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DIGITAL FINANCIAL INCLUSION AND PROFITABILITY OF AGRO-BASED SMEs IN NORTH-EASTERN NIGERIA

Kwanti, Alfred Anthony[1]; Eleje, Edward Ogbonnia[2]; Valentine, I Osayi[3]; Ogbole, Friday Ogbole[4]

[1]*Department of Accounting, Faculty of Management Science, Taraba State University, Jalingo.*

[2,3&4] *Department of Finance, Faculty of Management Science, Federal University, Wukari*

Email: kwantianthony@tsuniversity.edu.ng

ABSTRACT

This study examined the effect of digital financial inclusion channels on the profitability of agro-based Small and Medium Enterprises (SMEs) in Northeastern Nigeria. The study was motivated by the persistent underperformance of agro-based SMEs in the region, despite the increasing proliferation of digital banking channels, and the limited empirical attention given to how these channels specifically influence agro-based enterprise performance in infrastructural and security-challenging environments. Digital financial inclusion was operationalized through five digital banking channels- mobile banking, Internet Banking, Virtual Banking, Point-of-Sale, and automated teller machines- as explanatory constructs, and profitability as the dependent variable. A cross-sectional survey research design was adopted, with primary data collected through structured questionnaires administered to owners and managers of registered agro-based SMEs across the six states of Northeastern Nigeria, including Adamawa, Bauchi, Borno, Gombe, Taraba, and Yobe States, giving 277 usable responses (87% of 317 distributed). Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed to analyse the data, using SmartPLS software. The measurement models demonstrates satisfactory indicator reliability, internal consistency reliability, convergent validity, and discriminant validity across all constructs, while the structural models exhibited acceptable model fit indices. The results revealed that mobile banking, virtual banking, internet banking, and Point of Sale have statistically significant positive effects on profitability, establishing them as consistent drivers of agro-based SMEs' profitability, while automated teller machines have no significant effect on profitability. The study concludes that digital financial inclusion exerts a broadly significant, though channel and outcome-specific, effect on the profitability of agro-based SMEs in Northeastern Nigeria. The study recommends that banks and policymakers adopt a differentiated approach to digital financial inclusion strategy, expanding virtual and mobile banking infrastructure while addressing the connectivity barriers that limit the profitability benefits of Automated Teller Machines for agro-based SMEs in the region.

Keywords: *Digital financial inclusion, Profitability, Agro-based SMEs, PLS-SEM, North-Eastern Nigeria.*

INTRODUCTION

Digital financial inclusion has become an indispensable catalyst for enterprise development, economic diversification, and inclusive growth worldwide. Over the past decade, rapid technological innovations have significantly expanded access to financial services through digital platforms, fundamentally altering how individuals and businesses interact with the formal financial system. Globally, the proportion of adults with an account at a financial institution or via a mobile money provider surged from 51% in 2011 to 74% in 2021 and to 79% in 2024 (World Bank, 2025). Central to this transformation is the proliferation of mobile banking and agent banking services, which have substantially lowered transaction costs, increased financial intermediation efficiency, and bridged geographic barriers that historically constrained banking outreach (Demirgüç-Kunt et al., 2022). For small and medium-sized enterprises (SMEs), particularly those operating in primary sectors such as agriculture, digital financial tools have opened up new avenues for accessing working capital, managing supply chain payments, and expanding market networks.

In Countries such as Kenya, Tanzania, and Ghana have leveraged mobile banking penetration to accelerate SMEs growth, enhance rural financial inclusion, and deepen market participation for agricultural enterprises (Beck et al., 2020). The competitive dynamics within banking sectors in these economies have further stimulated innovation in service delivery, with fintech partnerships and regulatory frameworks fostering inclusive financial ecosystems. However, despite this growth, challenges related to uneven infrastructure deployment, financial literacy gaps, and limited trust in formal banking institutions have continued to impede the full realisation of digital financial inclusion's potential to support enterprise expansion, especially in rural and agrarian regions (Cull et al., 2022).

In Nigeria, the strategic importance of deepening financial inclusion through digital channels is highlighted by the country's ambitious of National Financial Inclusion Strategy (NFIS), which aims to achieve a 95% financial inclusion rate by 2024 (Central Bank of Nigeria CBN, 2022). According to the data from Enhancing Financial Innovation and Access [EFInA] (2023) about 64% of Nigerian adults are financially included, with mobile banking and virtual banking playing increasingly pivotal roles. Mobile money transactions alone rose by over 142% to reach ₦19.4 trillion in 2022 (Nigeria Inter-Bank Settlement System [NIBSS], 2024).

However, these aggregate figures mask significant regional disparities, with Northern Nigeria, and particularly the North-East zone, lagging considerably behind national averages due to infrastructural deficiencies, prolonged security challenges, and socio-economic disruptions that have strained traditional banking operations and deterred private investment (National Buruea of Statistics [NBS], 2022). Within this context, banking penetration remains thin, while competition among financial institutions is often muted, limiting the variety and reach of banking products that could otherwise stimulate SMEs' growth.

Adamawa, Bauchi, Borno, Gombe, Taraba, and Yobe States exemplify the agrarian profile and structural vulnerabilities of North-eastern Nigeria. Agriculture employs more than 60% of the population across these states, underpinning livelihoods through cultivation, aggregation, and small-scale processing activities (NBS, 2022). Agro-based SMEs in these regions play a crucial role in generating employment, enhancing food security, and facilitating value addition. However, persistent financing constraints, driven by limited physical banking presence and underdeveloped digital financial infrastructure, have stifled their growth potential (Small Medium Enterprises Development Agency of Nigeria

[SMEDAN], 2022). Mobile banking emerges as an up-and-coming channel in these states by enabling payments, savings, and even microcredit without the need for extensive branch networks. Nonetheless, empirical evidence on how mobile banking drives the growth of agro-based SMEs in these states remains sparse.

However, these competitive dynamics are less pronounced in fragile regions, potentially dampening the incentive for financial institutions to design products tailored to the specific needs of agro-based SMEs.Against this backdrop, this study was situated to rigorously examine the specific pathways through which digital financial inclusion dimensions, namely Mobile Banking (MB), Virtual Banking (VB)services, Internet Banking (IB), Point of Sale (POS) provisions, and Automated Teller Machines (ATM) availability, affect the performance of agro-based SMEs in Adamawa, Bauchi, Borno, Gombe, Taraba, and Yobe States. By focusing on these underexplored determinants, this research addressed these salient empirical gaps. The study's motivation was anchored on the urgent need to generate granular evidence that informs policies on deploying digital financial tools to catalyse SMEs development in fragile agrarian economies. The findings of this study would guide financial regulators, commercial banks, fintech operators, and development agencies in crafting interventions that not only broaden financial access but also translate digital financial inclusion into tangible growth outcomes for agro-based SMEs in North-eastern Nigeria

According to EFInA (2024), North-eastern Nigeria, is among the most severe financial excluded region with about 38% population without access to financial services, compared to only 5% in the Southwest and 10% in the South-South. Region of Nigeria.Digital financial inclusion (mobile, virtual and internet banking, POS terminal and ATMs) can reduce the distance and cost barriers that branch banking leaves in place. It is not known, however, which channels are associated with better performance, sales growth and operational efficiency. Earlier studies were done in southern or urban Nigeria, covered SMEs in general, or treated performance as a single measure. Banks, Regulators and development agencies therefore lack channel specific evidence for the Northeast and risk investing in channels that may not benefit the SMEs they aim to reach. This study addresses these problem, by examining how five digital banking channels relate to the profitability, sales growth and operational efficiency of agro-based SMEs in Adamawa, Bauchi, Borno, Gombe, Taraba and Yobe States.

