Consumers' perception towards Fintech and Traditional Financial Institution (A case study of Nigeria)

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Olayinka Abolade
Student ID: 21176817

School of Computing
National College of Ireland

Supervisor: **Brian Byrne**

National College of Ireland

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School of Computing

Student Name: ……. OLAYINKA ABOLADE ………………………………………………………………

Student ID: ………………………21176817…………………………………………………..……

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Consumers' perception toward Fintech and Traditional Financial Institutions. A case study of Nigeria

Abolade Olayinka
21176817
M.sc Fintech
National college of Ireland

Abstract

The global transition towards a digital economy, influenced by rapid technological advancements, is intimately connected to consumer perceptions. How consumers perceive and adapt to these changes can either accelerate or hinder this worldwide shift. Nigeria, recognizing the pivotal role of consumer perceptions, prioritizes its transformation into a digital economy. The Nigerian financial sector, as a central player in this transformation, requires a strategic, coordinated approach to not only adopt digital technologies but also align with evolving consumer preferences. Factors such as trust, perceived risk, and convenience play a critical role in navigating these preferences between fintech and traditional financial institutions. Through the application of the UTAUT framework, this study discerns key determinants influencing consumer choices. Machine learning analysis highlighted determinants such as convenience that a consumer enjoy are crucial and control of their financial transaction is paramount while including social constructs like peer and family influence play a less significant role in switching to digital payment. Another determinant for switching to digital payment includes security, under the umbrella of performance expectancy (PE), which emerged as pivotal, but effort expectancy (EE) had little significance. Ensuring facilitating conditions, crucial for the uptake of digital financial services, showcases the nuanced dance between consumer perceptions and the strategic trajectory of Nigeria's financial sector in the global digital economy narrative.

Keywords; Consumers, Digital financial service, traditional Financial Institution, UTAUT.

1.0 Introduction

The financial system is central to any robust economy, shaped by various components that cater to a nation's economic goals. Financial services are key in this structure, adjusting according to the needs of end users (Mouna & Jarboui, 2021). The digital shift in financial services is driving inclusivity, pushing nations to formulate policies supporting secure financial innovation. Such technological leaps are transforming the financial realm, demanding strategies that match evolving market trends with vital policy goals (Feyen et al., 2023). Fintech, through its unique approaches, is shaking up the financial world, challenging long-established institutions (Chong et al., 2019).

Traditional financial institutions, once the primary service providers, are now faced with challenges posed by the digital age, such as the advent of the internet and widespread smartphone usage. These institutions grapple with their limited outreach, large customer base, and lengthy banking procedures. Conversely, fintech firms, with their innovative models, present a flexible alternative to these traditional banks (Chong et al., 2019).

As digitalization sweeps across economies, fintech entities are emerging as key players. Their rise and the consequent shift to a digital economy has been shaped by various stakeholders, including investors lured by government regulations. Fintech's growth has compelled traditional banks to become more competitive, ensuring they remain relevant amidst a plethora of choices from fintech enterprises. Beyond offering attractive services, fintech also champions financial inclusion, a government priority, as it can catalyze significant economic growth. Thus, adopting digital financial services can spur transactions and greatly impact economies (Zaghlol, Ramdhan, and Othman, 2021).

However, despite their disruptive nature and introduction of novel models, fintech firms face challenges. Their innovations sometimes don't align with traditional offerings, and although they invest heavily to remain competitive, not all meet their market expectations due to factors influencing customer perceptions, such as the unpredictable nature of innovation (Ryu and Ko, 2020).

Nigeria, with a vast population of over 200 million, presents a fertile ground for fintech's expansion. Traditional institutions have struggled to cater to this huge demographic, especially in rural areas. However, fintech companies, addressing these gaps and employing technology to their advantage, are primed to make significant inroads in the financial sectors (PwC, 2020).

1.1 Study Justification

With fintech firms gaining a strong foothold in Nigeria over the past decade, there's a need to understand their impact compared to century-old traditional institutions. Key areas of focus include understanding shifts in consumer behaviour due to increased technology use and the significance of trust in financial services, given concerns like data privacy, regulatory adherence, and cybersecurity.

1.2 Research Focus

This study aims to answer:

To what extent do Nigerian consumers trust and adopt specific types of digital financial services compared to Traditional Financial Institutions?

• What factors drive their preferences using the UTAUT with the four constructs model to determine the impact this has on consumers' adoption of fintech services?

• To what extent are the behaviour of consumers impacted by trust, and perceived risk on the intent for adopting fintech services in the financial sector in Nigeria?

Research Hypotheses

- There is a significant difference in consumer perception of convenience between digital financial services and traditional financial services.
- There is a significant relationship between consumer expectations of digital financial services and their perceived enhancement control, security, and fraud protection compared to traditional financial services.
- There is a significant relationship between recommendations and positive experiences from friends and family and the adoption of digital financial services.
- There is a significant relationship between infrastructure reliability and technical support from digital service providers in the adoption of digital financial services**.**

1.4 Nigeria Digital Financial Service

In the past decade, Nigeria has seen significant growth in its digital financial services, with companies like Paga, Cellulant, OPay, and others leading the charge. This research focuses on digital payments and lending.

