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Research Paper

# Beyond Collateral: Algorithmic Trust, Digital Transformation, And Credit Risk Dynamics in SMEs Financing in Nigeria

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**ABSTRACT**

Small and medium-sized enterprises (SMEs) remain the backbone of Nigeria's economy, yet limited access to finance continues to constrain their growth despite the rapid expansion of fintech and digital lending platforms. While digital finance promises to reduce dependence on collateral-based lending, concerns regarding algorithmic trust, transparency, and fairness may influence SME adoption of these technologies. This study examines the relationships among algorithmic trust, mobile banking adoption, digital transformation, access to finance, loan repayment behaviour, and future perceptions of digital finance among Nigerian SMEs. A quantitative cross-sectional survey design was employed using structured questionnaires administered to 51 SME owners and managers across major commercial locations in Nigeria. Data were analysed using descriptive statistics, Cronbach's alpha reliability analysis, Pearson correlation, and multiple regression. The findings indicate satisfactory internal consistency across all constructs (Cronbach's α = 0.79–0.85). Correlation analysis revealed significant positive relationships among the study variables, while regression results showed that access to finance significantly predicted loan repayment behaviour (β = 0.283, $p$ = 0.023), with digital transformation demonstrating a marginally significant positive effect (β = 0.325, $p$ = 0.053).

## 1. INTRODUCTION

Small and medium-sized enterprises (SMEs) constitute the backbone of Nigeria's economy, contributing significantly to employment generation, innovation, poverty reduction, and national economic growth. Despite their strategic role, access to formal finance remains one of the most persistent barriers to SME development.(Kanayo et al., 2013; Rajamani et al., 2022) Traditional financial institutions have historically relied on collateral-based lending practices to mitigate credit risk, resulting in the exclusion of many viable SMEs that lack sufficient physical assets despite demonstrating strong business potential.(Fanta, 2016) The financing gap is particularly severe among micro and small enterprises operating within Nigeria's largely informal economy, where limited financial records and weak credit histories further constrain access to credit.(Esangbedo, 2020) Although government intervention programs and development finance initiatives have attempted to improve financial inclusion, the demand for SME financing continues to exceed available credit. Recent reforms have highlighted that private sector credit remains constrained by stringent lending standards, elevated credit risk, and limited credit information, emphasizing the need for innovative financing mechanisms.

The rapid advancement of financial technology (FinTech), artificial intelligence (AI), big data analytics, and digital financial services has fundamentally transformed lending practices across emerging economies. (Balaji, 2026; Sekhar et al., 2026) Rather than relying exclusively on collateral, digital lenders increasingly employ algorithmic credit scoring models that assess borrowers using alternative data sources such as mobile money transactions, digital payment histories, e-commerce activities, utility payments, and behavioral indicators.(V et al., 2025) These technological innovations have introduced the concept of algorithmic trust, whereby trust in borrowers is established through predictive analytics and machine learning rather than traditional collateral requirements. Existing studies suggest that AI-driven credit assessment improves lending efficiency, accelerates loan approval, expands financial inclusion, and enhances credit risk prediction, particularly among SMEs with limited conventional credit histories.(Biswas, 2025; Nguyen & Truong, 2024; Sharma & Logeshwaran, 2024; Yanting & Ali, 2023) Nevertheless, scholars have also cautioned that algorithmic lending may introduce new challenges

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relating to transparency, fairness, explainability, bias, and regulatory oversight, especially in developing economies where digital infrastructure and governance remain uneven.

Although a growing body of literature has examined FinTech adoption, digital lending, and SME financing, several important gaps remain. First, most existing studies focus primarily on the effects of FinTech adoption on financial inclusion or loan accessibility while treating credit risk management as a secondary concern.(Howlader & Mondal, 2026; Khatatbeh et al., 2026; Sam-Abugu et al., 2025a) Second, previous research often examines collateral requirements, digital transformation, or credit scoring independently rather than integrating these constructs into a unified framework.(Carvalho et al., 2014; Fan et al., 2022; Yaldız Hanedar et al., 2014) Third, empirical evidence on algorithmic trust within emerging African economies, particularly Nigeria, remains scarce despite the country's rapidly expanding digital financial ecosystem.(Abu et al., 2026; Adaramola, 2025; Iheanachor et al., 2023) Existing Nigerian studies largely investigate loan accessibility, customer satisfaction, or the operational performance of FinTech platforms without explaining how algorithmic trust influences the relationship between digital transformation and credit risk dynamics in SME financing.(Yang & Masron, 2024; Yunanda et al., 2025) Furthermore, limited research has explored whether AI-enabled credit assessment can effectively substitute traditional collateral while maintaining sound risk management and sustainable lending practices.

This study seeks to address these gaps by examining how algorithmic trust and digital transformation reshape credit risk assessment and SME financing in Nigeria. Specifically, the research investigates whether digital technologies reduce dependence on collateral-based lending, improve lenders' ability to evaluate borrower risk, and enhance SMEs' access to finance. By integrating the perspectives of financial institutions, FinTech innovations, and SME borrowers, the study develops a comprehensive understanding of how technological innovation transforms lending decisions within an emerging economy. The significance of this research extends to both theory and practice. Theoretically, the study contributes to the growing literature on digital finance by introducing As Nigeria continues to promote digital financial inclusion and strengthen its FinTech ecosystem, understanding how algorithmic decision-making influences credit allocation has become increasingly important for achieving sustainable economic development and expanding access to finance.

