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# Fintech adoption dynamics in a pandemic: An experience from some financial institutions in Nigeria during COVID-19 using machine learning approach

Onome Christopher Edo
*Auburn University at Montgomery*

Egbe Etu Etu
*San Jose State University*, egbe-etu.etu@sjsu.edu

Imokhai Tenebe
*San Jose State University*

Oluwarotimi Samuel Oladele
*Federal University, Oye-Ekiti*

Solomon Edo
*Auchi Polytechnic*

*See next page for additional authors*

Authors
Onome Christopher Edo, Egbe Etu Etu, Imokhai Tenebe, Oluwarotimi Samuel Oladele, Solomon Edo, Oladapo Ayodeji Diekola, and Joshua Emakhu

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# Fintech adoption dynamics in a pandemic: An experience from some financial institutions in Nigeria during COVID-19 using machine learning approach

Onome Christopher Edo[1]*, Egbe-Etu Etu[2], Imokhai Tenebe[3], Oluwarotimi Samuel Oladele[4], Solomon Edo[5], Oladapo Ayodeji Diekola[6] and Joshua Emakhu[7]

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*Corresponding author: Onome Christopher Edo, Auburn University at Montgomery, College of Business, Department of Information systems, 7071 Senators Dr, Montgomery, AL 36117, USA
E-mail: chrisovik@gmail.com

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Hung-Che Wu, Business School, Nanfang College Guangzhou, China

Additional information is available at the end of the article

**Abstract:** The novel coronavirus caused a lifestyle shift, and the acceptance of offsite financial transactions is still a case for financial technology (fintech). Mobile financial transactions continue to be at an all-time low, and financial institutions are developing approaches for financial digitalization acceptability. The present study attempts to understand users' motivations for fintech adoption. The technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTUAT) were utilized to uncover the rationale behind technology adoption. This study explored the drivers inhibiting the adoption of financial technology in Nigeria during the pandemic. A machine learning (ML) approach was implemented to examine fintech adoption predictors using a self-administered consumer survey of 480 account holders. Survey responses were analyzed using a set of ML models (naïve Bayes, logistic regression, K-nearest neighbors, decision trees, and support vector machines), revealing the features and decision criteria for predicting perceived technology adoption. The decision tree outperformed the other models, with an accuracy of over 84%, precision of 88%, recall of 86%, F1-score of 84%, and area under the curve of 87%. The result indicates that customers are concerned about their safety. Thus, furthering their sense of risk. These results provide a roadmap for financial institutions and policymakers to understand behavioral attitudes toward adopting fintech and suggest strategies for attracting customers to the fintech space.

**Subjects: Information & Communication Technology (ICT); Banking; Business, Management and Accounting;**

**Keywords: financial technology; technology adoption; Covid-19; technology acceptance model; machine learning; perceived ease of use; perceived risk**

## 1. Introduction

The emergence of COVID-19 left the entire world in distress. The pandemic caused a severe health crisis, leaving the world at an impasse with millions of infections and deaths (WHO, 2020). Despite relentless attempts by scientists and medical professionals worldwide, the pandemic defied medical efforts in many ways. The effect has been catastrophic to healthy living and lifestyles, and it has further exerted pernicious consequences globally, resulting in the disruption of commerce and social interactions, unprecedented recessions in some countries, and massive job losses in many parts of the world (Aji, Berakon, & Md Husin, 2020; Alshari & Lokhande, 2022; Ang & Edo, 2022; Edo et al., 2020; Ikechukwu et al., 2021; Onakpa & Alfred, 2022; von Wachter, 2020)

Most notably, the banking sector initially suffered a major setback from the pandemic, as banking activities plunged with the mandatory closure of businesses, leading to credit and liquidity risk (Akomolafe, 2022; Amaihian et al., 2022; Deloitte, 2020). Meanwhile, bank customers suffered an ill fate because transactions were limited to alternative financial technology channels, such as online banking, mobile apps, point-of-sale transactions, and web payments.

Alternative and self-service banking has become popular in the millennial era. However, customers remain resolute in utilizing the brick-and-mortar banking system. Therefore, technological innovation has thus far been rejected. These channels would offer quick services to customers and save costs; the dereliction remains a mirage, and worthy of investigation. This phenomenon worsened during the pandemic, as long lines of account holders were observed squeezing themselves to be physically present in banking premises.

Numerous studies have explored technology adoption factors (Alnsour, 2022; Baicu et al., 2020; Edo et al., 2023; Fawzy & Esawai, 2017; Jehan & Ansari, 2018; Jibril et al., 2020; Mwiya et al., 2022; Shu'ara & Amin, 2022; Yoon et al., 2020). These studies employed statistical tools using regression-based techniques and software applications such as SPSS to determine the linear function between variables. However, X. Li and Zheng (2020) opined that such linear functions distort prediction accuracy and are incapable of modeling complex nonlinear relationships (Anouze & Alamro, 2020).

Consequently, researchers have adopted machine learning (ML) techniques to close the data prediction expectation gap. Conceptually, ML is focused on predicting and creating structures from unstructured data (Buchanan & Miller, 2017). Consumer behavior and technology adoption studies often involve complex data, and ML is an effective technique for researchers to distinguish and demonstrate complex designs in a data-driven manner (Bhamare & Suryawanshi, 2018; Neal, 2007).

Standard parametric statistics follow a clear set of rules and patterns with fixed conditions (Bishop, 2007), whereas ML eliminates sets of rules that are often constrained (Hastie et al., 2016; Rajula et al., 2020), enabling the identification of subtle patterns and features in training data. These insights can then be used to assess new data for predictive purposes (Buchanan & Miller, 2017; Hayes et al., 2019).

Although a handful of studies have investigated the technology adoption domain, few have addressed concerns relating to the subject matter in an ML context, with little or none in Africa and Nigeria. Moreover, the extant literature has identified mono-or bi-technological channels, and thus the results cannot be generalized. Moreover, the lingering impact of the pandemic and the discovery of new variants continues to impact social interactions; retail customers still opting for in-person banking increases the vulnerability of contracting and spreading viruses.

Against this backdrop, the present study investigates fintech adoption factors using an ML predictive model. This study deviates from the standard methodology adopted by prior studies and contributes to the literature by considering the impact of the COVID-19 pandemic as an extraneous factor. Furthermore, prior studies have investigated a particular technological constraint. Here, a structured questionnaire was developed to accommodate several fintech alternatives, which are within the context of electronic payment systems.

To this end, the findings will help technology-driven financial institutions gain a more holistic understanding of customer motivation for technology adoption and discontinuation. Furthermore, it will provide guidance for effective fintech policy development.

Implementation of the results has the potential to reduce turnaround time in banking premises, increase productivity, and improve the user experience. Additionally, it will reduce the spread of communicable diseases via social interaction, particularly during the pandemic era.

The remainder of this paper is organized as follows: section two is the review of related literature, section three is the methodology of the study, the results and discussions are presented in section four, and section five concludes the study.

## 2. Literature review

Existing studies have expressed concerns about technology adoption perceptions and motivations for adopting new technology, especially regarding financial technology. Technology adoption motivation and discontinuance studies have identified variables such as security, ease of use, transaction cost, cognitive capacity, and user innovativeness (Alshari & Lokhande, 2022; Amoroso & Lim, 2014; Ly et al., 2022; Nguyen et al., 2022; Singh & Sinha, 2020; Sudarsono et al., 2022; To & Trinh, 2021; Yoon et al., 2020).