OPay (Opay Digital Service Limited)

Opay is a subsidiary of the Opera browser company, is a prominent mobile payment service in Nigeria, backed by major investors like Source Code Capital, IDG Capital, and Sequoia China. Founded in 2018, following the acquisition of Opera by Yahui Zuoh in 2016, OPay began with a substantial capital of $50 million, outmatching its rival's $10 million investment (Bright, 2019). Licensed by the Central Bank of Nigeria (CBN), OPay provides a myriad of services, from payments and transfers to loans, catering to over 18 million users. Currently, CBN has licensed 17 mobile money operators in Nigeria, of which OPay is a notable player, ensuring smooth financial transactions especially when traditional banks face digital disruptions (Akintaro, 2023).

2.0 Related Literature

2.1 Overview of the Fintech Industry

The gap in access to financial services prompted the introduction of the Unified Financial Access (UFA) by the World Bank Group, highlighting the necessity of individual financial system access for overall economic development (Allen et al., 2022). UFA aimed to make financial transactions such as safe money storage and payments more appealing, promoting financial inclusion as a key driver for economic prosperity. Remarkably, UFA's six-year success led to 1.2 billion global account openings.

Emerging economies can leverage digitization to boost financial inclusion, bypassing geographical barriers and bridging credit information gaps. However, the adoption of digitization varies based on factors like economies' scale, customer preferences, and regulatory policies (Feyen et al., 2023). With fintech posing as a disruptive innovation, it challenges traditional business models, providing efficient, accessible, and affordable services, especially in remote financial areas (Suryanto et al., 2022).

Marinova (2022) asserts that the fintech competition has significantly shifted traditional banking models, emphasizing the importance of ethical standards in this evolving landscape. Additionally, fintech's digital inclusion has transformed risks linked to new banking products/services. Riikkinen and Pihlajamaa (2022) encourage banks to collaborate with fintech start-ups to sustain profitability and stay competitive in a rapidly changing tech environment. In such a backdrop, fintech enhances financial accessibility, particularly benefiting SMEs by providing alternative funding methods, thereby promoting overall economic growth (Coffie et al., 2020).

Technology's continual advancement has reshaped businesses and customer perspectives (Kim and Kang, 2023; Sari et al., 2023). This technological innovation has consequently impacted the finance system, with fintech innovations challenging traditional financial structures (Ukwueze, 2021). Studies further emphasize fintech's positive impact on economic development, notably in areas with previously limited financial infrastructures (Elliot, Cavazos, and Ngugi, 2022).

A particular study in the MENA region highlighted financial inclusion gaps, revealing low savings among women and limited digital financial service adoption. The research advocated for enhanced government-financial sector collaboration, emphasizing the role of digital financial services in enhancing economic growth and wealth accumulation (Mouna and Jarboui, 2021).

The fintech industry, marked by its rapid evolution and disruption of traditional financial systems, stands at the crossroads of technological advancement and economic growth. With its ability to bridge access gaps, cater to changing consumer preferences, and offer innovative solutions, fintech promises to reshape the financial landscape, with implications for stakeholders ranging from individuals to global economies.

2.2 Global Fintech Investment Overview

McKinsey's analysis reveals a promising forecast for Africa's financial services market, projecting growth at about 10% yearly and anticipating revenues of roughly $230 billion by 2025. This excludes South Africa, the continent's mature market, which stands separately at $150 billion. Fintech startups are thriving in Africa, driven by increased smartphone usage, reduced internet costs, improved network coverage, and a youthful, urbanizing populace. The COVID-19 pandemic has amplified this digital shift, benefiting tech firms even amidst its disruptive effects. While South Africa holds 40% of the continent's market value, countries like Ghana and Francophone West Africa show promising growth rates (15% and 13% respectively until 2025). Nigeria and Egypt follow closely. The focal points for fintech growth include 11 key markets, namely: Cameroon, Côte d'Ivoire, Egypt, Ghana, Kenya, Morocco, Nigeria, Senegal, South Africa, Tanzania, and Uganda, representing 70% of Africa's GDP and half its population (McKinsey, 2022).

PwC's report outlines the exponential global growth of fintech firms, from 1,076 in 2010 to around 4,464 in 2017. Investment in this sector surged from USD 12.2 billion to a staggering USD 153.1 billion between 2010 and 2016. This impressive ascent has been fueled by leveraging cutting-edge technologies such as AI, cloud computing, big data, and blockchains, which have refined operational efficiency and increased sector competitiveness. However, consumer perception of fintech services varies worldwide, and research offers diverse insights into the determinants of their preferences (Shahzad et al., 2022).

