The Nexus between Cashless Banking Policy and Returns of License Deposit Money Banks (DMBs) in Nigeria: A Comparative Study

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DOI: https://dx.doi.org/10.47772/IJRISS.2025.914MG00130

Received: 25 July 2025; Accepted: 31 July 2025; Published: 30 August 2025

ABSTRACT

Cashless banking has gained significant trend over the years, with the increasing embracement of electronic transaction channels such as Global Pay (GPAY), Corporate Internet Banking (CIB), Mobile Banking (MB), Pay-Direct (PD), and Remita (RMT). This study, therefore, examines the nexus between the cashless banking policy and the performance of Deposit Money Banks (DMBs) in Nigeria. Using mixed method sources of data, the qualitative data was sourced from the employees of licensed DMBs via a closed-ended questionnaire, and secondary data was gathered from the annual reports of the sampled DMBs covering the period from 2012 to 2023. The SEM-PLS models reveal that CIB ($p = 0.001$), MBS ($p = 0.005$), and PDS ($p = 0.01$) are strongly associated with a bank's financial performance. The panel regression models indicate that the global pay (GPAY), with a p-value of 0.018, proved to be a significant predictor of ROE of the sampled DMBs. Furthermore, the regression results show that the cashless banking has no significant relationship with the ROA of the sampled banks during the period under review. These findings revealed different stakeholder perceptions and financial outcomes, suggesting that improved digital infrastructure, user education, and policy alignment are required to realise the cashless banking's benefits fully. The study recommends that DMBs avoid a one-size-fits-all digital strategy. Instead, they should tailor digital tools to specific financial performance objectives such as deposit mobilisation, cost efficiency, and profitability.

Keywords: Cashless Banking Policy, Global Pay, Corporate Internet Banking, Mobile Banking, Pay Direct and Remita.

INTRODUCTION

The growth of technology worldwide has influenced the adoption of a cashless banking policy in Nigeria, aimed at reducing the physical movement of cash and promoting electronic transactions. The cashless banking policy seeks to reduce the amount of physical currency in circulation by discouraging the usage of money and promoting the development of electronic payment systems. This system is not intended to eliminate cash usage in transactions, but rather to limit physical cash handling and the amount of currency in circulation (Gbanador, 2021). The Central Bank of Nigeria (CBN) launched the cashless banking policy in 2012. On January 1, 2012, a cashless banking policy test run began in Lagos state. The second stage of this strategy was implemented in Abia, Anambra, Kano, Ogun, Rivers, and the FCT on July 1, 2013, with statewide implementation beginning on July 31, 2014 (CBN, 2019).

The cashless banking aims to increase the usage of electronic payment channels such as automated teller machines (ATM), point of sale (POS), mobile banking, NIBSS instant payment, NIBSS electronic fund transfer, and alternative payment channels such as cheques. Through e-payments, electronic banking is the foundation for a cashless system, which will ultimately lead to a cashless economy. Point of sale terminals (POS), mobile banking, online/internet banking, and others are examples of e-payment methods. The overall impact of the cashless banking policy on the performance of DMBs is complex and multifaceted.

Even though high operating costs characterise a cash-based economy, most Nigerian banks are well-known for the enormous profits they report each year (Okafor, 2020). Nigeria's cashless banking policy is significantly

improving the business environment. However, certain disadvantages exist, such as the possibility of fraud and observing fraudulent activities linked to the cashless banking system. Nigeria has seen several cybercrimes and frauds over the years due to the cashless banking system's emphasis on electronic money transactions and the country's high degree of unreliable networks (Ogbeide & Fapohunda, 2017).

Studies have been conducted on the relationship between the cashless policy and the performance of DMBs (Makinwa, 2021; Okechukwu & Yua, 2021; Akani & Obiosa, 2020; Usman, 2020; Akindayo, Shadera & Solomon, 2020; Gambo, 2020; Nwakoby, Chukwu & Ogbenetega, 2020; Ul-Hug & Hossain, 2020; James & Eloho, 2020; Agu & Agu, 2020; Okafor, 2020; Ignoroje & Okoroyibo, 2020; Ogutu & Fatoki, 2019; Agu & Nwakwo, 2019). These studies have been characterised by inconclusive findings ranging from positive to negative and non-significant relationships. This study will therefore be conducted to establish the relationship between the cashless policy and the performance of listed DMBs in Nigeria.

Furthermore, from extant literature, it is observed that most studies have employed variables such as Automated Teller Machine (ATM), Mobile Banking (MB), Point of Sales (POS), Internet Banking (IB), and Nigeria Electronic Fund Transfer (Akindayo, Shadera & Solomon, 2020; Gambo, 2020; Nwakoby, Chukwu & Ogbenetega, 2020; Ul-Hug & Hossain, 2020; Agu & Agu, 2020; Okafor, 2020) as proxies for measuring cashless policy. Therefore, this study extends the frontier of knowledge by examining the relationship between Pay-direct, Corporate Internet Banking, Global Pay, and Remita transactions and the performance of licensed DMBs in Nigeria.

Furthermore, the period covered by most of the studies, as seen in the reviewed literature (Akani & Obiosa, 2020; Usman, 2020; Agu & Agu, 2020; Okafor, 2020; Ignoroje & Okoroyibo, 2020; Ogutu & Fatoki, 2019), stopped at the 2021-year end, indicating that activities for the years 2022 and 2023 remained uncovered. It should be noted that 2020, 2021, 2022, and part of 2023 were characterised by the global pandemic, which saw the restriction of banks' operations emanating from the social distancing and also cash crises in 2022 and 2023, hence the usefulness of the various cashless system platforms by the populace in Nigeria and around the world. Against this backdrop, the study examines the nexus between the cashless banking policy and the performance of licensed DMBs in Nigeria, covering 12 years from 2012 to 2023.

CONCEPTUAL FRAMEWORK

Concept of Cashless Banking Policy in Nigeria

The definition of cashless banking has remained consistent over time and across borders. Kamboh and Leghari (2016) define it as the execution of and banking transactions without using banknotes, bills, or coins, but rather through credit and debit cards, telephonic and electronic fund transfers, the internet, and mobile banking. Datta (2021) described cashless transactions as those that occur using an ATM, debit or credit card, EFTs, or other media that do not require actual cash. Cashless banking is a system that aims to decrease the actual currency in circulation, without eliminating it, by promoting electronic transactions for payments, transfers, and other activities. (Ernest & Fadiya, 2022). It signifies a transition period in the advancement of payment systems in most developing nations (Ikpefan, 2018). A cashless economy is the intermediate stage of a three-phase payment system economic model. This suggests that nations, particularly those in the development process, would shift from a mostly cash-based economic system to a cashless economy (Ighoroje & Okoroyibo, 2020).

A cash-based economy is characterised by using physical banknotes and coins for everyday transactions and commercial exchanges (Kket & Egu, 2022). A cashless economy refers to a system where the usage of real currency is restricted, and instead, digital forms of payment, such as electronic transactions, are mostly used. A cashless economy may be defined as a combination of cash-based and electronic payment systems, where electronic payments surpass the use of currency (Morufu, 2021). In a cashless economy, non-cash payment technologies are predominant, and the Central Bank ceases to produce physical currency for circulation. As to Claudia and Grauwe (2001), a cashless society refers to a state where the currency issued by the central bank no longer exists. All the funds consist exclusively of privately produced currency in bank deposits or more advanced electronic money generated by non-banking entities (Muotolu & Nwadialor, 2019).

