

The Role of Digital Footprints in Determining the Creditworthiness and Sustainability of MSMEs: A Risk-Based Scoring Approach

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Article Information:

Received August 02, 2026

Revised September 22, 2026

Accepted October 21, 2026

Published October 27, 2026

Keywords: *digital footprint; alternative credit scoring; creditworthiness; MSME sustainability; financial inclusion*

Abstract

Micro, Small, and Medium Enterprises (MSMEs) face a structural financing gap because they lack formal credit histories, financial statements, and collateral. At the same time, the digitalization of transactions, payments, and e-commerce generates digital footprints that can serve as signals of creditworthiness, yet their use remains fragmented and is rarely linked to business sustainability. This study aims to develop a digital-footprint-based risk-based scoring framework that assesses both the creditworthiness and the sustainability of MSMEs. It adopts a qualitative design in the form of a systematic literature review following the PRISMA 2020 protocol, covering 30 publications (2021–2026), followed by thematic analysis and conceptual synthesis. The synthesis shows that digital payment data, e-commerce transaction behavior, and business network relationships consistently strengthen the predictive power of models compared with conventional financial data, particularly for unbanked MSMEs. However, higher accuracy does not automatically translate into inclusion: data bias, limited model explainability, and privacy risks give rise to a paradox of digital financial inclusion. Theoretically, this article extends information asymmetry theory by positioning digital footprints as codified soft information. Practically, it offers a layered scoring architecture that integrates default risk and business resilience

INTRODUCTION

MSMEs are the backbone of the economy in many developing countries, including Indonesia, owing to their contribution to employment, gross domestic product, and the equitable distribution of economic opportunity. Nevertheless, this strategic position is not matched by their access to formal financing. The main obstacle facing MSMEs is not a lack of demand for credit but the inability of financial institutions to assess the risk of businesses that are not formally documented. Most micro enterprises lack standardized financial statements, borrowing histories with credit bureaus, and fixed assets that can be pledged as collateral. As a result, they are trapped in a classic cycle: they cannot obtain credit because they have no credit history, and they have no credit history because they have never obtained credit. Charfeddine et al. (2024) show that MSME credit constraints are shaped not only by financial characteristics but also by financial literacy, perceived access to

finance, ICT use, and the degree of business digitization. This finding suggests that digitalization is not merely an operational tool but a variable that shapes how legible a business is to lenders.

Theoretically, the MSME financing gap is rooted in the problem of information asymmetry. Lenders cannot accurately distinguish between low-risk and high-risk borrowers and therefore tend to ration credit or require collateral as a screening mechanism. Collateral serves to mitigate adverse selection before lending and moral hazard after the loan is disbursed. The problem is that this mechanism systematically discriminates against the businesses that most need financing, namely small firms without assets. The banking literature also distinguishes between hard information, which is quantified and easily transmitted, such as financial statements and credit bureau scores, and soft information, which is contextual, such as the owner's reputation, closeness to customers, and day-to-day business dynamics. Until recently, soft information could only be captured through personal relationships between loan officers and borrowers, making it costly, difficult to scale, and prone to subjectivity. Hardik (2023) shows that digitalization has in fact encouraged Indian banks to adopt soft information in SME credit evaluation, because information that was previously hidden now leaves a processable trail.

This is where the digital footprint becomes relevant. A digital footprint refers to the totality of data recorded as a result of a business owner's activities in the digital sphere: electronic payment transactions, sales histories on online marketplaces, customer interactions on social media, device usage patterns, and connections with suppliers and business partners. Pioneering studies in consumer credit have demonstrated that simple digital footprint variables can predict default with a power comparable to, and even complementary to, credit bureau scores. Djeundje et al. (2021) confirm that alternative data can improve the performance of credit scoring models, while Orlova (2021) develops a methodology for managing individual creditworthiness using digital footprint data and machine learning. Gambacorta et al. (2023) advance an even more radical thesis: data can replace collateral. Big tech lenders exploit the data-network-activity loop to assess credit quality directly, thereby reducing reliance on collateral values and making lending more responsive to actual business performance.