Before the COVID-19 pandemic, Zhang and Mao (2020) investigated behavioral factors influencing mobile payment adoption in the United States, with special attention to proximity mobile payment technologies. The study was based on the technology acceptance model (TAM) and the Theory of reasoned action (TRA). Data from an online survey were collected from 394 non-users of payment systems. Structural equation modeling was used to test the data, and the results showed that TAM variables, including perceived usefulness, perceived ease of use, and relative advantage, affected adoption decisions. Furthermore, other characteristics, such as responsiveness and perceived mobility influenced mobile payment usage.

Similarly, Flavián et al. (2020) investigated electronic payment usage intention in the United States and Spain. The study incorporated mindfulness in the TAM and collected data from 414 respondents in the United States and 380 respondents in Spain. An empirical investigation was conducted using a structural equation modeling approach. The results revealed that perceived ease of use, mindfulness, perceived usefulness, subjective norms, and consumer attitudes affect the intention to use mobile payment.

From an ML perspective, Carbo-Valverde et al. (2020) investigated the digitization of banking customers using random forest and causal forest ML approaches. This study involved over 3005 Spanish participants between the ages of 18 and 75 years on digital banking preference payment services within the banking sector. The study revealed that ease of viewing account balances and making transfers is one of the factors that influences digital technology adoption.

However, consumer perception can be influenced by environmental and situational factors, such as the COVID-19 pandemic (Ojo et al., 2022; Sutharattanagul et al., 2022; Yu & Chen, 2022). The discovery of new SARS-CoV-2 variants continues to distort social acclimatization (Yan et al., 2021; Zhao & Bacao, 2021). This motivated researchers to investigate the impact of the pandemic on fintech adoption.

For example, Daragmeh et al. (2021) investigated fintech adoption factors among consumers during the pandemic era in Hungary. Data was collected through an online survey of 1120 consumers. The data were analyzed using structural equation modeling, and the results showed that perceived usefulness, subjective norms, and perceived COVID-19 risk significantly influenced mobile payment adoption decisions.

Mensah, Zeng, Luo, Zhi-Wu, and Lu (2021) researched the adoption factor of electronic payment systems in China from a group of college students, premised on the unified theory of use and acceptance (UTUAT). The data collected were analyzed using a partial least squares structural equation modeling technique. Their findings revealed that perceived security, performance expectancy, and effort expectancy significantly affected the intention to use electronic payment systems, whereas perceived trust had no significant influence on users' intentions.

Similarly, Al-Qudah et al. (2022) investigated the impact of the COVID-19 pandemic on technology adoption intention with respect to mobile payment usage in the United Arab Emirates. Primary data were collected from 422 respondents through an online survey and analyzed using a structural equation modeling technique. The findings revealed that perceived skillfulness, perceived ease of use, and convenience had a positive influence on mobile wallet adoption during the pandemic and further revealed a weak negative relationship between risk and the intention to adopt a mobile wallet.

Likewise, Coskun et al. (2022) studied online payment adoption factors among Turkish banking customers. The study was founded on TAM, and data were collected from 348 banking customers through an online survey. The collected data were analyzed using a linear regression model, and their results revealed that perceived risk negatively impacted online payment usage. However, trust, perceived usefulness, perceived ease of use, personal innovativeness, COVID-19 effects, and relative advantage positively influenced online payment decisions.

Yu and Chen (2022) investigated the perceived risk of contracting SARS-CoV-2 as a mediating factor in mobile payment usage in Taiwan. Data was collected through a survey of 590 customers using both cash and electronic payment channels. The data were analyzed using a structural equation modeling technique, and the results revealed that customers embraced digital payment systems because of fear of contracting SARS-CoV-2. This explains why the shift in the adoption of electronic payment systems was significantly influenced by the perception of fear.

Similarly, Jayarathne et al. (2022) investigated electronic payment adoption factors during the COVID-19 pandemic in Sri Lanka. The study aimed to unravel these factors from a customer and retailer perspective and, therefore, adopted a dual research design. Data from 304 customers were collected and analyzed using a structural modeling technique based on TAM and UTUAT. Their findings revealed that perceived security, performance expectancy, hedonic motivation, and facilitating conditions significantly influenced mobile payment adoption during the pandemic.

In another study, Abdus Salam et al. (2021) empirically explored the impediments and motivation to adopt mobile banking technology during the COVID-19 pandemic using the extended TAM model. This study gathered 249 responses from banking customers in Bangladesh and used a structural equation model. The results identified several inhibitors of technology adoption, such as Internet reception, customer satisfaction, the quality of mobile banking services, perceived cost, privacy, and user capability.

Yan et al. (2021) investigated the role of fintech and factors influencing the adoption of mobile financial services during the COVID-19 pandemic. This study used the UTUAT model and included two exogenous variables: risk and trust. Survey responses were obtained from 227 banking customers in Bangladesh and a structural equation model was used to analyze the data. The study concluded that perceived trust, perceived value, and social influence significantly influence decisions to adopt mobile financial services. However, perceived risk had no impact on the adoption of mobile financial services during the pandemic period. In summary, this study established that performance expectancy, effort expectancy, and perceived risk jointly affect perceived value.

### *2.1. Model and hypothesis development*

To achieve the objective of this study, a dual model was adopted to reinforce this investigation, employing both the UTUAT (Venkatesh et al., 2003) and the TAM (Davis, 1989). These models have been significant in probing user acceptance and behavioral intention in technology adoption studies. Researchers have often theorized models for investigating technology adoption behavior, for example, the theory of reasoned action (Ajzen & Fishbein, 1977; Fishbein & Ajzen, 1975), diffusion of innovation (Rogers et al., 2019), social cognitive theory (Bandura, 1992), and the model of PC utilization (Thompson et al., 1991).

The UTUAT model has been effective in investigating behavioral intention causality. Marikyan and Papagiannidis (2021) affirm that behavioral intention and technology use are validly explained by the UTUAT model with approximately 74% accuracy; the model is depicted in Figure 2. Similarly, TAM has been regarded for its contribution in explaining consumer acceptance and use in the information system domain (He et al., 2018; Olumide, 2016).

Both theories rely on predicting behavioral intention with the assumption that individuals make logical and reasoned choices through conscious evaluation of facts within the scope of available information and the ease with which the action could be performed. Fundamentally, TAM is based on two major constructs: perceived ease of use and perceived usefulness (Figure Figure 1). The former involves "the degree to which a person believes that using the system will be free of effort" (Davis, 1986, 1989), and the latter involves "the extent to which a person believes that using a particular technology will enhance her/his job performance" (Davis, 1986, 1989). Relying on both theories, the study provides a model for predicting technology adoption behavior as depicted in Figure 3.

The UTUAT model consists of six significant constructs: performance expectancy, effort expectancy, social influence, facilitating condition, behavioral intention, and use behavior (Venkatesh et al., 2003). This study adopts both models with the inclusion of other external factors.

**Figure 1. Technology acceptance model. Adapted from (Davis, 1989).**

Note: An information system theory to assess how users perceive and accept the use of technology.

