

Loan Default Prediction Practices and Machine-Learning Readiness of Microfinance Banks in Bauchi State, Nigeria

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<https://doi.org/10.33003/fujafr-2026.v4i3.431.524-536>

Abstract

Purpose: This study investigated loan-default prediction practices and machine-learning readiness of MFBs in Bauchi State, Nigeria with emphasis on loan appraisal and approval practices, loan default factors, information and risk-prediction practices, and institutional and technological machine-learning readiness.

Methodology: An exploratory qualitative research design was adopted. Data were collected through key informant interviews with MFB personnel involved in loan appraisal, credit assessment, approval, monitoring and recovery. The interview data were analysed thematically using NVivo 14, following Braun and Clarke's thematic analysis framework. The analysis generated four major themes: loan appraisal and approval practices; contextual factors contributing to loan default; information and tools used for loan-default risk assessment; and institutional and technological readiness for machine-learning adoption.

Results and conclusion: Findings indicate that MFBs rely on repayment history, borrower and business information, guarantor or collateral information, loan-monitoring records, and loan officers' professional judgement when assessing default risk. Default was associated with business and income instability, household financial pressures, loan diversion, borrower-related factors and broader economic conditions. The findings further indicate that potential machine-learning adoption is constrained by data quality and availability, ICT infrastructure, staff analytical capabilities and management support. The study concludes that effective machine-learning-based loan-default prediction requires more than access to predictive algorithms; it requires reliable and standardised credit data, appropriate digital infrastructure, skilled personnel and organisational readiness.

Implication of findings: The study recommends incremental adoption of machine-learning decision-support systems alongside strengthened data management, staff capacity development and systematic loan monitoring.

Keywords: Microfinance Banks, Loan Default Prediction, Credit Risk, Machine Learning

1. Introduction

Microfinance banks (MFBs) serve as indispensable socio-economic catalysts within developing economies, bridging the persistent financial inclusion gap by extending credit facilities to micro-enterprises, informal entrepreneurs, and low-income households underserved by conventional commercial banking institutions (World Bank, 2022; Shittu & Michael, 2025). In Nigeria, where a substantial portion of the labour force operates within the informal economy, microfinance institutions provide essential liquidity for subsistence agriculture, micro-trade, and grassroots entrepreneurship (Fadeyi et al., 2021; Falola, 2022). However, the institutional sustainability and operational viability of microfinance banks are intrinsically bound to effective credit risk management. Because micro-lenders operate on thin capital buffers, loan repayment defaults directly erode institutional liquidity, impair profitability, and jeopardize long-term organizational survival (Ajah et al., 2025; CBN, 2011).

Despite their systemic importance to financial inclusion, Nigerian microfinance banks continue to navigate severe operational vulnerabilities stemming from poor loan portfolio quality (Fadeyi et al., 2021). Managing loan default risk is particularly complex in microfinance lending because borrowers predominantly operate within informal, cash-driven economic ecosystems characterized by irregular

cash flows, unorganized financial records, and an absence of verifiable credit histories or tangible collateral (Babalola, 2025). Consequently, traditional credit appraisal frameworks such as formal credit bureau scoring, audited financial statements, and structured transaction history analysis deployed by commercial banks are largely inapplicable in the microfinance sub-sector (Chen et al., 2022).

To evaluate creditworthiness, microfinance institutions historically rely on relationship lending models, qualitative borrower interviews, local community intelligence, loan officer experience, and social guarantor arrangements (Babalola, 2025). While these subjective, human-centered approaches yield rich contextual knowledge regarding borrower character, they introduce substantial cognitive bias, inconsistency, and administrative delay into credit decision-making processes (Ajah et al., 2025). Recent empirical evidence demonstrates that loan appraisal procedures, borrower monitoring mechanisms, and institutional characteristics significantly dictate default outcomes, highlighting the urgent need for more structured predictive approaches (Shittu & Michael, 2025; Abdulrauf & Hassan, 2022).

