills and digital literacy are crucial determinants of FinTech adoption.

Table 2 Descriptive statistics. Source: Author's calculations

Variables	Categories	Digital Transaction			Mobile Money Account			Chi2	P-value
		No n (%)	Yes n (%)	Chi2	No n (%)	Yes n (%)	Chi2		
Formal account ownership	No	16,129(71.84)	6,322(28.16)	11,392.89	0.0000	16,129(71.84)	6,322(28.16)	1941.79	0.0000
	Yes	1,719(13.14)	11,363(86.86)			6,341(48.47)	6,741(51.53)		
Mobile phone ownership	No	7,146(83.17)	1,446(16.83)	4918.76	0.0000	7,686(89.46)	906(10.54)	3350.73	0.0000
	Yes	10,702(39.72)	16,239(60.28)			14,784(54.88)	12,157(45.12)		
Internet access	No	13,775(67.04)	6,772(32.96)	5508.14	0.0000	15,691(76.37)	4,856(23.63)	3612.45	0.0000
	Yes	4,073(27.18)	10,913(72.86)			6,779(45.24)	8,207(54.76)		
Income quintile	Poorest 20%	3,913(66.01)	2,015(33.99)	1740.35	0.0000	4,513(76.13)	1,415(23.87)	1201.95	0.0000
	Second 20%	3,539(59.64)	2,395(40.36)			4,196(70.71)	1,738(29.29)		
	Middle 20%	3,482(53.06)	3,080(46.94)			4,299(65.51)	2,263(34.49)		
	Fourth 20%	3,509(47.46)	8,884(52.54)			4,481(60.61)	2,912(39.39)		
	Richest 20%	3,405(35.05)	6,311(64.95)			4,981(51.27)	4,735(48.73)		
Employment	Out of work-force	6,805(64.09)	3,813(35.91)	1163.60	0.0000	7,989(75.24)	2,629(24.76)	938.48	0.0000
	In the work-force	11,043(44.32)	3,872(55.68)			14,481(58.12)	10,434(41.88)		
Education	Primary	11,109(68.89)	5,016(31.11)	4570.08	0.0000	12,487(77.44)	3,638(22.56)	2719.96	0.0000
	Secondary	6,500(37.31)	0,920(62.69)			9,217(52.91)	8,203(47.09)		
	Tertiary	239(12.02)	1,749(87.98)			766(38.53)	1,222(61.47)		
Gender	Male	7,337(44.62)	9,108(55.38)	385.94	0.0000	9,729(59.16)	6,716(40.84)	218.79	0.0000
	Female	10,511(55.07)	8,577(44.93)			12,741(66.75)	6,347(33.25)		

Table 2 (continued)

Variables	Categories	Digital Transaction			Mobile Money Account			P-value
		No n (%)	Yes n (%)	Chi2	No n (%)	Yes n (%)	Chi2	
Region	Urban	7,473(45.30)	9,022(54.70)	599.26	9,844(59.68)	6,651(40.32)	210.93	0.0000
	Rural	9,990(58.66)	7,039(41.34)		11,463(67.31)	5,566(32.69)		

Furthermore, demographic factors reveal important disparities in FinTech adoption. A gender gap persists across both measures, with men more likely to use digital transactions (55.38% vs. 44.93%; $\chi^2 = 385.94$, $p < 0.001$) and mobile money accounts (40.84% vs. 33.25%; $\chi^2 = 218.79$, $p < 0.001$) than women. This suggests the presence of gender-based barriers to digital financial inclusion that may require targeted interventions. Geographic location also plays a crucial role. Urban residents show higher adoption rates for digital transactions (54.70% vs. 41.34%; $\chi^2 = 599.26$, $p < 0.001$) and mobile money accounts (40.32% vs. 32.69%; $\chi^2 = 210.93$, $p < 0.001$) compared to their rural counterparts. This urban–rural divide likely reveals disparities in infrastructure, accessibility, and exposure to FinTech services (Table 2).