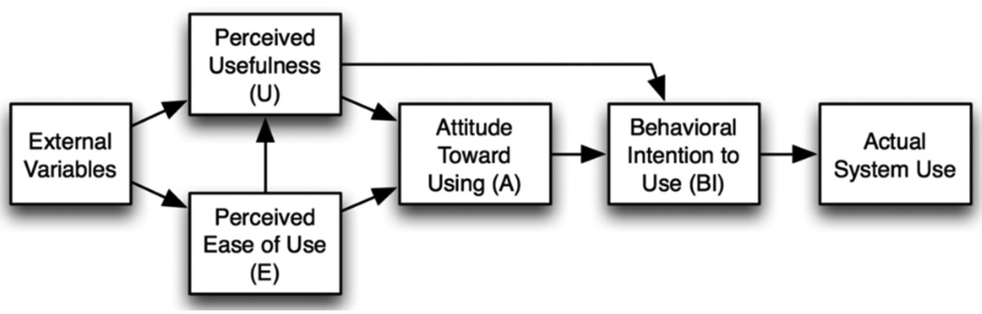
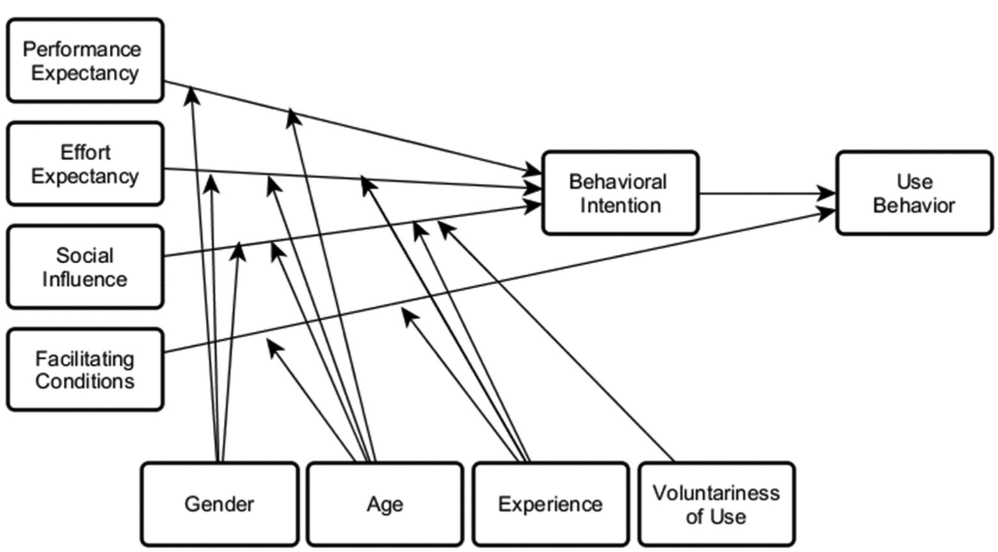



**Figure 2. Unified theory of use and acceptance of technology. Adapted from (Venkatesh et al., 2003).**

Note: The unified theory of acceptance and use of technology (UTUAT 2) model aimsto explain behavioral perception and intentions to use technology and subsequent usage.



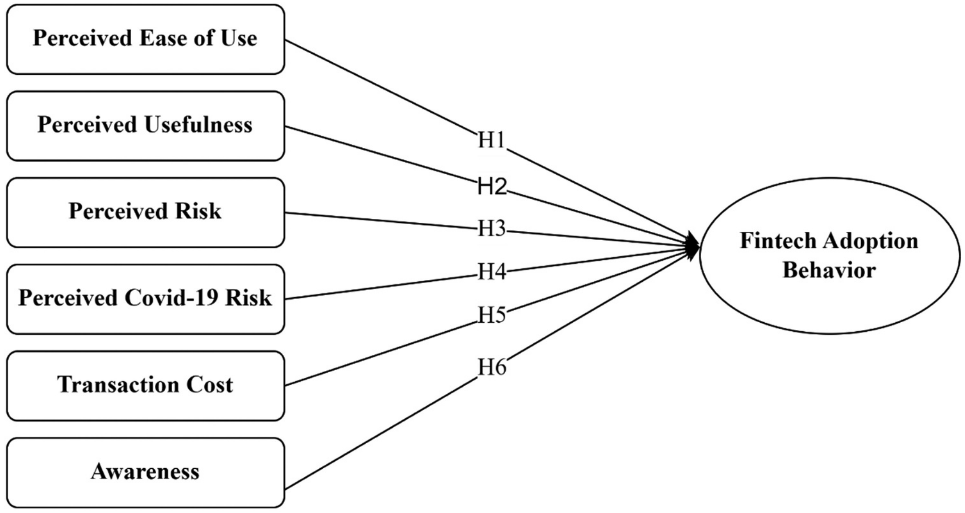



**Figure 3. Framework for predicting fintech adoption.**

Note: This model is an extrapolation from the technology acceptance model (TAM) with the extension of risks factors by Featherman and Pavolu, (2003), and the unified theory of acceptance and use of technology UTUAT 2. used to predict and assess technology adoption intentions in this study.

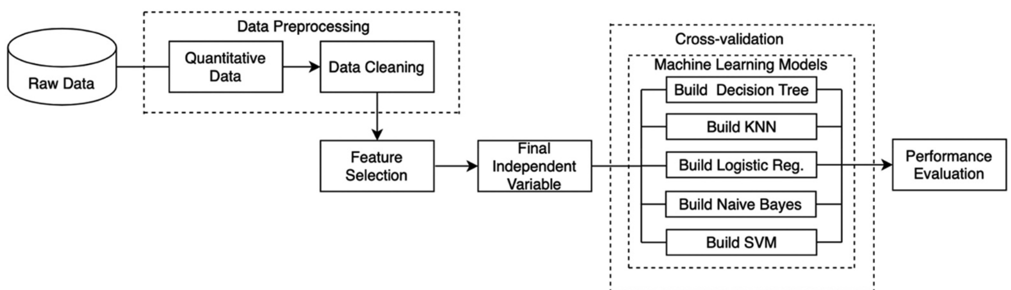



**Figure 4. Architecture of proposed model.**

Note: The machine learning steps used for measuring and evaluating the data to predict user intentions.

### *2.1.1. Perceived ease of use*

Perceived ease of use explains users' adoption decisions. Davis (1986) defines perceived ease of use as "the degree to which a person believes that using a particular system will be free of effort." It is based on an individual's perception that the use of a particular technology will be without exertion (Davis, 1986), and it encapsulates technological devices and user applications. The literature on mobile payment adoption has often found a connection between perceived ease of use and adoption behavior. For example, Coskun et al. (2022) found a significant influence of perceived ease of use on technology adoption decisions in the COVID era, and other studies have found similar results (Prastiawan et al., 2021; Yin & Lin, 2022). Therefore, the following hypothesis is proposed:

**$H_1$:** Perceived ease of use positively affects mobile financial technology adoption.

### *2.1.2. Perceived usefulness*

Perceived usefulness is defined as the degree to which an individual feels that employing a given technology would be advantageous (Davis, 1986). As an individual's perceived utility of a particular technology improves, so do their plans to utilize the technology. Usefulness is perceived when it is believed to add value to an activity. In essence, the user experience is personified. Consumer experiences often vary. However, the performance of technology and mobile applications has been evaluated using perceived usefulness as a construct to probe mobile payment usage. However, various results have been reported. For example, Bitkina et al. (2022) found no significant influence of perceived usefulness on fintech adoption behavior. In contrast, other studies affirmed the influence of perceived usefulness on fintech adoption (Alalwan et al., 2016; Kumar et al., 2021; Prastiawan et al., 2021; Yin & Lin, 2022). Thus, the second hypothesis is proposed as follows:

**$H_2$:** Perceived usefulness positively influences technology adoption.

*2.1.3. Perceived risk*

Perceived risk is a "subjective feeling about an objective risk surrounding the circumstances based on knowledge, past experiences, and/or intuitive judgment of the individual" (Lu, Xie, & Xiong, 2015, p. 200). Risk is associated with uncertainty and levels of quality that diverge from expectations. This is accompanied by a lack of control over the outcomes of events. Consumers are likely to evaluate the positive and negative outcomes of the adoption of new technologies and are likely to seek opportunities to reject innovation and decline to adopt technology platforms when they experience a sense of negativity. Bauer (1960) held that consumers anticipate risks and thus determine usage and adoption decisions. Moreover, the risk of contracting COVID-19 sparks some concerns among respondents. Weinstein (1982) explains the concept of "unrealistic optimism" and "unrealistic pessimism," and pessimism, where people are asked to estimate their risk of experiencing a disease or an adverse outcome.