At the technological frontier, rapid advancements in artificial intelligence (AI) and machine learning (ML) offer transformative potential for financial risk modelling (Orumwense, & Ogbebor, 2026). Unlike traditional linear statistical models, machine learning algorithms possess the capacity to process unstructured, non-linear, and high-dimensional data, uncovering hidden behavioral patterns to generate highly accurate credit risk predictions (Efekodo et al., 2025; Xiong, 2024). Contemporary financial technology research emphasizes the growing utility of explainable artificial intelligence (XAI) and interpretable machine learning models, which not only optimize prediction accuracy but also provide actionable, transparent reasoning for automated credit decisions, a critical requirement for regulatory compliance and managerial trust (Bussmann et al., 2021; Chen et al., 2022; Xiong, 2024).

However, the theoretical superiority of predictive algorithms does not automatically translate into seamless operational deployment, particularly within resource-constrained organizational environments (Abdulquadri et al., 2021). The effective adoption of machine learning requires an underlying matrix of organizational, technological, and data readiness, including digitized historical loan archives, robust information systems infrastructure, technical analytical skills, supportive managerial leadership, and coherent digital governance frameworks (Aguegboh et al., 2023; Kubua, 2026). For microfinance banks in sub-Saharan African contexts like Bauchi State, Nigeria, digital transformation is constrained by structural bottlenecks such as fragmented paper-based records, inadequate ICT infrastructure, budget limitations, and a shortage of data analytics talent (Fadeyi et al., 2021; Babalola, 2025).

Despite the growing theoretical literature extolling machine learning as a revolutionary tool for credit default prediction, a profound conceptual and practical divide persists between algorithm development and real-world institutional implementation (Xiong, 2024). Existing scholarly literature suffers from three major limitations:

The overarching majority of credit risk research focuses on developing, benchmarking, and comparing mathematical algorithms using clean, pre-packaged historical datasets, while ignoring the operational, human, and institutional environments in which these models must function (Efekodo et al., 2025).

Studies examining Nigerian microfinance banks have predominantly utilized quantitative surveys to investigate the determinants of non-performing loans, debt recovery strategies, and repayment performance (Afolabi, 2021; Abdullahi & John, 2026). Very little qualitative inquiry has been conducted to capture the nuances of existing credit appraisal workflows, loan officers' decision-making heuristics, and the institutional readiness of micro-lenders to adopt advanced predictive technologies.

Extant digital transformation research in African banking focuses heavily on tier-one commercial banks and urban FinTech firms in major commercial centres such as Lagos and Abuja (Aguegboh et al., 2023; Abdulquadri et al., 2021). Ground-level empirical evidence regarding machine learning readiness among microfinance banks operating in North-Eastern Nigeria, specifically Bauchi State, remains virtually non-existent.

Like other states in Nigeria, microfinance banks in Bauchi state continue to suffer from high loan default rates, which undermine institutional liquidity and restrict credit expansion to micro-enterprises (Babalola, 2025). While automated machine learning systems could theoretically mitigate these credit risks, it remains unknown whether local microfinance banks possess the requisite data infrastructure, technical capabilities, financial resources, and organizational willingness to adopt AI-driven solutions. Prematurely advocating for machine learning deployment without understanding these underlying institutional conditions risks implementing unsuitable, expensive, or unusable technologies.

Therefore, the central problem of this study is not simply whether machine learning can mathematically predict loan defaults, but whether microfinance banks in Bauchi State possess the operational foundation, data infrastructure, and organizational readiness required to adopt machine learning approaches within their credit management environments.

The primary objective of this study is to assess loan default prediction practices qualitatively and to assess the machine-learning readiness of microfinance banks in Bauchi State, Nigeria.

2. Literature review

2.1 Loan Default Prediction and Machine Learning

Microfinance banks (MFBs) play an important role in extending credit to economically active but underserved borrowers, particularly micro-entrepreneurs and low-income households. In Nigeria, the Central Bank of Nigeria (CBN) identifies MFBs as institutions that provide small loans, often without conventional asset-based collateral, making effective borrower assessment and monitoring particularly important. Nigerian evidence indicates that loan default is associated with both borrower- and institution-related factors. For example, Ademola (2024) found that high interest rates, short repayment periods, rigid loan conditions, overleveraging and loan diversion were associated with non-performing loans among selected Nigerian MFBs. Similarly, Olateju (2024) shows that repayment behaviour cannot be adequately understood through a single set of borrower characteristics, suggesting the importance of examining the broader lending context.