The objective of this study was to examine the effect of digital financial inclusion on the profitability of agro-based SMEs in North-eastern Nigeria.The study focused on the effect of digital financial inclusion, specifically Mobile Banking, Virtual Banking services, Internet Banking, Point of Sale services, and Automated Teller Machine provisions on the profitability of agro-based SMEs in Adamawa, Bauchi, Borno, Gombe, Taraba, and Yobe States in Northeastern Nigeria. It was concentrate on SMEs involved in farmers' cooperatives, and food processing companies. The geographical focused on these states is justified by their predominantly agrarian economies and their persistent challenges with low financial inclusion and sparse banking infrastructure, which make them ideal for assessing the transformative potential of digital financial services in fragile, underserved contexts.

The study covered registered agro-based SMEs in Adamawa, Bauchi, Borno, Gombe, Taraba, and Yobe States, and data were collected in the month of February to March, 2026. The revised National Financial Inclusion Strategy of 2018 was used only as the policy background for the growth of digital channels. This time frame also captures a surge in mobile and digital transactions, offering a relevant window to observe the evolving impact of

digital financial services on SMEs' profitability. By situating the analysis within this period and across these specific states, the study aimed to provide timely, policy-relevant and insights into how digital financial inclusion can affect the profitability of agro-based SMEs in structurally disadvantaged regions. The study examined the digital financial inclusion and profitability of agro-based SMEs in Northeastern Nigeria, with mobile banking (MB), virtual banking (VB), internet banking (IB), point of sales (POS), and automated teller machine (ATM) as indicators of digital financial inclusion, and profitability (PROF).

The aim of this study to provide commercial banks, microfinance banks, mobile money operators, and fintech companies operating in or seeking to expand into Northeastern Nigeria, in identifying the specific digital financial inclusion channels that most significantly influence the profitability of agro-based SMEs. This study provides actionable policies to guide product development, agent network expansion, and customer acquisition strategies targeted at the underserved agro-based SMEs segment in the Northeast. The study findings were also helpful to financial institutions to design and tailor digital financial products that address the unique challenges faced by agro-based SMEs in conflict affected environments.

2. REVIEW OF RELATED LITERATURE

This study draws on conceptual, theoretical, and empirical literature to explain how mobile banking, internet banking, virtual banking, point of sales, and automated teller machines platforms influence SMEs profitability.

2.1 Conceptual Review

The conceptual review were examined the interrelationships between digital financial inclusion and the growth of agro-based SMEs in Northeastern Nigeria. By exploring theoretical frameworks and empirical findings, this review aimed at addressing gaps in existing literature and provided insights into the context-specific nature of digital financial inclusion practices and their contributions to the development of effective agro-based SMEs in Northeastern Nigeria.

2.1.2 Digital Financial Inclusion

Digital financial inclusion refers to the use of digital technologies to provide affordable, accessible, and user-friendly financial services to individuals who have traditionally been excluded from the formal financial system. Digital financial inclusion empowers underserved populations, including rural communities, women, and the unbanked, to engage with the global financial system, enabling them to save, invest, and grow economically. These services include mobile money services, internet banking, virtual banking, digital lending, e-wallets, and digital savings platforms. It is also a state where everyone has access to the financial services and products they want to manage their money well. Financial inclusion is a condition in which everyone has access to a variety of high-quality financial services, provided to clients who have the financial means to pay for them, in a stable, competitive market, with ease, dignity, and consumer protection (Abbas & Atanda, 2019).

2.1.3 Mobile Banking (MB) and Profitability of Agro-Based SMEs

Mobile banking refers to all banking transactions that include payments, account balance checking, fund transfers, and accessing other banking products and services through mobile phone devices. Mobile banking is a technological innovation implemented in the financial sector, which leverages wireless tools and devices to provide customers with real-time service based on network protocols. Such protocols include general packet radio services (GPRS) and code division multiple access (CDMA) (Muchandigona & Kalema, 2022).

Mobile banking refers to the use of mobile devices, particularly smartphones and tablets, to access financial services such as account management, payments, transfers, and other banking operations.

2.1.4 Virtual Banking (VB) and Profitability of Agro-Based SMEs

Virtual banking or digital-only banking, represents the provision of financial services through digital platforms without the need for physical branches. This banking model has emerged as a transformative innovation in the financial services industry, driven by advances in information technology and the growing demand for convenience in financial transactions (Zhang & Tang, 2020). Unlike traditional banks that rely on brick-and-mortar structures, virtual banks operate primarily online, offering services such as savings and current accounts, fund transfers, bill payments, loans, and investment management through websites or mobile applications (Mhlanga, 2020). The absence of physical branches significantly reduces operational costs, enabling virtual banks to provide customers with lower service charges and competitive interest rates (PwC, 2021).

2.1.5 Internet Banking (IB) and Profitability of Agro-Based SMEs

According to Laudon and Traver (2021), internet banking refers to the delivery of financial services through online platforms that allow customers to access accounts, transfer funds, make payments, and apply for credit without visiting physical branches. The availability of internet banking has transformed the financial landscape by providing convenience, reducing transaction costs, and expanding access to financial services for both individuals and enterprises. For agro-based SMEs, access to internet banking is particularly crucial. Agro-based SMEs often face structural barriers, including limited access to formal credit, geographical remoteness, and seasonal income fluctuations, which hinder their growth (Beck & Demirguc-Kunt, 2006). Ensures timely payment for agricultural inputs and sales proceeds, improving cash flow and working capital management (Nguyen, 2020). Second, internet banking provides access to financial records and digital statements, which agro-SMEs can use to build creditworthiness and secure financing from banks or microfinance institutions (Aminu, 2021).

2.1.6 Point of Sale (POS) and Profitability of Agro-Based SMEs

The Point of Sale (POS) system is a payment channel that enables customers to complete transactions electronically through debit/credit cards or mobile payments. In many economies, especially developing countries, POS devices serve as mini-bank branches, bringing banking services closer to rural and underserved areas (Okeke & Eze, 2021).