4.2 Logistic and probit regression results

To grasp the determinants of FinTech adoption, this study estimated four models, logit and probit estimations for two dependent variables: digital transaction and mobile money account adoption. Columns (1) and (2) present logit estimates, while columns (3) and (4) display results from probit models as elaborated in Table 3 below. The consistent patterns in sign, statistical significance, and direction of influence across models confirm the robustness of results, capturing the key structural drivers of digital financial service adoption, including financial inclusion, access to technology, and socioeconomic characteristics.

A compelling observation arises from the comparison of digital transactions and mobile money models. Although both are forms of FinTech usage, the magnitude of predictors differs systematically between them. Notably, ownership of a formal bank account emerges as the most influential determinant of digital transaction adoption. The estimated odds ratio in the logit model is 2.43, while the corresponding probit coefficient is about 1.42, underscoring a strong and statistically significant association. In contrast, the effect is substantially lower for mobile money usage with coefficients ranging from 0.30 to 0.49, indicating that digital payments are far more dependent on formal financial infrastructure. While strongly supporting hypothesis 1, the relationship highlights the complementary role of traditional banking systems in promoting FinTech adoption across Sub-Saharan Africa. These findings are consistent with earlier studies by Kumar and Pradhan (2024) in the case of South Asia, Adaba et al., 2019 and David-West et al. (2018), who observed that individuals with existing bank accounts were more inclined to use mobile money platforms in Ghana and Nigeria, respectively. In contrast, mobile money appears to operate more independently, possibly reflecting its accessibility for unbanked and underprivileged populations. This divergence highlights the structural differences between bank-based and mobile-based financial ecosystems.

Access to technology also has a strong influence across models. Mobile phone ownership increases the likelihood of both digital transaction and mobile money adoption, with nearly identical effects across both types, between 1.25 to 1.32 for logit and 0.72 to 0.76 probit model, respectively. This underscores the central role of mobile penetration in facilitating broader access to FinTech services. These findings

Table 3 Logit and Probit regression results

Variables	Logit Regression		Probit Regression	
	Digital Transaction	Mobile Money Account	Digital Transaction	Mobile Money Account
Formal account ownership	2.4256*** (0.0336)	0.4862*** (0.0276)	1.4193*** (0.0187)	0.2994*** (0.0167)
Mobile phone ownership	1.2473*** (0.0392)	1.3236*** (0.0406)	0.7183*** (0.0218)	0.7576*** (0.0221)
Internet access	0.7499*** (0.0331)	0.7045*** (0.0292)	0.4403*** (0.0193)	0.4310*** (0.0178)
Income quintile – second 20%	0.2399*** (0.0500)	0.1941*** (0.0471)	0.1333*** (0.0285)	0.1126*** (0.0275)
Income quintile – middle 20%	0.3744*** (0.0487)	0.3380*** (0.0453)	0.2112*** (0.0278)	0.1960*** (0.0266)
Income quintile – fourth 20%	0.4411*** (0.0477)	0.4347*** (0.0439)	0.2514*** (0.0272)	0.2546*** (0.0259)
Income quintile – richest 20%	0.5374*** (0.0470)	0.5344*** (0.0425)	0.3044*** (0.0268)	0.3154*** (0.0252)
Employment	0.5608*** (0.0328)	0.5411*** (0.0302)	0.3209*** (0.0187)	0.3201*** (0.0178)
Education – secondary education	0.6639*** (0.0318)	0.5767*** (0.0293)	0.3836*** (0.0185)	0.3455*** (0.0175)
Education – tertiary education	0.9557*** (0.0886)	0.7272*** (0.0618)	0.5439*** (0.0490)	0.4400*** (0.0373)
Gender	0.0285 (0.0294)	0.0176 (0.0260)	0.0133 (0.0169)	0.0098 (0.0155)
Region	0.1766*** (0.0303)	0.2536*** (0.0270)	0.1006*** (0.0174)	0.1481*** (0.0161)
Age	0.0247*** (0.0047)	0.0208*** (0.0044)	0.0140*** (0.0027)	0.0119*** (0.0026)
Age squared	−0.0002*** (0.0001)	−0.0003*** (0.0001)	−0.0001*** (0.0000)	−0.0001*** (0.0000)
Constant	−3.8447***	−3.6911***	−2.2260***	−2.1700***
Pseudo R2	(0.1026)	(0.0960)	(0.0576)	(0.0549)
Observations	33,494	33,494	33,494	33,494