Loan appraisal and prediction also depend on the information available to loan officers. Ajah et al. (2025) found that Nigerian MFB loan officers rely on information such as borrowers' repayment calendars, borrowing capacity, interest rates, appraisal procedures and loan-monitoring practices when judging credit risk. However, most existing Nigerian studies have relied predominantly on questionnaires and quantitative models, providing limited insight into how loan officers actually make decisions, which informal information they trust, and how institutional practices shape those decisions.

Machine learning offers possibilities for improving credit-risk assessment, particularly where conventional assessment may not capture complex relationships in borrower data. Recent research demonstrates the predictive potential of machine-learning models (Sanusi et al., 2026), while also emphasising the importance of explainability in credit decisions; for example, Loan default predictability with explainable machine learning. However, technological capability alone does not guarantee successful adoption. Data quality, governance, staff capability, cybersecurity, model explainability and organisational oversight are important considerations in financial-sector AI adoption (Kubua, 2026).

The literature therefore reveals an important contextual gap; limited qualitative evidence exists on the actual loan appraisal practices, information needs, perceived causes of default, and organisational and technological conditions that shape ML readiness among Nigerian MFBs, particularly in Bauchi State. Addressing this gap requires exploring the experiences and perspectives of those directly involved in credit appraisal and risk management.

2.2 Theoretical Review

This study is guided by the Lens Model of Brunswik (1952), complemented by the Technology-Organisation-Environment (TOE) framework developed by Tornatzky and Fleischer (1990). The Lens Model provides a useful perspective for understanding how loan officers make credit-risk judgements by interpreting multiple information needs, such as repayment history, business characteristics, borrower behaviour, cash flows and collateral. It recognises that decision makers may combine formal and informal information when assessing the likelihood of loan repayment. This is particularly relevant to understanding existing appraisal practices and the information used by microfinance banks.

The TOE framework complements this perspective by explaining organisational readiness for technological innovation. It considers technological conditions, organisational characteristics and the external environment as factors shaping adoption decisions. In this study, the framework provides a structure for exploring the data availability, technological infrastructure, staff capabilities, organisational processes and institutional conditions that may facilitate or constrain machine-learning adoption. Together, the frameworks enable the study to examine both existing human decision-making practices and the contextual conditions surrounding potential ML adoption among microfinance banks in Bauchi State.

2.3 Empirical Review

Empirical studies have examined loan appraisal, determinants of default, credit-risk information, and the application of machine learning in lending. In the Nigerian microfinance context, recent evidence indicates that loan appraisal and monitoring remain important components of credit-risk management. Babalola (2025), using survey data from 400 respondents in selected microfinance banks in Southwest Nigeria, found that both loan appraisal and loan monitoring had significant negative relationships with loan default. The study recommended stronger borrower profiling, improved loan monitoring and the use of digital credit-assessment tools. These findings demonstrate the importance of institutional lending practices in managing default, but the quantitative approach provides limited insight into how loan officers actually conduct appraisal, interpret borrower information, and make decisions where available information is incomplete or contradictory.

Studies have also identified a range of borrower and loan-related factors associated with repayment outcomes. Umar (2022), for example, found that family size, gender and business age significantly influenced loan default among microfinance beneficiaries in Kano State, while several other demographic and business characteristics were not significant. Similarly, evidence from Nigerian microfinance banks has associated default with factors such as loan terms, interest rates, repayment periods, overleveraging and loan diversion. These findings suggest that default is influenced by a combination of borrower circumstances and lending conditions rather than by a single measurable characteristic. However, much of this evidence is based on predetermined variables and statistical relationships, leaving less understood how practitioners themselves interpret the contextual circumstances surrounding default.

Of particular relevance to the present study is the work of Ajah et al. (2025), which examined the information used by loan officers in predicting loan default and credit risk across 207 Nigerian

microfinance banks. The study identified borrowing capacity, interest rate, appraisal procedures, monitoring plans, and the number of active borrowers on repayment calendars among the information used by loan officers. Its findings indicated a high degree of consistency in loan officers' judgments and suggested that practitioners possessed considerable knowledge of relevant credit-risk information. The authors nevertheless argued that increasing default may also reflect factors beyond the direct control of loan officers. This finding provides an important basis for the present qualitative inquiry because it raises questions about how loan officers select, interpret, and prioritise information during actual appraisal and risk assessment.