Despite these benefits, challenges persist. Network downtime, high transaction charges, fraud risks, and limited POS penetration in remote areas hinder full adoption (Mhlanga, 2020). To maximise the impact of POS on agro-SMEs' profitability, policies must focus on strengthening digital infrastructure, reducing transaction costs, and building trust in cashless payment systems.

2.1.7 Automated Teller Machines (ATMs) and Profitability of Agro-Based SMEs

The Automated Teller Machine (ATM) is one of the most significant technological innovations in the banking industry, designed to provide customers with 24/7 access to financial services, including cash withdrawals, deposits, balance enquiries, and fund transfers (Laudon & Traver, 2021). For agro-based SMEs, the availability of ATMs has important implications for growth and sustainability. Agro-SMEs often operate in rural and semi-urban areas where banking infrastructure is limited, making access to financial services a significant

challenge (Beck & Demirguc-Kunt, 2006). ATMs help bridge this gap by providing quick and reliable access to cash, enabling entrepreneurs and farmers to meet urgent business needs such as purchasing inputs, paying workers, and transporting produce to markets (Okeke & Eze, 2021).

Furthermore, ATMs reduce transaction costs and save time. Instead of travelling long distances to bank branches, SME operators can access ATMs in nearby locations, which lowers operational overheads and improves productivity (Mago & Chitokwindo, 2014). Additionally, the presence of ATMs in rural communities fosters trust in formal financial institutions, encouraging more agro-SMEs to adopt banking services, which in turn improves their creditworthiness and access to loans (Aminu, 2021).

2.1.8. Profitability

Profitability is the clearest financial outcome linked to digital financial inclusion in SMEs, including agriculture-adjacent firms. Across SME studies, digital finance is associated with higher profitability through digital credit, digital savings, lower debt costs, and stronger innovative investment capacity (Oduor, 2025; Yu, 2023 & Thathsarani, 2022). Digital credit and savings both showed positive profitability effects in Kenyan SMEs (Oduor, 2025). Nigerian SMEs reported a strong profit link with digital financial tools, with a profitability correlation r = 0.71 (Jude, 2026). In agricultural systems, DFI improved profitability indirectly through climate-smart agriculture and supply-chain agility (Xu, 2025)

2.2 Theoretical Review

2.2.1 Diffusion of Innovations (DOI)

Rogers' (1962) DOI explains technology adoption through relative advantage, compatibility, Complexity, trialability, and observability. Recent work confirms its relevance for digital finance (Alshahrani et al., 2022). For MSMEs, adoption depends on perceived benefits and usability of Mobile banking, mobile money, and fintech, with outcomes varying across urban and rural Niger State (Okeke, 2021).

2.2.2 Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

UTAUT2 (Venkatesh et al., 2012) emphasizes performance expectancy, effort expectancy, social Influence, facilitating conditions, hedonic motivation, price value, and habit. Studies extend it with trust and risk to explain financial technology adoption (Dwivedi et al., 2020; Boateng et al., 2022). For MSMEs, beliefs about sales benefits, ease of use, peer influence, and infrastructure shape adoption.

2.2.3 Resource-Based View (RBV)

Barney's (1991) RBV highlights competitive advantage through valuable, rare, inimitable, and Non-substitutable resources. In the digital era, fintech capabilities payment integration, data driven lending, and platform partnerships can be strategic resources (Ferreira et al., 2020). Yet, critiques note RBV's difficulty in capturing dynamic environments (Kozlenkova et al., 2021; Wilden & Teece, 2023). For MSMEs, leveraging digital tools requires embedding them into operations such as invoicing, collections, and online marketplaces to drive sales growth. Together, DOI and UTAUT2 explain adoption, while RBV clarifies how digital tools translate into sustained performance.

2.3 Empirical Review

Muchiri et al. (2026) examined the impact of mobile banking services on the performance of small and medium agro-processing enterprises in Kiambu County, Kenya. A descriptive cross-sectional survey design was adopted, with a total population of 254 registered agro-processing SMEs in Kiambu County, from which a sample of 154 owners and managers was selected using stratified random sampling. Data were collected through structured questionnaires, with 147 completed questionnaires returned, representing a response rate of 95.5%, and were analyzed using descriptive statistics, Pearson correlation analysis, and regression analysis with the aid of SPSS Version 29. The findings revealed that mobile banking services had a positive and statistically significant influence on financial performance, recording a strong positive correlation with financial performance. The study concluded that mobile banking services were the most influential determinant of financial performance among agro-processing SMEs in Kiambu County, enhancing transaction efficiency, financial accessibility, liquidity management, and business growth. The study recommends continued investment in digital financial infrastructure, strengthening the security and reliability of mobile banking platforms, deeper integration of mobile banking with savings, credit, insurance, and payment services, and implementation of digital financial literacy programs for agro-processing enterprises.

Ankrah et al, (2023) examined the impact of mobile money account ownership on farmers' participation in farmer-based organisations (FBOs), structured market and off-farm work. The study collected data from smallholder maize farmers in the Brong-Ahafo Region of Ghana between September and December 2021. A multistage sampling technique was used to select 1440 farmers, with 480 farmers selected from each of the three districts-Kintampo South, Kintampo North and Jaman. The first stage involved selecting Brong-Ahafo, one of the leading maize-producing regions in Ghana, purposively. The second stage involved selecting the three districts based on their significant maize production. The third stage involved the random selection of five communities from each district, resulting in a total of 96 sampled farmers. The selection of communities was based on the size of farmland or the number of maize farmers in each community. The final sample size was 1431 maize farmers due to incomplete responses. The structured questionnaire used in the data collection gathered information on farmers' attributes, farm level, institutional factors, digital financial inclusion variables and maize production within the study area. Relying on recursive bivariate probit model, our results reveal that owning a mobile money account increases the likelihood of farmers' participating in an FBO, structured market and off-farm work by 15.4%, 33.3% and 37.5%, respectively. Furthermore, mobile money account ownership is influenced by socioeconomic and institutional factors as well as the presence of mobile money vendors within a community. Our finding calls for sustained efforts to deepen digital financial inclusion for increased participation in FBOs, structured market and off-farm work.

Jaydevsinh and Janvi(2025) explores the potential of digital financial inclusion to empower farmers and enhance agricultural productivity. This research, conducted among 100 farmers in Palaj, Gandhinagar, utilized a descriptive research design, combining both qualitative and quantitative data to address the research questions and generate precise predictions about digital financial inclusion among farmers. The target population consisted of farmers from Palaj, Gandhinagar, with a sample size of 100 respondents, selected using a convenient sampling technique. Primary data were collected using a self-designed questionnaire, and data collection was carried out using a survey method, with physical questionnaires analyzed through Google Forms. The data was analyzed and presented in graphical and tabular formats

using Microsoft Excel. The study revealed the role of government programs and local organizations in promoting digital financial literacy and emphasizes the need for targeted educational initiatives, improved infrastructure, and tailored financial products. Findings suggest that digital financial tools enhance financial security and productivity, offering long-term socioeconomic benefits. The study concludes that, challenges such as mistrust of digital systems and insufficient internet access remain significant.

