© JUL 2025 | IRE Journals | Volume 9 Issue 1 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I1-1712949

Alternative Data Scoring for MSME Lending: A Blueprint for Financial Inclusion

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Abstract- Access to credit remains a critical constraint for Micro, Small, and Medium Enterprises (MSMEs) in emerging economies, largely due to information asymmetries and the limitations of traditional collateral-based credit scoring frameworks. Banks and formal financial institutions typically require audited statements, fixed-asset collateral, and long banking histories—criteria that systematically exclude informal but viable MSMEs. This paper proposes an Alternative Data Scoring Framework (ADSF) that leverages mobile usage metadata, digital transaction footprints, behavioural psychometrics, supply-chain analytics, social capital signals, and open banking information to assess creditworthiness. Drawing on global evidence from Sub-Saharan Africa, Asia, and Latin America, the study develops a composite scoring model tailored to emerging markets. The ADSF is conceptualized as a multidimensional risk assessment engine designed to improve predictive accuracy, reduce credit rationing, and expand lenders' ability to serve previously excluded MSMEs. The paper also explores the regulatory and policy implications of alternative data scoring, including issues related to privacy, data protection, algorithmic bias, and consumer rights. The findings suggest that, when embedded within robust regulatory frameworks, alternative data scoring can significantly deepen financial inclusion and unlock new growth for MSMEs.

Keywords: Alternative Credit Scoring; Msmes; Financial Inclusion; Behavioural Economics; Mobile Metadata; Psychometrics; Open Banking; Emerging Markets; Fintech; Credit Risk.

I. INTRODUCTION

Micro, Small, and Medium Enterprises (MSMEs) represent the productive backbone of most emerging economies. They account for the majority of non-farm employment, contribute significantly to gross domestic product, and provide critical livelihoods in both urban and rural communities. Yet, despite their importance, MSMEs remain chronically underserved by formal financial institutions. The core challenge is not the absence of viable businesses, but the inadequacy of traditional tools used to assess creditworthiness in environments where formal documentation is limited.

According to the International Finance Corporation (IFC, 2022), the global MSME financing gap exceeds US$5 trillion, with Sub-Saharan Africa among the regions most severely affected. In Nigeria, enterprise survey data suggest that approximately two-thirds of MSMEs lack access to formal credit (World Bank, 2023). Traditional credit assessment frameworks are inherently biased toward larger, formally structured firms with audited financial statements, registered collateral, and long banking histories. Micro and small enterprises that rely on cash transactions, informal records, and community-based trading relationships are systematically excluded.

At the same time, digital transformation has been accelerating. The proliferation of mobile phones, mobile money platforms, point-of-sale (POS) devices, e-commerce platforms, and fintech applications is generating unprecedented volumes of data. These "digital exhaust" streams—mobile usage patterns, transaction histories, geolocation traces, supply-chain data, and online reputational signals—offer alternative ways to infer enterprise behaviour and repayment capacity.

This paper argues that creditworthiness is often visible in behavioural and transactional patterns long before it appears in audited statements. It develops an Alternative Data Scoring Framework (ADSF) tailored to MSME lending in emerging markets. The ADSF is a multi-pillar conceptual model that integrates mobile metadata, digital transactions, psychometric indicators, supply-chain relationships, community reputation, and open banking data into a coherent credit scoring system. The goal is to provide banks, fintechs, and microfinance institutions with a blueprint to evaluate MSMEs more accurately and inclusively.

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The remainder of the paper proceeds as follows: Section 2 reviews the literature on information asymmetry, digital lending, behavioural scoring, and supply-chain finance. Section 3 outlines the methodology. Section 4 presents the ADSF conceptual framework. Section 5 describes the composite scoring model. Section 6 discusses regulatory and policy implications. Section 7 concludes with recommendations for practitioners and policymakers.

II. LITERATURE REVIEW

2.1 Information Asymmetry and Credit Market Failures

The exclusion of MSMEs from formal finance is rooted in the theory of information asymmetry. Stiglitz and Weiss (1981) famously demonstrate that when lenders cannot accurately distinguish between high-risk and low-risk borrowers, they respond not by increasing interest rates indefinitely but by rationing credit. This leads to a situation in which many creditworthy borrowers are denied loans simply because lenders lack sufficient information. MSMEs—especially microenterprises—are textbook examples of this problem. They rarely produce audited accounts, have limited collateral, and often operate outside the formal banking system.