2.3 Factors Driving Fintech Growth

The rise of fintech firms in the financial ecosystem can be attributed to multiple factors. As reported by Sari et al. (2023), the vast number of internet users (4.66 billion in 2017) has played a pivotal role, with 5.22 billion being mobile phone users. This digital accessibility coupled with the ease and convenience of fintech products has made them a go-to choice for consumers.

Digital trust, or "e-trust", has emerged as a cornerstone for fintech's success. Due to the absence of physical interaction in the digital realm, trust becomes a composite of beliefs about the provider's capability, reliability, and benevolence. Observing peers utilizing digital services amplifies this trust (Zolfaghari et al, 2022). Social media platforms, as highlighted by Yadav Devi Prasad Behera et al. (2019), further enhance this trust by enabling brand interaction and customer reviews, which significantly influence consumer perceptions.

However, fintech's rise hasn't been without challenges. The digital space has seen predatory lenders exploit regulatory gaps, offering short-term loans with hefty interests. This exploitation has been particularly rife in India, with lenders resorting to invasive tactics against defaulters, especially during the COVID-19-induced financial strain (Kaur and Ilavarasan, 2021).

Moreover, the potential of digital financial services, like mobile money, is overshadowed by security and privacy concerns. Addressing these concerns necessitates industry-wide collaboration to ensure robust security protocols for these emergent systems (Traynor et al., 2017). Additionally, consumer perceptions of risks – spanning financial, privacy, and performance domains – play a significant role in their acceptance of electronic services, as indicated by studies in regions like Kosovo (Beqaj and Baca, 2022). Ryu and Ko (2020) emphasize that trust and risk perception play instrumental roles in fintech adoption. They argue that high IT quality in the fintech realm can alleviate user uncertainties, driving sustained usage.

Choudrie et al. (2018) shed light on the dynamics between older individuals and mobile-based digital financial services. The increasing importance of digital financial services worldwide, especially amid demonetization laws in countries like India and Nigeria, underscores the potential of this market. Meanwhile, African nations face unique challenges like low financial literacy and the influence of social circles, which affect the broad adoption of digital financial services (Elliot, Cavazos, and Ngugi, 2022).

Lastly, financial inclusion disparities, particularly for adolescents and women, are evident in MENA regions. Age and gender emerge as key demographic variables affecting financial exclusion here. Policymakers in emerging economies are urged to prioritize financial inclusion as a step towards achieving a cashless society, emphasizing investments in ICT infrastructure. A conducive policy framework in MENA regions can thus drive ICT usage and reduce bureaucratic hindrances (Mouna and Jarboui, 2021).

In essence, the growth of fintech is a combination of technological adoption, consumer trust, and the perceived value of digital financial services. Simultaneously, the industry must navigate challenges like security concerns, predatory practices, and demographic exclusions to ensure sustained, inclusive growth.

2.4 Nigeria's Fintech Landscape

Nigeria's fintech landscape has seen substantial growth due to factors like increased smartphone use and internet connectivity. The younger generation primarily drives this growth, being more technologically adept compared to their older counterparts (Ogege and Bolupremo, 2020).

A comparative analysis indicates that while countries like the UK and US have high rates of digital finance adoption, Nigeria leans more towards debit card usage. Notably, Nigeria and the US both show a correlation between increased debit card usage and more domestic credit offerings to the private sector (Ozili, 2020).

Despite advancements, Nigeria grapples with challenges like insufficient online security, costly broadband, and low financial literacy. Many rural dwellers remain outside formal financial systems, often preferring cash transactions. However, with rising mobile penetration, there's potential to engage these users in mobile financial services. The Central Bank of Nigeria (CBN) has been proactive, licensing Mobile Money Operators (MMOs) and Payment Service Banks (PSBs) to tap into this potential (Ahmed et al., 2022).

Interestingly, while cryptocurrencies gained traction in Nigeria, the CBN and the Securities and Exchange Commission (SEC) initially showed skepticism. The SEC gradually shifted towards recognizing cryptocurrencies, while the CBN took stricter stances, even prohibiting financial entities from cryptocurrency transactions (Ukwueze, 2021).

Research indicates that Nigerians have found fintech offerings more satisfying than traditional banking services. The innovative business models of fintech companies, combined with tailored financial services, have steadily eroded the dominance of traditional banks (Ogege and Bolupremo, 2020).

In light of these findings, it's imperative for policymakers in developing countries to prioritize digital finance systems, aiming for financial inclusion and growth while remaining cautious of potential risks (Ozili, 2020).

2.5 Comparison between Traditional Payment with Digital Payments

The COVID-19 pandemic in 2020 catalyzed a swift pivot towards fintech payment solutions, especially contactless payments, as health concerns arose regarding physical cash. Traditional banks, hampered by outdated IT infrastructure, found it challenging to adapt to these evolving preferences (EY, 2021). Jeff Allen et al., (2022) emphasized the role of micro, small, and medium retailers (MSMRs) in promoting regular digital transactions. A World Bank study highlighted a potential $19 trillion growth opportunity, given that a vast portion of MSMRs' payments remained non-digital.

