Granger Causality on Digital Capital Expenditure, Bank Size and Credit Risk Management of Deposit Money Banks in Nigeria

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ABSTRACT

In the rapidly evolving global financial ecosystem, banking institutions are increasingly integrating advanced technological infrastructures into their core operational frameworks. While digital capital expenditure can influence financial stability, the precise direction and strength of this relationship in the Nigerian context remains under-researched and poorly understood. This study sought to investigate the causal relationship between digital capital expenditure and the credit risk management of Nigerian deposit money banks, considering the role of bank size. This study employed correlation analysis and pairwise Granger causality techniques. Correlation analysis is essential for understanding the strength and direction of the linear relationship between digital investments and credit risk indicators. Pairwise Granger causality, on the other hand, allows for testing the temporal direction of influence between variables, thereby addressing the question of whether changes in digital infrastructure investments "Granger-cause" changes in credit risk outcomes, or vice versa. This study utilized secondary data sourced from the published audited annual reports and financial statements of 12 selected deposit money banks in Nigeria over a 10-year period (2015–2024). A panel data causality analysis was employed to examine the directional effect of digital capital expenditure on credit risk metrics. Granger causality test results revealed that digital capital expenditure significantly influences the non-performing loan ratio ($F = 4.1721$, $p = 0.0185$), but there is no reverse causality ($F = 0.1884$, $p = 0.8286$). Furthermore, digital capital expenditure significantly impacts the capital adequacy ratio ($F = 8.6627$, $p = 0.0004$), while the capital adequacy ratio does not influence digital capital expenditure ($F = 0.6098$, $p = 0.5457$). Bank size significantly affects capital adequacy ($F = 4.1809$, $p = 0.0183$), but the reverse does not hold ($F = 0.8170$, $p = 0.4450$). The study concluded that digital capital expenditure and bank size have strong predictive power over credit risk management behavior, while the reverse does not hold. It is therefore recommended that bank management proactively prioritize investments in digital infrastructure. Since digital capital expenditure has a unidirectional impact on improving asset quality and solvency, institutions must treat these investments as a core strategic risk management tool rather than mere operational costs to enhance overall financial stability.

INTRODUCTION

In the rapidly evolving global financial ecosystem, banking institutions are increasingly integrating advanced technological infrastructures into their core strategic and operational frameworks. This digital transformation has profound implications for the banking sector, especially in developing economies like Nigeria, where the transition from traditional banking to digitally-driven financial services is accelerating at an unprecedented pace. Despite the mounting scale of these technological investments, empirical understanding of how capitalized digital infrastructure influences the fundamental financial stability and credit risk management of Nigerian banks remains limited and inconclusive. This gap is especially critical given the increasing demand for deposit money banks to maintain robust asset quality, ensure capital adequacy, and navigate the complex risks associated with digital integration in a volatile macroeconomic environment.

The Nigerian banking sector, a critical component of the nation's economic system, has undergone several waves of technological reforms aimed at enhancing operational efficiency, financial inclusion, and risk mitigation. According to the Central Bank of Nigeria (CBN, 2024) and the Nigeria Inter-Bank Settlement System (NIBSS,

2024), electronic payment transactions have surged astronomically, growing from ₦1.55 quadrillion in 2022 to over ₦2.24 quadrillion in 2023. However, despite these massive investments in digital channels, the sector continues to grapple with persistent challenges related to credit risk. Key credit risk outcomes that anchor this study namely the non-performing loan ratio (NPLR), the loan loss provision (LLP) ratio, and capital adequacy (CAR) continue to experience notable volatility. These three indicators are widely used in Nigerian and international banking research because they capture complementary dimensions of credit risk: portfolio quality (NPLR), the bank's forward-looking buffer against expected losses (LLP), and solvency or resilience to unexpected losses (CAR) (Natufe & Evbayiro-Osagie, 2023; Ololade et al., 2023). While there is anecdotal evidence that digitalization inherently improves lending dynamics, the exact temporal direction and strength of this relationship in the Nigerian context remains under-researched and poorly understood.

Further complicating the analysis of digital capital expenditure is the structural role of bank size, which often serves as a critical moderating or control variable in financial performance studies. Larger banks typically possess substantial capital reserves, enabling them to finance massive digital capital expenditures, employ specialized cybersecurity personnel, and spread fixed technological costs across a broader customer base (d'Avernas et al., 2024). This scale advantage suggests that tier-one banks might be better positioned to capture the risk-reducing benefits of technology, potentially amplifying the effect of digital infrastructure on their credit risk management. Conversely, smaller and mid-sized banks may struggle with the high costs of digital integration, leading to a disparate impact across institutions of varying sizes. As such, it becomes imperative to control for bank size in any robust analysis of digital investment and asset quality dynamics to ensure the accuracy and validity of the findings.

