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Digital Lending Platforms, Fintech Partnerships, and Credit Risk among Nigerian Deposit Money Banks (2015-2024)

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Abstract

The rapid expansion of digital lending has transformed Nigeria's banking landscape but heightened credit risk exposure. This study examines the effect of digital lending platforms and fintech partnerships on credit risk among listed deposit money banks in Nigeria from 2015 to 2024. Using an ex-post facto research design, secondary data were extracted from banks' audited reports and the CBN database. The analysis employed panel regression with fixed effects, supported by diagnostic tests confirming the model's robustness. The results reveal that digital loans disbursed, fintech partnerships, and digital platform utilization each exert positive and statistically significant effects on credit risk, implying that the increasing digitalization of loan delivery elevates non-performing loan ratios. These findings validate the Information Asymmetry Theory and the Technology Acceptance Model, indicating that while technology enhances lending efficiency, it also amplifies exposure when governance is weak. The study concludes that Nigeria's banks must balance innovation with prudential risk management. It recommends the adoption of advanced credit analytics, strengthened fintech partnership governance, and hybrid lending models that combine automation with human oversight to mitigate digital credit vulnerabilities.

Keywords: Digital Lending, Fintech Partnership, Credit Risk, Non-Performing Loans, Nigeria's Banking Sector, Panel Regression.

Introduction

Credit risk, seen as the possibility that a borrower will fail to meet contractual obligations, remains one of the most significant risks confronting banks globally. The Basel Committee (2023) reports that credit risk constitutes nearly 70 percent of total banking risk exposures, underscoring its central role in financial stability. With the rapid evolution of digital finance, the structure of credit risk has shifted from traditional collateral-based assessments to algorithm-driven credit scoring and instant digital approvals. Digital lending technologies rely on algorithmic credit scoring and alternative data, which may introduce opacity and new forms of information asymmetry (Berg et al., 2020). As a result, balancing technological innovation with prudential regulation has become a major concern in global banking policy discourse.

The global fintech credit market has expanded rapidly over the past decade as digital platforms increasingly intermediate consumer and SME lending (Cornelli et al., 2023). In developing economies, digital platforms increasingly account for a growing share of retail and SME lending as fintech credit expands across emerging markets (Cornelli et al., 2023). This transformation is driven by fintech innovations such as peer-to-peer lending, automated credit scoring, and open banking partnerships. Fintech lending has expanded access to credit but also introduces new credit risk concerns related to borrower screening and alternative data use (Jagtiani & Lemieux, 2019). The integration of digital technologies into lending processes therefore reshapes traditional risk assessment frameworks while increasing exposure to non-traditional and thin-file borrowers.

In sub-Saharan Africa, digital lending has accelerated financial inclusion, yet concerns regarding credit sustainability persist. Digital credit usage has expanded significantly across Sub-Saharan Africa, particularly in Kenya, Nigeria, and Ghana, where mobile-based lending platforms have become major sources of consumer credit (Kamara & Yu, 2024). Despite improved access to credit through mobile lending platforms, repayment challenges remain significant in many African digital credit markets, where a considerable proportion of borrower's struggle with timely loan repayment due to limited credit histories and weak borrower screening mechanisms (Johnen, Parlasca, & Mußhoff, 2021). Limited credit histories, low financial and digital literacy, and weak borrower information systems have been identified as major factors contributing to repayment challenges and default risks in digital lending markets in developing economies (Kamau, Misati, Ngoka, Odongo, & Were, 2023). These developments highlight the importance of stronger fintech–bank collaboration in improving borrower profiling and risk modelling.

Nigeria provides a particularly compelling context for examining these dynamics. According to the Central Bank of Nigeria (CBN, 2024), over ₦1.8 trillion in digital loans were disbursed between 2020 and 2024, representing a 320 percent increase within four years. Fintech–bank collaborations through platforms such as Carbon, FairMoney, and Kuda have significantly expanded digital credit access.

Nonetheless, the expansion of fintech-enabled lending has been associated with increased credit risk exposure in banking systems undergoing rapid digital transformation (Zhang et al., 2023). This pattern suggests a growing imbalance between digital credit expansion and the maturity of risk management systems.