Adesiyan (2025) investigates how digital market access platforms and mobile financial technologies are transforming agribusiness productivity, efficiency, and sustainability in rural farming communities. The study adopts a mixed-methods approach, combining geospatial analysis of mobile network penetration with impact assessments from case studies in Sub-Saharan Africa and South Asia. It critically examines the digital divide in access and literacy, revealing how mobile penetration, gender dynamics, and infrastructural deficits influence tool adoption. Further, it explores how mobile finance ecosystems integrate with government-led subsidies, agricultural input delivery systems, and climate insurance programs to enhance economic resilience in the face of climate and market volatility. The findings demonstrate that well-structured digital ecosystems not only improve rural farmers' access to buyers and capital but also enable inclusive value chain participation. The study concludes that policy framework for scaling digital finance and market access strategies, anchored in public-private partnerships and targeted digital inclusion programs for marginalized farmer groups.

Enaigbe and Ezeliora (2025) investigated the role of mobile banking as a fintech innovation in enhancing financial inclusion and promoting the growth of small and medium-sized enterprises (SMEs) in Sub-Saharan Africa, using a quantitative research design, and primary data were collected through structured questionnaires administered to SME owners across Nigeria, Ghana, and Kenya. The data were analysed using descriptive statistics and regression analysis via SPSS and STATA software. Findings indicate a strong positive correlation between mobile banking usage and improvements in SME financial accessibility, operational efficiency, and revenue growth. The study also concludes that digital literacy, regulatory support, and infrastructure quality as critical moderating factors in mobile banking adoption.

3. Methodology

This study adopts a quantitative survey research design to test the relationships between digital financial inclusion and profitability of agro-based SMEs in the North Easter Nigeria. The population comprises 1527 registered Using Yamane's (1967) formula at a 5% precision level produced a target sample of 317 respondents, proportionally allocated across all the state and selected by multistage, sampling. Primary data were collected with a structured questionnaire administered to owners/managers; items used a 5-point Likert scale (Strongly Disagree = 1 to Strongly Agree = 5). Instrument validity was checked through a pilot (10% of sample = 40 respondents) and expert review, and reliability was confirmed by Cranach's alpha coefficients for key scales (all $\alpha > 0.70$), indicating acceptable internal consistency for use in analysis. Data analysis proceeds from descriptive statistics to inferential testing using PLS-SEM. Reliability and construct validity are assessed via Cronbach's alpha. While hypothesis testing uses linear regression with the model specification:

$$PROF=\beta_0+\beta_1MB+\beta_2IB+\beta_3VB+\beta_4POS+\beta_5ATM + \varepsilon$$

Where:

PROF = Profitability of Agro-based SMEs
MB = Mobile Banking
IB = Internet Banking

VB = Virtual Banking
POS = Point of Sales
ATM = Automated Teller Machines
β_0 = Intercept
β_1, β_2, β_3 = Regression coefficients
ε = Error term

The null hypothesis tested is: Ho_1: Mobile banking, Internet Banking services, Virtual banking, Point of Sales, and Automated Teller Machine has no combined significant effect on the profitability of agro-based SMEs in North-Eastern Nigeria.

4.0 Results and Discussions

4.1 Data Presentation

This study employed PLS-SEM analytical method to analyse the collected data and to test the hypotheses. There are two different stages of PLS-SEM, which include measurement model and structural model. The model was appropriately configured to establish whether the indicators are formative or reflective, as the approach differs significantly for each (Hair, Gabriel, et al., 2019; Hair, Risher, et al., 2019). This study considered all indicators of the latent variables as reflective. The independent variables include Mobile Banking, Internet Banking, Virtual Banking, Point of Sale, and Automated Teller Machine, while the dependent variables is Profitability. The measurement model assessment is the first step in PLS-SEM analysis and deals with how well the indicators load and relate to their respective constructs, thereby ensuring reliability and validity. Reliability and validity are the two main criteria used to evaluate the measurement model (Hair, Gabriel, et al., 2019; Hair, Risher, et al., 2019), as the predictive capacity of the structural model depends largely on them. The appropriateness of the outer model was assessed based on internal consistency and individual item reliability using Composite Reliability (CR) and Cronbach's Alpha; convergent validity using Average Variance Extracted (AVE); and discriminant validity using the Fornell-Larcker criterion, indicator outer loadings, and the Heterotrait-Monotrait (HTMT) criterion.

4.1.2 Measurement Model

4.1.3 Indicator Reliability / Outer Loadings

This result checks whether the questionnaire items properly measure the constructs. Indicator reliability (also referred to as item reliability) examines the extent to which each observed indicator (item) reliably measures its associated latent construct. This is assessed through outer loadings, which represent the correlation between an indicator and its corresponding construct. Following the guidelines of Hair et al. (2021, 2022) and Hulland (1999), outer loadings should ideally be 0.708 or higher, as this threshold indicates that the construct explains more than 50% of the indicator's variance (loading$^2 \geq 0.50$), thereby demonstrating satisfactory indicator reliability. Loadings between 0.40 and 0.70 should only be retained if their removal does not improve composite reliability or AVE; loadings below 0.40 should generally be removed.

Table 1: Indicators Loading, Composite Reliability, and AVE of Construct

latent Construct	Items	Item Loading	Composite Validity	AVE
Automate Teller Machine	ATM1	0.839	0.963	0.839
	ATM2	0.843		
	ATM3	0.864		
	ATM4	0.869		
	ATM5	0.850		
Internet Banking	IB1	0.882	0.967	0.854
	IB2	0.850		
	IB3	0.825		
	IB4	0.881		
	IB5	0.830		
Mobile Banking	MB1	0.882	0.968	0.858
	MB2	0.856		
	MB3	0.888		
	MB4	0.855		
	MB5	0.882		
Point of Sale	POS1	0.844	0.97	0.865
	POS2	0.840		
	POS3	0.858		
	POS4	0.854		
	POS5	0.858		
Profitability	PROF 1	0.859	0.97	0.867
	PROF 2	0.845		
	PROF 3	0.863		
	PROF 4	0.860		
	PROF 5	0.819		
Virtual Banking	VB1	0.861	0.968	0.857
	VB2	0.869		
	VB3	0.859		
	VB4	0.865		
	VB5	0.865		

Source: SmartPLS 4, 2026.