Forecasts by PwC (2021) suggest a dramatic rise in global cashless payment volumes, predicting an almost threefold increase by 2030 from 2020 figures. The Asia-Pacific region is set to lead this growth, followed by Africa and Europe. North American growth is anticipated to be slightly slower.

Internet technology has been instrumental in shifting payment methods from traditional forms to digital payment. The rise of digital payments is endorsed not only by private sectors but also by governments, pushing for digital transitions (Ahmed et al., 2021). Various digital payment modes, encompassing Unified Payments Interface (UPI), Unstructured Supplementary Service Data (USSD), mobile wallets, and others, are promoted by central banks globally to enhance commerce in a cashless framework (Manohar S Singh et al., 2022).

3. RESEARCH METHODOLOGY

3.1. INTRODUCTION

This section elucidates the strategies employed for the questionnaire's development, respondents' engagement, and the subsequent analysis of data. It also justifies the chosen statistical approach and describes the interpretation plan for research outcomes.

3.2. DATA COLLECTION, PREPARATION, AND ANALYSIS

3.2.1 SAMPLE SIZE AND TECHNIQUE

The study involved 250 individuals from Nigeria, aged 18 to 65, ensuring broad representation across various demographics. The questionnaire was created using Google Forms and shared via social media platforms. Participants responded using a five-point Likert scale, assessing their agreement levels with different statements. This structured questionnaire consists of demographic details and sections gauging factors influencing perceptions of fintech adoption.

https://docs.google.com/forms/d/1xiUC1zMMwN6sZbuQgr0Hvx00gHtc8G5331sulQCUhwQ/edit

3.3. TECHNIQUES AND METHOD OF ANALYSIS

Descriptive and Inferential Analysis

Descriptive Analysis will depict key data attributes, providing insights into participants' perceptions and discerning patterns in their viewpoints regarding Fintech and traditional financial institutions in Nigeria. On the other hand, Inferential Analysis will employ sample data to infer or predict perceptions of the larger Nigerian consumer population about these institutions. This aids in a broader understanding of consumer attitudes across Nigeria .

4. DESIGN SPECIFICATION

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a prominent model for understanding Behavioral Intention (BI) to embrace new technology (Jameel and Alheety, 2022). Originally rooted in the Technology Acceptance Model (TAM) presented by Davis in 1989 and grounded on Fishbein and Ajzen's (1975) Theory of Reasoned Action (TRA), the UTAUT was later introduced by Venkatesh et al. (2003). It emerged after analyzing eight significant theories, encapsulating TRA and TAM, and highlights four primary determinants: performance expectancy, effort expectancy, social influence, and facilitating conditions, while also accounting for moderating factors like age, gender, experience, and voluntariness of use (Tewari et al, 2023).

Performance expectancy: Central to many studies, it reflects the anticipated positive outcomes on individual performance and satisfaction from a technology, impacting fintech adoption.

Effort expectancy: Pertaining to the ease of technology usage, it indicates that people favor simpler, user-friendly solutions, influencing their inclination towards fintech services.

Social influence: Research highlights individuals' inclination to adopt technologies popular within their social circles or endorsed by influential entities, implying that societal endorsements significantly impact fintech adoption.

Facilitating conditions: They denote the organization's support and the broader regulatory environment promoting technology use. An amalgamation of these internal and external elements can enhance the fintech services' adoption rate.

5. IMPLEMENTATION

The research commenced with the transformation of survey data from a Microsoft Excel format into a numeric structure based on the five-point Likert scale, with (5) signifying "Strongly Agree" and (1) as "Strongly Disagree." Utilizing Jupyter Notebook, Python codes were crafted, saved as an .ipynb file, and subsequently executed in Google Colab for an in-depth analysis.

A detailed analysis of the respondents' demographic data was conducted to understand the participant's profiles. The Chi-Square tests were then applied to determine the significance of these demographic factors in relation to the UTAUT constructs. To ensure the consistency and reliability of the data, Cronbach's Alpha coefficient was calculated.

Next, Exploratory Factor Analysis was employed to visually comprehend the distribution of the variables and identify correlations. After this thorough analysis, key factors shaping Nigerian consumers' perceptions of fintech were discerned. The findings were crucial in predicting the propensity of consumers to shift from traditional banking to fintech solutions.

6. Evaluation

A survey was conducted involving 250 respondents, who were reached via a Google Form link. The questionnaire captured demographics such as age, gender, educational level, and employment status. Additionally, it delved into the respondents' current usage of digital payment platforms and probed their willingness to transition to such platforms. Similarly, their inclination towards adopting digital financial platforms was also assessed.

https://colab.research.google.com/drive/1rlxcSYg3V-qdy6JusuG5HpaAqEryCXGW?usp=sharing

6.1 Descriptive Statistics

Questionnaire	Frequency	Percentage
Valid	**223**	**89.2%**
Invalid/unfilled	**27**	**10.8%**
Total	**250**	**100%**

Table 6.1 showing the number of valid and invalid form.