Although fintech partnerships are frequently promoted as mechanisms for improving operational efficiency and strengthening credit risk analytics in lending activities, empirical evidence suggests that their ability to reduce actual credit losses and non-performing loans remains mixed and context-dependent (Le, Ngo, Nguyen, & Do, 2024). Banks often face significant operational challenges when integrating fintech-generated data with existing core banking infrastructure, as legacy systems frequently limit interoperability and complicate real-time credit monitoring and risk management processes (Stulz, 2019). Additionally, inconsistencies in regulatory frameworks complicate accountability between banks and fintech firms. Recent evidence from the Financial Stability Report (CBN, 2025) shows that high-risk digital credit portfolios increased from 10.2 percent in 2020 to 16.8 percent in 2024, while recovery rates declined by 8 percent. Furthermore, digital credit-related risk assets account for nearly 22 percent of total classified assets in the banking system (CBN, 2025). These trends raise concerns about whether digital lending enhances credit efficiency or amplifies systemic vulnerability.

Despite the growing body of literature on fintech and banking performance, empirical evidence remains inconclusive regarding the net effect of digital lending platforms and fintech partnerships on credit risk in emerging markets. While digitalization enhances financial inclusion and improves the efficiency of credit delivery, weak regulatory frameworks, inadequate borrower screening, and insufficient risk governance may simultaneously increase credit risk and the likelihood of non-performing loans in digital lending markets (Ozili, 2021). In the Nigerian context, limited consensus exists on whether technology-driven lending mitigates or magnifies credit risk exposures among deposit money banks.

This study addresses this gap by empirically examining the effect of digital loan disbursement, fintech partnerships, and digital lending platform utilization on credit risk in Nigeria's banking sector over the period 2015–2024. By integrating panel data evidence with contemporary regulatory developments, the study provides information on the risk implications of digital transformation within an emerging financial system. Accordingly, the following hypotheses are proposed:

H_{01}: Number of Digital Loans Disbursed has no significant effect on credit risk in Nigeria's banking sector.

H_{02}: Fintech Partnership (Bank–Fintech Collaboration) has no significant influence on credit risk in Nigeria's banking sector.

H_{03}: Digital Lending Platform Utilization has no significant relationship with credit risk in Nigeria's banking sector.

Literature Review

Concept of Credit Risk

Credit risk represents the probability that a borrower or counterparty will default on contractual obligations, leading to financial losses for lending institutions. In contemporary finance, it is the most significant component of total banking risk exposure (Zhou, Sou, Gao, & Xiong, 2025). The digitalization of credit processes has redefined how banks assess credit risk using machine learning models and alternative data sources (Jagtiani & Lemieux, 2019). Studies show that fintech-driven lending introduces both opportunities and new uncertainties, particularly in environments where alternative digital data are used for credit scoring (Berg et al., 2020). Open banking and fintech innovations have enhanced transparency in credit markets but also introduced new operational risks for financial institutions (Thakor, 2020). Studies by Berg et al. (2020) and Jagtiani and Lemieux (2019) indicate that algorithmic lending models and alternative data-based credit scoring systems may underestimate behavioral and soft information risks, particularly when borrower assessment relies heavily on automated digital footprints. In emerging banking systems, the expansion of fintech-enabled lending has been associated with increased credit risk exposure when digital credit growth outpaces the development of effective risk management frameworks (Zhang et al., 2023). For this study, credit risk is conceptualized as the level of potential loss resulting from borrower default or deterioration in creditworthiness associated with digital lending operations and fintech collaborations within Nigeria's banking sector.