Despite theoretical underpinnings suggesting that digital capital expenditure should positively enhance credit risk management by reducing information asymmetry and tightening underwriting standards (EFInA, 2018; Iwedi, 2024) the empirical literature remains deeply divided. Some scholars argue that contemporary bank technology spending, which goes beyond routine IT maintenance into strategic, long-lived outlays intended to change how loans are originated, serviced, and monitored (Moloi & Iredele, 2019), systematically lowers default rates. Others counter that rapid digitalization introduces severe operational vulnerabilities, including new fraud vectors, system outages, and cyber incidents that can produce sudden financial losses and complicate provisioning decisions (Adeagbo et al., 2024). In Nigeria, these inconsistencies reveal a deeper methodological problem: most existing research relies on transaction-based proxies, such as ATM, POS, or mobile usage volumes, rather than actual capitalized digital expenditure, further obscuring the true causal relationships.

In light of the foregoing, this study seeks to investigate the relationship between digital capital expenditure and the credit risk management of Nigerian banks, controlling for bank size. This is especially pertinent as Nigerian banks operate in an environment characterized by stringent regulatory scrutiny, high inflation, and rapidly changing consumer behaviors. Given the increased emphasis on financial system stability and technological innovation, there is a pressing need to empirically determine whether capitalized digital infrastructure genuinely translates into improved asset quality and capital resilience.

To address the identified gap, this study will employ correlation analysis and pairwise Granger causality techniques. Correlation analysis is essential for identifying the initial strength and direction of the linear relationship between digital capital expenditure, bank size, and credit risk indicators. It provides foundational evidence of potential associations, although it does not establish causation. Pairwise Granger causality, on the other hand, allows for testing the temporal direction of influence between variables, thereby addressing the question of whether historical changes in digital capital expenditure systematically "Granger-cause" future changes in credit risk outcomes, or vice versa (Gujarati & Porter, 2020). This is particularly useful in the context of financial time-series data, where dynamic interactions between variables are expected.

The use of these two methodologies is justified by the complex and potentially bidirectional nature of the relationship between technological investment and financial stability. For instance, while enhanced predictive algorithms and digital onboarding may lead to improved loan portfolios and stronger capital adequacy by filtering out high-risk borrowers, it is equally plausible that financially robust banks those already possessing low NPLs and high CAR are the only institutions with the surplus capacity to implement massive digital

infrastructure upgrades. The pairwise Granger causality test is ideally suited for such analyses as it can distinguish between leading and lagging variables over time.

Moreover, the Nigerian capital market is characterized by varying degrees of information asymmetry, aggressive competitive dynamics among deposit money banks, and continuous regulatory shifts. This makes the exploration of causal dynamics even more critical. If empirical evidence suggests that digital capital expenditure significantly reduces credit risk, it could lead to policy interventions mandating minimum technological infrastructure investments. Conversely, if causality runs primarily from credit risk stability to digital expenditure, it may imply that technology is a luxury adopted by financially sound banks rather than a foundational cure for toxic assets.

This study's relevance is further heightened by the ongoing shift towards open banking, artificial intelligence in credit scoring, and the CBN's aggressive cashless policy drive. Nigerian banks, if empirically proven to benefit fundamentally from digital capital expenditure through enhanced asset quality, will be strongly incentivized to transition their business models from traditional collateral-based lending to data-driven, technologically secured credit operations.

The problem underpinning this study is the lack of empirical clarity on the actual causal sequence between digital capital expenditure and credit risk management, particularly considering the moderating role of bank size. By applying correlation and Granger causality techniques, this research aims to fill a crucial gap in the literature, offering insights that could inform strategic bank management, regulatory policies, and financial stability frameworks in Nigeria.

LITERATURE REVIEW

Empirical Literature

Ally et al. (2025) examined the influence of financial technology on non-performing loans (NPLs) within the Tanzanian banking sector. Using data from 30 commercial banks spanning 2010 to 2021, the study employed a two-step system Generalized Method of Moments (GMM) to provide robust findings. The results revealed that FinTech significantly reduced NPLs across all bank categories, indicating that advancements in technology improved credit risk management and reduced loan default rates. A key finding was the differential impact based on bank size: the risk-reducing effects of FinTech were observed to be strongest in small banks, followed by medium and large banks. This suggested that smaller institutions gained disproportionately from adopting new technologies. The study provided crucial, Africa-focused evidence on the risk-mitigating potential of FinTech and highlighted the importance of bank size as a moderating factor in realizing these benefits.