The relationship between perceived risk and technology adoption is documented in extant studies (Aji et al., 2020; Hossain, 2019; Kumar et al., 2021; Ojo et al., 2022; Siyal et al., 2019). Likewise, consumer perceptions of COVID-19 risk have been highlighted as a factor in technology adoption studies (Coskun et al., 2022; Ramtiyal et al., 2022; Yu & Chen, 2022). Consequently, the following hypotheses were formed:

**$H_3$:** Perceived risk negatively affects mobile financial technology adoption

**$H_4$:** COVID-19 risk negatively affects mobile financial technology adoption.

*2.1.4. Transaction cost*

Transaction costs are related to expenses incurred when engaging in the purchase or exchange of goods and services. The use of fintech services incurs some costs. For instance, transfer charges, ATM withdrawal fees, card maintenance fees, and debit card issuance fees, to mention but a few. These fees are incurred when customers elect to use these services and are likely to influence the decision to use such technology, especially with high-end transactions. Agarwal et al. (2020) reported that reduced transaction costs increased consumer spending, while Lu and Wung (2021) reported that transaction costs had a pull-and-push effect on mobile payment usage behavior. Likewise, Abdus Salam et al. (2021) and Kar (2021) affirm that transaction costs significantly affect mobile payment adoption. Therefore, the following hypothesis is conjectured:

**$H_5$:** Transaction cost affects financial technology adoption.

*2.1.5. Awareness*

Awareness is the knowledge or perception of a situation. It is the knowledge of the existence of a phenomenon, and this is founded on the level of information available to the person. Consumers accept a technology if they are aware of its existence and the direct benefits of its adoption. Awareness drives a shift in thought and an increased knowledge status regarding a particular service and the benefits associated with its acceptance. Raza et al. (2017) argued that mobile financial technology acceptance was significantly linked to perceived service awareness. Similarly, Siyal et al. (2019), Sona and Swain (2018), and Oyelami et al. (2020) reported that perceived awareness affects mobile financial payment system adoption. Therefore, the following hypothesis is proposed:

**$H_6$:** Perceived awareness affects financial technology adoption.

## 3. Methodology

The primary aim of this study was to propose a framework for investigating ML models to explain financial technology adoption. The proposed framework was built in three phases. The schema of the proposed model is shown in Figure 4. The first phase involved data preprocessing, data cleaning, missing data imputation, and standardization. In the second phase, feature selection was performed, which involves a dimensionality reduction approach suitable for detecting the most practical features; this approach aids in the development of a more dependable model, minimizing overfitting, enhancing accuracy, and reducing model training time. Finally, 10-fold cross-validation was performed on several evaluation metrics to evaluate the performance of the trained ML models, i.e., decision trees (DTs), K-nearest neighbors (KNN), logistic regression (LR), naïve Bayes (NB), and support vector machines (SVMs). Six trials were conducted for this study. The first three trials each had a dependent variable as a stand-alone target variable. Simultaneously, two dependent variables were included as independent variables for the last three trials with the last one as the target variable. The evaluation metrics included accuracy, precision, recall, F1-score, and area under the curve (AUROC).

### *3.1. Measures and questionnaire*

Three items per construct were measured in this study. Responses to all questions were measured using a 5-point Likert scale ranging from "strongly disagree" to "strongly agree". The draft questionnaire was tested with 30 responses to check for ease of understanding and ambiguity. The feedback received was incorporated to improve the level of understanding. The measures were adapted from prior literature and revised to align with the context of the study, The constructs of perceived ease of use and perceived usefulness were adapted from Davis (1986) and Venkatesh et al. (2003), perceived risk from Featherman, and Pavlou (2003), and Liébana-Cabanillas et al. (2014) and technology adoption Venkatesh et al. (2003).

With respect to perceived COVID-19 risk, the study builds on the foundation of prior research where disease outbreaks were considered a significant determinant of technology adoption (Aji et al., 2020; CC & Prathap, 2020; Daragmeh et al., 2021). Similarly, the construct of transaction cost was founded on the extension of the UTUAT theory leading to the UTUAT 2 theory of Venkatesh et al (2012) and has been explored in prior studies (Mustafa et al., 2022; Oliveira et al., 2016).

The author-developed construct was in consonance with the study of Oliveira et al. (2016) and as such adapted. The concept of awareness was author developed. However, the ideation was drawn from Mustafa et al. (2022) who explored the influence of environmental awareness as a possible factor for 5 G technology acceptance, in this study, awareness is framed in the light of product awareness and channels. The sources and respective questionnaire items are presented in Table 1.

Exploratory factor analysis was used to test the validity of the constructs. Specifically, the Kaiser—Meyer–Olkin (KMO) test was used to test the sample adequacy of each construct, and a Cronbach's alpha test was carried out to test the reliability and consistency of the scales in the study. The calculations were extrapolated using the STATA 17 software, and the indicators are presented in the Results section.

### *3.2. Data collection*

Over 1000 self-administered questionnaires were distributed to participants, with an invitation to participate and a brief introduction to the research objectives. Respondents were randomly chosen and screened based on a preliminary question. Specifically, they must have either a bank account or a mobile phone with Internet connectivity. Those who consented to participate were requested to respond to the questions. In total, 578 responses were retrieved, with 480 valid responses. A total of 51% were male and 49% were female. Detailed statistics are presented in Tables 2 and 3.

### *3.3. Machine learning models*

In this study, five different ML models were implemented: NB, LR, KNN, DT, and SVMs. DT uses a supervised ML algorithm that can be used in both classification and regression algorithms. A DT is like a tree with nodes with its branches relying on several factors. It divides data into branches until a threshold value is reached. A decision tree consists of root nodes, child nodes, and leaf nodes (Sharma et al., 2021) to build the tree, and the entropy is computed using frequency tables. The entropy formula can be written as:

$$E(S) = \sum_{i}^{c} -p_i p_i \tag{1}$$

The KNN algorithm is a simple, easy-to-implement supervised ML algorithm that can solve classification and regression-related problems. The KNN algorithm computes the likelihood of the test data belonging to the classes of "K" training data, and the class with the highest probability is selected. KNN attempts to predict the correct class for the test data by computing the distance between the test data and all training points. Then, at that point, the K number of points are selected that are in proximity to the test data. In the case of regression, the value is the mean of the selected training points (Anthony, 2021). The KNN algorithm is typically calculated using Euclidean, Manhattan, and Minkowski distances. The Minkowski distance can be expressed as:

$$Minkowski = \left( \sum_{i=1}^{k} (|x_i - y_i|)^q \right)^{\frac{1}{q}} \tag{2}$$

LR is a statistical model that, in its basic form, utilizes a logistic function to model a binary dependent variable, although many more remarkable extensions exist. LR (Tolles & Meurer, 2016) (or logit regression) estimates the parameters of a logistic model (a type of binary regression). Statistically, a binary logistic model has a dependent variable with two potential values, such as pass/fail, characterized by an indicator variable, where the two values are labeled "0" and "1." In the logistic model, the log-odds (i.e., the logarithm of the odds) for the value categorized as "1" is a linear combination of one or more independent variables ("predictors"'). Independent variables can be binary (i.e., two classes coded by an indicator variable) or continuous (i.e., any real value). The logistic curve relates the independent variable (typically denoted by $X$, to the rolling mean of the dependent variable (typically denoted by $Y$. The formula is written as:

$$P = \frac{e^{a+bX}}{1 + e^{a+bX}} \tag{3}$$

NB classifiers are a group of straightforward "probabilistic classifiers" based on Bayes' theorem, with strong (naïve) independence assumptions between the features. These are among the simplest Bayesian network models and are combined with kernel density estimation. NB classifiers are profoundly scalable and require various linear parameters for the number of variables (features or predictors) in the learning problem. They can also attain high accuracy levels (Hastie et al., 2017; Piryonesi & El-Diraby, 2020). Maximum-likelihood training can be achieved by evaluating a closed-form expression (Brewka, 1996), which requires some time, rather than using expensive iterative estimates as utilized for many other types of classifiers. NB typically uses Bayes' theorem to compute conditional probabilities. The formula can be written as:

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)} \tag{4}$$

SVMs, also known as support vector networks, are supervised learning models with related learning algorithms that analyze data for classification and regression analysis. SVMs are perhaps the most robust prediction methods, and they are based on statistical learning frameworks. In addition to performing linear classification, SVMs can effectively perform non-linear classification utilizing the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces. The SVM maps training examples to points in space to maximize the width of the gap between the two categories. New examples are then mapped into the same space and predicted to belong to a category based on the size of the gap. One possible form of the prediction equation for SVM classification is:

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**Table 1. Organization of construct**

| Constructs | Items | Sources |
|---|---|---|
| **Perceived Ease of Use** | | (Davis, 1986) |
| PEU1 | Learning to use mobile payment platforms would be easy for me | |
| PEU2 | It will be comfortable for me to use mobile payment systems overtime for financial transactions | |
| PEU3 | Using mobile payment platforms would require a lot of mental effort | |
| **Perceived Usefulness** | | (Davis, 1986) |
| PU1 | Using fintech applications for financial transaction is useful for me | |
| PU2 | Using mobile payment system can increase my efficiency when making payments | |
| PU3 | Using payment platforms for my transactions can increase my productivity | |
| **Perceived Risk** | | (Liébana-Cabanillas et al., 2014; Featherman & Pavlou, 2003) |
| PR1 | The chances of losing money if I use mobile banking apps are high | |
| PR2 | Internet hackers (criminals) might take control of my account if I use mobile banking apps | |
| PR3 | It is risky transacting on other alternative channels. Eg. POS, web, Online Banking, Mobile app | |
| **COVID-19 Risk** | | (Aji et al., 2020) |
| CVR1 | It is better to use other channels because of hazards, e.g COVID-19 | |
| CVR2 | It is safe to use mobile banking platforms because of COVID-19 | |
| CVR3 | Mobile banking platforms can protect me from contracting COVID-19 | |
| **Transaction Cost** | | (Oliveira et al., 2016) |
| TC1 | Using mobile applications channel is more expensive | |
| TC2 | Other fintech channels are expensive | |
| TC3 | Other fintech channels are reasonably priced | |
| **Awareness** | | (Author developed) |
| AW1 | I do not know a suitable banking alternative | |
| AW2 | I know little about other banking channels | |
| AW3 | I rarely see an advert about alternative banking channels | |
| **Technology Adoption** | | (Venkatesh et al., 2003) |
| TA1 | I intend to use mobile banking apps in the future | |

(*Continued*)

| Constructs | Items | Sources |
|---|---|---|
| TA2 | I will always try to use mobile banking apps in my daily life | |
| TA3 | I plan to continue to use mobile banking apps frequently | |
| TA4 | If I have the resources, knowledge, and ability, I will use available fintech platforms | |

$$h(x_i) = sign\left(\sum_{j=1}^{s} \alpha_j y_j K(x_j, x_i) + b\right) \tag{5}$$

$$K(v, v') = exp\ exp\left(\frac{\|v - v'\|^2}{2\gamma^2}\right) \tag{6}$$

### *3.4. Performance metrics*

The performance metrics used for this analysis were the accuracy, recall, precision, F1-score, and AUROC. All analyses were performed using Python software. The equations for these metrics are as follows:

$$Accuracy = \frac{True\ Positives\ + True\ Negatives}{True\ Positives + False\ Positives + True\ Negatives + False\ Negatives} \tag{7}$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{8}$$

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{9}$$

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{10}$$

$$AUC = \int Recall \times d\left(\frac{False\ Positives}{True\ Positives + False\ Positives}\right) \tag{11}$$

## 4. Results and discussion

### *4.1. Reliability and validity test*

Reliability and validity tests were conducted using Cronbach's alpha to measure the internal consistency of the construct. The Cronbach alpha is a measure of reliability, and an index of 0.7 and above is considered suitable for research of this nature (Bonett & Wright, 2015; Taber, 2018; Tavakol & Dennick, 2011). In this case, the alpha value was greater than 0.7, indicating the reliability and consistency of the scales. The results are provided in Table 3.

### *4.2. Construct validity*

The construct for the study was adapted from prior literature, with the inclusion of a self-developed construct. The variables were reexamined for construct validity. The KMO test was used to validate the suitability of the variables for factor analysis. A threshold of 0.5 and above is usually considered as a good fit, and in this case, the KMO measure was greater than 0.5, which is an acceptable range for the study.

**Table 2. Demographic profile of respondents**

| | | Frequency | Percent |
|---|---|---|---|
| Gender | Male | 243 | 50.6 |
| | Female | 237 | 49.4 |
| Age | 18–30 | 160 | 33.3 |
| | 31–45 | 137 | 28.5 |
| | 45–55 | 81 | 16.9 |
| | 56–65 | 81 | 16.9 |
| | 66 and above | 21 | 4.4 |
| Educational level | High school | 82 | 17.1 |
| | Associate degree | 231 | 48.1 |
| | Bachelor's degree | 105 | 21.9 |
| | Master's degree | 50 | 1.4 |
| | Doctorate degree | 12 | 2.5 |
| Income | Below 80,000 Naira | 67 | 14.0 |
| | 81,000–150000 | 138 | 28.8 |
| | 151,000–200,0000 | 150 | 31.3 |
| | 201,000–300,000 | 83 | 17.3 |
| | 301,000–500,000 | 32 | 6.7 |
| | Above 500,000 | 10 | 2.1 |
| Do you have an operational bank account? | Yes | 421 | 87.7 |
| | No | 57 | 11.9 |
| | 2 | 1 | .2 |
| | 3 | 1 | .2 |
| Frequency of transaction | None | 193 | 40.2 |
| | 1–3 times | 213 | 44.4 |
| | 4–5 times | 27 | 5.6 |
| | More than 5 times | 21 | 4.4 |
| Frequency of bank visit | yes | 358 | 74.6 |
| | no | 120 | 25.0 |
| | 2 | 2 | .4 |
| Nature of visit | Complaint/Irregular charges | 88 | 18.3 |
| | Payment transaction | 84 | 17.5 |
| | Cash withdrawals | 126 | 26.3 |
| | Balance enquiry | 17 | 3.5 |
| | Personal Information update | 45 | 9.4 |

### *4.3. Significant predictors*

Survey studies on technology adoption have used theoretical models to investigate users' intentions. These models often require multidimensional questions to reiterate user perception, which creates room for a bloated dataset and results in poor prediction accuracy. However, to close the gap in the data prediction accuracy, a dimension-reduction technique can be utilized to reduce the number of features in a dataset. The feature selection approach was chosen for this study, and important features were selected from 22 questions in the dataset. A report of these significant features is shown in Table 4 and discussed below. ML models of the three dependent variables (DV) were produced using DTs, KNN, LR, NB, and SVM from questionnaire data obtained.