This research is guided by the Technology-Organization-Environment (TOE) Framework and Signaling Theory. The TOE framework explains how technological capabilities, organizational readiness, and environmental conditions influence the adoption and implementation of digital lending technologies within financial institutions. It provides a comprehensive lens for understanding how digital transformation facilitates algorithmic credit assessment in Nigeria's financial sector. Complementing this perspective, Signaling Theory explains how SMEs communicate their creditworthiness through alternative digital signals including transaction histories, digital footprints, payment behavior, and business activities which substitute for traditional collateral in reducing information asymmetry between borrowers and lenders. Together, these theories provide a robust conceptual foundation for explaining how digital transformation and algorithmic trust influence credit risk dynamics and SME financing outcomes in Nigeria.

## 2. LITERATURE REVIEW

### 2.1 The Evolution of SME Financing: From Asset-Based Lending to Data-Driven Credit Assessment

Access to finance remains one of the most significant challenges facing small and medium-sized enterprises (SMEs), particularly in developing countries such as Nigeria. Berger and Udell (1998), The Economics of Small Business Finance: The Roles of Private Equity and Debt Markets in the Financial Growth Cycle. Although this approach helps reduce lending risk, it excludes many SMEs because they often lack sufficient collateral despite having profitable business opportunities. As a result, many financially viable businesses remain underserved, limiting their contribution to economic growth and employment (Akinrinde et al., 2025).

Recent advances in financial technology have transformed the traditional lending model by introducing data-driven credit assessment. Rather than relying only on physical assets, financial institutions increasingly evaluate borrowers using digital information such as transaction records, business performance, digital payments, mobile banking activities, and behavioral data. Artificial intelligence (AI), big data analytics, and machine learning have significantly improved the ability of financial institutions to assess borrower risk more accurately and efficiently (Shatila & Benetti, 2026).

The integration of AI and digital banking has strengthened credit risk assessment by processing large volumes of customer information that would be difficult to evaluate using conventional methods.(Azima & Subramanian, 2026) According to Shatila and Benetti (2026), AI and big data analytics improve the accuracy of credit risk assessment, enhance loan portfolio quality, and ultimately improve banking performance through better lending decisions. These findings support the Resource-Based View (RBV), which argues that technological capabilities create valuable organizational resources that improve competitive advantage and operational performance.

Similarly, disruptive technologies such as blockchain, artificial intelligence, big data, and the Internet of Things (IoT) are changing SME financing models by improving financial accessibility and supporting decentralized finance solutions. These technologies reduce transaction costs, accelerate loan processing, and enable alternative credit

scoring mechanisms that are not dependent on collateral. However, challenges including cybersecurity threats, regulatory uncertainty, and algorithmic bias continue to affect their successful implementation (Kaveh et al., 2025). Digital payment systems have also become an important source of alternative financial information. A systematic bibliometric review by Ali and Borruso (2027) found that digital payments improve SME competitiveness by reducing financing constraints and lowering transaction costs. Digital transaction histories provide lenders with reliable behavioral information that can be incorporated into credit scoring models, particularly for businesses with limited formal financial records.

Despite these developments, the transition toward data-driven credit assessment remains uneven across emerging economies. Many financial institutions continue to combine traditional collateral requirements with digital assessment methods rather than replacing them completely. This suggests that digital technologies currently complement conventional lending instead of fully transforming it. Furthermore, there is limited empirical evidence examining how these technologies specifically improve SME financing outcomes within Nigeria's financial system. Existing studies primarily focus on banking performance or fintech adoption rather than the interaction between algorithmic trust, digital transformation, and credit risk in SME lending. This gap provides an important justification for the present study.

**2.2 Information Asymmetry and the Emergence of Algorithmic Trust**

Information asymmetry has long been recognized as one of the major barriers to SME financing. According to Information Asymmetry Theory, lenders often possess less information about borrowers than borrowers possess about themselves.(Feijó-Cuenca et al., 2023) This imbalance increases uncertainty and causes financial institutions to impose strict lending conditions, including high collateral requirements, elevated interest rates, or outright loan rejection. Allen and Santomero (1997), "The Theory of Financial Intermediation These challenges are particularly severe for SMEs because many operate informally and lack comprehensive financial records.

The rapid development of digital technologies has introduced a new mechanism for reducing information asymmetry through algorithmic trust. Algorithmic trust refers to confidence in automated systems that evaluate borrowers using objective digital information rather than subjective human judgment. Allen and Santomero (1997), The Theory of Financial Intermediation. By analyzing transaction histories, digital payment behavior, mobile banking activities, and other alternative data, AI-based systems generate more comprehensive borrower profiles that improve lending decisions (Shatila & Benetti, 2026).