The results indicate that all twenty five (25) indicators across the five constructs examined in this study recorded outer loadings ranging from 0.819 to 0.888, well above the recommended minimum threshold. This confirms that every item is a strong and reliable measure of its intended construct, and no items required removal from the measurement model. With respect to individual constructs, the Automated Teller Machine items (ATM1 to ATM5) recorded loadings between 0.839 and 0.869, reflecting consistent measurement of the

construct across all five indicators. The Internet Banking items (IB1 to IB5) ranged from 0.825 to 0.882, with IB1 and IB4 emerging as the strongest indicators. Mobile Banking recorded the highest loadings in the entire model, ranging from 0.855 to 0.888, suggesting that its indicators are the most robust measures across the six constructs. Point of Sale items showed a tightly clustered range of 0.840 to 0.858, indicating high internal consistency among its indicators. Profitability loadings ranged from 0.819 to 0.863, with PROF5 recording the lowest loading in the entire model, although this value still substantially exceeds the acceptable threshold. Virtual Banking indicators ranged narrowly between 0.859 and 0.869, reflecting excellent and highly stable measurement of the construct. Since all outer loadings exceeded the 0.708 benchmark, with the majority above 0.80, it can be concluded that indicator reliability was satisfactorily established for all six constructs. Each indicator shares a substantial proportion of variance with its respective latent construct, providing a sound basis for the subsequent assessment of internal consistency reliability and convergent validity in the measurement model.

4.1.4. Discriminant Validity

Table 2 below shows whether one construct is statistically different from other constructs

Table 2: Fornell-Larcker Criterion

	ATM	IB	MB	POS	PROF	VB
ATM	**0.853**					
IB	0.362	**0.854**				
MB	0.349	0.431	**0.873**			
POS	0.323	0.296	0.276	**0.851**		
PROF	0.305	0.342	0.353	0.323	**0.849**	
VB	0.401	0.356	0.434	0.364	0.376	**0.864**

Source: SmartPLS 4, 2026.

As presented in Table2 above, the results confirm that discriminant validity was established for all constructs in the measurement model. Specifically, the square root of the AVE for each construct comprising Automated Teller Machine (0.853), Internet Banking (0.854), Mobile Banking (0.873), Point of Sale (0.851), Profitability (0.849), and Virtual Banking (0.864) was greater than its corresponding correlations with all other constructs in the model. This satisfies the Fornell-Larcker (1981) threshold criterion and indicates that each construct shares more variance with its own indicators than with indicators measuring other constructs.
Notably, the highest inter-construct correlation observed was between Mobile Banking and Virtual Banking (r = 0.434), followed by Internet Banking and Mobile Banking (r = 0.431). Although these values indicate a moderate degree of association, theoretically plausible given that both are electronic/digital banking delivery channels, they remain substantially lower than the respective AVE square roots of the two constructs (0.873 and 0.864), confirming that the two constructs, while conceptually related, are empirically distinguishable.

Conversely, Point of Sale and Mobile Banking recorded the lowest inter-construct correlation (r = 0.276), suggesting these are the most empirically distinct constructs in the model. Therefore, since no off-diagonal value exceeds its corresponding diagonal value in any row or column, it can be concluded that discriminant validity was satisfactorily established for the constructs examined in this study (ATM, Internet banking, Mobile banking, Point of Sale, Profitability, and Virtual banking. This finding provides empirical support for the

distinctiveness of the measurement model and confirms that the constructs, though conceptually related as electronic banking channels influencing profitability, are not redundant. This satisfies a key prerequisite for proceeding to structural model (inner model) evaluation and hypothesis testing.

Table3: Cross Loadings

	ATM	IB	MB	POS	PROF	VB
ATM1	0.839	0.293	0.318	0.274	0.232	0.347
ATM2	0.843	0.309	0.280	0.251	0.236	0.334
ATM3	0.864	0.318	0.333	0.308	0.318	0.343
ATM4	0.869	0.310	0.274	0.267	0.261	0.344
ATM5	0.850	0.311	0.276	0.269	0.233	0.345
IB1	0.323	0.882	0.393	0.257	0.315	0.320
IB2	0.323	0.850	0.384	0.265	0.294	0.316
IB3	0.302	0.825	0.370	0.279	0.285	0.332
IB4	0.296	0.881	0.383	0.257	0.294	0.313
IB5	0.300	0.830	0.305	0.202	0.270	0.237
MB1	0.302	0.399	0.882	0.260	0.314	0.395
MB2	0.334	0.363	0.856	0.227	0.274	0.367
MB3	0.267	0.387	0.888	0.216	0.321	0.362
MB4	0.339	0.354	0.855	0.250	0.298	0.401
MB5	0.289	0.377	0.882	0.253	0.329	0.372
POS1	0.291	0.243	0.223	0.844	0.284	0.300
POS2	0.283	0.244	0.240	0.840	0.254	0.276
POS3	0.275	0.269	0.216	0.858	0.314	0.330
POS4	0.288	0.251	0.251	0.854	0.240	0.337
POS5	0.239	0.249	0.253	0.858	0.271	0.303
PROF1	0.253	0.277	0.324	0.272	0.859	0.334
PROF2	0.264	0.327	0.319	0.290	0.845	0.351
PROF3	0.265	0.278	0.302	0.239	0.863	0.320
PROF4	0.264	0.308	0.297	0.292	0.860	0.309
PROF5	0.248	0.256	0.251	0.278	0.819	0.275
VB1	0.299	0.315	0.397	0.310	0.342	0.861
VB2	0.373	0.291	0.361	0.335	0.288	0.869
VB3	0.352	0.301	0.393	0.319	0.308	0.859

VB4	0.348	0.336	0.365	0.310	0.330	0.865
VB5	0.365	0.294	0.359	0.300	0.346	0.865

Source: Smart PLS 4, 2026

Table 3 above present's cross-loadings, a second approach for assessing discriminant validity, which requires that each indicator load more strongly on its own construct than on any other construct in the model. The results confirm the condition for all thirty indicators. Each item's loading on its assigned construct is substantially higher than its loadings on the remaining five constructs. For instance, ATM1 to ATM5 loaded between 0.839 and 0.869 on Automated Teller Machine, compared to loadings below 0.35 on all other constructs. Similarly, IB1 to IB5 loaded between 0.825 and 0.882 on Internet Banking, well above their loadings elsewhere. Mobile Banking indicators (MB1 to MB5) loaded between 0.855 and 0.888 on their own construct, exceeding cross-loadings on other constructs, which remained below 0.40. Point of Sale, Profitability, and Virtual Banking indicators followed the same pattern, with own-construct loadings ranging from 0.819 to 0.868 and cross-loadings consistently below 0.40.

Since every indicator loaded highest on its intended construct, with a clear margin over its cross-loadings, discriminant validity is further confirmed through the cross-loadings criterion, corroborating the earlier Fornell-Larcker results and supporting the distinctiveness of all six constructs in the measurement model.