**Table 3. Reliability test**

| Constructs | Items | Item test correlation | Item rest correlation | Inter-item covariance | Cronbach alpha |
|---|---|---|---|---|---|
| **Perceived Ease of Use** | | | | | |
| PEU1 | Learning to use mobile payment platforms would be easy for me | 0.55 | 0.51 | .0.94 | .77 |
| PEU2 | It will be comfortable for me to use mobile payment systems overtime for financial transactions | 0.56 | 0.51 | .0.94 | .78 |
| PEU3 | Using mobile payment platforms would require a lot of mental effort | 0.36 | 0.28 | .097 | .78 |
| **Perceived Usefulness** | | | | | |
| PU1 | Using fintech applications for financial transaction is useful for me | 0.58 | 0.54 | .095 | .78 |
| PU2 | Using mobile payment system can increase my efficiency when making payments | 0.61 | 0.57 | .094 | .78 |
| PU3 | Using payment platforms for my transactions can increase my productivity | 0.57 | 0.52 | .095 | .78 |
| **Perceived Risk** | | | | | |
| PR1 | The chances of losing money if I use mobile banking apps are high | 0.34 | 0.27 | .099 | .79 |
| PR2 | Internet hackers (criminals) might take control of my account if I use mobile banking apps | 0.35 | 0.28 | .098 | .79 |

(*Continued*)

**Table 3. (Continued)**

| Constructs | Items | Item test correlation | Item rest correlation | Inter-item covariance | Cronbach alpha |
|---|---|---|---|---|---|
| PR3 | It is risky transacting on other alternative channels. Eg. POS, web, Online Banking, Mobile app | 0.33 | 0.28 | .098 | .79 |
| **COVID-19 Risk** | | | | | |
| CVR1 | It is better to use other channels because of hazards, e.g COVID-19 | 0.13 | 0.07 | .11 | .79 |
| CVR2 | It is safe to use mobile banking platforms because of COVID-19 | 0.24 | 0.15 | .10 | .79 |
| CVR3 | Mobile banking platforms can protect me from contracting COVID-19 | 0.20 | 0.13 | .10 | .79 |
| **Transaction Cost** | | | | | |
| TC1 | It cost more to use mobile application channels | 0.38 | 0.32 | .098 | .78 |
| TC2 | Other fintech channels are expensive | 0.44 | 0.33 | .097 | .78 |
| TC3 | Other fintech channels are reasonably priced | 0.42 | 0.36 | .097 | .79 |
| **Awareness** | | | | | |
| AW1 | I do not know a suitable banking alternative | 0.24 | 0.16 | .10 | .79 |
| AW2 | I know little about other banking channels | 0.22 | 0.14 | .10 | .79 |
| AW3 | I rarely see an advert about alternative banking channels | 0.29 | 0.20 | .09 | .78 |
| **Technology Adoption** | | | | | |
| TA1 | I intend to use mobile banking apps in the future | 0.49 | 0.44 | .09 | .78 |

(*Continued*)

| Constructs | Items | Item test correlation | Item rest correlation | Inter-item covariance | Cronbach alpha |
|---|---|---|---|---|---|
| TA2 | I will always try to use mobile banking apps in my daily life | 0.57 | 0.53 | .09 | .78 |
| TA3 | I plan to continue to use mobile banking apps frequently | 0.59 | 0.55 | .09 | .77 |
| TA4 | If I have the resources, knowledge, and ability, I will use available fintech platforms | 0.49 | 0.45 | .09 | .78 |

Independent dependent variables were created to determine their effect on the prediction model. Figure 1 shows the contribution of each feature to the prediction of the dependent variables using BorutaShap, where the green, yellow, and red bars represent accepted, tentative, and rejected features, respectively. For the first DV trial (i.e., “It was risky to transact on other alternative channels”), three attributes were reported to contribute significantly. These features include the following and are represented by the acronyms of the constructs from Table 1. (AW2, PEU3 and CVR1).

In the second DV trial (i.e., “Internet hackers—criminals might take control of my account if I use mobile banking apps”), five features were reported to contribute significantly. These features include the following: (AW2, PR1, CVR3,TA4 AND PEU1). For the third DV trial (i.e. “The chances of losing money if I use mobile banking apps are high”), three features were reported to contribute significantly: (TS2, AW3 AND TA4). For the fourth DV trial (i.e., “The chances of losing money if I use mobile banking apps are high”), five features were reported to contribute significantly. These features include the following: (AW1, PEU3, PR3, Gender and CVR2).

For the fifth DV trial (i.e., “It is risky to transact on other alternative channels and the chances of losing money if mobile banking apps” included in the independent variables), five features were reported to significantly contribute. These features include: (PR2, PEU3, PR3, TS2 AND AW1). Finally, for the sixth DV trial (i.e., “It is risky to transact on other alternative channels and the chances of losing money if I use mobile banking apps are high”), six features were reported to significantly contribute. These features include: (PR2, PR3, TS1 CVR3 AW2 respondent age).

Table 5 presents a performance comparison of the models. For the first DV trial, the decision trees outperformed the other models in terms of accuracy, precision, recall, and F1-score of 72%, 69%, 72%, and 72%, respectively. Furthermore, in terms of the AUROC, KNN and SVM had the best scores of 77%. For the second DV trial, the decision trees outperformed the other models in terms of accuracy, precision, recall, and F1-score of 68%, 72%, 70%, and 67%, respectively.

Furthermore, in terms of AUROC, the SVM had the best score of 71%. For the third DV trial, the decision trees outperformed the other models in terms of accuracy, precision, recall, and F1-score of 80%, 82%, 79%, and 78%, respectively. Furthermore, in terms of the AUROC, decision trees and an SVM were used to obtain the best score of 80%. For the fourth DV trial, SVM outperformed the other models in terms of accuracy, precision, F1-score, and AUROC of 78%, 75%, 77%, and 80%, respectively.

**Table 4. Item prediction**

| **Variable** | Predictor item | Confirmed in Sample |
|---|---|---|
| **Perceived Ease of Use** | | |
| PEU1 | Learning to use mobile payment platforms would be easy for me | |
| PEU2 | It will be comfortable for me to use mobile payment systems overtime for financial transactions | |
| PEU3 | using mobile payment platforms would require a lot of mental effort | |
| **Perceived Usefulness** | | |
| PU1 | Using fintech applications for financial transaction is useful for me | |
| PU2 | Using mobile payment system can increase my efficiency when making payments | |
| PU3 | Using payment platforms for my transactions can increase my productivity | |
| **Perceived Risk** | | |
| PPC1 | The chances of losing money if I use mobile banking apps are high | |
| PPC2 | Internet hackers (criminals) might take control of my account if I use mobile banking apps | |
| PPC3 | It_ is risky transacting on other alternative channels. Eg. POS, web, Online Banking, Mobile app | |
| **COVID-19 Risk** | | |
| CVR1 | It_ is better to use other channels because of hazards, e.g Covid19 | |
| CVR2 | it is safe to use mobile banking platforms because of covid 19 | |
| CVR3 | mobile banking platforms can protect me from contracting covid 19 | |
| **Transaction Cost** | | |
| TS1 | It cost more to use mobile application channels | |
| TS2 | Other fintech channels are expensive | |
| TS3 | Other fintech channels are reasonably priced | |
| **Awareness** | | |
| AW1 | I do not know a suitable banking alternative | |
| AW2 | I_ know little about other banking channels | |
| AW3 | I_ rarely see an advert about alternative banking channels | |
| **Technology Adoption** | | |
| TA1 | I intend to use mobile banking apps in the future | |
| TA2 | I will always try to use mobile banking apps in my daily life | |
| TA3 | I plan to continue to use mobile banking apps frequently | |
| TA4 | If I have the resources, Knowledge, and ability, I will use available fintech platforms | |