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

are consistent with existing literature, such as GSMA (2023), Meli et al. (2022), and Akinyemi and Mushunje (2020). However, internet access, while significant for both, has a slightly greater impact on digital transactions. This aligns with the nature of digital transaction systems, which often require stable connectivity, suggesting that mobile money may be more feasible in areas with lower internet penetration or digital infrastructure. These results are consistent with hypothesis 2, underlining the significant role of access to technology in driving FinTech adoption. They are also align with the findings Asongu et al. (2021) and Hasbi and Dubus (2019), who showed that increased mobile phone usage and internet connectivity substantially contribute to greater financial inclusion and the adoption of mobile money services across African nations.

The findings generally support hypothesis 3 as the impact of income and educational levels reveal important comparative insights. A clear socioeconomic gradient is observed, with increasing income and higher educational attainment significantly raising the probability of FinTech usage, consistent with existing literature (Zins & Weill, 2016). However, the effect sizes are consistently higher for digital transactions than for mobile money. Yet, the middle and richer-income groups exhibit more obvious increases for digital transactions, suggesting that digital financial tools are more economically stratified. This perspective is supported by findings from Asuming et al. (2019). Likewise, having a tertiary education boosts the odds of engaging in digital transaction, with probability increasing from 0.54 to 0.96. In comparison, the increase in mobile money usage ranges from 0.44 to 0.73. This differential effect likely reflects higher digital and financial literacy requirements for navigating formal systems for digital transactions.

Demographic variables exhibit more delicate distinctions. Although gender emerges as a positive determinant of FinTech use, its substantive effect is insignificant across all models. This indicates that, after controlling other factors, gender-related disparities in engaging in digital transaction and using mobile money accounts are not significant. This study aligns with earlier research that found no statistically significant link between gender and the adoption of mobile money services (Akinyemi & Mushunje, 2020; Batista & Vicente, 2020; Chamboko, 2022; Johnen et al., 2023). However, the findings diverge from those of Coulibaly (2021), Fall et al. (2020), and Zins and Weill (2016), who observed that women were significantly less likely to be financially included and showed lower rates of FinTech adoption. Regional disparities are more evident in the adoption of mobile money services. This suggests that mobile money is more geographically adaptable and better aligned with local infrastructural realities. Its higher usage in rural areas, where the probability of adoption rises from 0.15 to 0.25, indicates that it is often more accessible in regions with limited internet connectivity. In contrast, digital transactions remain less prevalent in these areas, with adoption rates ranging only from 0.10 to 0.18, highlighting a digital divide shaped by regional infrastructure. Urban populations generally have greater access to both mobile money and more advanced systems for digital transactions. These findings are consistent with Ahmad et al. (2020), who emphasized that in rural regions where conventional banking infrastructure is lacking, mobile money serves as a vital alternative. It enhances access to financial services and plays a key role in supporting the

sustainability of livelihoods by connecting majority of the unbanked rural communities (Demirguc-Kunt et al., 2022; Wieser et al., 2019). Urban residence and male gender are associated with higher adoption rates, reflecting persistent digital divides as hypothesized in H4. In comparison to other variables, age shows a negligible positive association in both digital transactions and mobile money models, implying that age, although significant, is not a very meaningful determinant once education, income, and technology access are accounted for. The negative and significant coefficient of the age squared term reveals a non-linear relationship, indicating that the likelihood of FinTech adoption increases with age up to a certain point before declining, thereby forming an inverted U-shaped pattern. This suggests that while younger individuals are early adopters due to their tech-savviness, they may lack financial means, whereas older individuals, despite having more financial resources, may face technological barriers. Middle-aged users, combining both financial capacity and digital familiarity, are most likely to adopt FinTech services. Lwoga and Lwoga (2017) and Kikulwe et al. (2014) also found non-linear patterns in the case of Tanzania and Kenya, respectively.