The table below shows the demographic information of 223 people after removing the invalid questionnaire. it shows that the age range of 18 to 65 years while a category was category was created for people not willing to share. Persons from age 26 to 35 has the highest count while the least are people not willing to share theie age information and persons in the age range of 56 to 65. Information about the employment status is also examined which shows that 161 persons are employed representing 72.2% of the valid respondents. The education status was examined to have in insight to the literacy level of the respondents which showed that 60.54% have a masters degree while 1.79% have a PhD or equivalent . finally, the gender comprises mainly of male respondents of 145.

Criterion	Response	Count	%
Age	18-25 26-35 36-45 46-55 56-65 Prefer not to say	31 92 89 9 1 1	13.90 41.30 39.90 4.03 0.45 0.45
Current Employment level	Employed Student Unemployed Other	161 37 12 13	72.2 16.59 5.38 5.83
Level of Education	Bachelor's degree Master's degree Secondary school PhD or equivalent	135 75 9 4	60.54 33.63 4.04 1.79

Gender	Male Female **Prefer not to say**	145 77 **1**	65.4 34.5 **0.005**

Table 6.2 showing the demographic information of respondent.

6.2 Cronbach alpha

In evaluating the internal consistency of the UTAUT construct concerning digital payment, Cronbach's Alpha value was determined to be 0.9077. This falls within the "Excellent" category, indicating that the dataset has a high level of internal consistency. Furthermore, the confidence interval for this Cronbach's Alpha value is given by the range [0.889, 0.925]. This implies that 95% confidence showed that inference can be made based on the broader population based on sample data.

6.2.1 Chi-square

Some features of the construct show that some key elements can be important to predict the behavioural intention to adopt digital the use of digital payment platforms. A P-value below 0.05 is statistically important therefore analyzing the p-values reveals which features significantly influence user behavior towards digital payment adoption.PE7 (0.0043) shows high significance, highlighting its crucial role in predicting adoption also PE8 (0.0164) is notably significant. While FC12 (0.0207), FC13 (0.0427) and FC24 (0.0410) show that they are statistically significant, reinforcing their relevance in the model. However, features like PE6, EE9, EE10, and SI11 are close to the 0.05 threshold, suggesting weaker significance. Overall, PE7, PE8, and FC12 emerge as primary determinants in the adoption of digital payment platforms.

6.2.2 Bartlett's Test of Sphericity

Bartlett's Test of Sphericity is used in factor analysis to validate the assumption of sphericity. Essentially, it compares the observed correlation matrix to the identity matrix to see if the observed variables intercorrelate at all. If the test is shown to be statistically significant, it indicates that the observed matrix is not an identity matrix, implying that factor analysis is acceptable. In this case: The chi-square value is 1239.972which is quite large. The p-value is 2.6177×10−2302.6177×10 −230, which is virtually zero. The p-value is extremely near to zero and significantly lower than the commonly used alpha threshold (0.05). This implies that the observed correlation matrix is not an identity matrix and that component analysis will be relevant in predicting the adoption of digital payment.

6.2.3 The Kaiser-Meyer-Olkin (KMO)

The Kaiser-Meyer-Olkin (KMO) Test is a method for determining sample size for factor analysis. The KMO assesses the data's suitability for factor analysis. It determines the appropriateness of each observed variable as well as the overall model. The KMO statistic ranges from 0 to 1. The KMO value ranging from 0.8 to 1 indicates that the sampling is adequate. In this situation, the KMO value is 0.9240. This number is more than 0.8, indicating exceptional sampling adequacy. This result shows that factor analysis on the dataset provided should produce distinct and reliable factors. In other words, the variables included in a digital payment are appropriate for factor analysis.

6.2.4 Factor Analysis

Eigenvalue which is used in factor analysis should be greater or equal to 1. Based on the KMO the factors for digital payment when loaded shows that one factor is important having a value of 5.660226 while other are below the threshold of 1 based on the Kaiser criterion.