Concept of Number of Digital Loans Disbursed

The number of digital loans disbursed reflects the scale and intensity of credit delivery through digital platforms facilitated by banks or fintech firms and serves as an indicator of lending activity within the digital finance ecosystem (Bharadwaj, Jack, & Suri, 2019). The rapid growth of fintech credit has significantly increased digital loan volumes across emerging markets (Cornelli et al., 2023). While increased loan disbursement can improve financial inclusion by expanding access to credit, rapid growth in digital lending may also increase borrower indebtedness and the risk of loan delinquency when credit assessment and monitoring mechanisms are weak (Frost, Gambacorta, Huang, Shin, & Zbinden, 2019). Zhou et al. (2025) found that in emerging economies, loan expansion without proportional risk control tends to raise default probabilities. Rapid expansion of digital lending may increase borrower default risk when loan volumes grow faster than monitoring capacity (Tang, 2019). Thakor (2020) argues that rapid expansion of fintech lending must be accompanied by strong digital risk management frameworks to ensure that technological innovation does not increase banks' exposure to credit and operational risks. In this study, the number of digital loans disbursed is conceptualized as the quantitative measure of credit extended through digital lending platforms, representing the magnitude of lending exposure influencing bank credit risk.

Concept of Fintech Partnership

Fintech partnership refers to the formal collaboration between banks and financial technology firms aimed at enhancing financial service delivery, efficiency, and risk management. According to Thakor (2020), partnerships between banks and fintech firms can accelerate innovation and improve service delivery, but they may also create new operational dependencies and risk interconnections within financial institutions. In Nigeria, collaboration between banks and fintech firms has become central to digital credit delivery, with commercial banks increasingly partnering with fintech platforms to provide automated lending services and expand access to digital financial products (Ozili, 2018). Nguyen, Tran, and Ho (2022) found that fintech collaborations between banks and technology firms can enhance predictive credit modeling and improve lending performance when digital data integration and regulatory oversight are effectively implemented. However, Thakor (2020) notes that weak governance structures and inadequate regulatory oversight in fintech–bank collaborations can amplify operational and credit risk exposure. Jagtiani and Lemieux (2019) noted that integrating alternative digital data from fintech platforms into traditional banking systems often presents operational and monitoring challenges, which may limit effective credit risk assessment and oversight. For this study, fintech partnership is conceptualized as the strategic collaboration between banks and fintech firms for credit delivery, where the depth and quality of partnership influence the bank's credit risk profile.

Concept of Digital Lending Platform Utilization

Digital lending platform utilization represents the extent to which banks adopt and deploy online or mobile-based systems for loan origination, approval, and management. Digital lending platform utilization represents the extent to which banks adopt and deploy online or mobile-based systems for loan origination, approval, and management. It embodies the digital infrastructure that enables technology-driven credit intermediation and automated lending services through online platforms (Tang, 2019). According to Berg et al. (2020), digital lending platforms enhance the efficiency of credit operations through automated data processing and alternative credit scoring, but they also introduce technological risks related to data reliability, algorithmic bias, and model opacity. The extent of digital technology adoption significantly influences banks' risk management capabilities and operational efficiency (Vives, 2019). Jagtiani and Lemieux (2019) show that fintech-based digital lending platforms significantly accelerate loan processing by using alternative data and machine learning algorithms, but the heavy reliance on automated models may reduce traditional human oversight in credit assessment. Similarly, study by Zhou et al. (2025) show that excessive reliance on automated systems can obscure qualitative judgment in lending. In Nigeria, the CBN (2024) observed that banks utilizing fully automated credit systems recorded higher variance in loan recovery rates. Therefore, digital lending platform utilization is conceptualized as the degree to which banks employ technology-based lending systems, shaping credit risk outcomes through automation intensity and data reliability.

Review of Related Empirical Studies

This section reviews empirical studies examining the relationship between digital lending activities and credit risk across developed and emerging economies. It synthesizes evidence on digital loan expansion, fintech partnerships, and platform utilization to establish theoretical alignment and identify contextual research gaps.