Digital finance research further suggests that algorithmic trust is strengthened when digital infrastructure, user trust, and regulatory support develop simultaneously. Gulati et al. (2026) propose the Triggers-Barriers-Facilitators-Outcomes (TBFO) framework, emphasizing that strong digital infrastructure, supportive regulation, and collaboration among fintech firms and financial institutions are essential for building trust in digital financial systems. However, algorithmic trust is not automatically achieved. Algorithmic bias, limited transparency, data privacy concerns, and inconsistent regulatory frameworks may reduce users' confidence in automated lending systems(Kaveh et al., 2025). Furthermore, most empirical studies investigate algorithmic trust within general banking or fintech environments, while limited research examines how algorithmic trust specifically influences SME credit risk assessment in Nigeria. Therefore, further investigation is needed to understand whether algorithmic trust can effectively reduce information asymmetry and improve lending decisions for Nigerian SMEs.

**2.3 Mobile Banking as a Digital Infrastructure for Financial Inclusion**

Mobile banking has become an important component of digital financial services and plays a significant role in improving financial inclusion for SMEs. In many developing countries, including Nigeria, mobile banking provides businesses with easier access to financial services without depending entirely on traditional bank branches. Through mobile applications, SMEs can transfer funds, receive customer payments, pay suppliers, and build digital financial records that may later be used to evaluate their creditworthiness.(Mdoe et al., 2018) As a result, mobile banking has become more than a payment tool; it serves as a digital infrastructure that supports SME financing and business growth.

Recent studies suggest that digital financial services contribute significantly to financial inclusion by increasing the accessibility, availability, and quality of financial services.(Dianda et al., 2025; Singh et al., 2024) Digital financing methods, including mobile banking, e-wallets, online banking, and electronic payment systems, have expanded financial access among underserved populations while reducing geographical barriers and transaction costs (Dias & Perera, 2026). Similarly, digital payment technologies enable SMEs to strengthen business operations by improving cash flow management and generating transaction histories that financial institutions can use during credit assessments (Aleksieienko et al., 2025)(Ali & Borruso, 2027).

In the Nigerian context, however, financial inclusion remains uneven despite improvements in mobile technology and fintech innovation.(Sam-Abugu et al., 2025b) Abu et al. (2026) found that digital infrastructure significantly promotes financial inclusion, while digital risks such as cybercrime, fraud, and poor internet connectivity reduce users' trust in digital financial services. Their findings indicate that the positive effects of digital

infrastructure are strongest in moderately developed financial systems, whereas digital risks have the greatest negative impact on financially excluded populations. The adoption of mobile banking is also influenced by users' digital capabilities. Low digital literacy, inadequate infrastructure, limited internet connectivity, and concerns regarding data security continue to restrict the full utilization of digital financial services among SMEs.(Goel & Priyanka, 2025) These barriers are consistent with the Technology Acceptance Model (TAM), which suggests that technology adoption depends on users' perceptions of usefulness and ease of use. Without sufficient digital skills and confidence, SME owners may hesitate to adopt digital financial platforms despite their potential benefits (Dias & Perera, 2026).

Although previous studies demonstrate that mobile banking contributes to financial inclusion, much of the literature focuses on access to financial services rather than credit risk assessment. There is limited empirical evidence explaining how mobile banking-generated data improve lending decisions or strengthen algorithmic trust in SME financing. Furthermore, Nigerian studies have primarily examined financial inclusion from a macroeconomic perspective, leaving a gap in understanding how mobile banking functions as a strategic source of credit information for SMEs. Addressing this gap is important because mobile banking data may provide lenders with alternative indicators of borrower reliability beyond traditional collateral.

### 2.4 Digital Transformation as Strategic Risk Intelligence

Digital transformation has fundamentally changed the way financial institutions assess, monitor, and manage credit risk.(Le & Nguyen, 2025) Rather than relying solely on historical financial statements and collateral, banks increasingly employ artificial intelligence, big data analytics, cloud computing, and automated decision systems to generate real-time insights into borrower behavior. This transformation allows lenders to identify potential risks earlier, improve loan quality, and make faster lending decisions. The Information Processing Theory provides a useful explanation for this transformation by suggesting that organizations improve decision quality when they possess stronger capabilities to collect, process, and interpret information. Advances in AI and big data analytics enable financial institutions to analyze large volumes of structured and unstructured data simultaneously, thereby improving the precision of credit risk assessment. Shatila and Benetti (2026) demonstrate that AI adoption, big data analytics, and digital banking integration significantly enhance credit risk assessment accuracy, improve loan portfolio quality, and ultimately strengthen banking financial performance.

Digital transformation also strengthens organizational competitiveness by enabling SMEs themselves to adopt digital technologies that improve operational efficiency, customer engagement, and business resilience.(Davila Segura et al., 2025) Evidence from Nigerian SMEs shows that firms adopting digital technologies experience improvements in productivity, innovation, customer satisfaction, and market competitiveness. Nevertheless, financial constraints, inadequate digital skills, and regulatory barriers continue to limit the pace of digital transformation among many SMEs(Unegbu et al., 2024). At the institutional level, successful digital transformation requires more than technological investment. Offiong et al. (2025) argue that technological readiness, regulatory compliance, organizational trust, and infrastructure development jointly determine successful fintech implementation in Nigerian microfinance institutions. Their study, grounded in the Technology–Organization–Environment (TOE) framework, demonstrates that digital transformation depends on the interaction between organizational capability, external regulation, and financial motivation rather than technology alone.