**Table 5. Performance metrics, comparison of proposed models**

| Trials | Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | AUROC (%) |
|---|---|---|---|---|---|---|
| | Decision Tree | 72 | 69 | 72 | 72 | 74 |
| | KNN | 72 | 68 | 68 | 71 | 72 |
| First DV Trial | Logistic Regression | 64 | 59 | 51 | 62 | 69 |
| | Naïve Bayes | 64 | 58 | 52 | 62 | 68 |
| | SVM | 68 | 65 | 57 | 62 | 77 |
| | Decision Tree | 68 | 72 | 70 | 67 | 68 |
| | KNN | 60 | 63 | 66 | 58 | 68 |
| Second DV Trial | Logistic Regression | 59 | 63 | 66 | 57 | 64 |
| | Naïve Bayes | 59 | 64 | 61 | 58 | 66 |
| | SVM | 65 | 67 | 64 | 74 | 71 |
| | Decision Tree | 80 | 82 | 79 | 78 | 80 |
| | KNN | 71 | 71 | 76 | 71 | 82 |
| Third DV Trial | Logistic Regression | 64 | 69 | 69 | 63 | 69 |
| | Naïve Bayes | 57 | 63 | 53 | 56 | 68 |
| | SVM | 70 | 71 | 75 | 70 | 80 |
| | Decision Tree | 78 | 72 | 74 | 76 | 76 |
| | KNN | 78 | 75 | 72 | 77 | 83 |
| Fourth DV Trial | Logistic Regression | 61 | 54 | 48 | 53 | 71 |
| | Naïve Bayes | 63 | 57 | 55 | 62 | 71 |
| | SVM | 78 | 75 | 73 | 77 | 84 |
| | Decision Tree | 78 | 80 | 79 | 77 | 78 |
| | KNN | 74 | 76 | 77 | 73 | 79 |
| Fifth DV Trial | Logistic Regression | 72 | 73 | 79 | 72 | 80 |
| | Naïve Bayes | 72 | 74 | 79 | 71 | 78 |
| | SVM | 77 | 77 | 85 | 77 | 83 |
| | Decision Tree | 84 | 88 | 86 | 84 | 87 |
| | KNN | 85 | 86 | 86 | 85 | 90 |
| Sixth DV Trial | Logistic Regression | 74 | 76 | 74 | 74 | 83 |
| | Naïve Bayes | 74 | 80 | 67 | 73 | 80 |
| | SVM | 82 | 84 | 82 | 82 | 91 |

DV: dependent variables, AUROC: area under the curve, KNN: K-nearest neighbors, SVM: support vector machines.

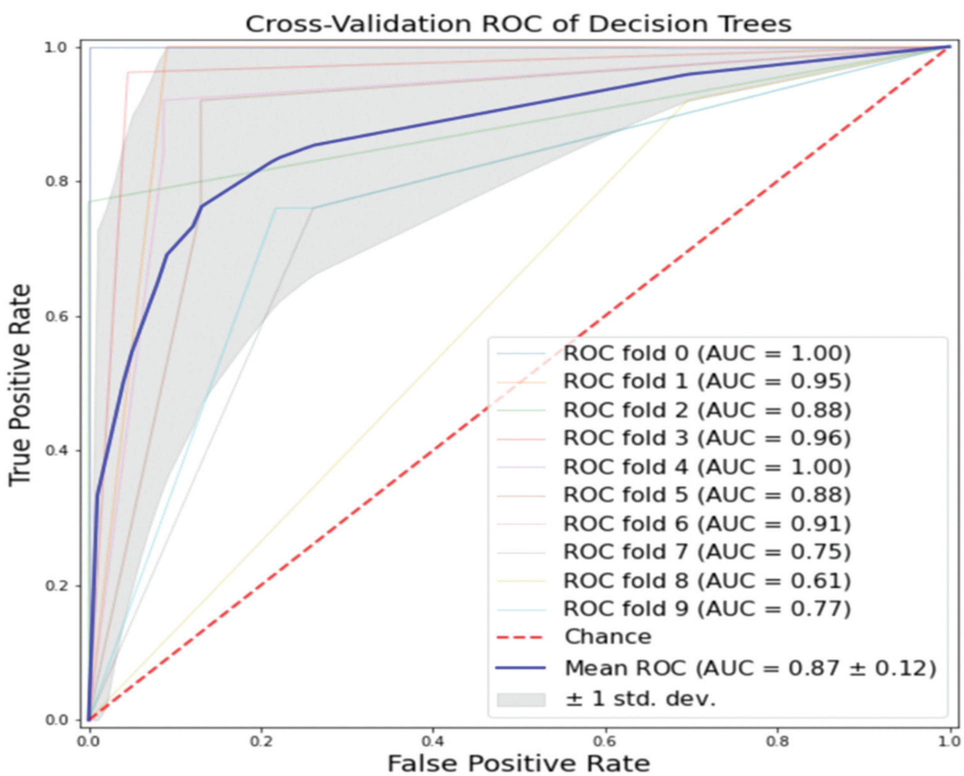
For recall, decision trees were obtained with a maximum score of 74%. For the fifth DV trial, the decision trees outperformed the other models in terms of accuracy, precision, and F1-score of 78%, 80%, and 77%, respectively. Furthermore, in terms of recall and AUROC, the SVM had the highest scores of 85% and 84%, respectively. Finally, the sixth DV trial decision tree outperformed the other models in terms of accuracy, precision, recall, and F1-score, which were 84%, 88%, 86%, and 84%, respectively. Furthermore, in terms of AUROC, the SVM had the best score of 91%.

**Table 6. Hypotheses results**

| Hypotheses | Result |
|---|---|
| Perceived Ease of Use—Fintech adoption behavior | Accepted |
| Perceived Usefulness—Fintech Adoption behavior | Rejected |
| Perceived Risk -Fintech Adoption Behavior | Accepted |
| COVID-19 Risk- Fintech Adoption Behavior | Accepted |
| Transaction Cost- Fintech Adoption Behavior | Accepted |
| Awareness- Fintech Adoption Behavior | Accepted |

**Figure 5. AUROC for decision trees.**

Note: This graph shows the aggregate measure of performance across the classification threshold using the area under the curve (AUROC).




Of all trials, it was evident that the sixth DV trial had the best performance, with decision trees outperforming the other models. Figure 5 shows the AUROC of the decision trees for the sixth DV trial.

### 4.4. Discussion

The focus of this study was to identify the variables that influence users' intention to adopt financial technology. Insights were drawn from the TAM and UTUAT models. To test the data, a machine-learning classification model was adopted. This analysis provides empirical results on users' intention to adopt financial technology during the COVID-19 pandemic. The results include an analysis of the model's performance based on several metrics, such as accuracy, precision, F1-score, recall, and AUROC, consistent with previous analyses (Akour et al., 2021; Allen et al., 2022; Barboza et al., 2017; Y. Li & Li, 2020; Rodriguez-Galiano et al., 2015).

Among these constructs, perceived risk and perceived ease of use were the most significant predictors. Other constructs that predicted financial technology adoption were also obtained. The results of the first and second DV trials indicated that the SVM and KNN classifiers performed better than the other classifiers in predicting technology adoption during the pandemic era, with an accuracy of 72% for both classifiers and an F1-score of 67% for the SVM classifier and 71% for KNN. The present results agree with prior studies (Al-Qudah et al., 2022; Carbo-Valverde et al., 2020; Coskun et al., 2022; Meyta Dewi et al., 2021; Ramtiyal et al., 2022) and confirm the hypotheses of the present study (Table 6).