From the various definitions stated above, the working definition of cashless policy is that a cashless policy is the application of technology in carrying out and banking activities, which include electronic fund transfer, global pay, corporate internet banking, mobile banking, pay-direct, and remita for performing different transactions in the bank

Benefits of Cashless Banking Policy in the Economy.

Implementing a cashless economy in Nigeria would enhance the standard of living by lowering the duration of transactions, boosting sales, simplifying cash collection, minimises transfer and processing costs, improves processing and transaction time, offers several payment options, and delivers instant notifications for all client account operations (Akhalumeh & Ohiakha, 2012; Andabai & Bina, 2019; Asenge, 2019). The predicted increase in the use of electronic payment systems is expected to provide many advantages for various stakeholders. For consumers, this entails enhanced convenience, a wider range of service alternatives, less susceptibility to cash-related crimes, and more cost-effective access to banking services and credit outside traditional branches. Businesses may benefit from improved accessibility, reduced revenue loss, and decreased expenses associated with cash handling (Atanda & Alimi, 2018): enhanced tax revenue, more access, and improved economic advancement for the government.

The Challenges of the Cashless Banking Policy in the Economy.

The Nigerian government and its regulatory authorities have made significant efforts to harmonise the rapidly evolving electronic banking landscape with the necessary regulations and institutional structures at the national level (Ernest & Fadiya, 2022). Consequently, the banks were vulnerable to various risks, such as transactional, strategic, reputational, and foreign currency threats. Lack of appropriate operational infrastructure, inadequate internet frameworks, and high expenses associated with acquiring and maintaining them sometimes prevent a significant portion of the population from using them, even in areas where they are available (Chison & Mike, 2018). However, it was not until 2003 that the first electronic banking standards were enacted.

Concept of Financial Performance

Financial performance measure's organizational ability to make money via its core operations. Financial performance is used to compare similar companies in the same industry and it also indicates a company's financial well-being over a specific period. There are various ways to evaluate an organization. However, profitability is the most common term (Kket & Egu, 2022; Hussein & Elyjoy, 2018). Profitability measures how much a company makes from its labor, management, and capital. Revenue-cost correlation and return magnitude in connection to corporate investment size are examined in profitability research (Gilbert & Wheelock, 2007). Return on assets (ROA), Return on Equity (ROE), Net Profit Margin (NPM), etc are common profitability measures. Return on Equity (ROE) is a commonly used profitability statistic in the banking sector. The banking sector has used ROE as a means of allocating capital within and between divisions. ROE is a financial metric that measures the ratio of a company's net income to its total assets book value (Mehran, 1995). The formula for calculating ROE is the ratio of earnings before tax to equity (EBT/Equity). The justification for using ROE is based on the principle that the primary objective is to optimise the financial gains for shareholders, who own ownership in the company.

Empirical Review and Hypotheses Development

A comprehensive investigation has been carried out on the relationship between the cashless banking system and the prosperity of Deposit Money Banks (DMBs). However, there is a significant lack of research that combines several elements to measure performance. Examples, Makinwa (2021), Okechukwu and Yua (2021), Akani and Obiosa (2020), Usman (2020), Akindayo, Shadera, and Solomon (2020), Gambo (2020), Nwakoby, Chukwu, and Ogbenetega (2020), Ul-Hug and Hossain (2020), James and Eloho (2020), analyse the impact of a cashless policy on the performance of banks in Nigeria.

Shedrack (2021), with the aid of a multiple regression model, demonstrates that the cashless policy significantly impacts the performance of banks in the Nigerian banking system. The study revealed that using Automated

Teller Machine (ATMVL) and Point of Sales (POSVL) positively impacted banks' performance; however, this effect was not statistically significant. The impact of web-based technique volume and bank size on the performance of banks was found to be negative and not statistically significant.

Adu and Williams (2022) investigate the impact of cashless policies on the performance of commercial banks in Nigeria. The goals include analysing the impact of ATM, NEFT, POS, and e-banking transactions on commercial banks' performance in Nigeria. The study found that ATM, NIP, mobile banking, and cheque transactions all had a major impact on the performance of commercial banks in Nigeria. As a result, the study advised that banks finance training for technical workers abroad so that they can learn and update themselves on new and innovative technologies employed in the banking sector. Adamu and Adaora (2023) examine the effect of inclusion initiatives on the performance of Nigeria's banking industry. Using an ex-post facto research technique, the OLS model reveals that POS and ATM substantially impact Nigeria's banking system's overall efficiency and effectiveness. The research recommends, among other things, that the Central Bank of Nigeria reduce electronic payment transaction rates to promote broader inclusion.

Charity, Victoria, Chima, and Udeoba (2024) explore the impact of automated teller machines (ATMs) and mobile banking on the performance of Nigerian deposit money institutions. The analysis used time series data from the Central Bank of Nigeria's Statistical Bulletin from 2009 to 2021. The findings indicate that automated teller machines have a significant impact on the performance of Nigerian DMBs. The study concluded that e-banking has enhanced banking access for users while also allowing banks to extend their operations to reach more people. Ajuonu and Uzodike (2024) investigate the impact of the Cashless Policy on the Accounting Performance of Some Selected DMBs in Nigeria. The ex-post facto research design was used, and the data were analysed using multiple regression analysis. The study discovered that ATM transactions substantially affected the ROE of DMBs in Nigeria. However, POS transactions significantly affect the NPM of selected DMBs. The study concluded that the volume of ATM and E-banking transactions substantially impacts Nigerian DMBs' revenues, as does the volume of POS transactions on client deposits. Prior research, including Agu and Agu (2020), Okafor (2020), Ignoroje and Okoroyibo (2020), Ogutu and Fatoki (2019), Agu and Nwakwo (2019), Itah and Ene (2014), and Abaenewe, Ogbulu, and Ndugbu (2013), has frequently employed metrics such as ROE, ROA, EPS, and NPAT. Nevertheless, there exist inconsistencies in their findings. Owing to these controversies in their findings, the study hypothesised that:

H_{01}: There is no significant impact between cashless banking transactions and Return on Equity (ROE) of Deposit Money Banks (DMBs) in Nigeria.

H_{02}: There is no significant impact between cashless banking transactions and Return on Asset (ROA) of Deposit Money Banks (DMBs) in Nigeria.

Theoretical Framework

The adoption of cashless banking policy can be explained using several theories that provide insights into the factors influencing the acceptance and impact of digital technologies. This study focuses on the Technology Acceptance Model (TAM). This theory offers a comprehensive framework for understanding the drivers of cashless banking policy adoption and its implications for the performance of deposit money banks in Nigeria.

The Technology Acceptance Model (TAM), developed by Fred Davis in 1989, is instrumental in understanding how individuals accept and use technology. The model posits that two primary factors, perceived usefulness (PU) and perceived ease of use (PEOU), influence users' attitudes towards a technology, which subsequently affects their intention to use it and, ultimately, their actual usage. In the context of cashless banking policy adoption, TAM can be applied to understand the attitudes of bank employees and customers towards cashless technologies. Perceived usefulness may include increased convenience, faster transactions, enhanced service quality, and improved security associated with cashless banking. Perceived ease of use encompasses the user-friendliness of the technology, accessibility across multiple devices, and availability of technical support. By focusing on these aspects, banks can encourage the adoption of cashless banking systems, potentially leading to better operational efficiency and higher customer satisfaction.