Parallel developments in machine-learning research demonstrate the potential of data-driven approaches to loan-default prediction. Efekodo et al. (2025) evaluated several machine-learning algorithms using 50,000 borrower records in Nigeria and reported differences in predictive performance across logistic regression, decision trees, gradient boosting, random forest and Gaussian Naive Bayes models. Faluyi et al. (2024) similarly compared machine-learning approaches for predicting online loan defaults in Nigeria using transaction data and found differences in the performance of random forest, XGBoost, CatBoost and AdaBoost models. Outside Nigeria, Xu et al. (2024) demonstrated that credit transaction history was an important predictor of loan default in peer-to-peer lending, while the importance of some predictors varied across economic conditions. Although these studies demonstrate the technical possibilities of machine learning, they largely begin with existing structured datasets and focus on predictive performance. They therefore provide limited understanding of whether microfinance institutions possess the data, infrastructure, expertise and organisational processes necessary to implement such approaches.

This implementation dimension has received increasing attention in research on AI and machine-learning adoption in banking. Eskandarany (2024), using qualitative interviews with bank board members, found that strategic leadership, resource provision, partnerships, infrastructure, data privacy and other organisational considerations influence AI and ML adoption. Such findings are particularly relevant to microfinance institutions, where technological capability and data maturity may differ considerably from those of larger commercial banks.

It was therefore established by the reviewed literature that any effective credit risk management involves getting the right information, borrower assessment, and loan monitoring, but most of these researches are quantitative-based. Meanwhile, there is need for qualitative evidence on how loan appraisal are conducted by the loan officers, the factors they associate with default, which information and tools they rely upon, and whether their institutions possess the technological, data-related, and organisational conditions required for potential machine-learning adoption. This study addresses this gap by exploring these issues among microfinance banks in Bauchi State, Nigeria.

3. Methodology

This study adopts a qualitative exploratory design to examine loan-default prediction practices and machine-learning readiness among microfinance banks (MFBs) in Bauchi State, Nigeria. A qualitative design is appropriate because the study seeks to understand participants' experiences, perceptions, and practices concerning loan appraisal, default risk assessment and potential adoption of machine-learning technologies rather than test predetermined statistical relationships.

The study population comprises relevant personnel of selected MFBs who are directly involved in loan appraisal, approval, monitoring, recovery or credit-risk management, including branch managers, loan officers, credit officers, and risk-management personnel. Participants are selected purposively based on

their knowledge and experience of the credit process. Sampling continued until thematic saturation is achieved.

Data were collected through semi-structured interviews guided by the four research objectives. The interviews explored current loan appraisal and approval practices, factors associated with loan default, information and tools used in assessing default risk, and institutional, technological, data-related and organisational factors affecting potential machine-learning adoption. Where accessible and appropriate, relevant institutional documents were also reviewed to complement interview evidence. With participants' consent, interviews were audio-recorded and transcribed verbatim.

Data collected were analysed thematically following Braun and Clarke (2006) approach. Initial codes were generated from the transcripts and subsequently organised into categories and themes. Both deductive and inductive coding were used while the analysis remained open to themes emerging directly from participants' accounts. Credibility was enhanced through comparison of perspectives across participants and MFBs, maintenance of an audit trail and reflexive engagement with the data. Ethical approval, informed consent, confidentiality and voluntary participation were ensured throughout the study.

4. Results and discussion

4.1 Qualitative Analysis Using NVivo

To examine loan-default prediction practices and assess the machine-learning readiness of microfinance banks (MFBs) in Bauchi State, qualitative data obtained through Key Informant Interviews (KIIs) with selected MFB personnel were analysed using NVivo 14. The informants comprised personnel directly involved in loan appraisal, credit assessment, approval, monitoring, recovery and related credit-risk functions.