Table 4: Collinearity Statistics (VIF)

	VIF
ATM1	2.348
ATM2	2.369
ATM3	2.301
ATM4	2.666
ATM5	2.471
IB1	2.827
IB2	2.405
IB3	2.119
IB4	2.897
IB5	2.228
MB1	2.897
MB2	2.632
MB3	2.995
MB4	2.504
MB5	2.841
POS1	2.283
POS2	2.352
POS3	2.305
POS4	2.574
POS5	2.498
PROF1	2.489
PROF2	2.271
PROF3	2.579
PROF4	2.473

PROF5	2.171
VB1	2.489
VB2	2.823
VB3	2.572
VB4	2.620
VB5	2.528

Source: Smart PLS 4.0, 2026

Table 4 reports the Variance Inflation Factor (VIF) values for all indicators, which assess collinearity among indicators within the same construct. Following the guideline proposed by Hair et al. (2021), VIF values below 5.0 are considered acceptable, indicating the absence of critical collinearity, while values below 3.0 are regarded as ideal, and values approaching or exceeding 5.0 signal potential collinearity concerns that may distort the significance and reliability of outer loadings.

The results show that all thirty indicator VIF values fall within the acceptable range, from a low of 2.119 (IB3) to a high of 2.995 (MB3), with none reaching or exceeding the conservative threshold of 3.0. Specifically, ATM indicators ranged from 2.301 to 2.666, IB indicators from 2.119 to 2.897, MB indicators from 2.504 to 2.995, POS indicators from 2.283 to 2.574, PROF indicators from 2.171 to 2.579, and VB indicators from 2.489 to 2.823. Since all VIF values are well below the critical threshold of 5.0, and indeed close to or under 3.0, it can be concluded that collinearity among the indicators is not a concern in this measurement model. This confirms that each indicator contributes unique, non-redundant information to its respective construct, supporting the reliability of the outer loading estimates and providing a sound basis for proceeding with structural model evaluation.

4.1.5 Measurement of R- Square

The coefficient of determination (R^2) measures the proportion of variance in the endogenous construct that is explained by its associated exogenous constructs, thereby indicating the predictive accuracy of the structural model. Following the guideline proposed by Chin (1998) and later reaffirmed by Hair et al. (2021), R^2 values of 0.75, 0.50, and 0.25 are generally interpreted as substantial, moderate, and weak, respectively, although in social science and behavioural research, values around 0.20 are often considered acceptable given the complexity of human and organisational behaviour.

Table 5: R-Square

	R Square	**R Square Adjusted**
Profitability	0.239	0.231

Source: Smart PLS4.0, 2026

The results indicate that the exogenous constructs, namely Automated Teller Machine, Internet Banking, Mobile Banking, Point of Sale, and Virtual Banking, collectively explain 23.9% ($R^2 = 0.239$) of the variance in Profitability, with an adjusted R^2 of 23.1% (0.231) after accounting for the number of predictors in the model and sample size. The small difference between the R^2 and adjusted R^2 values (0.008) suggests the model is not overfitted and that the number of predictors does not substantially inflate predictive power. Although this value falls below the moderate threshold of 0.50, it can be interpreted as a weak to moderate level of explanatory power, which is not uncommon in studies examining organisational or

financial performance outcomes such as profitability, given that such outcomes are typically influenced by numerous factors beyond the electronic banking channels considered in this model. This suggests that while digital banking channels make a meaningful, statistically significant contribution to explaining variation in profitability, approximately 76.1% of the variance in Profitability is attributable to other factors not captured in the current model, indicating opportunities for future research to incorporate additional predictors.

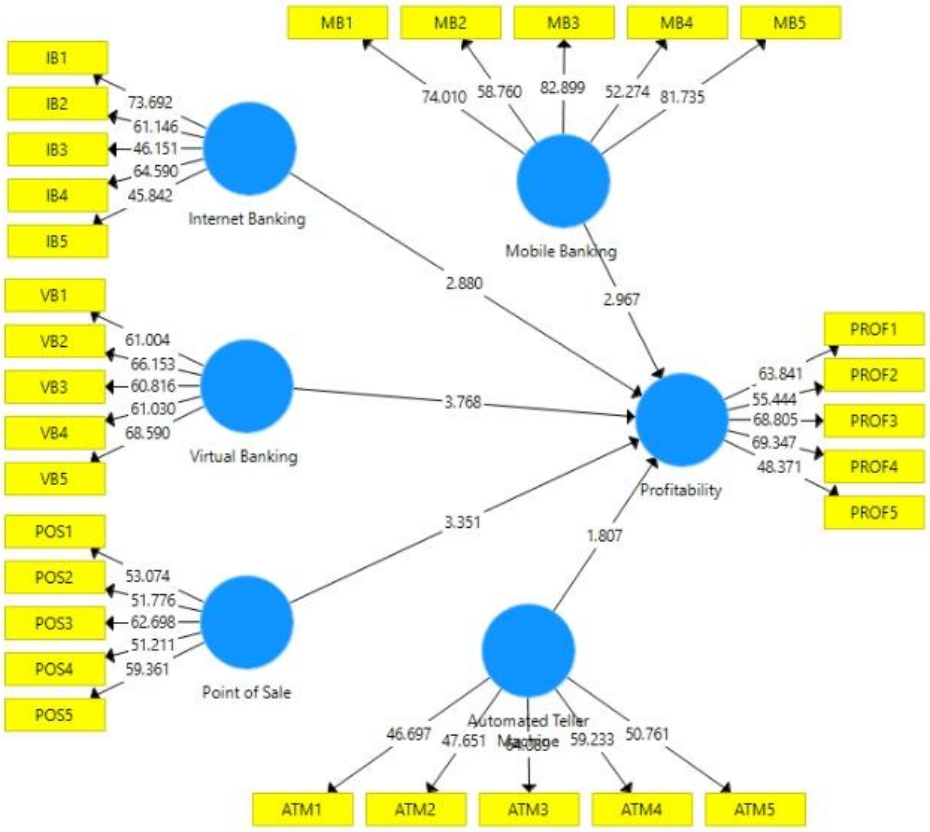


Figure 1: *Structural Model*
Source: Smart PLS, 2026

With respect to the outer loadings, all indicator t-values substantially exceed the critical threshold of 1.96 ($p < 0.05$), ranging from 45.842 (IB5) to 82.899 (MB3). This confirms that all indicators significantly and reliably measure their respective latent constructs, reinforcing the indicator reliability results reported earlier. Regarding the structural paths, the results indicate that four of the five electronic banking channels have a statistically significant effect on Profitability. Internet Banking recorded a t-value of 2.880, Mobile Banking 2.967, Point of Sale 3.351, and Virtual Banking 3.768, all exceeding the 1.96 threshold ($p < 0.05$), and in fact exceeding 2.58 ($p < 0.01$), indicating that these four constructs have a statistically significant positive effect on Profitability at the 1% significance level. Virtual Banking emerged as the strongest predictor of Profitability, evidenced by the highest t-value (3.768), followed by Point of Sale (3.351), Mobile Banking (2.967), and Internet Banking (2.880).