RESEARCH METHOD

Research Design

The study used a mixed-methods research strategy, using an ex post facto approach. The ex post facto research design, or a retrospective or non-experimental research design, is an observational study where the researcher examines the relationship between variables without actively manipulating them. The study population comprises nineteen (19) listed commercial banks classified into national and international licensed banks on the Nigerian Exchange Group (NGX) as of 2021. Census sampling techniques were employed since the entire population was studied.

Sources of Data

Data was sourced via structured/closed-ended questionnaire and annual accounts and reports of the sampled firms. A five-point Likert-type scale was used to seek response rate and reduce respondents' frustration level, as noted by Pondent (2017). In addition, a structured question is mostly recommended due to the desire to avoid a lacklustre response, which could result in common method bias (Dillman, Smyth & Christian, 2014). The data was analysed with the aid of SEM-PLS and panel regression techniques. The study covers 12 years, spanning from 2012 to 2023. The justification for selecting this time frame is based on the fact that the cashless system was introduced on January 1 2012, and since then, it has occupied a major policy applicable in the Nigerian banking sector.

Methods of Data Analysis

The study adopts both descriptive and inferential statistics as methods of data analysis. The panel regression analysis was employed to analysed the quantitative data and further show the significance level of the variables, from which a stance was made on the failure to reject or reject the earlier formulated hypotheses. In addition, the study used structural equation model, specifically Smart-PLS, to analysed the qualitative data and also ascertain the validity and reliability of the research instrument. These was undertaken after conducting preliminary analyses, including missing values, nonresponse bias, common method bias, detection of outliers, and normality tests using Statistical Package for Social Sciences (SPSS) version 27.

Instruments of Data Analysis

The instruments used in this study were adopted from past studies, with minor changes to suit the study. Firm performance was measured using ROE and ROA adopted from Spillan and Parnell (2006). The cashless system was measured using the adopted 7-item Adamson University Survey Questionnaire on Cashless Society (2018). A sample of a question is "Cashless payment is much more convenient". The reported Cronbach's alpha is 0.798, showing the instrument is reliable and adequate for the study.

Model Specification

The panel regression model to test the hypotheses was adopted from the study of Chikwemme and Nwadialor (2019). The models were specified as follows:

$FP = CS$……..……..…… (i)

Where the equation provided reads thus:

$FP = \beta_0+\beta_1 CIB_{it}+\beta_2 MB_{it}+\beta_3 GPAY_{it}+\beta_4 PD_{it}+\beta_5 RMT_{it}+\varepsilon_{it}$ ……..…….(ii)

$ROE = \beta_0 + \beta_1 CIB_{it} + \beta_2 MB_{it} + \beta_3 GPAY_{it} + \beta_4 PD_{it} + \beta_5 RMT_{it} + \varepsilon_{it}$ ….....(iii)

$ROA = \beta_0 + \beta_1 CIB_{it} + \beta_2 MB_{it} + \beta_3 GPAY_{it} + \beta_4 PD_{it} + \beta_5 RMT_{it} + \varepsilon_{it}$……..…….....(iv)

Where:

CS = Cashless System

GPS = Global Pay System

CIB = Corporate Internet Banking

MBS = Mobile Banking System

PDS = Pay Direct System

RMT= Remita

FP = Financial Performance

ROA = Return on Assets

ROE = Return on Equity

β_1 - β_5 = are the parameters to be estimated

i = represents individual firms

t = stands for time period

ε = is the error term of the model

Variables Description and Measurement

This sub-section describes the study's various variables, which are made up of both dependent and independent variables, and how they are measured (proxies) as presented in Table 3.1.

Table 3.1: Variables' Description and Measurement

Variables	**Measurement**	**Prior Studies**
Dependent Variables = Financial Performance		
Return on Asset (ROA)	Net Profit / Total Asset	Abdullahi (2021), Okechukwu and Yua (2021)
Return on Equity (ROE)	Net Profit / Net Equity	Ignoroje and Okoroyibo (2020), Ene (2020), Ighoroje (2021)
Independent Variables: Cashless Banking Policy		
Global Pay (GPAY)	Total volume of global pay transactions for DMBs	Very few studies have employed this variable to measure the cashless system.
Corporate Internet Banking (CIB)	Total volume of corporate internet banking transactions for DMBs	Ihpefan et al. (2018), Mustapha (2018), Oyomo (2018), and Okafor (2020).
Mobile Banking (MB)	Total volume of mobile banking transactions for DMBs	Ihpefan et al. (2018), Mustapha (2018), and Oyomo (2018).

Pay Direct (PD)	Total volume of direct pay transactions for DMBs	Ene (2020)
Remitta (RMT)	Total volume of Remitta transactions for DMBs	Ene (2020)

Source: Author's Compilation (2024).

DATA PRESENTATION AND ANALYSIS

This section presents data collected by administering questionnaires to respondents, and the analysis is provided in Table 4.1.

Table 4.1: Questionnaire Distribution and Response Rate

Questionnaire	Frequency	Rate%
Distributed questionnaires	422	100
Unreturned/Not responded	5	1.2
Returned questionnaires	417	98.8
Rejected/Removed	15	3.6
Retained/Usable	402	95.2

Source: Field Work (2024).

The distribution and response rate of the questionnaires for the study comprised 422 questionnaires, 417 of which (98.8%) were returned. Among the returned questionnaires, 15(3.6%) were rejected or removed. Consequently, 402(95.2%) were retained and deemed usable for analysis. This high response rate and retention of usable questionnaires indicate a robust sample size, enhancing the reliability and validity of the study's findings. This is in tandem with Ryu (2020) and Ojeleye, Abu-Abdissamad, Umar, and Usman (2022), who postulate that there is no agreed-upon criterion for a minimum acceptable response rate. Also, Malhotra and Grover recommended that a 50% response rate is sufficient for data analysis and reporting.

Analysis of Missing Values

The analysis of the missing values is presented in Table 4.2.

Table 4.2 Computation of Missing Values

Latent Variables	Number of Missing Values
Global Payment System	6
Corporate Internet Banking	5
Mobile Banking System	7
Pay Direct System	5

Remita	3
Financial Performance	8
Total	34 out of 12,060 data points
Percentage of missing values: 0.28%	

Source: Researcher's Compilation (2024).

Note: The missing value percentage is derived by dividing the number of randomly missing values for the entire data set by the total number of data points multiplied by 100.

Table 4.2 shows that only 34(0.28%) data points from the initial data set were randomly missing. However, no "golden rule" exists for an acceptable percentage of missing values for valid statistical inference in a data set (Aliyu, 2020). Researchers have established that missing data of less than 5% for sample and variable missing data of less than 10% are generally acceptable and amenable to any imputation strategy (Hair et al., 2014). Since the missing data was less than 10%, the mean substitution imputation approach replaced the missing data. Furthermore, experts believe that mean substitution is the simplest technique for replacing missing data with a probability of less than 5% (Tabachnick & Fidell, 2012).

Normality Test

Wetzels, Odekerken-Schröder, Van Oppen (2009), Reinartz, Haenlein, and Henseler (2009) have demonstrated that SEM-PLS works flawlessly with non-normal data. Nonetheless, Hair et al. (2019) suggested that excessively skewed data increases bootstrap standard error, which may lead to underestimating the statistical significance of path coefficients. Therefore, this study used multivariate normality to examine the data distribution using Kurtosis and Skewness to check the normality. The scores for Skewness and Kurtosis of the research variables are shown in Table 4.3.