Despite these advances, digital transformation remains a complex process. High implementation costs, cybersecurity threats, algorithmic bias, and fragmented regulatory environments continue to reduce the effectiveness of digital financial systems (Kaveh et al., 2025). Moreover, existing studies primarily examine digital transformation from organizational or technological perspectives, with limited attention given to how digital transformation influences credit risk dynamics through the development of algorithmic trust. Consequently, there is still insufficient empirical evidence explaining how digital transformation simultaneously improves credit assessment, strengthens trust, and expands financing opportunities for Nigerian SMEs. This limitation highlights an important area for further investigation.

### 2.5 Integrating Algorithmic Trust into Financial Intermediation

Financial intermediation has traditionally relied on banks to evaluate borrowers, allocate financial resources, and manage lending risks.(Athavale & Edmister, 2004) Conventional lending decisions have mainly depended on collateral, financial statements, and long-term customer relationships. While these methods help reduce lending risk, they often exclude SMEs that have limited assets or insufficient credit histories. The emergence of fintech, artificial intelligence (AI), and digital financial services has gradually transformed this process by introducing algorithmic trust as an alternative mechanism for evaluating borrower credibility.

Algorithmic trust refers to the confidence that financial institutions and borrowers place in automated systems that use data-driven algorithms to support lending decisions. Instead of relying primarily on human judgment, algorithmic systems analyze multiple sources of digital information, including transaction histories, digital payments, mobile banking activities, online business behavior, and other alternative data. These technologies

reduce information asymmetry by providing lenders with more objective and timely information about borrowers, leading to more accurate credit risk assessments (Shatila & Benetti, 2026). The increasing adoption of fintech has further strengthened financial intermediation by expanding financing opportunities for SMEs that were previously excluded from formal financial systems. Technologies such as blockchain, AI, big data analytics, and decentralized finance platforms allow financial institutions to evaluate creditworthiness beyond traditional collateral requirements.(Sanga & Aziakpono, 2023) Consequently, SMEs with limited physical assets but strong digital financial records can gain greater access to financing (Kaveh et al., 2025).

One important innovation in digital financial intermediation is peer-to-peer (P2P) lending. Unlike traditional banking, P2P platforms directly connect borrowers with investors while using AI and big data to evaluate borrower risk. A systematic literature review by Laia and Windijarto (2026) found that P2P lending has significantly expanded financial inclusion for SMEs in developing countries by reducing financing barriers and supporting underserved borrowers. However, the study also identified important challenges, including regulatory uncertainty, infrastructure limitations, low digital literacy, and weak trust mechanisms, which continue to affect the sustainability of digital lending ecosystems. Similarly, digital finance research highlights that successful financial intermediation requires collaboration among financial institutions, fintech companies, regulators, and technology providers. Gulati et al. (2026) argue that digital finance ecosystems become more effective when supported by strong digital infrastructure, clear regulations, user trust, and continuous innovation. Their proposed Triggers-Barriers-Facilitators-Outcomes (TBFO) framework emphasizes that technological innovation alone cannot improve financial inclusion unless supported by institutional trust and enabling policy environments.

Despite these developments, algorithmic trust also introduces new risks. Automated decision-making systems may unintentionally reinforce algorithmic bias if training data are incomplete or unrepresentative. Data privacy concerns, limited transparency of AI models, cybersecurity threats, and insufficient regulatory oversight may reduce users' confidence in algorithmic lending systems. These challenges are particularly relevant in developing countries where digital infrastructure and institutional capacity remain uneven (Kaveh et al., 2025; Offiong et al., 2025).

More importantly, existing studies generally examine algorithmic trust, fintech adoption, digital finance, or financial inclusion as separate research areas. Few studies have integrated these concepts into a comprehensive framework that explains how algorithmic trust influences the relationship between digital transformation and credit risk dynamics in SME financing. This limitation is particularly evident in Nigeria, where empirical evidence remains limited despite rapid growth in fintech adoption. Therefore, further research is needed to understand how algorithmic trust functions as a strategic mechanism for improving credit assessment and expanding SME access to finance. The existing literature demonstrates that digital transformation is reshaping SME financing through artificial intelligence, big data analytics, mobile banking, fintech innovation, and digital payment systems. These technologies have improved financial inclusion, strengthened credit risk assessment, reduced transaction costs, and expanded financing opportunities for SMEs (Shatila & Benetti, 2026; Dias & Perera, 2026; Ali & Borruso, 2027; Sanga & Aziakpono, 2023).