4.3 Odds ratios results for determinants of fintech adoption: digital transactions vs mobile money

To complement the probit and logit regression results, Figs. 1 and 2 present the estimated odds ratios for various predictors influencing the use of digital payments and mobile money services. Figure 1 highlights formal account ownership as the most influential factor in driving digital transaction usage. Individuals with a formal bank account are significantly more likely to engage in digital transactions, underscoring the foundational role of traditional financial infrastructure

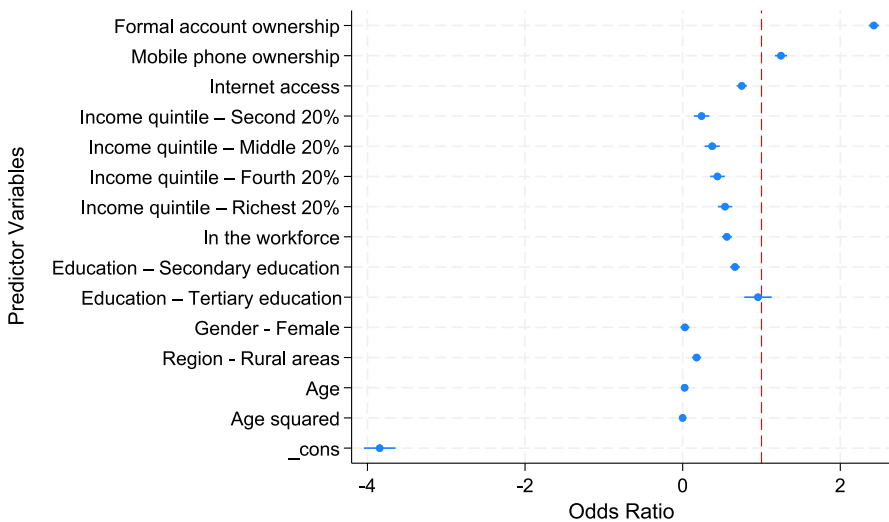


Fig. 1 Estimated Odds Ratios for Factors Influencing Digital Transaction Usage

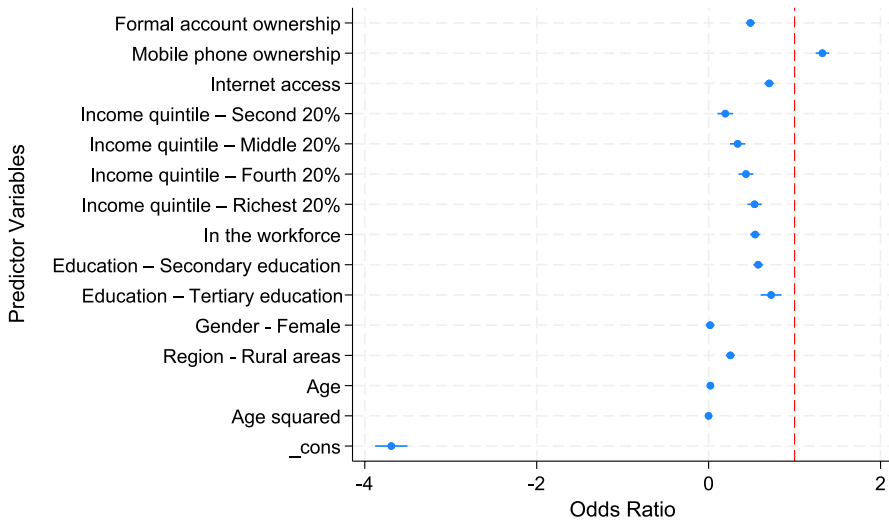


Fig. 2 Estimated Odds Ratios for Factors Influencing Mobile Money Usage

in enabling access to more advanced digital financial tools. In contrast, Fig. 2 shows that mobile phone ownership is the strongest predictor of mobile money usage. This reflects the accessibility and flexibility of mobile money platforms, particularly in contexts where formal banking services are limited or absent. The prominence of Mobile phone ownership in this context suggests that mobile money serves as a more inclusive financial tool, especially in underserved or rural areas.