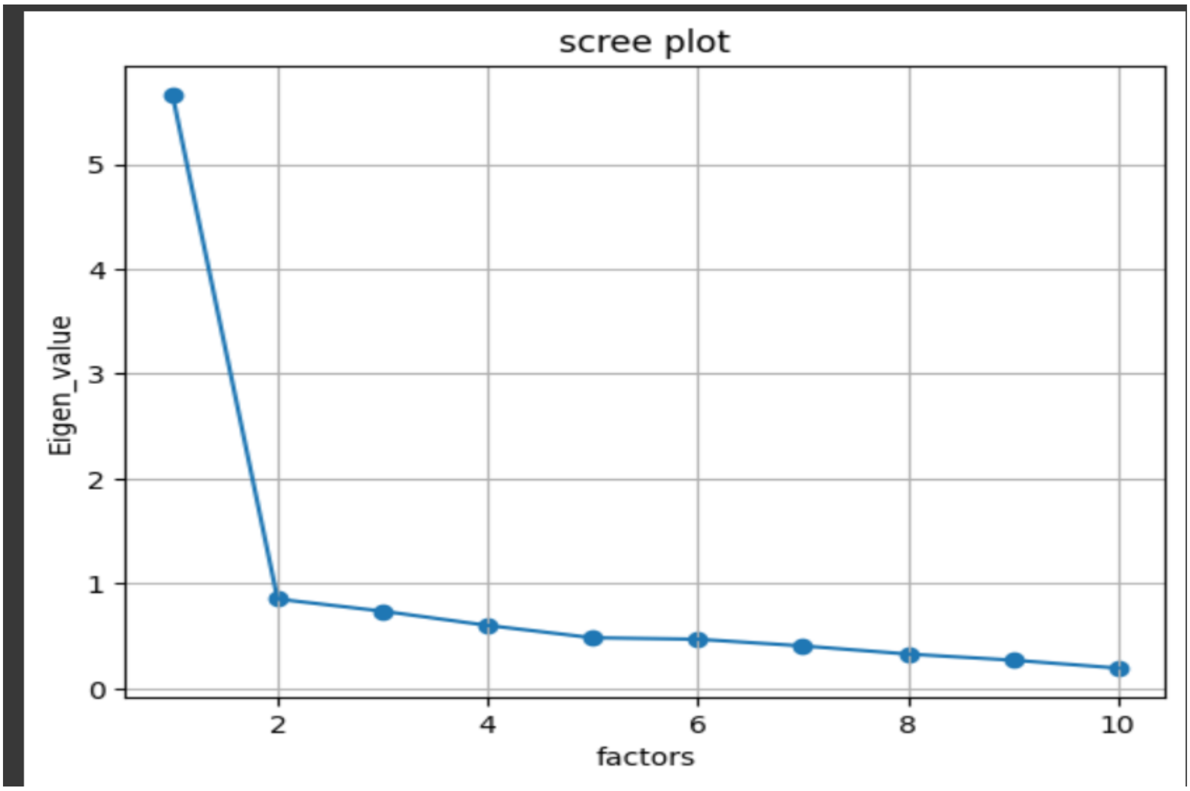

Table 6.3 shows the factors and eigenvalue plot.

6.2.5 Scree plot

The above scree plot shows that the 1 factor is above one while the closest to it where there is the elbow bend in the plot which is not up to one emphasizing that Kaiser criterion therefore second factor with a value of 0.852429 which is a little deviation from the Kaiser criterion is ignored.

6.2.6 Cumulative variance

After conducting factor analysis which shows one factor meets the eigenvalue criteria while the scree plot emphasized one factor in factor analysis. The cumulative variance shows a steady increase from one factor to four factors which ranges from 52.34% to 67.57% after which other factors showed different inconsistencies. Therefore, given these observations, combined with the eigenvalue criterion discussed earlier, it might be advisable to consider retaining 4 factors. They explain 67.57% of the variance, which is substantial, without adding the complexities and potential noise of additional factors to the prediction of the behavioural intent of digital payment. But the first showed the highest variance of 52.36% which shows the importance of one factor while the variance from the other three is not really substantial.

6.2.7 Factor loading

The number of factor loaded is based on the eigenvalue and the scree plot therefore one factor is loaded during the process.

FEATURES-NAMES	CHI2(P-VALUES)	FACTOR LOADINGS
PE6	0.06671	0.80
PE7	0.00433	0.80

PE8	0.01637	0.60
EE9	0.10365	0.80
EE10	0.10929	0.70
SI11	0.08298	0.60
FC12	0.20723	0.80
FC13	0.04268	0.80
SI21	0.34258	0.40
FC24	0.04103	0.70

Table 6.4 showing the p-value of the UTAUT construct and the factor loading based on the set criteria.

Based on the eigenvalue analysis, cumulative variance, and observations from the Scree plot, a single factor aligns with the Kaiser criterion. This choice is aimed at achieving a balanced extraction of meaningful constructs while ensuring a refined exploratory process. Notably, the factor loading analysis underscores the significance of variables PE6, PE7, EE9, EE10, FC12, FC13, and FC24, all exhibiting factor loadings at or above 0.7. This reinforces their relevance to consumer behavioral intent concerning digital payments. It's worth noting that while this factor loading evidence is substantial, it's not the sole predictor for prediction purposes. Additionally, the chi-square test was employed for feature selection, confirming its statistical significance with a p-value less than 0.05.

6.3 Prediction

The research employed three machine learning algorithms to predict whether a consumer would transition from a traditional to a digital payment system. The predictors encompassed variables PE6, PE7, PE8, EE9, EE10, FC12, FC13, and FC24, derived from the UTAUT construct, along with demographic details functioning as moderators.

Here's a summary of the predictive performance:

Logistic Regression: Achieved an accuracy of 94.39%.

Random Forest: Scored the highest with an accuracy of 94.95%.

Decision Tree: Registered an accuracy of 92.17%.

Given these results, the Random Forest emerges as the most adept model for forecasting a consumer's inclination to adopt a digital payment platform in Nigeria.