Table 4.3: Normality Test: Skewness and Kurtosis Statistics (n=412)

	N Stat.	Min.	Max.	Mean	Std. Dev	Skewness	Std. Error	Kurtosis	Std. Error
CIB	402	1.235	5.000	3.743	0.484	1.031	0.122	0.332	0.244
GPS	402	1.342	5.000	3.943	0.348	0.238	0.122	-1.363	0.244
MBS	402	0.987	4.958	3.854	0.389	0.680	0.122	-0.520	0.244
PDS	402	1.123	4.896	3.847	0.386	0.398	0.122	-1.014	0.244
FP	402	1.286	5.000	2.765	0.904	0.702	0.122	-0.725	0.244
RMT	402	1.243	5.000	2.515	0.612	0.322	0.122	-0.459	0.244

Source: SPSS Version 27, (2024).

Based on the analysis in Table 4.3, it is determined that the data is normal because the absolute values of Skewness and Kurtosis for all items in this research are within the permitted ranges of < 2 and < 7, respectively. Skewness levels of less than 2 and Kurtosis values of fewer than 7 are advocated (Curran & Blackburn, 2001). Furthermore, Kline (2016) argues that absolute Skewness values larger than 3 and Kurtosis values greater than 10 may suggest an issue, while values greater than 20 may signal a more significant problem.

Multicollinearity Test

Two (2) techniques are used in this work to detect multicollinearity. The correlation matrix of the exogenous latent constructs was used as the initial strategy. A correlation value of 0.90 or above suggests multicollinearity between exogenous latent components (Hair et al., 2019). Table 4.5 shows that all the exogenous variables' correlations were below the threshold (i.e., r = 0.90). Based on the correlation matrix, this suggests that there is no multicollinearity among these variables. Secondly, the researcher looked at all the exogenous latent constructs' tolerance levels and variance inflation factor (VIF) values.

Hair et al. (2014) and Field (2017) advocated that the commonly recognised level of multicollinearity of a VIF value ≤ 10 indicates no multicollinearity, but a value more than 10 indicates severe multicollinearity. While a tolerance level of ≥ 0.1 indicates no multicollinearity, a number less than 0.1 indicates substantial multicollinearity. However, Kock (2015) argued that the presence of VIF more than 3.3 and less than 0.303 tolerance level is a sign of pathological collinearity and common method bias.

Table 4.4: Correlation Matrix (n=402).

Construct	GPS	CIB	MBS	PDS	RMT
GPS	1				
CIB	.031	1			
MBS	.681**	0.021	1		
PDS	.485**	0.021	.732**	1	
RMT	.812**	0.000	.553**	.553**	1

Source: SPSS Version 27 (2024).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 4.4 shows that multicollinearity is absent among the exogenous latent components since the VIF values are smaller than the 0.303 threshold Kock (2015) indicated. As a result, multicollinearity is not a concern in our investigation.

Table 4.5: Tolerance Level and Variance Inflation Factor (VIF) Values

		Collinearity Statistics	
Endogenous Variable	**Latent Constructs**	**Tolerance level**	**VIF**
	GPS	0.836	1.196
FP	CIB	0.996	1.004
	MBS	0.502	1.992
	PDS	0.389	2.574
	RMT	0.485	2.062

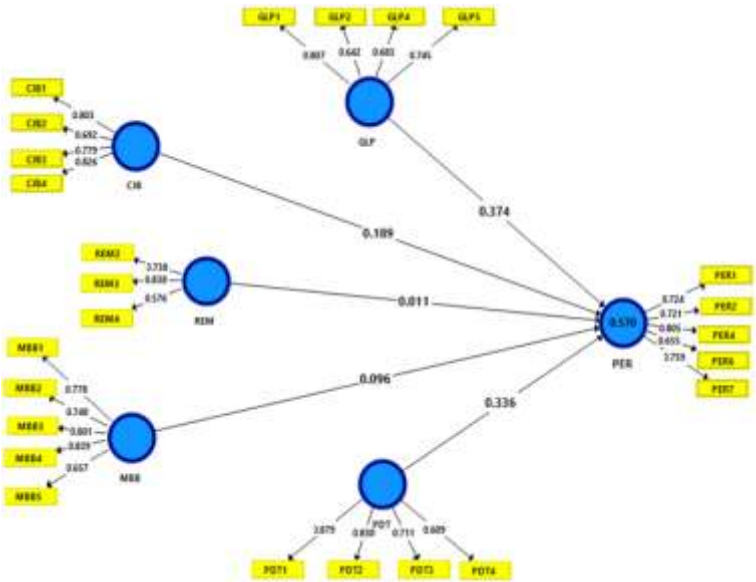
Source: SPSS Version 27 (2024).

Table 4.5 shows the Tolerance and Variance Inflation Factor (VIF) values for five latent constructs, assessing collinearity. A higher tolerance level (>0.2) and VIF values below 5 indicate low multicollinearity, suggesting reliable data for regression analysis. GPS (Tolerance: 0.836, VIF: 1.196) and CIB (Tolerance: 0.996, VIF: 1.004) have very low VIF values, indicating minimal multicollinearity.

Assessment of SEM-PLS Path Modelling

The statistical outcomes of the various analyses, such as the reliability of individual items measuring each latent construct, the internal consistency reliability, and discriminant validity, among others, were discussed. Therefore, the PLS algorithm was used to assess individual item reliability and other measurement model criteria, with outer loadings indicating the reliability of reflective constructs. According to Hair et al. (2014), an outer loading of 0.70 is ideal for established scales, but items with loadings between 0.40 and 0.70 may be retained if leaving them improves the Average Variance Extracted (AVE) and Composite Reliability (CR). Following Hulland's (1999) guideline, loadings below 0.5 should be excluded. Consequently, five items were removed, improving the AVE and CR, leaving the remaining items suitable for further analysis as shown in Figure 4.1 and Table 4.6.

Figure 4.1: Measurement Model



Source: Smart PLS version 3.2.8 (2024).

Figure 4.5.1 and Table 4.6 collectively present the measurement model's assessment, showcasing the evaluation of both item reliability and the overall construct validity and reliability for the reflective constructs examined in the study. The indicator loadings for each construct met the minimum threshold for acceptability, indicating sufficient individual item reliability for most items. However, five items—FP3, FP5, FP8, GPS3, and RMT1—fell below the acceptable loading criteria and were removed to enhance the model's quality. Eliminating these items improved Average Variance Extracted (AVE) and Composite Reliability (CR) metrics, strengthening construct validity. The remaining items, all of which met or exceeded the required loading threshold, were deemed reliable and valid for continued analysis in the study. This refinement ensures that the measurement model aligns with established academic standards for reliability and validity, enabling more robust and accurate structural model evaluations in subsequent analyses.

Table 4.6: Item Loadings, Internal Consistency, and Average Variance Extracted (AVE).