These findings support the idea that while digital transactions often build upon existing formal financial systems, mobile money offers a more accessible alternative that leverages widespread mobile penetration.

4.4 Machine learning results

This study employed nine different machine learning algorithms to evaluate classification performance. Following model training and evaluation, the top three performing models were selected for further analysis of feature importance, which serves to identify the most influential predictors contributing to model decisions.

Table 4 presents the performance metrics of the nine machine learning models implemented in this study. The selection of the top-performing models was primarily based on the Receiver Operating Characteristic – Area Under the Curve (ROC-AUC) metric. As a threshold-independent measure, ROC-AUC reflects a model's ability to distinguish between classes across all possible classification thresholds. It is widely endorsed in academic literature, particularly in contexts involving class imbalance or varying misclassification costs, due to its robustness and interpretability. Among the models evaluated, XGBoost demonstrated the highest discriminative capability, along with consistently strong performance across all complementary

Table 4 Model Evaluation. Source: Author's calculation

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC	MCC	Cohen's Kappa	G-Mean
XGBoost	0.788530466	0.81067961	0.7288	0.767564	0.871738059	0.57734	0.57459559	0.784039909
Random Forest	0.790023895	0.8066712	0.73878	0.7712333	0.871680773	0.57979	0.577886214	0.786430197
Gradient Boosting	0.787634409	0.81734186	0.71696	0.7638658	0.871246438	0.57648	0.572417019	0.781859977
AdaBoost	0.790621266	0.81617647	0.72662	0.7687995	0.871201217	0.58192	0.578653356	0.785654395
Logistic Regression	0.78927718	0.80929432	0.73286	0.7691804	0.870568213	0.57861	0.576209527	0.785146956
Extra Trees	0.788978495	0.81546573	0.72319	0.766562	0.870333886	0.57874	0.575288786	0.78379845
Support Vector Machine	0.7777180406	0.8539604	0.64526	0.7350852	0.867335898	0.56525	0.549157814	0.761428715
Decision Tree	0.783303465	0.78756137	0.75	0.7683219	0.863623312	0.56561	0.565015091	0.781313071
K-Nearest Neighbors	0.776284349	0.78557114	0.73317	0.758465	0.853887045	0.55172	0.550581637	0.77344723