Empirical studies in development finance reinforce this view. Ayyagari, Demirgüç-Kunt, and Maksimovic (2016) show that innovative firms in developing countries are often more credit constrained than their less innovative counterparts, partly because traditional lending criteria undervalue intangible assets and non-traditional business models. The outcome is a persistent gap between demand for credit and supply of appropriately structured finance.

2.2 Digital Lending and Alternative Data

The rise of digital financial services has catalyzed new forms of credit scoring. With the growth of mobile money, digital wallets, e-commerce platforms, and online banking, borrowers leave extensive data trails that can be analyzed for risk assessment. Björkegren and Grissen (2019) find that mobile-phone metadata—including call frequency, social network structure, handset type, and recharge patterns—predict loan repayment with surprising accuracy. GSMA (2022) documents similar findings across multiple African markets, highlighting digital transactions as important predictors of financial reliability.

Alternative data are not limited to mobile usage. POS-based merchant data, digital invoicing systems, and platform-based sales records all generate signals about revenue consistency and operational performance. These digital footprints can be analyzed using machine learning to generate more accurate risk profiles for MSMEs that lack formal financial statements.

2.3 Behavioural Economics and Psychometric Scoring

A parallel stream of literature explores psychometric and behavioural indicators as predictors of creditworthiness. Behavioural economics emphasizes that decisions under risk and uncertainty are influenced by cognitive biases, time preferences, and personality traits. LenddoEFL (2018) and de Mel, McKenzie, and Woodruff (2019) provide evidence that digital psychometric tests—capturing factors such as conscientiousness, honesty, patience, and risk aversion—can predict loan repayment, particularly for first-time borrowers.

These methods are especially valuable in low-documentation contexts because they do not depend on prior banking relationships. Instead, they infer credit behaviour from responses to carefully designed questionnaires, games, and cognitive tasks administered via smartphones or computers.

2.4 Supply-Chain Finance and Ecosystem Data

MSMEs are often embedded in value chains in which they transact with larger, more formal firms. Supply-chain finance literature demonstrates that data on purchase orders, invoices, delivery patterns, and payment cycles can be used to assess credit risk (Basel Committee, 2020). IFC (2022) notes that small enterprises linked to strong anchor firms tend to have lower default rates, as the stability of the buyer-seller relationship serves as a de facto risk mitigant.

Yet in many emerging markets, supply-chain data are not systematically collected or shared with financial institutions. This represents a missed opportunity. Incorporating ecosystem data into credit models can significantly improve lenders' ability to assess SME performance.

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2.5 Synthesis

Taken together, these strands of literature justify a multidimensional approach to credit scoring that goes beyond collateral and bank statements. What is missing, however, is a unified framework that systematically organizes these diverse data sources into a coherent scoring system tailored to MSME lending in emerging markets. The ADSF proposed in this paper seeks to fill that gap.

III. METHODOLOGY

This study employs a conceptual mixed-methods approach. Rather than estimating a specific econometric model, it synthesizes existing empirical evidence, regulatory developments, and industry practices to design a blueprint framework for alternative data scoring.

First, a structured literature review was conducted, focusing on empirical studies of digital credit scoring, mobile metadata, psychometric lending, and supply-chain finance in emerging markets such as Kenya, India, China, Brazil, and several African countries. Second, policy documents and regulatory frameworks—including open banking regulations, data protection laws, and digital ID initiatives—were analyzed to understand the enabling environment for alternative data use in credit scoring.

Third, insights from behavioural economics and credit-risk modelling were combined to define the key dimensions of the Alternative Data Scoring Framework (ADSF). Finally, a composite scoring model was constructed to show how these dimensions can be integrated into a single creditworthiness index for MSMEs. The resulting framework is normative and prescriptive, but anchored in documented practices and peer-reviewed research.

IV. THE ALTERNATIVE DATA SCORING FRAMEWORK (ADSF)

The ADSF is structured around six core pillars: mobile usage metadata, digital transactional behaviour, psychometric indicators, supply-chain data, community reputation, and open banking footprints. Each pillar captures a distinct dimension of MSME behaviour and operational performance. The central hypothesis is that these combined signals can significantly reduce information asymmetry and improve risk assessment for lenders.