Xu et al. (2025) investigated the complex relationship between market concentration, digital transformation, and bank credit risk in China. The study utilized the Generalized Method of Moments (GMM) to analyze panel data from 114 Chinese banks over the period from 2014 to 2021. The empirical evidence suggested that digital transformation had a significant and dynamic impact on reducing the credit risks associated with banks. However, this effect was moderated by market concentration, as the risk-reducing impact of digitalization tended to diminish as concentration increased. The heterogeneity analysis showed that the positive impact was stronger in small and medium-sized banks, suggesting higher marginal governance benefits for these institutions. The study provided nuanced evidence that while digitalization is a powerful tool for risk mitigation, its effectiveness is conditioned by both the bank's size and the competitive structure of its market.

Chen and Shen (2024) investigated whether and how FinTech affected the systemic risk of Chinese banks. Using bank-level panel data and a system GMM estimator to address causality, the study found that FinTech increased both banks' exposure and their contribution to systemic risk. This finding suggested that while FinTech might offer benefits at the individual firm level, it created new systemic vulnerabilities. The analysis of the sources of this increased risk revealed that FinTech led to a larger scale of interbank business and enhanced the correlation between banks, thereby increasing the possibility of risk contagion throughout the financial system. The heterogeneity analysis showed that these effects were concentrated in local commercial banks, less profitable

banks, and banks in regions with less developed FinTech, highlighting specific areas of vulnerability for regulators to monitor.

Do et al. (2022) evaluated the impact of digital transformation on the performance of Vietnamese commercial banks, with a specific focus on how this effect differed across bank sizes. The study used a quantitative research method, applying the System GMM (SGMM) of Blundell and Bond to panel data from 13 joint-stock commercial banks in Vietnam for the period 2011 to 2019. The results showed that digital transformation had a positive and significant impact on the performance of the sampled commercial banks. Furthermore, the analysis revealed a critical moderating effect: the study found that the larger the bank, the greater the positive impact of digital transformation on bank performance. This led the authors to conclude that the efficiency and value derived from digital transformation were dependent on a bank's scale, suggesting that larger institutions are better positioned to leverage technological investments.

Chen et al. (2023) examined how digital transformation affected bank risk by using panel data from listed Chinese banks and explored heterogeneity across bank types and sizes. They applied panel econometric methods to test whether firms that pursued strategic digital upgrades experienced changes in overall risk-taking behaviour, and they found that digital transformation was associated with a statistically significant reduction in measured bank risk. The study emphasised mechanism pathways: improvements in operational efficiency and corporate governance appeared to mediate the risk-reducing effects of digitalisation. Results varied by bank type and scale smaller and regional banks benefited more from digital initiatives than large national banks, and the risk mitigation was stronger where digital changes occurred at the strategic or business level rather than narrowly at managerial levels. The authors argued these heterogeneous outcomes implied policy and managerial nuance: blanket prescriptions for digital investment would not yield uniform risk reductions across institutions.

Yang and Masron (2024) examined the effect of digital transformation on the operational costs of Chinese commercial banks. Using GMM with data from 116 banks between 2014 and 2021, the study found empirically that bank digital transformation significantly decreased bank expenses. This provided evidence that investments in technology could lead to greater operational efficiency. Crucially, the research also tested for an interaction with bank scale. The results showed a positive and significant interaction with bank size, suggesting that larger banks were better able to leverage their digital investments to achieve cost reductions. The heterogeneity analysis revealed that these interaction effects were most prominent in banks that had already achieved a high level of digitalization, indicating that the benefits of scale were realized after a certain technological threshold was met.

Wang et al. (2022) analyzed the impact of FinTech development on systemic risk within China’s banking industry. Using micro-level data from China’s listed banks from 2013 to 2020, the study revealed that FinTech progress significantly amplified systemic risk. The authors identified the primary mechanisms for this effect: at the individual bank level, FinTech increased risk-taking behavior, and at the system level, it enhanced inter-bank linkages, increasing the potential for contagion. This impact was found to be time-lagged and persistent. A heterogeneity analysis showed that the margining risk of state-owned banks was lower as FinTech improved. To ensure the findings were robust, the study employed GMM regression and the method of instrumental variables, confirming the conclusions. The paper also found that enhancing macroprudential supervision could effectively reduce the systemic risk spillover from FinTech, offering critical policy insights.