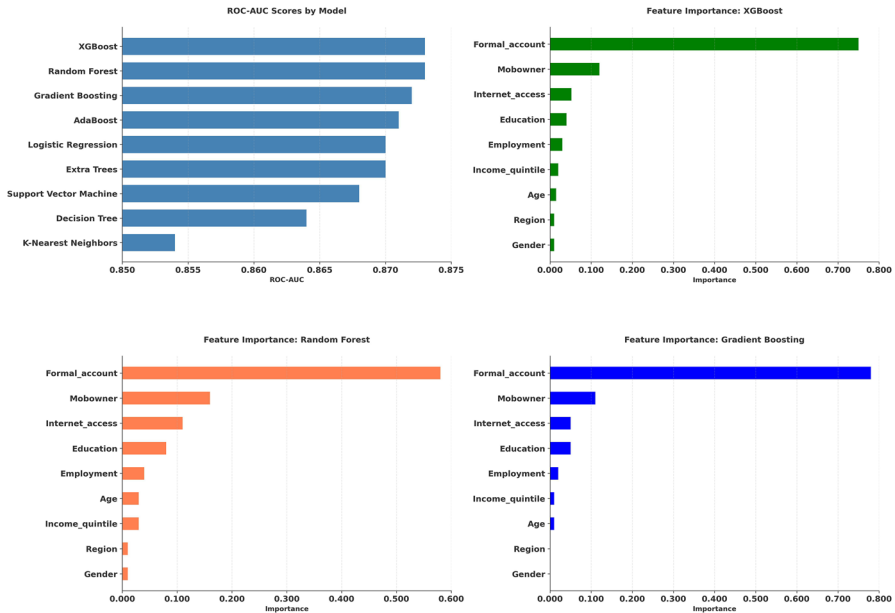


Fig. 3 Evaluating Model Performance and Feature Influence on Digital Payment Adoption

metrics, including accuracy, precision, recall, and F1-score. Random Forest achieved a nearly equivalent ROC-AUC score, while offering a marginally higher F1-score, suggesting a more favorable balance between precision and recall. Gradient Boosting also performed competitively, attaining a high ROC-AUC and robust overall results, although its recall was slightly lower relative to the top two models.

Building on the above analysis, this section aims to showcase the predictors that affect FinTech adaptation using feature importance from machine learning models. FinTech is represented by digital transactions and mobile money account adoption. That is, whether an individual has made or receive any digital payments, and whether they possess a mobile money account. As evidenced by Fig. 3, the ensemble learning algorithms, namely Random Forest, XGBoost, and Gradient Boosting, demonstrate superior predictive performance in identifying the key factors influencing FinTech adaptation. Therefore, validating hypothesis 5 that machine learning models outperform traditional econometric methods in predicting FinTech adoption patterns. Among these, formal account ownership, a proxy for formal financial inclusion, consistently emerges as the most prominent predictor. This finding strongly suggests that individuals integrated into the formal financial sector are significantly more likely to adopt FinTech solutions, underscoring the foundational role of traditional banking infrastructure in facilitating the uptake of digital financial services. Furthermore, access to relevant technologies, particularly Mobile phone ownership/network access, and internet connectivity, also play a substantial role in predicting FinTech adoption, highlighting the critical interplay between financial infrastructure and digital access in driving the diffusion of these innovations.

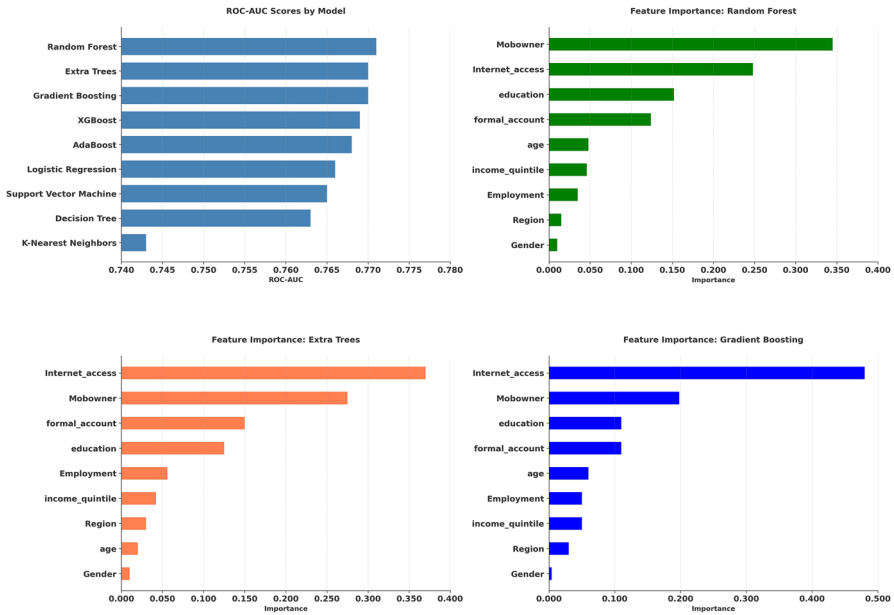


Fig. 4 Model Evaluation and Feature Importance in Predicting Mobile Money Account Use

Building on the analysis of digital transactions, mobile money account usage is introduced as the second dependent variable. This focus is particularly significant, as mobile money represents a transformative FinTech innovation that bridges the gap between the formally banked and the unbanked or underbanked populations, thereby enhancing financial inclusion. As shown in Fig. 4, mobile phone ownership and internet access emerge as significant predictors of mobile money usage, highlighting the critical role of technological access in facilitating FinTech engagement.