6.3.1 Confusion matrix

Logistic Regression: The confusion matrix which is based on the responses of 178 respondents which is 80% of the total 223 responses shows that False Positive (FP) equals 9 which means

there were 9 instances where the model incorrectly predicted the positive class when the actual class was negative when predicting the behavioural intent to switch to digital payment. True Positive (TP) equals 169 meaning there were 169 instances where the model correctly predicted the positive class. The model appears biased towards the positive class. This skewness might be attributed to factors like class imbalance in the training data, or it could arise from the model's architecture or training process.

Random forest: The confusion matrix produced by the Random Forest model's prediction accuracy shows the model accurately recognized 169 positive cases with no mistakes (TP = 169) and 9 negative cases (TN = 9). There are no misclassifications since the off-diagonal columns of the confusion matrix, which signal errors, have 0 values. This signifies that the model produced no errors although the test data can be a good means to check if the model is not overfitting for the intent of consumers to switch to digital payment.

Decision Tree model: It accurately predicts favourable intentions to migrate to a digital payment platform in 166 situations. However, it only detects three instances of negative intent correctly. In six situations, the model overpredicts positive intents and misses three instances of real positive intention. These errors indicate that the model is struggling with the negative class, which could result in resource misallocation or unduly optimistic solutions. Improvements are required, which may require more data or alternative methodologies.

6.3.2 Classification report

Logistic Regression: It shows a bias toward class 1 which are the people willing to switch to digital payment this is shown in the precision, recall, f1, accuracy, macro avg and weighted average. This is evident when class 1 has 95% precision while class 0 has 0%, also recall for class 1 is 1, meaning the model correctly identified all of the class 1 instances while recall for class 0 is 0 which means the model failed to correctly predict any of the true class 0 instances. The F1 Score is calculated by averaging precision and recall. The F1 Score for class 0 is 0, suggesting weak precision and recall for this class. It is 0.97 for class 1, which is fairly high. The model has a 0.95 accuracy rate, which indicates it correctly predicts outcomes in 95% of the test cases. However, due to the imbalanced nature of the dataset, with fewer instances of class 0 than class 1, this high accuracy may be deceiving and does not necessarily reflect the model's performance on both classes equally. Finally, the macro average and weighted average follow the same pattern suggesting imbalance.

Random forest: The model clearly is fair to both classes, precision is 1.00 for both classes, also recall is also 1.00 for both classes which essentially, there were no false negatives for either class representing individuals prepared to migrate to digital payment. The F1, accuracy, macro avg and weighted average performed without bias for both classes which is in accordance with what precision and recall achieved. The model may be suggesting overfitting to the training data because this is hardly achievable in real-world situations.

Decision Tree model: Precision, recall, F1-Score and accuracy (for class 1) shows metrics that are quite high for class 1, showing that this class performs well in classification but this was not the case for class 0 because it performed sub-optimally due to classification ability of average in below. The model has an accuracy of 0.95, suggesting good overall performance. However, it excels at identifying the majority class and suffers with the minority class. While the weighted average metrics show great results due to the model's ability to recognise the majority class, the macro average, which provides equal weight to both groups, indicates room for improvement. The difficulties experienced can be primarily attributed to the dataset's imbalance.

6.3.3Model Testing

This was conducted on the three machine learning models on test data was compared, the Logistic Regression model came out on top with an accuracy of

82.22%. The Random Forest model came in slightly behind at 80%, while the Decision Tree model came in at 68.89%. Based on these findings, the Logistic Regression model emerges as the most capable of predicting outcomes for the supplied dataset.

6.4 The SMOTE (Synthetic Minority Over-sampling Technique)

This was employed to balance the classes in this research, addressing the evident class imbalance. In the dataset, there were two classes represented: Class 0 had 16 responses, while Class 1 had 207 responses. Such an imbalance can result in overfitting, where the model excessively tailors itself to the majority class, potentially undermining its predictive accuracy for the minority class. By using SMOTE, we generate synthetic samples in the feature space to ensure a more balanced representation of both classes, leading to a more robust predictive model. The classes 0 and 1 after applying SMOTE indicate that the dataset now includes an equal representation of both classes of 169 each, which should aid in the development of a more trustworthy and unbiased model.

6.4.1 Performance of the models

The accuracy of our machine learning models improved noticeably when we used SMOTE to balance the training dataset. The accuracy of the Logistic Regression model increased to roughly 84.03%, while the accuracy of the Decision Tree model increased to around 83.44%. The Random Forest model, on the other hand, showed a tremendous improvement, with an astounding accuracy of approximately 95.86%. In light of these changes, the Random Forest model has emerged as the best option for making predictions on this balanced dataset.

6.4.2 Confusion matrix

The analysis of the confusion matrices of the three machine learning models was analysed, the Logistic Regression model performed well, accurately predicting 143 positive and 147 negative cases, but misclassifying 22 positive and 26 negative cases. The Random Forest model stood out for its perfect accuracy, identifying all 169 positive and 169 negative cases without any misclassifications. Meanwhile, the Decision Tree model had a little bias, correctly recognising 141 positive and 168 negative cases while misclassifying one case as positive and missing 28 true positive ones. The Random Forest model is the most reliable of the three, with the lowest rate of false negatives.