Constructs	Indicators	Loadings	Cronbach's Alpha	Composite Reliability	AVE
Corporate Internet Banking	CIB1	0.803	0.781	0.858	0.603

	CIB2	0.692			
	CIB3	0.779			
	CIB4	0.826			
Global Pay	GPS1	0.807	0.715	0.812	0.521
	GPS2	0.642			
	GPS4	0.683			
	GPS5	0.745			
Mobile Banking	MBS1	0.778	0.827	0.877	0.588
	MBS2	0.748			
	MBS3	0.801			
	MBS4	0.839			
	MBS5	0.657			
Pay Direct	PDS1	0.879	0.762	0.847	0.585
	PDS2	0.830			
	PDS3	0.711			
	PDS4	0.609			
Financial Performance	FP1	0.724	0.785	0.854	0.540
	FP2	0.721			
	FP4	0.805			
	FP6	0.655			
	FP7	0.759			
Remita	RMT2	0.738	0.705	0.765	0.526
	RMT3	0.838			
	RMT4	0.576			

Source: Researcher's Composition (2024).

Assessment of Discriminant Validity

The discriminant validity assessment used the cross-loadings approach, a common method for evaluating

reflective constructs. This technique involves comparing the loadings of each indicator on its associated construct with its cross-loadings on other constructs. For discriminant validity to be established, each indicator's loading on its designated latent variable should be higher than its corresponding cross-loadings on other constructs, indicating that the indicators are more strongly associated with their respective constructs than others. Hair et al. (2019) describes this criterion as relatively lenient for confirming discriminant validity, providing an initial check for the distinctiveness of constructs. The results of this examination, as presented in Table 4.7, confirm that the cross-loading values meet the threshold, supporting the discriminant validity of the constructs under study. This analysis ensures that each construct is empirically unique, which is critical for the validity of the structural model's subsequent interpretations.

Table 4.7: Measurement Model: Discriminant Validity (Cross Loading)

Indicators	CIB	GPS	MBS	PDS	FP	RMT
CIB1	0.803	0.442	0.539	0.067	0.477	0.484
CIB2	0.692	0.454	0.169	0.179	0.389	0.123
CIB3	0.779	0.472	0.480	0.103	0.319	0.432
CIB4	0.826	0.494	0.472	0.150	0.407	0.381
GPS1	0.384	0.807	0.448	0.317	0.598	0.532
GPS2	0.346	0.642	0.292	0.308	0.399	0.203
GPS4	0.559	0.683	0.457	0.083	0.377	0.302
GPS5	0.481	0.745	0.421	0.148	0.457	0.241
MBS1	0.432	0.395	0.778	0.021	0.286	0.507
MBS2	0.516	0.390	0.748	0.088	0.326	0.565
MBS3	0.474	0.563	0.801	0.325	0.523	0.502
MBS4	0.280	0.374	0.839	0.278	0.460	0.521
MBS5	0.412	0.387	0.657	0.450	0.314	0.333
PDS1	0.256	0.418	0.379	0.879	0.548	0.381
PDS2	0.153	0.165	0.185	0.830	0.357	0.185
PDS3	0.071	0.064	0.271	0.711	0.299	0.273
PDS4	-0.107	0.179	0.068	0.609	0.293	0.146
FP1	0.514	0.383	0.288	0.299	0.724	0.280
FP2	0.323	0.373	0.304	0.451	0.721	0.314

FP4	0.452	0.467	0.507	0.459	0.805	0.436
FP6	0.315	0.512	0.393	0.249	0.655	0.325
FP7	0.324	0.624	0.400	0.413	0.759	0.284
RMT2	0.329	0.286	0.457	0.181	0.313	0.738
RMT3	0.374	0.406	0.433	0.374	0.416	0.838
RMT4	0.310	0.326	0.480	0.129	0.204	0.576

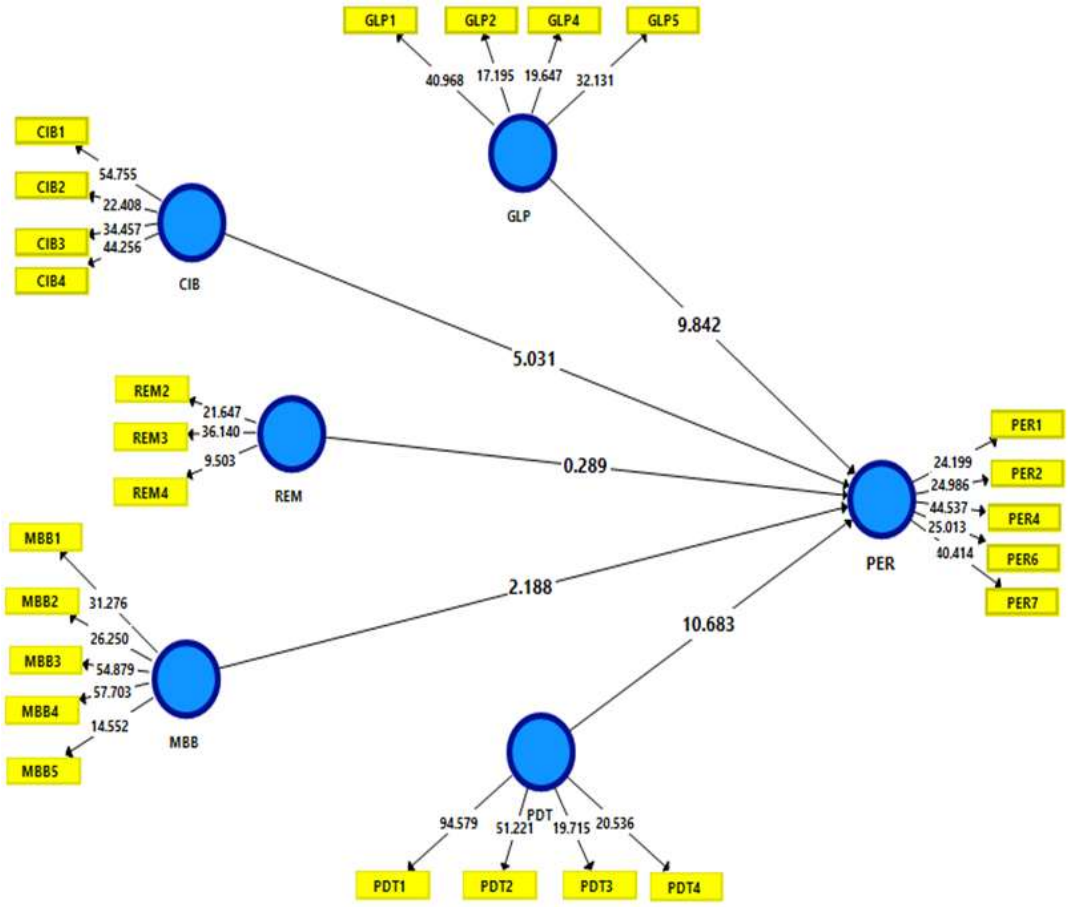
Source: SEM-PLS Version 3.2.8 (2024).

Based on the cross-loading analysis, it is clear from Table 4.6 that discriminant validity has been established for each of the reflective latent variables of this study, as the indicators' loadings (i.e., bolded loadings) of individual constructs are higher than their corresponding loadings diagonally.

Assessment of the Structural Model

This section showed the structural equation model of the data analysis for the direct and mediated relationship using bootstrap analysis. More specifically, a standard bootstrapping approach was used using 5000 bootstrap samples for 402 cases to investigate the significance of the path coefficients of the direct relationship (Hair et al., 2014; Hair et al., 2021).

Figure 4.2: Structural Model



Source: SEM-PLS Version 3.2.8 (2024).