In contrast, the path from Automated Teller Machine to Profitability recorded a t-value of 1.807, which falls below the 1.96 threshold required for significance at the 5% level. This

indicates that ATM does not have a statistically significant effect on Profitability at the conventional 5% level, though it remains marginally significant at the 10% level (t > 1.645). Therefore, the bootstrapping results provide statistical support for four of the five hypothesized relationships in the model, confirming that Internet Banking, Mobile Banking, Point of Sale, and Virtual Banking significantly and positively influence Profitability, while the effect of Automated Teller Machine on Profitability, though positive, is not statistically significant at the conventional threshold.

4.1.6 Path Coefficient

Table 6 below presents the path coefficients and their corresponding significance levels for the structural model, derived through the bootstrapping procedure with 5,000 subsamples. The path coefficient (Original Sample, O) indicates the strength and direction of the relationship between each exogenous construct and Profitability, while the t-statistic and p-value determine the statistical significance of each relationship, using the conventional thresholds of t > 1.96 and p < 0.05.

Table 6: Path Coefficient

	Original Sample, (O)β	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
ATM-> Prof	0.084	0.085	0.047	1.807	**0.071**
IB -> Prof	0.142	0.144	0.049	2.880	**0.004**
M B -> Prof	0.145	0.148	0.049	2.967	**0.003**
POS -> Prof	0.151	0.152	0.045	3.351	**0.001**
VB -> Prof	0.173	0.173	0.046	3.768	**0.000**

Source: Smart PLS 4.0, 2026

Mobile Banking recorded a positive and statistically significant effect on Profitability (β = 0.145, t = 2.967, p = 0.003), indicating that a one standard deviation increase in Mobile Banking is associated with a 0.145 standard deviation increase in Profitability, holding other constructs constant. This relationship is significant at the 1% level.

Virtual Banking exerted the strongest positive and statistically significant effect on Profitability among all five constructs (β = 0.173, t = 3.768, p = 0.000), significant at the 1% level, indicating that Virtual Banking is the most influential predictor of Profitability in the model. Internet Banking also showed a positive and statistically significant effect on Profitability (β = 0.142, t = 2.880, p = 0.004), significant at the 1% level, though it recorded the weakest effect among the four significant predictors. Point of Sale recorded a positive and statistically significant effect on Profitability (β = 0.151, t = 3.351, p = 0.001), stronger than the effects of Internet Banking and Mobile Banking, and significant at the 1% level.

Automated Teller Machine recorded a positive but statistically non-significant effect on Profitability (β = 0.084, t = 1.807, p = 0.071), as the p-value exceeds the 0.05 threshold and the t-statistic falls below the 1.96 critical value. This indicates that, holding other variables constant, ATM banking does not significantly predict Profitability at the conventional 5% level, although the relationship is marginally significant at the 10% level.

5.1.7 Model Fit

Table 7 below, presents the model fit indices for the structural equation model II, comparing the saturated model (which assumes all constructs are freely correlated) with the estimated model (the actual specified structural model), in order to assess how well the proposed model fits the observed data.

Table 7: Model Fit

	Saturated Model	Estimated Model
SRMR	0.035	0.035
d_ULS	0.561	0.561
d_G	0.264	0.264
Chi-Square	718.997	718.997
NFI	0.925	0.925

Source: Smart PLS, 2026

The Standardized Root Mean Square Residual (SRMR), which represents the average discrepancy between observed and predicted correlations, recorded a value of 0.035 for both the saturated and estimated models. Since this value is well below the recommended threshold of 0.08 (Hu & Bentler, 1999; Henseler et al., 2014), and even below the more stringent threshold of 0.05, it indicates a good model fit, suggesting minimal discrepancy between the model-implied and observed correlation matrices.

The unweighted least squares discrepancy (d_ULS) and geodesic discrepancy (d_G) recorded values of 0.561 and 0.264, respectively, identical for both the saturated and estimated models. These discrepancy measures are typically evaluated against bootstrap-based confidence intervals (HI99) rather than fixed thresholds; nonetheless, the equivalence of values across both models suggests no meaningful degradation in fit between the theoretical and estimated specifications.

The Chi-Square value of 718.997 is reported for both models. While Chi-Square is a traditional fit measure, it is highly sensitive to sample size and is generally not considered a reliable standalone indicator of model fit in PLS-SEM; consequently, it is typically interpreted alongside other indices such as SRMR rather than in isolation. The Normed Fit Index (NFI) recorded a value of 0.925 for both models. Since values closer to 1 indicate better fit, and the recommended threshold is generally 0.90 or above, an NFI of 0.925 indicates a good model fit.

Therefore, the fit indices, particularly the SRMR (0.035) and NFI (0.925), confirm that the structural model demonstrates a good and acceptable fit to the data.

4.1.8 Hypotheses Testing

The following hypotheses that relate to the Model are tested in table 8 below.

Table 8: Summary of Hypotheses Testing Results

Hypothesis	Relationship	Path Coefficient (β)	t-Statistics	P-Value	Decision
H_{01}	MB -> PROF	0.145	2.967	0.003	Rejected
H_{02}	VB -> PROF	0.173	3.768	0.000	**Rejected**
H_{03}	IB -> PROF	0.142	2.880	0.004	**Rejected**
H_{04}	POS-> PROF	0.151	3.351	0.001	**Rejected**
H_{05}	ATM->PROF	0.084	1.807	0.071	Accep**ted**

Source: SmartPLS 4, 2026.

4.1.9 Evaluation of R-square (Coefficient of Determination)

The R-square (R^2) value is a measure of the model's predictive accuracy and represents the proportion of variance in the dependent variables that is explained by the independent variables. According to Hair, Hult, et al. (2014) and Hair, Risher, et al. (2019), R^2 values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak, respectively. However, in disciplines such as social sciences and business research, R^2 values as low as 0.10 to 0.20 are acceptable, provided that the model includes significant predictors.

The results of the R-square evaluation for the dependent variable; Profitability

Table 9: R-Square Values of Dependent Variables

Dependent Variable	R-Square	R-Square Adjusted
Profitability (PROF)	0.239	0.231

Source: SmartPLS 4, 2026.

The R-square value for Profitability is 0.239, indicating that the independent variables collectively explain 23.9% of the variance in profitability among agro-based SMEs. The adjusted R-square value of 0.231 confirms the stability of this result. Although this value is relatively low, it is considered acceptable in social science and business research, particularly when dealing with complex human behaviours and business outcomes (Hair, Risher, et al., 2019). The finding suggests that while digital financial inclusion channels contribute to profitability, other significant factors such as market conditions, business strategies, and operational costs play a more dominant role in determining the profitability of agro-based SMEs in North-Eastern Nigeria.