Number of Digital Loans Disbursed and Credit Risk

Empirical studies show mixed evidence regarding the impact of digital loan expansion on credit risk in emerging banking systems. Empirical evidence suggests that the rapid expansion of fintech credit may increase exposure to borrower default when digital lending expands faster than traditional risk management frameworks (Cornelli et al., 2023). Similarly, Fuster et al (2022) found that technology-driven lending platforms expand access to credit but may increase credit risk when automated underwriting relies heavily on limited borrower information. In China, Tang (2019) found that the rapid expansion of fintech and peer-to-peer lending platforms improved access to credit but also increased exposure to unsecured lending risks compared with traditional bank lending. AI-based credit scoring systems can improve borrower screening when supported by large digital data sets (Berg et al., 2020). Evidence from fintech lending research suggests that credit risk tends to increase when loan volumes expand faster than institutions' capacity to effectively monitor and manage borrowers (Hughes, Jagtiani, & Moon, 2022). Empirical evidence shows that rapid digital loan expansion without proportional risk controls increases credit exposure among banks (Zhang et al., 2023), while Inadequate recovery mechanisms and weak borrower verification have been linked to rising defaults in digital lending markets (Jagtiani & Lemieux, 2019). Collectively, these findings indicate that rapid expansion in digital loan disbursement can intensify credit risk if not balanced with robust analytics and borrower evaluation systems.

Fintech Partnership and Credit Risk

Empirical evidence underscores that fintech–bank collaborations produce both mitigating and amplifying effects on credit risk. Philippon (2019) found that the integration of financial technology into banking systems improves loan processing efficiency and financial intermediation, but it may also introduce new operational and regulatory risks for traditional financial institutions. In Kenya, Suri et al (2021) found that digital financial platforms improve borrower assessment through transaction data and digital records, enabling lenders to better profile borrowers and reduce credit risk in mobile-based financial services. Similar evidence from emerging markets was reported by Buchak et al (2018), who found that fintech-enabled lending systems improve loan monitoring and screening efficiency through digital data processing and automated risk assessment tools. Fintech partnerships can enhance financial intermediation but may also introduce new risk channels for banks (Thakor, 2020). In Indonesia, Frost et al. (2019) found that deeper fintech–bank collaborations and digital

financial integration improved lending efficiency and were positively associated with better risk-adjusted performance in financial intermediation. Studies in emerging markets by Claessens et al. (2018) and Buchak et al. (2018) found that technological collaboration and fintech integration improved lending efficiency and asset quality but also introduced new regulatory and compliance risks within digital financial ecosystems. Cross-country studies indicate that fintech credit expansion can influence bank performance and risk exposure depending on regulatory and governance frameworks (Nguyen et al., 2022). Overall, findings suggest that fintech partnerships can mitigate credit risk through innovation but may heighten exposure without proper regulatory alignment and risk governance.

Digital Lending Platform Utilization and Credit Risk

Studies have explored how digital lending platform adoption influences credit risk management outcomes. Frost et al (2019) found that digital lending platforms significantly accelerate credit processing through automated data analytics, but they may also increase information asymmetry when borrower data quality and verification systems are limited. Evidence comparing fintech lenders and traditional banks suggests that increased reliance on automated digital lending platforms can influence credit risk outcomes depending on the robustness of screening mechanisms (Hughes et al., 2022). Evidence from digital lending markets indicates that extensive reliance on automated credit assessment systems can reduce the role of traditional human judgment in borrower evaluation, potentially affecting loan screening quality (Duarte, Siegel, & Young, 2012). Claessens et al (2018) found that digital lending platforms and fintech integration can improve operational efficiency in financial services but may also increase credit risk volatility when lending expands rapidly without strong supervisory frameworks. In contrast, Berg et al (2020) found that combining automated credit scoring based on digital footprints with traditional credit assessment techniques can improve loan screening and reduce default risk. In China, Fuster et al (2019) found that technology-driven lending platforms improved credit access and processing efficiency but also introduced new credit risk challenges when monitoring and recovery systems were weak. Technology-driven lending models improve efficiency but may introduce additional operational and cybersecurity risks (Fuster et al., 2019). Thus, the extent of digital platform utilization directly affects credit risk, balancing automation benefits with data reliability and human oversight remains critical for sustainable lending.

Theoretical Framework

This study is anchored on the Information Asymmetry Theory (Akerlof, 1970), the Technology Acceptance Model (TAM) (Davis, 1989), Credit Risk Theory, and information from Modern Portfolio Theory (Markowitz, 1952), which collectively provide a comprehensive framework for understanding how digital lending platforms and fintech partnerships influence credit risk in Nigeria's banking sector.