Path Coefficient (Direct Effect)

Hypotheses	R.Ship	Beta	Std. Dev.	T Statistics	P Values	Decision
H_{01}	GPAY -> FP	0.374	0.038	9.842	0.000	Rejected
H_{02}	CIB -> FP	0.189	0.037	5.031	0.000	Rejected
H_{03}	MB -> FP	0.096	0.044	2.188	0.029	Rejected
H_{04}	PD -> FP	0.336	0.031	10.683	0.000	Rejected
H_{05}	RMT -> FP	0.011	0.040	0.289	0.773	Accepted

Source: SPSS Version 27 (2024). ***p<0.01, **p<0.05.

Table 4.8 presents path coefficients representing the direct effects on licensed DMBs' performance in Nigeria. The first hypothesis (H_{01}) posits a relationship between Global Pay (GPAY) and financial performance (FP), with a beta coefficient of 0.374. The standard deviation (STDEV) associated with this coefficient is 0.038, yielding a T statistic of 9.842 and a p-value of 0.000 at 1% ($p<0.01$) significance level. Therefore, the null hypothesis is rejected, suggesting that GPAY significantly influences the performance of License DMBs in Nigeria. The second hypothesis (H_{02}), which examines the relationship between Corporate Internet Banking (CIB) and FP, exhibits a beta coefficient 0.189. The associated STDEV is 0.037, resulting in a T statistic 5.031 and a p-value of 0.000. Consequently, H_{02} is rejected, indicating a significant impact of CIB on the performance of licensed DMBs in Nigeria.

The third hypothesis (H_{03}) focuses on Mobile Banking (MB) and its effect on FP, revealing a coefficient of 0.096, a standard error of 0.044, a t-statistic of 2.188, and a p-value of 0.029. These figures indicate significance at the $p<0.05$ level. Therefore, H_{03} is rejected, suggesting a significant relationship between MB and the performance of licensed DMBs in Nigeria. Hypothesis four (H_{04}) explores the influence of Pay-direct (PD) on financial performance (FP), yielding a beta coefficient of 0.336. The associated STDEV is 0.031, resulting in a T statistic of 10.683 and a p-value of 0.000. With a significance level of $p<0.01$, H04 is rejected, indicating a significant impact of PDS on the performance of license DMBs in Nigeria. Hypothesis five (H_{05}) examines the relationship between remita (RMT) and financial performance (FP), revealing a beta coefficient of 0.011. The STDEV associated with this coefficient is 0.040, yielding a T statistic of 0.289 and a p-value of 0.773, failing to reject the null hypothesis. This suggests that RMT does not significantly influence the financial performance of DMBs in Nigeria. Furthermore, the computation of the coefficient of determination (R^2) is presented in Table 4.10.

Table 4.10 Coefficient of Determination (R^2).

Construct	R^2
Performance	0.570

Source: SPSS Version 27, (2024).

An R-square (coefficient of determination) value of 0.570 indicates that approximately 57% of the variance in the dependent variable is explained by the independent variables included in the model. In other words, factors such as Global Pay System and Corporate Internet Banking account for about 57% of the variability observed in the financial performance of licensed DMBs in Nigeria. Therefore, while the model provides valuable insights into the factors affecting DMBs' performance, it does not capture the entire complexity of the phenomenon. As a result, by Chin's (1998) submission, which stated that R^2 values of 0.67, 0.33, and 0.19, respectively, should

be considered substantial, moderate, and weak. It can be concluded that the R^2 value explained by exogenous latent variables on the target endogenous latent variable of 0.570 is moderate.

Assessment of Effect Size *(f^2)*

Effect size (f^2) provides a measure of how strong the relationship is between variables in a statistical analysis. It goes beyond just determining if the relationship is statistically significant, helping researchers understand the practical importance of their findings (Ojeleye et al., 2023). A larger effect size indicates a stronger relationship between variables, while a smaller one suggests a weaker connection. By considering effect size alongside significance testing, researchers can better assess the real-world significance of their results and understand the impact of independent variables on the dependent variable (Haie et al., 2010). Essentially, effect size helps researchers gauge the actual strength of relationships in their data, making their interpretations more meaningful and applicable to real-life situations. Thus, the computation of the effect size is achieved using Cohen's formula (Cohen, 1988; Hair et al., 2021) given as:

$$f^2 = \frac{R^2 \text{ Included} - R^2 \text{ Excluding}}{1 - R^2 \text{ Included}}$$

Where:

f^2 = *the f-square value that specifies the effect size of an exogenous variable's influence on an endogenous variable.*

$R^{2Included}$ = *is the R^2 value of the endogenous variable before omitting a particular exogenous construct.*

$R^{2excluded}$ = *represents the changes in the R^2 value of the endogenous variable after excluding a particular exogenous variable from a model.*

Based on the above formula, the *f2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects,* respectively (Cohen, 1988). Similar to indirect relationship hypothesis testing, the change in R^2 value when a certain exogenous variable is removed from the model is used to determine if an omitted variable significantly influences the latent endogenous variable (Hair et al., 2014). Table 4.11 shows the effect size results.

Table 4.11: Assessment of Effect Size (f^2)

Constructs	FP	Effect Size
CIB	0.047	Small
GPS	0.176	Medium
MBS	0.010	Small
PDS	0.220	Medium
RMT	0.000	Nill

Source: SEM-PLS Version 3.2.8 (2024).

Table 4.11 assesses the effect size (f^2) for various constructs in the analysis. The effect sizes indicate the magnitude of each construct's impact on the financial performance (FP) of license DMBs in Nigeria. CIB's effect size is 0.047, which is a small effect, suggesting a modest influence on bank performance. GPS shows a larger effect size of 0.176, classified as a medium effect, indicating a more substantial impact on bank performance than CIB.

Predictive Relevance *(Q^2)*

Aside from assessing the degree of the R^2 value as a measure of predictive relevance, the Stone-Q2 Geisser's value is critical (Garson, 2016). This criterion denotes a model's predictive significance (Hair et al., 2014). However, this criterion may be viewed as an extra evaluation of the model fit in the PLS-SEM analysis (Duarte & Raposo, 2010), and so the Q^2 indicates how effectively the observed values are formed in the model as well as its parameter estimations (Chin, 1998). Consequently, the exogenous latent variables' predictive relevance (Q2) on the reflective endogenous latent variable was assessed using a cross-validated redundancy criterion (Hair et al., 2014). As a result, a model with a Q^2 greater than zero is assumed to have predictive relevance or practical utility (Reinartz, Haenlein & Henseler, 2009). As a result, the higher the Q^2, the more predictive value the external latent factors have on the endogenous latent variable (Duarte & Raposo, 2010). Table 4.11 displays the Q^2 value acquired using the blindfolding process.