The empirical evidence obtained revealed that transaction costs predicted fintech adoption, with a KNN accuracy of 70% and SVM of 80%. This result agrees with results from previous studies (Abdus Salam et al., 2021, Al-Sabaawi, Alshaher, and Alsalem, 2023; Jahan & Shahria, 2022; Kar, 2021; Lu & Wung, 2021). Regarding the influence of transaction cost, one possible explanation is that Nigerian customers are charged fees for using alternative channels, which are based on a graduated level; as such, low-income earners are most likely to avoid this cost. Hence, they are likely to prefer to visit banks in person. Furthermore, high-end-volume transactions incur high costs. Thus, users would also opt to visit the bank in a bid to boycott these charges.

This analysis further revealed the role of perception of the COVID-19 pandemic in predicting user intentions in contrast to the results of a recent study in which the pandemic had no influence on user intention (Nguyen Thi et al., 2022). The present results showed that COVID-19 hazards predicted fintech use and is consistent with the extant literature (Hasan et al., 2021; Kim & Kim, 2022; Yu & Chen, 2022; Zhao & Bacao, 2021).

Evidence on the influence of product awareness predicted the intention to adopt financial technology; based on the results of the third, fourth, and fifth trials, KNN revealed an accuracy of 78%, 74% and 85% respectively, with a F1-scores of 77%, 73%, and 85% respectively. Thus, user intention is influenced by the level of awareness or information available, which is also mediated by customer service level. These results align with those of Alam et al. (2021) and Sudarsono et al. (2022). This analysis supported the research model utilized in this study and conformed with the findings of other studies (Coskun et al., 2022; Hidayat-Ur-Rehman et al., 2022, Istijanto & Handoko, 2022; Ojo et al., 2022).

Moreso, ease of use is driven by users' awareness of information related to a service or product. Nigerian users are more susceptible to adopting other fintech channels if it is perceived as less complex; in the same vein, ease of use is also driven by the possibility of having a guide to direct usage, which is more common with embedded "do it yourself" videos in apps and other awareness channels that provide a simple analogy on the usage of the terminal. However, Nigerian consumers place more emphasis on the safety of their funds, this is not unrelated to several complaints on loss of funds, unauthorized debits, and dispensing errors via technology channels such as POS terminals, website merchants, and ATMs which continue to linger overtime with no substantial assurance, resolutions, or refunds. Consequently, an experience that leaves users in a dilemma tends to spur negative perception.

### *4.5. Theoretical implication*

This study offers the following theoretical contributions. The research contributes to the literature by investigating technology adoption factors in Nigeria and testing the extending framework in predicting fintech adoption in a pandemic era, which provides insights to customer perception of fintech channels during the pandemic. Furthermore, the research emphasizes a multi-dimensional construct, as is evident in the fintech space. The inclusion of these constructs conjointly predicted user intentions in the context of this study. Prior studies in Nigeria have not considered a holistic approach to incorporating more variables for technology adoption in fintech investigations (Ojo et al., 2022; Oyelami et al., 2020). In addition, this study adopted a complex methodological approach (machine learning), which is considered suitable for investigating technology adoption prediction studies. This methodology facilitates the prediction of usage intention, and its results can be adopted for policy implications.

### *4.6. Managerial implications*
This study has implications for banks and other fintech companies. First, people are skeptical about adopting other banking channels and would opt for physical banking, where they are assured of the validity of the transaction, irrespective of the pandemic. Customers are more likely to adopt technology when they are convinced that their funds are secure, and this should remain a priority in the financial industry.

Strategies to ensure the security and safety of funds should be embedded in applications and other channels. Similarly, while convenience may be an important variable in technology adoption, users will choose a product or service if they find it easy to trust. Therefore, the fintech industry must adopt measures to manage user distrust and risk perception and develop a path to simplify the use of these services. Similarly, the quality of customer service is a significant driver of technology adoption: a well-informed customer is assumed to be armed with the information required to process transactions on other channels. However, the reverse is true. As such, Nigerian customers prefer banks that push all liabilities to the bank.

### *4.7. Limitations and scope for further research*
This study contributes to the literature and practice and provides recommendations for improved fintech adoption in Nigeria. However, this study had some limitations. First, the study adopted a machine-learning approach that leverages on prediction of the outcome rather than investigating causal relationships or effects between two or more variables (Hastie et al., 2016; Hayes et al., 2019). The results were based on predicting usage intention, and the effects of the variables were not investigated. Second, the construct of behavioral intention was included to identify significant predictors among the overall questionnaire items. Hence, the study did not investigate behavioral intention but predicted technology adoption based on a significant predictor, which was identified as perceived risk. Thus, further studies investigating behavioral intention and actual behavior are recommended. Finally, the study was conducted in Nigeria, and the results cannot be generalized globally because of differences in Internet penetration, availability of technological resources, and the framework to drive payment systems on a global scale. Considering these factors, future researchers could consider the import of Internet penetration and its association with the ease of acquiring mobile telecommunications gadgets for fintech transactions.

## 5. Conclusion
Undoubtedly, the COVID-19 pandemic has significantly influenced society, accompanied by numerous policies aimed at safeguarding people from its spread. This has bolstered the use of several financial services and associated technologies in the fintech space and the use of technology to interact with financial service platforms. The adoption of financial technology leaves no room for a vacuum and offers numerous benefits; however, it is still underutilized. This calls for an investigation into the factors driving financial technology adoption, with an emphasis on consumer behavior during the COVID-19 pandemic era. To achieve this objective, this study employed an ML approach to predict and validate the significant factors influencing financial technology service adoption. An ML approach allowed us to predict repetitive tasks and trends, which is advantageous in a study of this kind. This study adopted several models, such as DTs, KNN, LR, NB, and SVM to extrapolate the observed findings.

The empirical results indicate that perceived risk, ease of use, awareness, and transaction costs are significant factors influencing the intention to adopt financial technology. This study strengthens technology adoption theories and provides a pathway for further investigation in Africa and other developing countries where technology adoption remains slow. Understanding the factors that promote financial technology adoption is a valuable asset for revealing financial sector users' intentions, which is crucial in achieving financial technology digitization.

To further expand the fintech adoption base, financial institutions must proactively address user concerns, strengthen awareness campaigns, and provide adequate information to users, given that consumer behavior is influenced by the amount and quality of information available. Finally, it was more likely for users to choose alternative banking channels during the COVID-19 era. However, given the prevalence of fraud and perceived ease of use, consumers are likely to return to the brick-and-mortar system if their concerns are not adequately addressed. In this study, the observed frequency was approximately 75% for respondents visiting the bank immediately after an ease on lockdowns, with the major reason for their visit reported as the intention to make complaints and cash withdrawals. Financial institutions and other payment systems must create a roadmap to ease customer concerns and develop a simple pathway for educating customers about transaction risks through alternative channels.

**Author details**
Onome Christopher Edo[1]
E-mail: chrisovik@gmail.com
ORCID ID: http://orcid.org/0000-0002-8081-8106
Egbe-Etu Etu[2]
Imokhai Tenebe[3]
Oluwarotimi Samuel Oladele[4]
Solomon Edo[5]
Oladapo Ayodeji Diekola[6]
Joshua Emakhu[7]
[1] College of Business, Department of Information Systems, Auburn University at Montgomery, Mongomery, AL, USA.
[2] Department of Marketing and Business Analytics, Lucas College and Graduate School of Business, San Jose State University, One Washington Square, USA.
[3] Mineta Transportation Institute, San Jose State University, California, USA.
[4] Department of Demography and Social Statistics, Federal University Oye-Ekiti, Oye-Ekiti, Ekiti, Nigeria.
[5] Department of Agricultural Engineering, Auchi Polytechnic, Auchi, Nigeria.
[6] Department of Computer Information Systems, University of Houston, Victoria, TX, USA.
[7] Department of Public Health Sciences, Henry Ford Health, Michigan, USA.

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