The qualitative analysis followed Braun and Clarke (2006) six-phase thematic analysis framework, operationalised with the aid of NVivo 14. First, the interview transcripts were imported into NVivo and organised according to participant characteristics, including institutional role, functional responsibility and years of experience. Second, transcripts were read repeatedly and subjected to line-by-line open coding to identify concepts relating to loan appraisal, borrower assessment, default risk, information use and technological practices. Third, related initial codes were grouped into parent and child nodes reflecting the study objectives. Fourth, NVivo coding queries were used to examine the distribution of coded references and the coverage of themes across participants. Finally, the emerging themes were interpreted in relation to the Brunswik Lens Model and the Technology-Organisation-Environment (TOE) framework.

The analysis produced four major thematic areas which are loan appraisal and approval practices; factors contributing to loan default; information and tools used in loan-default risk assessment; and institutional and technological readiness for machine-learning adoption. The themes and sub-themes provided an empirical basis for understanding how MFB personnel currently make credit-risk decisions and the conditions that may facilitate or constrain the adoption of machine-learning-based loan-default prediction.

4.2 Thematic Structure and Coding Density Analysis

The NVivo 14 analysis generated 51 coded references across 21 interview transcripts. The coding structure was developed from the interview data while remaining sensitised by the four research

objectives and the study's theoretical perspectives. Table 4.1 presents the thematic hierarchy, source coverage and coding density.

Table 1: Thematic Node Hierarchy, Source Coverage and Reference Frequency

S/N	Parent (Theme)	Node	Child Node (Sub-Theme)	NVivo Node Code	Sources (N=21)	Total Coded Ref.	Node Coverage (%)
1.	Loan Appraisal and Approval Practices	Capacity	Repayment Assessment	LAA_RCA	19	42	14.60%
			Borrower and Business Verification	LAA_BBV	21	51	17.80%
			Collateral and Guarantor Assessment	LAA_CGA	17	31	10.80%
			Officer Judgement in Approval	LAA_OJA	15	24	8.40%
2.	Loan Default Factor	Default	Business and Income Instability	LDF_BII	18	38	13.20%
			Household and Personal Pressures	LDF_HPP	16	29	10.10%
			Loan Diversion and Borrower Behaviour	LDF_LDB	20	48	16.70%
			Economic and Environmental Conditions	LDF_EEC	19	41	14.30%
3.	Information and Risk-Prediction Practices		Repayment and Credit History	IRP_RCH	21	53	18.50%
			Business and Financial Information	IRP_BFI	14	22	7.70%
			Borrower Characteristics and Social Information	IRP_BCS	16	27	9.40%
			Monitoring and Informal Information	IRP_MII	13	19	6.60%
4.	Institutional and Technological ML Readiness		Data Availability and Quality	MLR_DAQ	18	36	12.50%
			ICT and Digital Infrastructure	MLR_IDI	17	33	11.50%
			Staff Skills and Analytical Capacity	MLR_SSA	20	45	15.70%
			Management Support and Organisational Readiness	MLR_MSO	19	40	13.90%

Source: Author's NVivo 14 Analysis Output (2026).

4.3 Discussion of Findings

The thematic analysis revealed that loan-default prediction within the participating MFBs is predominantly embedded in conventional credit-appraisal procedures, staff experience, and a combination of formal and informal information required. The findings further indicate that although

MFB personnel recognise the potential value of data-driven and machine-learning approaches, the transition towards such systems is constrained by limitations in data quality, digital infrastructure, analytical skills and organisational preparedness.

4.3.1 Loan Appraisal and Approval Practices

The first theme concerned the processes through which MFBs assess and approve loan applications. NVivo coding under the nodes relating to repayment capacity, borrower and business verification, collateral or guarantor assessment, and officer judgement indicates that loan appraisal is based on multiple sources of information rather than a single formal criterion.

Participants explained that assessment commonly begins with establishing the borrower's identity, business activity, business worth, income-generating capacity, turnover, business performance and intended use of the loan. Information relating to previous repayment behaviour, existing obligations and the perceived ability of the borrower to meet scheduled repayments also forms part of the assessment process. In some cases, guarantors, collateral and the applicant's relationship with the institution provide additional assurance.

A recurring feature of the accounts was the role of loan officers' professional judgement. While formal appraisal procedures provide a structure for decision-making, officers often interpret information based on their knowledge of the borrower, business circumstances and local economic conditions. This suggests that loan decisions involve both structured information and human judgement.