4.1 Mobile Usage Metadata

Mobile phones are ubiquitous in emerging markets and have effectively become proxies for digital identity and economic participation. Mobile usage metadata—such as the duration of SIM ownership, the regularity of airtime top-ups, geolocation stability, call and SMS frequency, and mobile-money account activity—contains behavioural signals that correlate with economic stability and reliability (GSMA, 2022). For example, an MSME operator who has maintained the same SIM card for several years, consistently tops up airtime, and operates within a stable geographic radius is likely to exhibit greater stability than someone frequently changing numbers or locations. These variables can be transformed into quantitative indicators of behavioural consistency and incorporated into credit-scoring algorithms.

4.2 Digital Transaction Behaviour

Digital transaction data are generated when MSMEs use POS terminals, mobile money, online banking, or e-commerce platforms. These data capture the timing, volume, and frequency of financial inflows and outflows. In contrast to static financial statements, transactional data provide near real-time insight into cash flow cycles, seasonality, customer concentration, and revenue volatility.

In the context of the ADSF, variables such as daily sales volume, transaction frequency, average ticket size, refunds, chargebacks, and supplier payments are aggregated into patterns that help lenders estimate business resilience. A small retailer with frequent, stable point-of-sale transactions and regular supplier settlements may, from a risk perspective, be more creditworthy than a larger but irregular operation.

4.3 Psychometric and Behavioural Indicators

Psychometric scoring complements transactional and mobile data by capturing underlying personality traits that influence financial behaviour. Through standardized questionnaires and behavioural tests, lenders can infer factors such as honesty, responsibility, planning horizon, and risk tolerance. These tests typically employ validated scales from

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psychology and behavioural economics and have been adapted for mobile and low-literacy contexts.

In the ADSF, psychometric indicators are particularly important for first-time borrowers who lack substantive financial footprints. A high psychometric score on integrity and conscientiousness, for instance, may significantly increase the predicted probability of repayment, even if formal documentation is limited.

4.4 Supply-Chain and Ecosystem Data
Many MSMEs operate within structured value chains, supplying goods to wholesalers, manufacturers, or large retailers. Data from these ecosystems—including regularity of orders, timeliness of delivery, payment cycles, and contract renewals—provide rich indicators of business performance. IFC (2022) and the Basel Committee (2020) highlight that supply-chain integration can act as a risk mitigant, as anchor firms have incentives to maintain stable supplier relationships.

For ADSF, supply-chain data can be sourced from corporate buyers, digital procurement systems, logistics platforms, or sector-specific aggregators. For example, a produce supplier whose delivery and payment records show consistent activity over multiple seasons may be an excellent credit candidate, even without traditional financial records.

4.5 Community Reputation and Social Capital
In many developing economies, social capital functions as a powerful informal enforcement mechanism. Community-based financial schemes, trade associations, cooperatives, and religious groups maintain strong norms around trust and reputation. Group lending programs in East Africa and South Asia have demonstrated that peer monitoring and social sanctions can significantly reduce default rates.

The ADSF incorporates community reputation via digital or semi-digital mechanisms: association membership registries, peer endorsements, group guarantees, and community-based rating systems. These signals help differentiate between borrowers with strong social backing and those with weaker reputational capital.

4.6 Open Banking and Aggregated Digital Footprints
Open banking frameworks allow customers to grant lenders permissioned access to financial data held by banks, fintechs, and other financial service providers. Countries such as the United Kingdom, Brazil, and India have implemented robust open banking regimes, while Nigeria's Central Bank has issued an Open Banking Framework (CBN, 2023) that sets the stage for similar practices.

In the ADSF, open banking data supply a holistic view of an MSME's financial interactions—bank account balances, loan histories, utility payments, insurance premiums, and recurring subscriptions. When combined with mobile, transactional, psychometric, and supply-chain data, these records provide a comprehensive foundation for credit assessment.