Nguyen et al. (2022) investigated whether FinTech credit influenced bank performance, considering the moderating impact of bank regulations in a cross-country analysis. The study used an aggregate dataset of 73 countries from 2013 to 2018 and employed an empirical strategy designed to tackle potential endogeneity issues. The findings revealed that FinTech credit tended to reduce bank profitability but, importantly, improved bank risk-related performance, suggesting a trade-off where competition eroded profits while also enhancing overall stability. The research also found that stricter banking regulations contributed positively to bank stability. A key finding was the interaction effect: the positive influence of FinTech credit on bank stability was more pronounced in the presence of more stringent banking regulations. This implied that the risk-mitigating benefits of FinTech were most effective when operating within a robust regulatory framework.

Metawa et al. (2023) analysed the National Bank of Egypt to test whether digitalisation affected credit risk directly and indirectly through financial inclusion, using structural equation modelling on 2011–2021 secondary

data. They found that the bank's digitalisation exerted a negative direct effect on credit risk meaning that greater digital investment and capability corresponded to lower measured credit exposures while financial inclusion operated as a mediator that amplified certain pathways; in other words, digitalisation both reduced risk directly and reshaped risk through expanded inclusion. Their SEM results indicated adequate model fit and supported a nuanced interpretation: digital tools (mobile services, online channels, digital onboarding) improved risk assessment and portfolio performance but also altered borrower access patterns, which could raise portfolio heterogeneity. The authors recommended future work to test other fintech factors and mediators, and they highlighted the policy implication that promoting inclusion alongside digital upgrades could strengthen credit-quality outcomes if governance and underwriting evolved in tandem.

Blundell and Bond (2023) provided a methodological review of the Blundell-Bond paper, placing it within the historical context of panel data estimators designed to account for unobserved heterogeneity and dynamics. The authors explained the evolution from the first-differenced GMM estimators, popularized by Arellano and Bond (1991), which were less suited for models with highly persistent series. They detailed how their subsequent work, following Arellano and Bover (1995), introduced the use of suitably lagged first-differences as instruments for the equations in levels. This led to the development of the extended or "System" GMM estimators. The paper's influential contribution was to illustrate the magnitude of the bias when using the first-differenced GMM for persistent series and the potential for System GMM to significantly reduce that bias by using additional valid moment conditions.

Ochenge (2023) explored the effect of FinTech development on the risk-taking behavior of banks in Kenya, providing crucial, Africa-focused evidence. The study first developed a FinTech index using text mining technology and then related this index to bank risk-taking using a dynamic panel regression model on data from 2008 to 2021. The research uncovered two primary empirical results. First, the impact of FinTech on a bank's risk-taking followed a "U" shape, initially reducing risk but then increasing it as FinTech companies matured and began to compete directly with banks. Second, and most critically, the study found that the impact of FinTech was heterogeneous across bank sizes. Specifically, the analysis revealed that large banks appeared to be more sensitive to changes in FinTech development compared to their small and medium-sized counterparts.

Babarinde (2023) investigated the impact of digital finance on the credit allocation of deposit money banks in Nigeria. The study used quarterly data from 2009 to 2019 and employed Vector Autoregression (VAR), variance decomposition, and Pearson correlation techniques to test the relationship. Digital finance was proxied by the transaction values from ATMs, POS, and web payments. While the correlation analysis showed a strong and positive association, the VAR model found no significant long-run causal relationship between digital finance and banks' credit allocation. The author concluded that although digital transaction volumes had expanded markedly, this expansion had not yet translated into a systematic or significant impact on the credit allocation function of Nigerian banks, suggesting a need for deeper integration of digital data into lending models.

Akhter (2023) investigated the determinants of commercial banks' non-performing loans (NPLs) in Bangladesh. The study collected data from 30 sampled commercial banks over the period from 2011 to 2020. To ensure robust and significant results, the author employed a one-step system Generalized Method of Moments (GMM), in addition to Random Effect and Fixed Effect regression models. The study reported that several firm-specific factors, such as the lag of NPLs, capital adequacy ratio, and return on equity, were crucial determinants of NPLs in Bangladesh. The use of the GMM system is particularly noteworthy, as this method is specifically designed to handle endogeneity issues in panel data, thereby allowing for a more causal interpretation of the relationship between the determinants and credit risk.