'...before giving any loan, the customer must have been operating an account with the bank for not less than 6 months, and we have to assess the business worth of the customer, their turnover, business performance, and we confirm the previous credit history through our records and the CRC (Credit Risk Certification) Credit Bureau platform.' Participant 15.

'...we do visit the customers, to observe their business and ensure it's in line with what they fill in the form.' Participant 21.

Overall, the finding indicates that existing MFB appraisal practices reflect a combination of formal procedures and experiential judgement. From the perspective of the Brunswik Lens Model, loan officers appear to rely on multiple observable pieces of information to conclude on borrower repayment risk.

4.3.2 Loan Default Contributory Factors

The second theme focused on the factors that cause loan default based on the participants. The NVivo analysis identified borrower-related, business-related, household, loan-related and wider economic conditions as recurring explanations.

Participants identified fluctuations in business income, economic conditions like inflation, poor business performance, and relationship lending/ favouritism as important sources of repayment difficulty. Borrowers whose businesses experience declining sales, unexpected losses or disruption may struggle to maintain scheduled repayments. Household financial pressures were also identified as competing demands on income that can affect repayment capacity.

Another recurring issue was the diversion of borrowed funds from their intended business purpose. Participants indicated that where loan proceeds are used for consumption, household emergencies or other activities rather than income-generating purposes, the borrower's capacity to repay may be weakened. Participants also referred to borrower behaviour, existing indebtedness and broader economic pressures as factors that can alter repayment outcomes.

‘One of the reasons for loan default is giving a loan to a customer based on favouritism; maybe the customer was introduced by a board member, and the board member insists he or she must be given...’ Participant 18

‘...giving customer less than what they requested may cause loan default, and importantly poor economic condition like inflation which may lead to low sales...’ Participant 16

The findings therefore suggest that default cannot be explained exclusively by borrower characteristics available at the time of loan application. Some important risk factors emerge dynamically after disbursement and are influenced by changes in business, household and economic circumstances.

4.3.3 Information and Tools Used for Loan-Default Risk Assessment

The third theme focused on the information and tools currently used by MFB personnel to assess potential default risk. The analysis indicates that repayment history, borrower characteristics, business information, and loan-monitoring records constitute important sources of evidence.

Repayment history emerged as an important indicator because previous repayment behaviour provides officers with information about a borrower's reliability and credit behaviour, which can be gotten from the banks' records and also from the CRC (Credit Risk Certification) Credit Bureau platform. Business information was also considered relevant, particularly information concerning business activity, income generation and the stability of the enterprise.

However, participants' accounts indicate that risk assessment is not necessarily based exclusively on formally structured numerical information. Officers may also consider information obtained through direct interaction with borrowers, field visits, community knowledge and observations of business operations. Such practices demonstrate the continued importance of information in MFB credit decisions.

‘...apart from our own record, we also do confirm the credit history of the customer from CRC (Credit Risk Certification) Credit Bureau platform, which will tell us if the customer is owing another bank or not.’ Participant 14

This finding is consistent with the logic of the Lens Model, which recognises that decision-makers use multiple sources of information to make judgements under conditions of uncertainty. It also highlights an important consideration for machine-learning adoption: information that is currently used informally by experienced loan officers may not be immediately available in a structured, standardised and machine-readable form.

4.3.4 Institutional and Technological Readiness for Machine-Learning Adoption

The fourth theme addressed the extent to which MFBs possess the institutional, technological and data-related conditions necessary to adopt machine-learning approaches for loan-default prediction.

The NVivo analysis identified four closely related dimensions, which are; availability and quality of historical loan data, ICT and digital infrastructure, staff analytical capabilities, and organisational or management support. Participants generally recognised that historical borrower and repayment data could potentially support more systematic prediction of default risk, but not enough. However, concerns were raised regarding the completeness, consistency, accessibility and standardisation of available data.

Technological capacity was another important consideration. Participants indicated that the effectiveness of machine-learning systems would depend on appropriate digital infrastructure, reliable information systems and integration of relevant borrower and loan records. Limited technical expertise among

existing personnel was also identified as a potential constraint, particularly where staff have limited experience with advanced analytics or AI-based decision-support systems.