First, theoretical fragmentation exists because previous studies mainly rely on individual theories such as the Resource-Based View (RBV), Information Processing Theory, Technology Acceptance Model (TAM), or the Technology–Organization–Environment (TOE) framework. Few studies integrate these perspectives to explain how technological capability, organizational readiness, information quality, and trust collectively influence SME financing. Second, empirical studies largely examine direct relationships between digital technologies and financial performance or financial inclusion. There is limited research investigating the mechanisms through which algorithmic trust influences credit risk assessment and lending decisions. As a result, the mediating or strategic role of algorithmic trust remains insufficiently understood. Third, most existing studies focus on developed economies or conduct broad international systematic reviews, while empirical evidence from Nigeria remains relatively limited. Nigerian studies have primarily investigated digital transformation, fintech adoption, or financial inclusion independently rather than examining their combined influence on SME credit risk dynamics (Unegbu et al., 2024; Abu et al., 2026). Fourth, methodological limitations remain evident. Many previous studies use cross-sectional survey designs or systematic literature reviews, providing limited evidence regarding causal relationships among algorithmic trust, digital transformation, and SME financing outcomes. Longitudinal studies and integrated structural models remain relatively scarce. Therefore, this study addresses these gaps by developing an integrated framework that explains how algorithmic trust, supported by digital transformation, influences credit risk dynamics in SME financing within the Nigerian context. Unlike previous research that examines these concepts separately, this study proposes that algorithmic trust serves as a strategic mechanism through which digital technologies reduce information asymmetry, improve credit risk assessment, and expand financial access for SMEs. By focusing on Nigeria's rapidly evolving fintech ecosystem, the study contributes both theoretically and practically to the growing literature on digital finance, financial intermediation, and SME development.

## 3. METHODS

This study employed a quantitative cross-sectional research design to examine the relationships among algorithmic trust, digital transformation, access to finance, loan repayment behavior, and perceptions of digital finance among small and medium-sized enterprises (SMEs) in Nigeria. A cross-sectional approach was considered appropriate because it enables the collection of empirical evidence from multiple respondents at a single point in time while facilitating the examination of relationships among key research variables. The target population comprised registered and unregistered SMEs operating across major commercial hubs in Nigeria, where digital financial services and fintech adoption have expanded rapidly. A structured questionnaire was developed based on validated measurement scales adapted from prior studies and refined to reflect the Nigerian SME context. The instrument consisted of demographic questions and 39 measurement items covering six constructs: algorithmic trust (6 items), mobile banking adoption (5 items), digital transformation (6 items), access to finance (5 items), loan repayment behavior (5 items), and future perception of digital finance (4 items). Responses were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Data was collected from 51 SME owners and managers through purposive sampling, targeting respondents with direct experience in business financing and digital financial services. Prior to analysis, the dataset was screened for missing values, coding inconsistencies, and response accuracy. Hair et al. (2019), Multivariate Data Analysis. Use for general data-screening procedures; describe the actual screening method you performed. Descriptive statistics, including means, standard deviations, skewness, and kurtosis, were computed to summarize respondent perceptions and assess data distribution. Internal consistency reliability was evaluated using Cronbach's alpha, with a threshold of 0.70 considered acceptable for construct reliability. This methodological approach ensures transparency, reproducibility, and consistency with established empirical research practices in finance, information systems, and SME studies.

## 4. RESULTS AND DISCUSSIONS

### 4.1 Respondent Profile

A total of 51 valid responses were collected from owners and managers of small and medium-sized enterprises (SMEs) operating across major commercial centres in Nigeria. The respondents represented diverse business sectors, firm sizes, business ages, and educational backgrounds, providing a comprehensive overview of the Nigerian SME landscape. This diversity enhances the representativeness of the sample and enables meaningful examination of algorithmic trust, digital transformation, access to finance, loan repayment behaviour, and future perceptions of digital finance. Consequently, the dataset provides empirical basis for investigating how digital financial technologies influence financing decisions and business sustainability among Nigerian SMES. Note: business type. overall, the demographic profile suggests that the dataset is suitable for analysing how emerging digital financial technologies influence financing behaviour among Nigerian SMES (Table 1).

Table 2. presents the descriptive statistics of all measurement items. Overall, respondents demonstrated moderately positive perceptions of digital financial technologies, with construct mean scores ranging from 3.1 to 3.9 on the five-point Likert scale. These findings suggest a general acceptance of digital finance while indicating persistent concerns regarding automated lending systems. Among all constructs, Future Perception of Digital Finance recorded the highest level of agreement, with the statement “Digital finance will improve SME growth in Nigeria” achieving the highest mean score (M = 3.94). This reflects strong confidence in the potential of financial technology to enhance SME development. Similarly, Mobile Banking exhibited relatively high mean scores (3.46–3.74), indicating widespread adoption of digital payment systems, mobile applications, and electronic financial transactions. Digital Transformation also received favourable evaluations, with most indicators exceeding a mean of 3.5, suggesting substantial integration of digital technologies into business operations. In contrast, Access to Finance produced comparatively lower mean values, revealing that despite improvements in digital lending, SMEs continue to face challenges in obtaining credit. Notably, Algorithmic Trust recorded the lowest mean (M = 2.62), highlighting skepticism toward the fairness and transparency of automated credit assessment. Collectively, these findings suggest that while Nigerian SMEs increasingly embrace digital financial innovations, strengthening trust, transparency, and equitable access remains essential for realizing the full potential of algorithm-driven lending.