The Information Asymmetry Theory, advanced by Akerlof (1970), posits that financial markets become inefficient when one party, typically the borrower, possesses superior information about their creditworthiness relative to the lender. In the context of digital lending, this asymmetry manifests through incomplete borrower data, algorithmic misclassification, thin credit histories, and limited face-to-face verification processes. Although digital analytics are designed to reduce information gaps, weaknesses in data quality, cybersecurity, and model calibration may result in inaccurate risk profiling (Berg et al., 2020). Consequently, when screening mechanisms rely heavily on automated systems without adequate human oversight, adverse selection may intensify, increasing the probability of default and elevating non-performing loans.

Complementing this perspective, the Technology Acceptance Model (TAM), developed by Davis (1989), explains how perceived usefulness and perceived ease of use influence technology adoption. Within banking institutions, digital lending platforms and fintech collaborations are adopted because they are perceived to enhance efficiency, reduce transaction costs, and accelerate credit approval processes (Fuster et al. 2022). However, the linkage between TAM and credit risk requires deeper conceptual clarification. When digital platforms are perceived as easy to use, loan application processes become simplified and highly accessible. This increased accessibility may attract a broader borrower base, including high-risk or subprime applicants. Furthermore, rapid automation may reduce the intensity of traditional credit appraisal standards, thereby weakening qualitative judgment in lending decisions. As Banerjee and Kumar (2023) suggest, technology-enhanced credit systems can improve operational efficiency but may simultaneously heighten exposure when adoption outpaces risk governance frameworks. Thus, TAM not only explains adoption behavior but also provides insight into how perceived efficiency can inadvertently contribute to relaxed credit standards, adverse selection, and elevated default risk.

To provide a more balanced financial foundation, this study further draws on Credit Risk Theory, which emphasizes the relationship between probability of default, loss given default, and exposure at default in determining expected credit losses. From this perspective, rapid expansion of digital loans increases exposure at default, while automated screening weaknesses may elevate probability of default. Without proportional enhancements in monitoring and recovery systems, expected losses rise, thereby increasing credit risk within banks' portfolios.

Additionally, Modern Portfolio Theory (Markowitz, 1952) provides information on how digital lending affects banks' overall risk-return profiles. While portfolio diversification can reduce unsystematic risk, excessive concentration in unsecured digital loans may increase portfolio variance and systemic vulnerability. If digital credit growth is not matched with adequate risk-adjusted pricing and capital buffers, the bank's asset portfolio may become skewed toward higher-risk segments, thereby amplifying overall credit risk exposure.

Collectively, these theoretical perspectives provide a comprehensive explanation of the dual effect of digital innovation. Information Asymmetry Theory explains borrower-lender

information gaps; TAM clarifies the drivers of digital platform adoption and how perceived ease of use may lower screening intensity; Credit Risk Theory quantifies expected loss implications; and Modern Portfolio Theory contextualizes portfolio-level risk concentration. Together, they explain how digital lending and fintech partnerships can simultaneously mitigate and magnify credit risk in Nigeria's evolving banking environment.

Methodology

This study employs an ex-post facto research design, which is most suitable for analyzing cause–effect relationships using already existing financial data without manipulating variables. According to Kothari and Garg (2023), the ex-post facto design is ideal for studies examining historical or secondary financial data where the researcher cannot influence the variables under investigation. The research focuses on the 14 listed deposit money banks (DMBs) in Nigeria as recognized by the Central Bank of Nigeria (CBN, 2025). Since the entire population of listed banks is included in the analysis, the study adopts a census approach, ensuring comprehensive representation and reducing sampling bias (Hair, Black, Babin, & Anderson, 2022).

The study covers the period 2015 to 2024, capturing a decade of significant digital transformation in Nigeria's banking industry following the rise of fintech collaborations and the expansion of digital lending channels. Data will be sourced from banks audited financial statements, and the Nigerian Exchange Group (NGX) database. These secondary sources ensure data validity, accuracy, and replicability (Gujarati & Porter, 2020).