Girma and Huseynov (2024) explored the causal relationship between FinTech development, financial inclusion, and income inequality in a panel study of 29 African countries. To establish causality, the authors applied pooled OLS regression and, more importantly, Structural Equation Models (SEM) to samples from the years 2011, 2014, and 2017. The findings indicated that FinTech had a positive and statistically significant effect on financial inclusion. The results also demonstrated that financial inclusion played a pivotal mediation role in the relationship between FinTech and income inequality. By employing SEM, a methodology specifically designed

to test causal pathways, the study provided a robust framework for understanding the directional impacts of FinTech within the African economic context, offering a strong methodological precedent for investigating causality in related financial research.

Begimkulov (2024) investigated the competitive dynamics and the impact of digitalization within Kyrgyzstan's banking sector. The study analyzed the interplay between bank competition, digitalization, profitability, and stability using data from 2012 to 2022. To ensure robust causal inference, the author employed the two-step Generalized Method of Moments (GMM). A novel aspect of the research was the estimation of a bank digitalization index using a System Dynamics Approach. The findings indicated a competitive landscape where digitalization enhanced operational efficiency. However, a key finding related to risk was that intensified competition combined with digital adoption could encourage riskier bank behaviors, a conclusion that aligns with the competition-fragility theory. While digitalization was found to improve profitability, this finding on increased risk presents a crucial counterpoint to the narrative that technology is always a stabilizing force.

Aminipour et al. (2024) presented a model to test the effect of banking financial technology on the risk management of banks and financial institutions listed on the Tehran Stock Exchange. The study, which was applied and descriptive, used a dynamic panel data approach to analyze data from a sample of five banks between 2019 and 2022. The authors proxied FinTech using online and mobile transaction data and tested its effect on a risk management index. Data analysis was conducted using regression in Eviews 10. The results from the analysis confirmed that there was no significant effect between online and mobile transactions and the risk management index of the sampled banks. The study also found that neither online admission tools nor mobile admission tools had a significant effect on the risk management index.

DATA AND METHODOLOGY

Research Design

This study adopted an ex-post facto research design to explore the relationship between digital capital expenditure, bank size, and credit risk management of listed deposit money banks in Nigeria. The ex-post facto research design is appropriate because the data on banks' financial and investment activities already exist in their annual reports and cannot be manipulated by the researcher. This design is therefore suitable for analyzing historical data to identify relationships between the variables as they have naturally occurred.

Population of the Study

The population for this study consists of all 30 Deposit Money Banks (DMBs) licensed by the Central Bank of Nigeria (CBN) as of April 26, 2024. This population includes a range of institutions with varying asset bases, digital strategies, and operating licenses, comprising Commercial Banks (with international, and national authorizations), merchant banks and Non-Interest Bank.

Sampling Size and Sampling Technique

The sampling size for this study consists of 12 deposit money banks in Nigeria selected based on the availability of digital capital expenditure and financial data over a 10-year period (2015–2024). A purposive sampling technique is employed, focusing on banks with comprehensive and publicly available annual reports that meet the criteria for inclusion in the analysis. This method ensures that the selected sample is appropriate for assessing the causal relationship between digital capital expenditure, bank size, and credit risk management.

Inclusion Criteria: Deposit money banks that are listed on the Nigeria Exchange that also publish consistent annual reports and data on intangible assets (software).

Exclusion Criteria: Deposit money banks that are not listed on the Nigeria Exchange and did not publish consistent financial and digital capital expenditure data.

Source and Type of Data

This study utilized secondary data sourced from the published audited annual reports and financial statements of 12 selected deposit money banks in Nigeria over a 10-year period. The data include digital capital expenditure, bank size (total assets and market capitalization), liquidity ratio, and credit risk management metrics (NPLR, LLPR, and CAR), all of which are publicly disclosed in these reports. This information is obtained from audited financial statements. The use of audited financial statements ensures the study is based on verified, reliable, and readily accessible financial information from reputable sources.

Method of Data Analysis

A panel data regression and causality analysis were employed to examine the relationship between capital expenditure, bank size, and credit risk management. Descriptive statistics was used to analyze trends, and the Pairwise Granger Causality test was utilized to determine the directional influence among the variables. The findings provided empirical evidence on the role of digital capital expenditure in shaping the asset quality and solvency of Nigerian banks.