6.4.3 Classification report

When the classification reports of the three models are compared, the Logistic Regression model has balanced precision, recall, and F1-score for both classes, obtaining an overall accuracy of 86%. Similarly, the Random Forest model exhibits an extraordinary level of precision, recall, and F1-score, with perfect accuracy of 100%. The Decision Tree model, on the other hand, maintains high precision but shows a difference in recall across the two classes, resulting in an accuracy of 91%. Overall, the Random Forest model stands out due to its flawless precision, recall, and F1 score, suggesting its robust performance in classification tasks. The Logistic Regression model gives balanced prediction performance, however, the Decision Tree model's recall fluctuation may deserve additional examination.

6.4.4 Model testing

The classification report evaluates the model that performed the best out of the three on the test dataset. This model, the Random Forest model, demonstrated exceptional precision, recall, and F1-score for both classes. By properly identifying all instances in the test set, it obtained a flawless accuracy of 100%. Notably, it obtained 100% precision and recall for both classes, suggesting that there were no false positives or false negatives. This outstanding performance demonstrates the Random Forest model's supremacy in predicting outcomes on this particular dataset.

6.5 Observation of the study

There is a significant difference in consumer perception of convenience between digital financial services and traditional financial services:

People usually want life to be easier so convenience is paramount to choosing a digital payment platform this is established with the mean score of 4.219731 of PE6 which relate the disposition of consumers to ease and convenience but and a p-value of PE6 which 0.06 does not meet the criteria for p value to be less than 0.05 to be significant (Sari et al., 2023). The correlation of 0.213846 though is positive but shows weak relationship to a consumer switching to digital service. Therefore, it is noteworthy that service providers should offer a service which will be convenient for consumers

There is a significant relationship between consumer expectations of digital financial services and their perceived enhancement control, security, and fraud protection compared to traditional financial services:

People want control over their financial transactions and this flexibility is not offered by the traditional financial service but with 3.923767 as the mean score and a p-value of PE7 is 0.0043 which shows that consumers want control over their financial transactions and this influences their decision-making process in choosing digital financial services (Zolfaghari et al., 2022) . Security against fraud is vital to consumers of digital financial services this is evident with a p-value of PE8 0.016 and 3.300448 for the mean value (Yadav Devi Prasad Behera et al., 2019).

There is a significant relationship between recommendations and positive experiences from friends and family and the adoption of digital financial services:

A p-value of SI11 is 0.08 which is above the criteria of p-value significance which the threshold of $p<0.05$ this means that recommendations and positive experiences from friends and family and the adoption of digital financial services do not really influence their decision but a mean score of 3.605381 show the people agree that they are influenced to adopt of digital financial services (Ryu and Ko, 2020).

There is a significant relationship between infrastructure reliability and technical support from digital service providers in the adoption of digital financial services:

The infrastructure reliability provided by the digital service provider has a positive impact on consumers' perception this is evident in the p-value of FC12 which is 0.02 (Traynor et al., 2017). Furthermore, the p-value of FC13 is 0.04 which relates to the technical support provided for consumers has a huge influence on consumers' perception. A correlation value of 3.914798 and 3.973094 for them respectively emphasize the importance to consumers (Elliot, Cavazos, and Ngugi, 2022.

7. Conclusion

This thesis addresses the extent Nigerian consumers trust and adopt specific types of digital financial services compared to Traditional Financial Institutions, digital payment area was critically evaluated to know what shapes their decision to switch or adopt the use of digital financial services. The huge number of people willing to switch to digital financial services shows their attitude towards dissatisfaction with traditional financial institutions because of the low flexibility offered by traditional financial institutions. The UTAUT four constructs which are Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating Conditions (FC) were examined to determine the Behavioral Intent (BI) towards the attitude of consumers switching from services offered by the traditional financial institution to digital financial service. PE relating to consumers having control over their financial transactions was important also the security against fraud was another important consideration for consumers. FC which deals with accessibility to technical tools such as smartphones, and internet connection seems to be an important factor in addition technical support and infrastructure reliability by the digital service provider are key to consumers' decision to switch. Effort Expectancy and Social Influence have little or no role in affecting consumer decision-making. Therefore, the stakeholders should create an enabling atmosphere for adoption and invest in technologies that will improve efficiency which translates to good consumers views

The researcher was restricted based on time factors to examine the attitude of consumers switching to digital lending platforms to make a comparison among the various offerings of digital financial services and also the sample size may be inadequate to make a general assumption for consumers. It is noteworthy that Nigeria is a big country with a huge population with diverse cultural backgrounds, therefore, the cultural background was not examined in this research future research may be carried out to examine consumers' perceptions based on culture. Furthermore, this research solely focuses on digital payment other areas such as digital lending, digital currency and digital investment may be various areas for further studies.

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