TABLE 1. Summary of Alternative Data Dimensions and Credit-Relevant Insights

ADSF Pillar	Data Types	Credit-Relevant Insights
Mobile Metadata	Call/SMS logs, SIM tenure, geolocation, mobile money use	Behavioural stability, mobility patterns, digital engagement
Digital Transactions	POS records, mobile money flows, e-commerce sales	Cash flow cycles, revenue stability, customer and supplier behaviour
Psychometrics	Personality assessments, cognitive tasks	Integrity, planning horizon, risk tolerance, repayment likelihood
Supply-Chain Data	Purchase orders, invoices, delivery and payment records	Operational discipline, demand stability, anchor-firm linkages
Social Capital	Cooperative membership, peer endorsements, group guarantees	Community trust, informal enforcement,

ADSF Pillar	Data Types	Credit-Relevant Insights
		reputational standing
Open Banking Footprint	Bank transactions, utility bills, formal loan history	Financial discipline, liquidity patterns, formal financial integration

Table 1. Summary of Alternative Data Dimensions and Credit-Relevant Insights.

V. ADSF COMPOSITE SCORING MODEL

To make the ADSF operational, the six pillars must be combined into a single composite score. Conceptually, this composite score can be represented as:
ADSF Score=w1X1+w2X2+w3X3+w4X4+w5X5+w6X6\text{ADSF Score} = w_1X_1 + w_2X_2 + w_3X_3 + w_4X_4 + w_5X_5 + w_6X_6ADSF Score=w1X1+w2X2+w3X3+w4X4+w5X5+w6X6
where X1X_1X1 to X6X_6X6 represent standardized scores for each pillar (mobile metadata, digital transactions, psychometrics, supply-chain data, social capital, and open banking footprints), and w1w_1w1 to w6w_6w6 are weights derived from historical loan performance data. The weights sum to one and reflect the relative predictive power of each dimension in a given context.

In a market with high mobile penetration but weak open banking infrastructure, mobile and transactional data may receive higher weights. Conversely, in a more digitized financial system, open banking data might be assigned greater importance. The model is therefore flexible and can be calibrated to country-specific realities.
Empirical evidence from digital lenders suggests that integrating alternative data can improve predictive accuracy by 20–35 percent compared to traditional models and significantly reduce default rates for thin-file borrowers. While the precise gains depend on data quality and model design, the general direction is clear: multidimensional scoring outperforms single-channel assessment.

VI. REGULATORY AND POLICY IMPLICATIONS

The successful deployment of ADSF depends on the broader regulatory environment. Three key regulatory pillars are particularly important: digital identity systems, data protection frameworks, and open banking regulations.

Digital ID systems such as India's Aadhaar, Nigeria's National Identification Number (NIN), and Bank Verification Numbers (BVN) provide unique identifiers that can link disparate data sources to a single economic actor. Without reliable identity infrastructure, integrating alternative data becomes technically challenging and potentially risky.

Data protection and privacy laws determine how alternative data can be collected, processed, and shared. Poorly regulated systems may expose borrowers to misuse of their data or opaque algorithmic decisions. Robust legal frameworks are needed to ensure that data are collected with informed consent, used proportionately, stored securely, and subject to oversight.

Open banking regulations define the conditions under which financial and non-financial institutions can share data via APIs. These rules must balance innovation with consumer protection. Clear standards for consent, liability, cybersecurity, and competition are essential to ensure that alternative data scoring benefits MSMEs without creating new vulnerabilities. Ethical considerations are equally critical. Algorithms trained on biased data may systematically disadvantage certain demographic groups or business segments. Policymakers and lenders should require regular fairness audits, explainability measures, and grievance redress mechanisms to ensure responsible use of alternative data.

VII. CONCLUSION

This paper has developed an Alternative Data Scoring Framework (ADSF) designed to improve access to credit for MSMEs in emerging markets. By integrating mobile metadata, digital transaction patterns, psychometric assessments, supply-chain relationships, community reputation, and open banking footprints,

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the ADSF offers a comprehensive approach to reconstructing creditworthiness beyond traditional collateral-based models.

The framework is not merely theoretical; it draws on documented experiences from digital lenders, mobile network operators, value-chain partners, and development finance institutions across multiple emerging economies. While the implementation of ADSF requires investment in infrastructure, regulatory reforms, and capacity-building, the potential benefits are substantial. With appropriate safeguards, alternative data scoring can help financial institutions serve millions of entrepreneurial but underserved MSMEs, deepen financial inclusion, and contribute to more inclusive economic growth.

Future research should focus on empirical testing of ADSF variants in specific markets, quantifying the marginal predictive value of each pillar and examining long-term repayment outcomes. Nonetheless, the conceptual model offered here provides a practical starting point for policymakers, financiers, and technologists seeking to modernize MSME credit assessment.

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