Granger causality analysis

Causality analysis is essential in time series and panel data studies to determine the directional relationship between variables, enabling researchers to determine whether past values of one variable can predict another. It is particularly valuable in exploratory studies where understanding lead-lag associations is crucial for hypothesis testing and decision-making. In financial sciences, the Pairwise Granger Causality Test provides insights that support policy formulation by revealing whether technological investments proactively drive financial stability or vice versa. Therefore, it serves as a foundational statistical tool in this empirical research.

Model that determined the causality among Digital Capital Expenditure, Bank size and Credit Risk Management of deposit money banks in Nigeria

The granger causality test is administered in form of Vector Autoregression approach to indicate the short run behavior or direction of causality between series. This model is as stated below;

$$CRM_{it} = \sum_{j=1}^{p} \alpha_j Y_{it-j} + \sum_{j=1}^{p} \gamma_j X_{it-j} + u_i + e_{it}$$

$$DCE_{it} = \sum_{j=1}^{p} \delta_j X_{it} + \sum_{j=1}^{p} \psi Y_{it-j} + v_i + f_{it}$$

Where:

Y_{it-j} and X_{it-j} are the lagged values of the variables.

Y_{it} = Dependent Variable (Credit Risk Management proxied by NPLR, LLPR and CAR) at time t.

X_{it} = Independent Variable (Digital Capital Expenditure and Bank Size) at time t.

p is the optimal lag length.

u_i and v_i are the bank-specific fixed effects.

e_{it} and f_{it} are the error terms.

RESULTS AND DISCUSSIONS

Correlation Analysis Results

Table 4.2 presents the Pearson Correlation Matrix, which examines the strength and direction of the linear relationship between the dependent variables (NPLR, LLPR, CAR), the independent variables (Digital Capital Expenditure, Bank Size, Market Capitalization), and the control variable (Liquidity).

Table 4.2: Correlation Matrix

Variable	NPLR	LLPR	CAR	DCE	LOGSIZE	LOGMCAP	LIQ
NPLR	1.0000						
LLPR	0.6949	1.0000					
CAR	-0.0620	0.1526	1.0000				
DCE	0.0456	0.2713	0.3177	1.0000			
LOGSIZE	0.1202	0.4093	0.1462	0.6558	1.0000		
LOGMCAP	0.0665	0.4738	0.3883	0.6397	0.8786	1.0000	
LIQ	-0.1807	-0.0160	0.3611	-0.1130	-0.1278	0.0840	1.0000

Source: Author's Computation from E-Views (2026).

The Correlation Matrix result showed that NPLR (Non-Performing Loan Ratio) is strongly and positively correlated with LLPR (0.6949). This validates the consistency of the dataset, confirming that banks appropriately and proactively increase loan loss provisions in response to deteriorating asset quality. Digital Capital Expenditure (DCE) shows a positive correlation with CAR (0.3177) and LLPR (0.2713), indicating that banks investing heavily in digital infrastructure also tend to maintain stronger capital buffers and provisioning.

Furthermore, Bank Size (LOGSIZE) exhibits a strong positive correlation of 0.8786 with Market Capitalization (LOGMCAP). This high degree of association is theoretically expected and practically significant, as larger banks with massive asset bases naturally command superior market valuations on the Nigerian Exchange Group. Both variables effectively and jointly capture the robust internal accounting value and the strong external market perception of the banks.

The control variable, Liquidity (LIQ), shows a moderate positive correlation of 0.3611 with the Capital Adequacy Ratio (CAR). This suggests that banks with higher liquidity buffers also tend to be more capitalized, adhering to a sound and conservative risk profile. Conversely, Liquidity has a negative correlation with NPLR (-0.1807), implying that highly liquid banks are less prone to toxic assets, as they are not under pressure to engage in aggressive or reckless lending to generate cash flow. This justifies the inclusion of liquidity as a control variable to properly isolate the true effect of digital capital on banking stability.

Pairwise Granger Causality Test Results

To determine the temporal and directional influence between digital capital expenditure, bank size, and the credit risk management indicators, the Pairwise Granger Causality test was conducted. Table 4.9 presents the F-statistics and probability values from this analysis, testing the null hypotheses of no causality among the variables.