4.1.10 Discussion of Findings

The results are compared with earlier studies in two groups, direct comparable studies examine SMEs performance and the same digital channel; they are used to judge whether the present findings agree with earlier evidence. Indirect studies examine banks, customers or national aggregates; they are cited only as background, because their outcomes differ from those measured here.

The finding of this study, which established that mobile banking has a statistically significant positive effect on profitability of agro-based SMEs in North-eastern Nigeria, is largely consistent with the weight of empirical evidence reviewed. Several recent studies corroborate this positive relationship across diverse contexts. Enaigbe and Ezeliora (2025) found a strong positive correlation between mobile banking usage and improvements in SME financial accessibility, operational efficiency, and revenue growth across Nigeria, Ghana, and Kenya,

findings that closely mirror the significant effects on operational efficiency and sales growth observed in the present study.

The study was also established that virtual banking exerts a statistically significant positive effect on the profitability of agro-based SMEs in North-eastern Nigeria, emerging notably as the strong predictor of profitability, was broadly consistent with the findings of extant empirical literature, although comparable studies specifically isolating "virtual banking" as a construct remain relatively scarce. Shreim and Al-Kasasbeh (2025), in one of the few studies directly examining virtual banking, found a significant positive relationship between virtual banking attributes, namely advantages, compatibility, simplicity, and trialability, and customers' intention to use virtual banking platforms in Jordan, lending indirect support to the present study's finding that virtual banking meaningfully influences user and business outcomes.

On the other hand, it was further established that internet banking has a statistically significant positive effect on the profitability.

Several studies lend strong support to the significant positive effects observed for profitability. Iyke-Ofoedu et al. (2022) found that internet effectiveness, convenience, and accessibility each significantly influenced SME business expansion, quality of job delivery, and income base expansion in Enugu Metropolis, findings that closely mirror the present study's significant sales growth result.

The study findings further revealed that, Point of Sale (POS) provisions have a statistically significant positive effect on the profitability of agro-based SMEs in North-eastern Nigeria, is largely consistent with the majority of the reviewed empirical literature, although some studies introduce important nuances regarding adoption barriers and mixed effects across contexts.

Finally, the finding of this study, also established that Automated Teller Machine (ATM) has no statistically significant effect on profitability, of agro-based SMEs in North-eastern Nigeria, is largely consistent with the reviewed literature, which similarly reveals a mixed and outcome-dependent pattern of ATM effects across studies.

5. Conclusion and Recommendations:

5.1 Conclusion

This study examined the effect of digital financial inclusion on the profitability of agro-based Small and Medium Enterprises in North-eastern Nigeria, with digital financial inclusion operationalized through five constructs, Mobile Banking, Virtual Banking, Internet Banking, Point of Sale, and Automated Teller Machines, and performance assessed across three dimensions, and profitability as dependent variable. Based on the findings from the five hypotheses tested across three structural models using Partial Least Squares Structural Equation Modelling (PLS-SEM), the study draws the following conclusions with respect to each independent variable.

The study concludes that Mobile Banking has a statistically significant positive relationship with profitability of agro-based SMEs in North-eastern Nigeria, as Mobile Banking emerged as the single strongest predictor among all five digital financial inclusion channels examined, underscoring its critical role in facilitating transactions, payments, and customer engagement for agro-based enterprises. This is consistent and robust performance across all three

outcome dimensions indicates that mobile banking services, encompassing platforms have become deeply embedded in the day-to-day financial operations of agro-based SMEs, enabling them to conduct business more profitably, expand their sales base, and operate more efficiently, even within the infrastructural challenged environment of North-eastern Nigeria.
The study concludes that Virtual Banking has a statistically significant positive relationship with the profitability, sales growth, and operational efficiency of agro-based SMEs in North-eastern Nigeria. Virtual Banking distinguished itself as the most consistently influential predictor across all three models, ranking as the strongest predictor of profitability and sales growth, and the second-strongest predictor of operational efficiency. This finding highlights the growing importance of virtual and agent-based banking platforms in extending financial services to agro-based SMEs operating in rural and semi-urban locations where traditional brick-and-mortar banking infrastructure remains limited, thereby positioning Virtual Banking as the most impactful digital financial inclusion channel for agro-based SME performance in the study area.

The study concludes that Internet Banking has a statistically significant positive effect on the profitability of agro-based SMEs in North-eastern Nigeria. This finding suggests that internet banking services, such as online fund transfers, bill payments, and account management, meaningfully support the revenue-generating and market-facing activities of agro-based SMEs, but have limited capacity to streamline their internal business processes and day-to-day operations. The study concludes that Point of Sale provisions have a statistically significant positive effect on the profitability of agro-based SMEs in North-eastern Nigeria. This finding reinforces the value of POS as a practical and accessible digital payment solution that resonates well with the operational realities of agro-based enterprises, even in areas with limited banking infrastructure.

The study concludes that Automated Teller Machines do not have a statistically significant effect on profitability. However, the non-significant effect on profitability suggests that, despite these operational and sales-related benefits, ATM usage does not translate into a proportionate increase in net earnings, possibly due to transaction charges, withdrawal limits, and cash-handling costs that offset the financial gains derived from improved transactional convenience.

5.2 Recommendations

Based on the findings and conclusions drawn from this study, the following recommendations are proposed for policymakers, financial institutions, and agro-based SME operators in North-eastern Nigeria.

i. Mobile Banking as one of the strongest predictor of profit and demonstrated significant performance dimensions, it is recommended that financial institutions operating in North-eastern Nigeria intensify the deployment and promotion of mobile banking platforms, particularly USSD-based services that do not require internet connectivity, given the region's infrastructural limitations.
ii. Given that Virtual Banking was found to be the most consistently influential digital financial inclusion channel on profitability, it is recommended that financial institutions and regulatory authorities prioritize the expansion of virtual and agent banking networks into rural and semi-urban communities where agro-based SMEs are predominantly located.
iii. Also, considering that Internet Banking significantly enhanced profitability, it is recommended that financial institutions invest in improving the reliability, speed, and

user-friendliness of internet banking platforms specifically tailored to the operational needs of agro-based SMEs.

iv. Given the consistent and significant positive effect of Point of Sale on profitability, it is recommended that banks and fintech companies increase the distribution of POS terminals to agro-based SMEs clusters and rural markets in North-eastern Nigeria, while also addressing recurring challenges such as network failures, high transaction charges, and fraud risks that could otherwise undermine merchant and customer confidence in POS usage.

v. Since Automated Teller Machines showed no significant effect on profitability, it is recommended that banks review the cost structure associated with ATM usage, including withdrawal charges and transaction fees, to ensure that the operational benefits derived from ATM services translate more directly into improved profitability for agro-based SME users. Additionally, financial institutions should expand ATM deployment in underserved agro-based SMEs locations.

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