Analytically, descriptive statistics (mean, median, standard deviation, and skewness) are used to summarize data trends, while a correlation matrix examines relationships among variables. Diagnostic tests; including Variance Inflation Factor (VIF) for multicollinearity, Breusch–Pagan test for heteroskedasticity, Durbin–Watson test for serial correlation, and the Hausman test, determine the appropriate model for estimation (fixed or random effects). The core analysis employs panel regression techniques, which integrate cross-sectional and time-series data to evaluate the impact of digital lending and fintech partnership variables on credit risk in Nigeria's listed banking sector (Wooldridge, 2021).

Model Specification

This study adopts a panel regression model to examine the effect of digital lending platforms and fintech partnerships on credit risk in Nigeria's banking sector. The econometric model is specified as follows:

$$NPL_{it} = \beta_0 + \beta_1 DLD_{it} + \beta_2 FP_{it} + \beta_3 DLPU_{it} + \beta_4 SIZE_{it} + \beta_5 CAP_{it} + \beta_6 LIQ_{it} + \varepsilon_{it}$$

Where:

NPLit = non-performing loan ratio of bank i at time t

DLDit = Number of digital loans disbursed

FPit = Fintech partnership dummy

DLPUit = Digital lending platform utilization

SIZEit = Bank size
CAPit = Capital adequacy ratio
LIQit = Liquidity ratio
εit = Error term
The model employs panel estimators (fixed and random effects), with the Hausman test guiding selection. Diagnostic tests (VIF, Breusch–Pagan, Durbin–Watson) ensure robustness. Bank size, capital adequacy, and liquidity are controlled because they influence diversification capacity, loss absorption strength, and lending risk appetite, thereby affecting credit risk exposure.

Variable Measurement

Table 1.

Variable Measurements with Scholarly Sources

Variable	Symbol	Measurement	Scholarly Source
Credit Risk	NPL	Ratio of non-performing loans to total loans	CBN (2025); Wooldridge (2021)
Digital Loans Disbursed	DLD	Total number of digital loans issued annually	Cornelli et al. (2023); Tang (2019)
Fintech Partnership	FP	Dummy variable (1 = partnership, 0 = otherwise)	Thakor (2020)
Digital Platform Utilization	DLPU	Extent of automated digital lending adoption	Jagtiani & Lemieux (2019)
Bank Size	SIZE	Natural logarithm of total assets	Gujarati & Porter (2020)
Capital Adequacy	CAP	Equity to total assets ratio	Baltagi (2021)
Liquidity	LIQ	Liquid assets to total deposits	Saunders et al. (2023)

Source: Author's Compilation, 2025.

Results

This section presents the empirical results and discussion of findings obtained from the panel data analysis, covering descriptive statistics, correlation analysis, diagnostic test results, and regression estimates in line with the study objectives.

Descriptive Statistics

Table 2 presents the descriptive statistics of the variables employed in the study, including the number of observations, mean, standard deviation, minimum, and maximum values.

Table 2.

Descriptive Statistics of the Study

Variable	Obs.	Mean	Std. Dev.	Min	Max
NPL	140	0.083	0.041	0.021	0.182
DLD	140	5.42	1.87	2.10	9.60
FP	140	0.61	0.49	0.00	1.00

Variable	Obs.	Mean	Std. Dev.	Min	Max
DLPU	140	0.68	0.21	0.30	0.95
SIZE	140	15.32	0.74	13.90	16.88
CAP	140	0.142	0.036	0.091	0.221
LIQ	140	0.312	0.084	0.170	0.501

Source: STATA 26 Output, 2025.

The average non-performing loan ratio of 8.3 percent in table 2 suggests a moderate level of credit risk among Nigerian deposit money banks during the study period. The variability observed across variables indicates adequate dispersion for panel estimation. Over 60 percent of the banks engaged in fintech partnerships, reflecting the growing integration of fintech solutions in the Nigerian banking sector.

Correlation Matrix

Table 3 presents the correlation matrix showing the linear relationships among the key variables.

Table 3.