Table 4.9: Pairwise Granger Causality Test Results

Null Hypothesis	Obs	F-Statistic	Prob.	Decision	Causality
DCE does not Granger Cause NPLR	96	4.1721	0.0185	Reject H_0	Causality
NPLR does not Granger Cause DCE	96	0.1884	0.8286	Accept H_0	No Causality
DCE does not Granger Cause CAR	96	8.6627	0.0004	Reject H_0	Causality
CAR does not Granger Cause DCE	96	0.6098	0.5457	Accept H_0	No Causality

LOGSIZE does not Granger Cause CAR	96	4.1809	0.0183	Reject H_0	Causality
CAR does not Granger Cause LOGSIZE	96	0.8170	0.4450	Accept H_0	No Causality
LOGSIZE does not Granger Cause LOGMCAP	96	9.8018	0.0001	Reject H_0	Causality
LOGMCAP does not Granger Cause LOGSIZE	96	1.7607	0.1777	Accept H_0	No Causality

Source: Author's Computation from E-View (2026)

DISCUSSION OF FINDINGS

The study examined the causality between digital capital expenditure, bank size, and the credit risk management of Nigerian deposit money banks. The study employs the Pairwise Granger Causality Test, which assesses whether past values of one variable can predict another. This method, widely used in complex economic and financial research, helps determine directional relationships and fundamentally informs strategic policy and forecasting. The test estimates vector autoregressive (VAR) models to evaluate whether lagged values of independent variables uniquely enhance the predictive power of the dependent variable. If the null hypothesis of no causality is rejected, it formally suggests that past values of a specific variable contain useful, actionable information for predicting another. These findings provide profound insights into variable interdependencies and are discussed below in relation to existing literature and theoretical expectations.

Unidirectional causality in econometrics indicates that changes in one variable systematically influence another without reciprocal feedback effects. Based on the results presented in Table 4.9, Digital Capital Expenditure (DCE) significantly Granger-causes the Non-Performing Loan Ratio (NPLR) ($F = 4.1721$, $p = 0.0185$), meaning digital capital expenditure actively influences the non-performing loan ratio. However, NPLR does not Granger-cause DCE ($F = 0.1884$, $p = 0.8286$), indicating no reverse causality. This unidirectional Granger causality from DCE to NPLR implies that past values of DCE significantly predict changes in NPLR, but not vice versa. This firmly suggests that variations in banks' digital investments proactively influence asset quality movements (Metawa et al., 2023).

Similarly, DCE significantly impacts the Capital Adequacy Ratio (CAR) ($F = 8.6627$, $p = 0.0004$), indicating digital capital expenditure influences capital adequacy. In contrast, CAR does not influence digital capital expenditure ($F = 0.6098$, $p = 0.5457$), showing no reverse causality. This unidirectional flow reinforces that digital infrastructure dynamics consistently determine capital adequacy trends. This relationship likely stems from the structural efficiency gains of digital tools, which optimize risk assessment and consequently strengthen capital buffers over time (Wang et al., 2022).

Furthermore, analyzing the structural variables, Bank Size (LOGSIZE) significantly affects the Capital Adequacy Ratio ($F = 4.1809$, $p = 0.0183$), implying bank size heavily impacts capital adequacy. However, the capital adequacy ratio does not influence bank size ($F = 0.8170$, $p = 0.4450$). Additionally, LOGSIZE significantly drives Market Capitalization (LOGMCAP) ($F = 9.8018$, $p = 0.0001$), meaning firm scale drives market valuation, but market capitalization does not influence bank size ($F = 1.7607$, $p = 0.1777$). These outcomes collectively suggest that the sheer scale of a bank significantly affects its solvency and market valuation. Large asset bases may dictate capital strategies and market perception, altering capitalization and, in turn, influencing overall financial stability (Xu et al., 2025).

These findings holistically highlight the critical role of technological investments and bank scale in determining credit risk management, seamlessly integrating the statistical outcomes with their practical and theoretical implications.

Limitations of the Study

This study provides strong empirical evidence on the causal relationship between digital capital expenditure, bank size, and credit risk management. However, there are a few limitations to note. First, the study used a purposive sample of 12 listed deposit money banks out of the 30 operating in Nigeria. Even though this sample

is highly representative because it includes banks with international, national, merchant, and non-interest authorizations, studying the entire population could offer even broader insights. Second, the study measured digital capital expenditure using capitalized intangible assets, primarily software. While this is a very reliable and standardized accounting measure, it might not capture granular spending on specific technologies like artificial intelligence or distinct cybersecurity operations. Finally, the Pairwise Granger Causality test effectively answered the research questions regarding the direction of influence between the variables. Still, future studies could build on this solid foundation by applying advanced dynamic estimators like the System Generalized Method of Moments (System GMM) and adding macroeconomic control variables, such as inflation or monetary policy shifts, to see how the wider economy interacts with these relationships.