The analysis further underlines the pivotal role of formal financial inclusion and educational attainment in shaping individuals’ propensity to adopt mobile money services. These findings underscore a complex interplay between technological infrastructure and socio-economic factors in driving the adoption and diffusion of FinTech solutions.

5 Conclusion

This study investigates the socio-demographic, financial, and technological determinants of FinTech adoption across 36 Sub-Saharan African countries, employing a novel hybrid methodological framework that integrates traditional econometric models with supervised machine learning algorithms. Using micro-level data from 35,533 individuals in the 2021 World Bank Global Findex survey, this study offers critical insights into the complex interplay of factors driving digital financial inclusion in the region.

The findings reveal that technological access and formal financial inclusion are the primary predictors of FinTech adoption, though their relative importance varies significantly across different digital financial services. Mobile phone ownership emerges as the strongest predictor of mobile money adoption, while formal account ownership dominates digital payment usage, revealing distinct pathways to digital financial engagement. This differential impact underscores the complementary rather than substitutive relationship between traditional banking infrastructure and emerging FinTech solutions, consistent with the conclusions of Kumar and Pradhan (2024), Adaba et al. (2019), and David-West et al. (2018). However, it challenges the existing assumptions about digital financial services as mere alternatives to conventional banking. The study also demonstrates that socioeconomic factors such as income, education, and employment status significantly shape adoption patterns, with effects consistently stronger for digital payments than mobile money services. However, gender is statistically insignificant, suggesting that structural barriers rather than inherent gender differences drive observed adoption gaps. The persistent urban–rural divide highlights the critical role of digital infrastructure in shaping access to financial technologies.

Methodologically, the hybrid approach used in this study demonstrates superior predictive performance compared to traditional econometric methods alone, with ensemble learning algorithms (XGBoost, Random Forest, and Gradient Boosting) achieving ROC-AUC scores exceeding 0.87. In addition to the robustness of the findings, this methodological advancement establishes a framework for future FinTech research in developing economies.

The policy implications are profound and actionable. First, governments and development agencies must prioritize digital infrastructure investments, particularly in rural areas, to bridge the connectivity divide that constrains FinTech adoption. Second, financial institutions should pursue integrated strategies that leverage existing formal banking relationships to facilitate digital payment adoption while simultaneously expanding mobile money services to reach unbanked populations. Third, targeted interventions addressing digital literacy and financial education are essential for maximizing the inclusive potential of FinTech innovations.

The findings contribute to the broader literature on financial inclusion and technology adoption by providing the first comprehensive machine learning-based analysis of FinTech determinants in Sub-Saharan Africa. The study advances theoretical understanding by demonstrating how the Technology Acceptance Model operates differently across various digital financial services and socio-economic contexts. Furthermore, the evidence of complementarity between formal and digital financial services offers new insights for designing inclusive financial ecosystems.

By integrating econometric analysis with machine learning techniques, this study provides a robust empirical foundation for evidence-based policymaking aimed at advancing digital financial inclusion across Sub-Saharan Africa. The findings underscore that realizing the transformative potential of FinTech requires coordinated efforts to address technological, institutional, and socio-economic barriers simultaneously.

Future research should explore the dynamic aspects of FinTech adoption, examining how individual usage patterns evolve over time and investigating the causal mechanisms through which digital financial services impact economic outcomes. Additionally, comparative studies across different regional contexts would enhance the generalizability of these findings and inform context-specific policy interventions.

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Declarations

Conflict of interests The authors declare no competing interests.

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