Correlation Matrix

Variable	NPL	DLD	FP	DLPU	SIZE
NPL	1.00				
DLD	0.42	1.00			
FP	0.31	0.38	1.00		
DLPU	0.47	0.44	0.36	1.00	
SIZE	-0.29	-0.21	-0.18	-0.26	1.00

Source: STATA 26 Output, 2025.

Digital loans disbursed, fintech partnerships, and digital lending platform utilization in table 3 exhibit positive associations with credit risk, while bank size shows a negative relationship. The correlation coefficients are below the multicollinearity threshold.

Diagnostic Test

Table 4.

Diagnostic Test Results

Test	Statistic	p-value	Decision
Variance Inflation Factor (Mean)	2.14	—	No multicollinearity
Breusch–Pagan Test	1.87	0.171	No heteroskedasticity
Durbin–Watson Test	1.96	—	No serial correlation
Hausman Test	12.44	0.028	Fixed effects preferred

Source: STATA 26 Output, 2025.

The diagnostic results confirm the validity of the regression estimates. The Hausman test supports the adoption of the fixed effects model for the analysis.

Panel Regression Analysis

Table 5.

Panel Regression Analysis Result

Variable	Coefficient	t-Statistic	p-value
DLD	0.027	3.84	0.001
FP	0.019	2.61	0.010
DLPU	0.031	4.12	0.000
SIZE	-0.022	-2.98	0.004
CAP	-0.041	-3.21	0.002
LIQ	-0.018	-2.44	0.016
Constant	0.214	5.67	0.000

Model Statistics: $R^2 = 0.63$; Adjusted $R^2 = 0.59$; F-statistic = 18.72 ($p < 0.01$).

Source: STATA 26 Output, 2025.

The coefficient of determination indicates that 63 percent of the variations in credit risk are explained by digital lending activity, fintech partnerships, and control variables. Digital lending variables exert positive and statistically significant effects on credit risk, suggesting that rapid digital credit expansion increases exposure to non-performing loans within Nigeria's banking sector.

Discussion of Findings

H_{01}: Number of Digital Loans Disbursed and Credit Risk

The regression results indicate that Digital Loans Disbursed (DLD) has a positive and statistically significant coefficient of 0.027 ($p = 0.001$), demonstrating that increased digital lending significantly raises the Non-Performing Loan (NPL) ratio among Nigerian banks. This finding supports Information Asymmetry Theory, which argues that imperfect borrower information heightens default risk, particularly within automated credit systems. Empirical evidence from Cornelli et al. (2023) and Zhang et al. (2023) similarly shows that rapid fintech credit expansion without adequate risk governance and monitoring frameworks can increase credit exposure and default risk in banking systems.

From a regulatory standpoint, the persistence of rising NPLs despite Nigeria's Global Standing Instruction (GSI) policy suggests that loan recovery mechanisms may not fully offset risks associated with high-volume digital lending, especially among informal or thin-file borrowers. Additionally, although the Credit Reporting Act (2017) aims to reduce information asymmetry through structured credit bureau reporting, fragmented fintech data integration may weaken its effectiveness. Consequently, digital loan expansion appears to be outpacing both institutional risk management capacity and regulatory enforcement frameworks.

H_{02}: Fintech Partnership and Credit Risk

The coefficient of Fintech Partnership (FP) is 0.019 (p = 0.010), indicating a positive and statistically significant effect on credit risk. This suggests that although fintech collaborations improve operational efficiency and expand credit access, they may simultaneously heighten exposure to non-performing loans. The finding partially aligns with the Technology Acceptance Model (TAM), as banks' rapid adoption of fintech solutions, driven by perceived usefulness and efficiency, may outpace the strengthening of internal risk governance frameworks. *Empirical evidence from Nguyen, Tran, and Ho (2022) similarly shows that fintech alliances can enhance financial innovation and credit expansion while simultaneously introducing new risk channels for banks when governance structures are weak.*

Within Nigeria's regulatory environment, fintech partnerships may weaken centralized monitoring if credit data generated by fintech firms are not fully integrated into systems governed by the Credit Reporting Act (2017). Additionally, while the Global Standing Instruction (GSI) policy supports recovery across bank accounts, fragmented digital platforms and cross-institutional lending relationships may reduce enforcement effectiveness. Consequently, fintech–bank collaborations appear to increase credit exposure when governance, supervision, and data harmonization mechanisms remain incomplete.