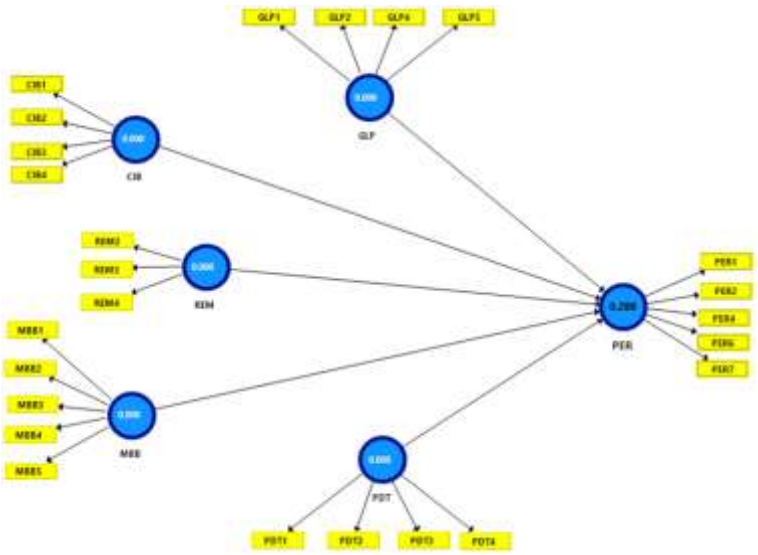
Table 4.11: Predictive Relevance(Q^2)

Constructs	SSO	SSE	Q^2 (=1-SSE/SSO)
CIB	2,056.000	2,056.000	
GPS	2,056.000	2,056.000	
MBS	2,570.000	2,570.000	
PDS	2,056.000	2,056.000	
FP	2,570.000	1,830.800	0.288
RMT	1,542.000	1,542.000	

Source: SPSS Version 27 (2024).

Depicted in Table 4.11 are the blindfolding outputs of the cross-validated redundancy (Q^2) of the endogenous latent variables of this model. It is glaring that cross-validated redundancy (Q^2) is greater than zero (0.288) as shown in Table 4.11. It simply signifies the existence of a path model predictive relevance on the performance of a deposit money bank (Chin, 1998; Hair et al., 2014). Presented in Figure 4.3 is the diagrammatic illustration of the blindfolding output indicating the predictive relevance variable.

Figure 4.3: Predictive Relevance



Source: Smart PLS Version 3.2.8 (2024).

Presentation of Quantitative Analysis

This sub-section summarises the results of the various post-estimation tests conducted on secondary data. These tests include the fixed random effect test, the Hausman test to select the best-fitted model for the study, and the Breusch-Pagan-Langford test to determine the existence or absence of heteroscedasticity. Heteroscedasticity was discovered in all models, prompting a robust regression test. The fixed and random effects findings can be found in the appendices, whereas the results of the Hausman test, Breusch Pagan Lagrangean test, and robust regression test are shown and described here.

Model 1

The analysis of the regression models commences with the determination of the Hausman specification test, as shown in Table 4.12. The Hausman test is used to determine which model is best suited for the study between the FE and RE models. The role, therefore, is that a P-value of less than 0.05 (5%) indicates that the FE should be chosen over the RE.

Table 4.12 Hausman Specification Test

Chi2	150.42
Prob Chi2	0.000

Source: STATA Version 14 (2025).

Table 4.12 reveals a P-value of 0.000, and the Chi-square statistic of 150.42 indicates a significant difference between FE and RE estimates. The significant p-value indicates that the null hypothesis is rejected in favour of FE. This implies that the Fixed Effects model better fits the data than the Random Effects model. Furthermore, the Breusch-Pagan Lagrangian Multiplier (LM) test was computed to analyse the presence of homoscedasticity.

Table 4.13 Breusch-Pagan Lagrangian Test

Chi2	14.35
Prob Chi2	0.002

Source: STATA Version 14 (2025).

The LM test produced a Chi-square statistic of 14.35 with a p-value of 0.002, providing strong support against the null hypothesis of homoscedastic residuals and no panel-level effect. This finding shows high unobserved heterogeneity between entities, which supports adopting the Fixed Effects model instead of the Pooled OLS estimator. Similarly, the Hausman test ($\chi^2 = 150.42$; $p = 0.000$) confirmed that the entity-specific effects are associated with the regressors, indicating that the Fixed Effects model is the most suitable estimation strategy for the data. The results of the FE model with Robust Standard Errors are presented in Table 4.14.

Table 4.14 FE Regression (Robust) Results

Dependent Variables = ROE			
Independent Variables	**Coeff.**	**Std. Error**	**P-value**
GPS	-0.046	0.017	0.018
CIB	0.034	0.022	0.142

MBS	0.022	0.019	0.283
PDS	0.013	0.015	0.388
RMT	-0.017	0.015	0.297
C	0.091	0.276	0.748

Source: STATA Version 14 (2025).

The results of the FE model with Robust Standard Errors as presented in Table 4.14 provide valuable insights into the relationship between several corporate internet banking instruments and Return on Equity (ROE) of the Nigerian DMBs. Global Pay (GPAY) is a statistically significant predictor of ROE, with a negative coefficient of -0.046 and a p-value of 0.018, suggesting a significant influence at 5%. This shows that the growing use of GPAY is associated with decreased corporate profitability. The negative association could be due to initial integration expenses, transaction processing fees, or inefficiencies during the adoption period. It could also reflect the nature of GPAY, which often has huge transaction volumes but potentially low profitability. Thus, while GPAY enables cashless and cross-border transactions, its short-term impact on businesses may be negative.

The Corporate Internet Banking (CIB) variable shows a positive coefficient of 0.034 but was not statistically significant (p = 0.142). This suggests that, while CIB may help to improve operational efficiency through automated payment processing, bulk transactions, and digital cash management, these operational gains are yet to translate into statistically measurable increases in profitability. Likely, enterprises are still in the transitional phase of adoption, or utilisation is concentrated among a few technologically sophisticated organisations. Mobile Banking (MB) exerts a positive coefficient of 0.022 on ROE, but it is not statistically significant (p = 0.283). This suggests that while mobile banking has increased accessibility and convenience, its direct contribution to returns is marginal or delayed due to market saturation, user preferences for low-cost services, or infrastructure limitations.

Other cashless solutions, such as Pay Direct (PD) and Remita (RMT), failed to show significant connections with ROE. PDS had a little positive coefficient (0.013; p = 0.388), but Remita had a negative value (- -0.017; p = 0.297). These findings reflect the platform's specialised functions, particularly in facilitating government-related or public-sector payments, when private institutions may have limited revenue creation potential.

Finally, the findings indicate that CIB can potentially improve operational efficiency. The only major and robust influence comes from GPAP, and it is negative, highlighting the importance of taking a cautious, cost-conscious approach to adopting and developing digital payment networks. These findings support the premise that shifting to a cashless economy may include short-term profitability trade-offs, with long-term gains only apparent with increased user adoption, regulatory support, and process improvement.

Model 2

The analysis commences with the computation of the Hausman specification test. Table 4.15 shows the results of the Hausman test. The Chi2 is 6.180 and the Prob Chi2 is 0.289. The relatively small Chi-squared value indicates insignificant differences between the fixed and random effects models. The p-value of 0.289 is the most significant indicator that evaluates the null hypothesis that the RE model is appropriate.

Table 4.15 Hausman Test

Chi2	6.180
Prob Chi2	0.289

Source: STATA Version 14 (2025).

The null hypothesis states no substantial difference between FE and RE effects estimates. A p-value greater than 0.05 indicates no significant difference between the FE and RE effects models; hence, the RE model is accepted. In this situation, as shown in Table 4.16, the p-value of 0.289 suggests the null hypothesis cannot be rejected. Thus, the RE model is applicable for this investigation. The result of the Breusch-Pagan Lagrange Multiplier (LM) test, which detects the presence of heteroskedasticity in a panel regression model, is presented in Table 4.16.