‘Yes, despite the use of CRC (Credit Risk Certification) Credit Bureau platform, we still record high loan default rate...’ Participant 18

‘Yes, our records are usually on Excel. Machine learning adoption will be of serious help for loan prediction, but it lies on the board's willingness and approval...’ Participant 20

Organisational support also emerged as important. The adoption of machine-learning systems would require management commitment, financial resources, staff training and willingness to integrate algorithmic outputs into existing credit-decision processes. Thus, machine-learning readiness extends beyond possession of software or computing infrastructure and includes the organisational capacity to generate, manage, interpret and act upon data-driven risk information. The findings therefore indicate that potential ML adoption is shaped simultaneously by technological conditions, organisational capabilities and the wider operating environment.

4.3.5 Themes Interpretation

Across the four themes, the findings reveal an interconnected pattern. MFB loan appraisal currently combines formal procedures with professional judgement; default risk is influenced by both observable borrower characteristics and changing contextual conditions; and risk assessment draws on both structured records and informal information. At the same time, the potential use of machine learning is dependent on whether these diverse sources of information can be systematically captured, standardised and converted into reliable datasets.

The qualitative evidence therefore suggests that the central challenge is not simply whether MFBs can acquire machine-learning technology, but whether they possess the data, infrastructure, human capabilities and organisational arrangements required to use such technology effectively. This provides an important empirical link between existing credit-appraisal practices and the technological and organisational conditions associated with ML readiness.

5. Conclusion

This study concludes that loan-default prediction among MFBs in Bauchi State is presently grounded largely in conventional credit-appraisal practices supported by professional judgement and multiple borrower-related information needs. Loan officers draw on repayment history, business circumstances, borrower characteristics, guarantor information and direct knowledge of clients when evaluating credit risk. While these practices provide important contextual information, their reliance on informal and experience-based judgement may limit the consistency and scalability of default-risk assessment.

The study further concludes that loan default is a multidimensional phenomenon. Business performance, household financial pressures, borrower behaviour, loan utilisation and wider economic conditions interact to influence repayment outcomes. Consequently, effective prediction systems should account for a broader range of variables than those traditionally considered during initial loan appraisal.

With respect to machine-learning readiness, the findings indicate that technological adoption should be understood as an organisational transformation rather than simply the acquisition of an algorithm or software. The availability and quality of historical loan data, digital infrastructure, staff analytical capabilities and management support are central conditions for developing and implementing reliable machine-learning applications.

The study therefore concludes that MFBs in Bauchi State have a potential foundation for data-driven loan-default prediction because they already generate and use substantial borrower and repayment information. However, converting these existing information resources into effective machine-learning systems requires systematic data capture, improved data quality, appropriate technological infrastructure, staff capacity development and organisational commitment.

It was therefore recommended that MFBs should establish consistent procedures for capturing borrower characteristics, loan characteristics, repayment behaviour, business information and post-disbursement monitoring data. This would improve the quality and comparability of historical datasets required for future predictive modelling. They should complement initial loan appraisal with systematic post-disbursement monitoring. Changes in business performance, repayment behaviour and borrower circumstances should be captured regularly so that emerging default risks can be identified earlier.

MFBs should reduce fragmented record-keeping and progressively integrate relevant borrower, loan and repayment information into reliable digital databases. Data quality should be treated as a prerequisite for any future machine-learning application, and also provide relevant personnel with training in digital credit assessment, data management, basic analytics and interpretation of predictive outputs. Such training would enable staff to work effectively with technology while retaining appropriate professional oversight.

However, rather than replacing existing credit officers' judgement immediately, MFBs should consider gradual adoption of machine-learning tools as decision-support systems. Pilot applications can initially be tested using historical data and evaluated for accuracy, consistency, usability and operational relevance before wider implementation.

Management should develop clear institutional strategies for data governance, technology adoption, staff responsibilities and resource allocation. Successful ML adoption requires organisational readiness alongside technological capability, and machine-learning predictions should complement rather than automatically replace professional credit judgement. MFBs should therefore adopt human-in-the-loop method and as well establish procedures for reviewing unusual or contested cases and ensure that predictive systems are based on relevant, accurate and appropriately governed data.

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