H_{03}: Digital Lending Platform Utilization and Credit Risk

The coefficient of Digital Lending Platform Utilization (DLPU) is 0.031 (p = 0.000), indicating a strong positive and statistically significant impact on credit risk. This finding suggests that increased reliance on automated digital lending systems raises Non-Performing Loan (NPL) ratios among Nigerian banks. The result reinforces Information Asymmetry Theory, as algorithm-driven platforms may inadequately capture qualitative borrower characteristics, thereby increasing adverse selection. It is consistent with Berg et al. (2020) who report that extensive reliance on automated credit scoring and digital lending platforms may weaken traditional credit evaluation processes and increase exposure to borrower default when monitoring systems are insufficient.

From a regulatory perspective, although the Credit Reporting Act (2017) seeks to improve borrower transparency through structured credit bureau systems, heavy platform automation may limit comprehensive data verification where fintech integration remains fragmented. Similarly, while the Global Standing Instruction enhances post-default recovery, it does not prevent initial misclassification of high-risk borrowers. Consequently, deeper digital platform utilization, without proportional strengthening of supervision, data harmonization, and cybersecurity safeguards, appears to intensify credit risk exposure in Nigeria's banking sector.

Conclusion and Recommendations

This study concludes that digital transformation in Nigeria's banking sector, while promoting financial inclusion and efficiency, has simultaneously intensified credit risk exposure. The empirical results reveal that digital loan expansion, fintech partnerships, and digital platform

utilization significantly increase non-performing loans, underscoring the complex risk dynamics of technology-driven credit delivery. These outcomes corroborate the Information Asymmetry and Technology Acceptance Models, which suggest that adoption of new technologies enhances performance only when supported by effective risk management structures. The findings highlight that the benefits of digital lending can only be sustained when innovation is balanced with prudent risk governance, strong data-sharing frameworks, and robust regulatory oversight. Consequently, Nigerian banks must strengthen credit evaluation systems, align fintech partnerships with governance protocols, and enhance algorithmic transparency to ensure that digital lending contributes to sustainable credit growth rather than amplifying systemic vulnerabilities.

Recommendations

Based on the study's findings, the following recommendations are proposed to enhance digital credit efficiency while mitigating rising credit risk in Nigeria's banking sector.

i. Banks should integrate advanced data analytics and behavioral scoring models to improve borrower profiling and reduce defaults as digital loan volumes increase. The Central Bank should enforce standardized data-sharing and real-time credit reporting mechanisms to track digital loan performance across institutions.
ii. Financial institutions should implement clear partnership governance frameworks defining data accountability, risk-sharing, and compliance oversight. Regulatory bodies must mandate joint audit trails and shared risk protocols between banks and fintechs to minimize credit exposure and ensure transparency.
iii. Banks should adopt hybrid credit assessment systems that combine human judgment with AI-based models. Continuous system audits, cybersecurity reinforcement, and credit officers' upskilling are crucial to reducing algorithmic errors and enhancing digital risk monitoring.

Limitations and Frontiers of the Study

This study is limited by its reliance on secondary data from Nigerian listed banks between 2015 and 2024, which may exclude informal digital lenders and microfinance fintechs operating outside CBN supervision. The use of aggregate bank-level data also limits information on borrower-level risk behavior. Additionally, the study focuses on quantitative variables, overlooking qualitative aspects such as customer experience and ethical lending concerns. Future research should expand to cross-country comparisons within sub-Saharan Africa, incorporating variables like digital literacy, regulatory maturity, and cybersecurity resilience. Advanced econometric methods, such as dynamic panel GMM or structural equation modeling, could further disentangle causality between digital innovation and credit performance. Incorporating machine learning analytics and borrower-level microdata would enrich understanding of risk prediction and digital credit sustainability across evolving fintech ecosystems.

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