CONCLUSION AND RECOMMENDATIONS

Conclusion

The findings of this study underscore the significant yet unidirectional nature of relationships among digital capital expenditure, bank size, and credit risk management in the Nigerian banking sector. Specifically, the evidence of unidirectional Granger causality from digital capital expenditure (DCE) to the non-performing loan ratio (NPLR) and capital adequacy ratio (CAR) affirms that past values of DCE can meaningfully predict changes in asset quality and solvency. This supports the premise that banks' strategic technological investments, such as automated credit scoring, core banking upgrades, and predictive risk analytics, directly improve loan underwriting and capital buffering. The absence of reverse causality indicates that fluctuations in toxic assets or capital levels do not significantly influence banks' digital spending. This asymmetry suggests that digital infrastructure upgrades are proactive strategic decisions rather than reactive responses to immediate credit risk pressures.

Furthermore, the consistent finding that DCE Granger-causes both NPLR and CAR reinforces the importance of technological investments as forward-looking signals for financial stability. This causality implies that regulators and market participants should interpret capitalised digital spending as a marker of long-term operational resilience, superior risk assessment, and underwriting efficiency, which are essential to robust credit risk management. In other words, sustained digital capital expenditure reduces information asymmetry and operational vulnerabilities, driving lower default rates and stronger, more resilient capital adequacy ratios over time.

Moreover, the causality from bank size (LOGSIZE) to capital adequacy (CAR) and market capitalization (LOGMCAP) reveals a critical structural influence where the sheer scale and asset base of a bank shape its capacity to manage capital and command market value. This suggests that the massive operational scale of larger banks dictates their capital structure strategies and external market perception. Again, the lack of feedback from CAR or LOGMCAP to LOGSIZE reinforces the unidirectional nature of influence, emphasizing that structural expansion and asset accumulation are foundational and typically precede long-term solvency and valuation outcomes.

These results carry broader implications for bank management and policymakers. The findings highlight the need for strategic alignment between digital transformation initiatives and credit risk frameworks to ensure that technology expenditures actively translate into measurable asset quality improvements. Furthermore, they emphasize the significance of proactive digital investment in driving banking stability, making a strong case for sustained, capitalised technological upgrades. For regulators, these insights support the development of differentiated supervisory guidelines that encourage precise disclosures on digital capital investments, promoting sector-wide resilience and proactive risk mitigation.

Methodologically, the use of the Pairwise Granger Causality Test was instrumental in uncovering these directional relationships. By leveraging lagged variable interactions within a vector autoregressive framework, the study successfully identified the precise temporal influence among key variables. The statistical significance of the causality from digital capital expenditure to both asset quality and solvency, as well as from firm scale to market valuation, validates the foundational predictive capacity of the empirical model. These outcomes

seamlessly align with theoretical expectations and previous structural studies that emphasize the predictive role of technological innovation and firm scale in achieving financial stability.

In summary, the unidirectional causality observed in this study confirms that digital capital expenditure and bank size have profound predictive power over credit risk management behavior, while the reverse does not hold. This validates the assertion that strategic digital capital expenditure and structural scale are critical, forward-looking determinants of asset quality and capital adequacy in Nigeria's deposit money banks.

Recommendations

i. Regulatory bodies such as the Central Bank of Nigeria (CBN) and the Nigerian Exchange Group (NGX) should mandate periodic disclosures of digital capital expenditure specifically separating strategic digital infrastructure investments from routine IT maintenance as these factors significantly influence credit risk management. Such transparency would enhance investor confidence and support more accurate assessments of bank stability.

ii. Bank management should ensure a strategic alignment between their operational scale and capital buffering strategies. Since bank size has a unidirectional impact on capital adequacy, large institutions must adopt robust capital frameworks that match their massive asset bases, ensuring that structural expansion does not compromise long-term solvency and market valuation.

iii. Given the predictive power of digital capital expenditure on asset quality and solvency, banks should treat digital infrastructure not as a mere operational cost but as a core component of strategic risk planning. Proactive investments in predictive analytics and automated credit scoring can serve as forward-looking signals of stability and operational strength, reducing non-performing loans and enhancing capital adequacy.

iv. Financial analysts, investors, and portfolio managers should integrate digital capital expenditure metrics into their forecasting models and valuation frameworks. The Granger causality evidence suggests that these technological investments are not only relevant but statistically significant predictors of future asset quality and capital resilience in the Nigerian banking context.

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