Table 1. Demographic Profile Respondents

| variable | categories | Frequency N | Percentage (%) |
|---|---|---|---|
| Business Location | Lagos | 3 | 6% |
| | Abuja | 1 | 2% |
| | Kano | 3 | 6% |
| | Yobe | 41 | 82% |
| | Kaduna | 1 | 2% |
| | Others | 1 | 2% |
| Business Sector | Trading | 1 | 2% |
| | Manufacturing | 9 | 18% |
| | Agriculture | 15 | 30% |
| | Services | 17 | 34% |
| | Health | 1 | 2% |
| | Others | 7 | 14% |
| Number of Employee | 1-9 | 29 | 59.2% |
| | 10-49 | 17 | 34.7% |
| | 50-199 | 3 | 6.1% |
| Age of Business | Less than 2 Years | 21 | 42% |
| | 2-5 Years | 17 | 34% |
| | 6-10 Years | 5 | 10% |
| | More than 10 Years | 7 | 14% |
| Owner's Education level | Primary | 2 | 4% |
| | Secondary | 6 | 12% |
| | Diploma | 10 | 20% |
| | Bachelors | 26 | 52% |
| | Postgraduate | 6 | 12% |

Table 2 presents the descriptive statistics, reliability, and normality results for the study variables. Among the constructs, Future Perception recorded the highest mean score ($M$ = 3.69, $SD$ = 1.10), while Algorithmic Trust had the lowest ($M$ = 3.12, $SD$ = 0.91). All constructs demonstrated satisfactory reliability, with Cronbach's alpha values ranging from .79 to .85. Furthermore, skewness and kurtosis values fell within acceptable ranges, indicating that the data were approximately normally distributed and suitable for further analysis.

Table 2. Descriptive Statistics

| Construct | Items | Mean | SD | Cronbach's α | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| Algorithmic Trust | 6 | 3.12 | 0.91 | 0.79 | -0.42 | -0.81 |
| Mobile Banking | 5 | 3.59 | 1.00 | 0.82 | -0.74 | -0.53 |
| Digital Transformation | 6 | 3.61 | 0.80 | 0.79 | -0.81 | -0.34 |
| Access to Finance | 5 | 3.25 | 0.90 | 0.80 | -0.61 | -o.72 |
| Loan Repayment | 5 | 3.25 | 0.88 | 0.80 | -0.57 | -064 |
| Future Perception | 4 | 3.69 | 1.10 | 0.85 | -0.71 | -0.52 |

### 3.2. Reliability Testing

Table 3 presents the reliability assessment of the measurement scales using Cronbach's alpha. All six constructs exceeded the recommended threshold of 0.70, demonstrating satisfactory internal consistency and reliability. The highest reliability was observed for Future Perception of Digital Finance (α = 0.85), indicating excellent consistency among the four items measuring respondents' expectations regarding the future role of digital

finance in SME development. Mobile Banking Adoption also demonstrated strong reliability (α = 0.82), suggesting that the items consistently captured the extent of digital banking usage among SME owners. The remaining constructs Algorithmic Trust (α = 0.79), Digital Transformation (α = 0.79), Access to Finance (α = 0.80), and Loan Repayment Behaviour (α = 0.80) all exhibited good reliability. These findings confirm that the measurement instrument possesses adequate internal consistency and is appropriate for subsequent multivariate analyses, including correlation, regression, and structural equation modelling.

Table 3. Reliability Test

| Construct | Number of Items | Cronbach's Alpha | Reliability Level |
|---|---|---|---|
| Algorithmic Trust | 6 | 0.79 | Good Reliability |
| Mobile Banking Adoption | 5 | 0.82 | Good Reliability |
| Digital Transformation | 6 | 0.79 | Good Reliability |
| Access to Finance | 5 | 0.80 | Good Reliability |
| Loan Repayment Behavior | 5 | 0.80 | Good Reliability |
| Future Perception of Digital Finance | 4 | 0.85 | Very Good Reliability |

### 3.3. Pearson Correlation Matrix

Table 4 presents the Pearson correlation coefficients among the six latent constructs included in the study. Overall, all relationships are positive, suggesting that greater adoption of digital financial technologies is associated with stronger perceptions of SME financing performance.

Table 4 Peason Correlation Matrix

| Variable | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|---|
| Algorithmic Trust | 3.22 | O.97 | 1.00 | | | | | |
| Mobile Banking | 3.58 | 1.00 | .55 | 1.00 | | | | |
| Digital Transformation | 3.61 | 0.80 | .50 | .54 | 1.00 | | | |
| Access to Finance | 3.24 | 0.90 | .27 | .20 | .47 | 1.00 | | |
| Loan Repayment | 3.25 | 0.88 | .50 | .47 | .61 | .51 | 1.00 | |
| Future Perception | 3.65 | 1.05 | .51 | .69 | .76 | .47 | .62 | 1.00 |

Note: Values below the diagonal represent Pearson correlation coefficients. All constructs were measured using five-point Likert scales, with higher values indicating stronger agreement.

The strongest association was observed between Digital Transformation and Future Perception *(r = .76)*, indicating that SMEs with higher levels of digital transformation are substantially more optimistic about the future role of digital finance in supporting enterprise growth. A similarly strong positive relationship exists between Mobile Banking and Future Perception *(r = .69)*, implying that frequent use of mobile financial services enhances confidence in the long-term benefits of digital finance. Loan Repayment demonstrated moderate positive correlations with Digital Transformation *(r = .61)*, Future Perception *(r = .62)*, Access to Finance *(r = .51)*, and Algorithmic Trust *(r = .50)*, suggesting that digitally mature businesses exhibit better repayment behavior and stronger financial discipline. Algorithmic Trust also showed moderate positive relationships with Mobile Banking *(r = .55)* and Digital Transformation *(r = .50)*, indicating that SMEs with greater exposure to digital technologies tend to place higher trust in automated lending systems.