Table 4.16 Breusch-Pagan Lagrangian Test

Chi2	108.32
Prob Chi2	0.000

Source: STATA Version 14, (2025)

Heteroskedasticity occurs when the variance of the error terms varies between data points, resulting in inefficient estimates and skewed test results. This test aids in deciding if a RE model is acceptable in heteroskedasticity or if a simpler model (such as the pooled OLS model) is sufficient. The Chi-squared value of 108.32 determines whether heteroskedasticity exists in the model. The higher the Chi-squared statistic, the greater the likelihood of substantial heteroskedasticity. In this situation, 108.32 is a reasonably significant value, indicating a high likelihood of heteroskedasticity in the models. The p-value of 0.000 is exceedingly small, far below the standard significance level of 0.05. This low p-value indicates that the null hypothesis of no heteroskedasticity is rejected. The significant heteroskedasticity emphasises the significance of proper methods (e.g., robust standard errors). Table 4.17 shows the RE regression results for the link between Return on Assets (ROA), a key indicator of the internet banking system in Nigeria.

Table 4.17 RE Regression (Robust) Results

Dependent Variables = ROA			
Independent Variables	**Coefficient**	**Robust Std. Error**	**P-value**
GPS	-0.229	0.200	0.253
CIB	-0.094	0.116	0.418
RMT	-0.670	0.107	0.533
CIB	-0.094	0.116	0.418
MBS	-0.114	0.220	0.604
PDS	-0.165	0.199	0.406
C	**16.338**	**4.755**	**0.001**

Source: STATA Version 14 (2025).

The regression was carried out with the Robust Standard Errors test to account for heteroskedasticity, as previously validated by the Breusch-Pagan test. The coefficient for ROA is statistically significant at the 1% level, with a coefficient value of 16.338 and a p-value of 0.001. This implies that changes in the explanatory variables have a substantial and meaningful link with company profitability. This shows that the model gives useful information, even though not all individual components have substantial effects. This indicates that,

holding all other factors constant, expenditure on the internet banking system will increase ROA by approximately 16%.

Global Pay (GPAY) has a negative coefficient of -0.229; however, this effect is statistically insignificant (p-value of 0.253). This implies that, while implementing Global Pay may modestly affect firm-level ROA, the impact is insufficient to be considered significant. The insignificance of GPAY contrasts with its negative and substantial connection with ROE, showing that its negative influence may be greater on equity-based returns than on asset-based returns. Similarly, Corporate Internet Banking (CIB) exerts a negative and insignificant coefficient of -0.094 with a p-value of 0.418. This finding suggests that, while CIB may be modestly linked with a decrease in ROA, the effect is small and most likely attributable to other unobserved firm-level variables or restricted consumption efficiency.

Mobile Banking (MB) shows a coefficient value of -0.114, a robust standard error of 0.220, and a p-value of 0.604. The P-value shows that mobile banking, despite being a significant driver of inclusion, has not resulted in meaningful asset-based profitability increases for businesses. This could be attributed to infrastructure hurdles, excessive transaction costs, or a lack of corporate integration. Pay Direct (PD) also reveals a negative coefficient of -0.165 and a p-value of 0.406, indicating no statistical significance. This supports the view that government-led cashless platforms such as Pay Direct may not immediately improve corporate profitability, presumably due to their administrative focus rather than operational cost savings for firms.

DISCUSSIONS OF FINDINGS

1. The study finds that the nexus between the cashless banking instruments and ROE demonstrates a significant difference in insights given by qualitative and quantitative data. This mismatch in empirical evidence provides fertile ground for Implications, theoretical reflection, and practical policy considerations. The FE model with Robust Standard Errors reveals that the cashless banking policy is associated with a decrease in ROE. A probable explanation for this could be the high initial and ongoing expenditures of establishing and maintaining the cashless infrastructure. However, the SEM-PLS results indicated that the cashless banking policy significantly impacts Nigeria's ROE of licensed DMBs. This finding could indicate a positive user experience, greater digital literacy, and institutional enthusiasm for digital transformation in Nigerian banking.

2. These findings align with the researches by Afolabi and Oluwole (2021), Johnson and Kim (2022), Khan and Ali (2022), Usman and Adeyemi (2021), Singh and Sharma (2020), who found that digital payment systems like Global Pay significantly improve operational efficiency and performance by streamlining transactions and reducing costs as well as increasing transaction speed and accuracy. Conversely, this contradicts the findings of Rodriguez and Lopez (2021) and Choudhury and Nandi (2022), who argue that the digital payment system is associated with high implementation and maintenance costs and security concerns.

3. The regression results further show that none of the cashless banking policy variables statistically significantly influence the ROA of the sampled DMBs in Nigeria. This finding is consistent with Ajayi and Ojo (2019) and Ekanem (2021), who found that adopting digital payment platforms does not always result in improved outcomes for firms, especially when usage inefficiencies, infrastructural deficits, or user inertia are present. On the other hand, the qualitative analysis observed that the cashless policy favoured the ROA of the licensed DMBs in Nigeria. This result is supported by Johnson and Kim (2022) and Khan and Ali (2022), who demonstrated that DMBs provide customers with convenient access to banking services and reduce the need for physical branches, thereby cutting costs and improving profit margins, leading to higher customer satisfaction and increased transaction volumes. In contrast, Choudhury and Nandi (2022) and Rodriguez and Lopez (2021) provide a differing perspective, suggesting that while mobile banking has potential benefits, the actual impact on performance can be limited by issues such as cybersecurity threats, customer trust concerns, and the digital divide. They argued that, in some contexts, these challenges may overshadow the advantages, leading to less pronounced improvements in performance metrics.

CONCLUSIONS

The study empirically investigates the nexus between the cashless banking policy and the performance of licensed DMBs in Nigeria. Therefore, this paper concludes that stakeholders, such as bank employees, perceive GPAY as a highly useful instrument for increasing performance, most likely because of its speed, efficiency, and convenience in making real-time payments. Similarly, staff viewed PD as beneficial for government payments and collections, reducing physical cash handling and improving process transparency. The study concludes that Bank personnel and managers opined that CIB is a crucial driver of digital banking efficiency, better customer service, and competitive advantage. The paper concludes that ROE exerts a substantial impact, whilst ROA demonstrates an insignificant influence. This implies that, while a cashless banking policy reduces operating costs and increases returns, its impacts are not evenly spread across all performance indicators. Certainly, cashless banking policy is well received, but results are determined by usage volume, transaction fees, and integration, which differ by bank.

RECOMMENDATIONS

The study finds that the cashless banking policy positively correlates with the financial performance of licensed Deposit Money Banks (DMBs) in Nigeria. The study therefore recommends integrating digital technologies like GPAY, CIB, and MB into their core banking operations. Linking these platforms to lending processes, investment opportunities, and cross-selling strategies will ensure digital advances directly impact revenue growth and shareholder return. The study further recommends management of listed DMBs and regulatory agencies, such as CBN and NDIC, to emphasise the benefits, security, and accessibility of technologies. Similarly, management should prioritise infrastructure upgrades such as dependable network systems, improved cybersecurity, and scalable cloud platforms.

IMPLICATIONS OF THE FINDINGS

The findings from this study reveal critical implications for banking policy, operational strategy, and digital transformation initiatives within the Nigerian sector. Consequently, the mixed results across various performance indicators imply that banks should avoid a one-size-fits-all digital strategy. Instead, they should tailor digital tools to specific performance objectives such as deposit mobilisation, cost efficiency, or profitability. The relatively favourable primary data outcomes indicate that customers and bank staff recognise the potential of cashless tools. However, unlocking that potential requires addressing usability challenges, ensuring service reliability, and building trust.

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