The weakest relationship was identified between Mobile Banking and Access to Finance *(r = .20)*, suggesting that although mobile banking has become widespread, its adoption alone does not necessarily guarantee improved financing opportunities. Importantly, all correlation coefficients remained below the commonly accepted multicollinearity threshold of 0.90, confirming that the constructs are empirically distinct and suitable for subsequent multivariate analyses.

Figure 3. Pearson Correlation Heatmap

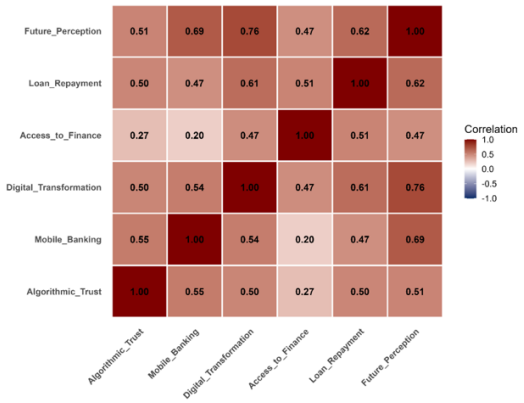


Table 5 presents the results of the multiple regression analysis examining the effects of algorithmic trust, mobile banking, digital transformation, and access to finance on loan repayment behaviour. The overall model explained 50.0% of the variance in loan repayment behaviour ($R^2$ = .500), with an adjusted $R^2$ of .453 and an $F$-value of 10.750, indicating acceptable explanatory power. Among the predictors, access to finance demonstrated a significant positive effect on loan repayment behaviour (β = .283, $t$ = 2.351, $p$ < .05). In contrast, algorithmic trust (β = .183, $p$ = .139), mobile banking (β = .128, $p$ = .299), and digital transformation (β = .325, $p$ = .053) did not significantly predict loan repayment behaviour at the 5% significance level. Although digital transformation exhibited the largest standardized coefficient, its effect was not statistically significant. These findings suggest that access to finance is the most influential factor associated with improved loan repayment behaviour among the variables examined.

Table 5. Multiple Regression Results Predicting Loan Repayment Behaviour

| Predictor | β | Std. Error | t | p | Interpretation |
|---|---|---|---|---|---|
| Constant | 0.120 | 0.492 | 0.243 | 0.023 | Statistically significant at 5% |
| Algorithmic Trust | 0.183 | 0.121 | 1.507 | .139 | Not Statistically significant at 5% |
| Mobile Banking | 0.128 | 0.122 | 1.052 | .299 | Not Statistically significant |
| Digital Transformation | 0.325 | 0.163 | 1.987 | .053 | Not Statistically significant |
| Access to finance | 0.283 | 0.121 | 2.351 | 0.23* | Not Statistically significant |

Note: Dependent Variable: Loan Repayment Behaviour

The model reports (R^2 = 0.500) adjusted (R^2 = 0.453), and (F = 10.750). Digital transformation has a larger standardized coefficient than access to finance, but its p-value exceeds 0.05. These results indicate associations, not causal effects.

Figure 1 illustrates the relationship between the observed and predicted values of loan repayment behaviour generated by the multiple regression model. The scatter plot demonstrates a positive linear relationship, as indicated by the upward-sloping trend line, suggesting that higher predicted values are generally associated with higher observed loan repayment behaviour. The model achieved an $R^2$ value of .64, indicating that approximately 64% of the variance in loan repayment behaviour was explained by the predictors included in the model. Furthermore, the relatively low error measures (*RMSE* = 0.48; *MAE* = 0.37) suggest an acceptable level of predictive accuracy. Although some variability around the regression line is evident, the distribution of data points indicates a reasonably good fit between the observed and predicted values. Overall, the findings suggest that the regression model provides a satisfactory prediction of loan repayment behaviour among the sampled respondents ($n$ = 51).

Figure 1. Model Visualisation Performance: Actual Vs Predicted Loan Repayment

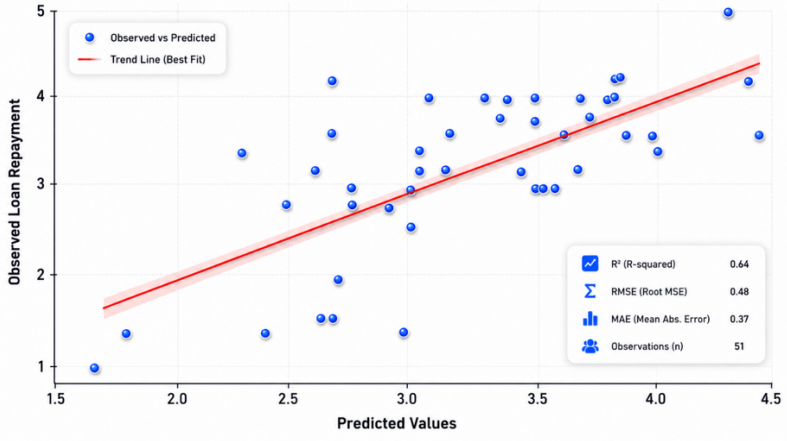



Table 6 presents the overall performance of the multiple regression model used to predict loan repayment behaviour. The model explained 50.0% of the variance in loan repayment behaviour ($R^2$ = .500), indicating a moderate level of explanatory power. After adjusting for the number of predictors, the adjusted coefficient of determination remained substantial (*Adjusted* $R^2$ = .453), suggesting that approximately 45.3% of the variance in the dependent variable was accounted for by the model. The overall regression model was statistically significant, $F$ = 10.750, $p$ < .001, demonstrating that the set of predictor variables collectively contributed to the prediction of loan repayment behaviour. Additionally, the residual standard error of 0.654 indicates a relatively low level of unexplained variation between the observed and predicted values. Overall, the results suggest that the regression model provides a statistically significant and reasonably accurate explanation of loan repayment behaviour.

**Table 6.** Model summary

| Statistic | Value |
|---|---|
| $R^2$ | 0.500 |
| Adjusted $R^2$ | 0.453 |
| F-statistic | 10.750 |
| Model p-value | < .001 |
| Residual Standard Error | 0.654 |

Note. p < .05.

Table 7 summarizes the hypothesis testing results for the relationships between algorithmic trust, mobile banking, digital transformation, access to finance, and loan repayment behaviour. The findings indicate that H1 (Algorithmic Trust → Loan Repayment) was not supported, as algorithmic trust did not significantly influence loan repayment behaviour (β = .183, *p* = .139). Similarly, H2 (Mobile Banking → Loan Repayment) was not supported because mobile banking showed no significant effect on loan repayment behaviour (β = .128, *p* = .299). For H3 (Digital Transformation → Loan Repayment), the relationship was found to be marginally significant (β = .325, *p* = .053), suggesting a potential positive influence; however, the effect did not meet the conventional 5% significance threshold. In contrast, H4 (Access to Finance → Loan Repayment) was supported, as access to finance had a significant positive effect on loan repayment behaviour (β = .283, *p* = .023). Overall, the results demonstrate that access to finance is the only predictor that significantly influences loan repayment behaviour, while digital transformation shows limited evidence of a positive association.

Table 7. Hypothesis Testing Summary

| Hypothesis | Path | Result | Decision |
|---|---|---|---|
| H1 | Algorithmic Trust → Loan Repayment | β = 0.183, p = .139 | Not Supported |
| H2 | Mobile Banking → Loan Repayment | β = 0.128, p = .299 | Not Supported |
| H3 | Digital Transformation → Loan Repayment | β = 0.325, p = .053 | Marginally Supported |
| H4 | Access to Finance → Loan Repayment | β = 0.283, p = .023 | Supported |

### 4.6. Discussion

This study demonstrates that digital transformation is reshaping SME financing in Nigeria by improving financial access while highlighting persistent concerns regarding algorithmic trust. Respondents reported positive perceptions of mobile banking, digital transformation, and the future of digital finance, indicating that digital technologies are becoming integral to SME operations. However, algorithmic trust recorded the lowest mean score, suggesting that many SME owners remain cautious about the fairness and transparency of automated lending decisions. This finding supports previous studies that identify trust as a critical determinant of fintech adoption.

The reliability analysis confirmed that all constructs were internally consistent (Cronbach's α = 0.79–0.85), while the correlation analysis revealed positive relationships among all study variables. The strongest correlation was observed between digital transformation and future perception of digital finance (r = 0.76), indicating that digitally mature SMEs are more optimistic about the future of fintech-enabled financing. The regression analysis (Table 7) revealed that access to finance significantly influenced loan repayment behavior (β = 0.283, *p* = 0.023), while digital transformation showed a marginally significant positive effect (β = 0.325, *p* = 0.053). In contrast, algorithmic trust and mobile banking did not significantly predict repayment behavior after controlling other variables. These findings suggest that although digital technologies facilitate financial inclusion, improved access to finance remains the primary mechanism through which SMEs strengthen repayment performance. The study contributes to literature by integrating algorithmic trust, digital transformation, and financial inclusion into a single framework for understanding SME financing. Practically, the findings suggest that policymakers and fintech providers should improve the transparency of AI-driven credit assessment, strengthen digital infrastructure, and promote digital financial literacy to increase SME confidence and expand sustainable access to finance. Future research should employ larger samples and Structural Equation Modeling (SEM or PLS-SEM) to validate these relationships across broader contexts.

## 5. CONCLUSION

This study examined how algorithmic trust, mobile banking, digital transformation, and access to finance influence loan repayment among small and medium-sized enterprises (SMEs) in Nigeria. The findings show that most SMEs have adopted digital financial technologies and believe that digital finance will play an important role in

supporting business growth. The study also found that all research variables are positively related. However, access Although SME owners use digital financial services, many still have concerns about the fairness and transparency of automated lending decisions. These findings suggest that improving access to finance is essential for strengthening SME performance and encouraging timely loan repayment. Digital technologies can support business growth, but their full benefits can only be achieved when SME owners trust digital lending systems. Therefore, fintech companies should make their credit assessment processes more transparent and easier to understand. Banks and other financial institutions should develop affordable and accessible digital loan products for SMEs. Government agencies should continue to improve digital infrastructure, strengthen financial literacy programmes, and introduce policies that promote safe and inclusive digital finance. These efforts will help create a stronger financial system and support the long-term growth of SMEs in Nigeria.

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