These developments are rapidly extending to the MSME segment. Gu et al. (2024) apply machine learning to assess the credit risk of small and micro enterprises, whereas Wang et al. (2024) integrate digital footprints into credit scoring models through model averaging. Network-based approaches are also emerging: Mitra et al. (2023) and Zhang et al. (2024) use knowledge graphs and inter-firm relationships to capture risk that spreads through supply chains. Shi et al. (2024) propose big data analytics based on fuzzy equifinality, acknowledging that different combinations of conditions can lead to equivalent levels of creditworthiness. In the Indonesian context, Buananta et al. (2026) develop a creditworthiness prediction model for unbanked MSMEs using e-commerce digital footprint data, while Mauliansyah and Aziz (2026) link digital payments to MSME financial profiles for bank financing. Pérez-Salazar et al. (2026) broaden the focus from credit risk to operational risk profiling in assessing micro-enterprise solvency.

However, enthusiasm for alternative credit scoring is not without problems. Mas'ud et al. (2026) identify a paradox of digital financial inclusion: the technology that promises wider access may instead create new gaps, because MSMEs with thin digital footprints remain invisible to algorithms. Mwesigwa et al. (2026) show that making credit scoring work in Kenya is a process of socio-technical alignment among risk, data, and institutional interests rather than simply a matter of statistical accuracy. Fuster et al. (2022) caution that machine learning can distribute its benefits unevenly across groups of borrowers, while Bussmann et al. (2021) stress the importance of model explainability so that credit decisions can be accounted for. Abdellatif et al. (2026) and Kamat and Haldar (2025) call for policy frameworks that treat responsible growth and financial sustainability as goals, not merely the efficiency of credit allocation.

The sustainability dimension is becoming increasingly important because creditworthiness is essentially a prediction of a business's future survival. Safira et al. (2025) find that financial technology and risk management affect the sustainability performance of MSMEs, while Martínez-Peláez et al. (2023) show that digital transformation supports sustainability through the roles of stakeholders, key capabilities, and technology. Studies of Indonesian financing platforms, such as Putri and Thayib (2025) on Akseleran, demonstrate that risk mitigation and social impact can be designed together. Mutamimah et al. (2023) propose a blockchain-based governance innovation to reduce MSME credit risk, and Hardjomidjojo and Sarma (2023) map the risks of an MSME credit process digitalization program at a regional bank. Taken together, these findings show that the digitalization of MSME credit operates on several layers at once: data, models, institutional processes, and governance.

Based on this review, three research gaps remain unaddressed. First, a conceptual gap: most studies treat digital footprints merely as predictive inputs for improving default classification accuracy, without theoretically explaining why digital footprints work and under what conditions they fail. Second, an orientation gap: creditworthiness models focus on short-term default probability, whereas business sustainability, that is, the ability of MSMEs to survive, adapt, and grow, is rarely included as an equally weighted dimension of assessment. Third, an integrative gap: technical studies of algorithms, policy studies of inclusion, and socio-technical studies of implementation have developed in separate spheres, so no framework yet combines accuracy, fairness, explainability, and sustainability within a single assessment architecture.

The novelty of this article lies in bridging these three gaps simultaneously. Theoretically, it positions digital footprints as codified soft information: contextual information that was once accessible only through personal relationships is now systematically recorded and can therefore be processed like hard information. This reading extends information asymmetry theory by explaining the mechanism through which data substitutes for collateral, as well as its limits when digital footprints are thin, biased, or easily manipulated. Methodologically, the article goes beyond comparing algorithmic accuracy by synthesizing cross-disciplinary literature to build a layered risk-based scoring architecture that first separates, and then integrates, a default risk score and a business resilience score. Practically, the proposed framework incorporates a governance layer consisting of model explainability, cross-segment fairness testing, and personal data protection as core components rather than add-ons. The article thus shifts the question from "do digital footprints improve accuracy?" to "how can digital footprints be designed to be accurate, inclusive, and supportive of MSME sustainability at the same time?"

Accordingly, this study aims to: (1) identify the categories of digital footprints that most consistently contribute to MSME creditworthiness assessment; (2) analyze the theoretical mechanisms that explain this contribution; (3) reveal the risks and paradoxes that accompany their use; and (4) formulate a risk-based scoring framework that integrates creditworthiness and business sustainability

METHODS

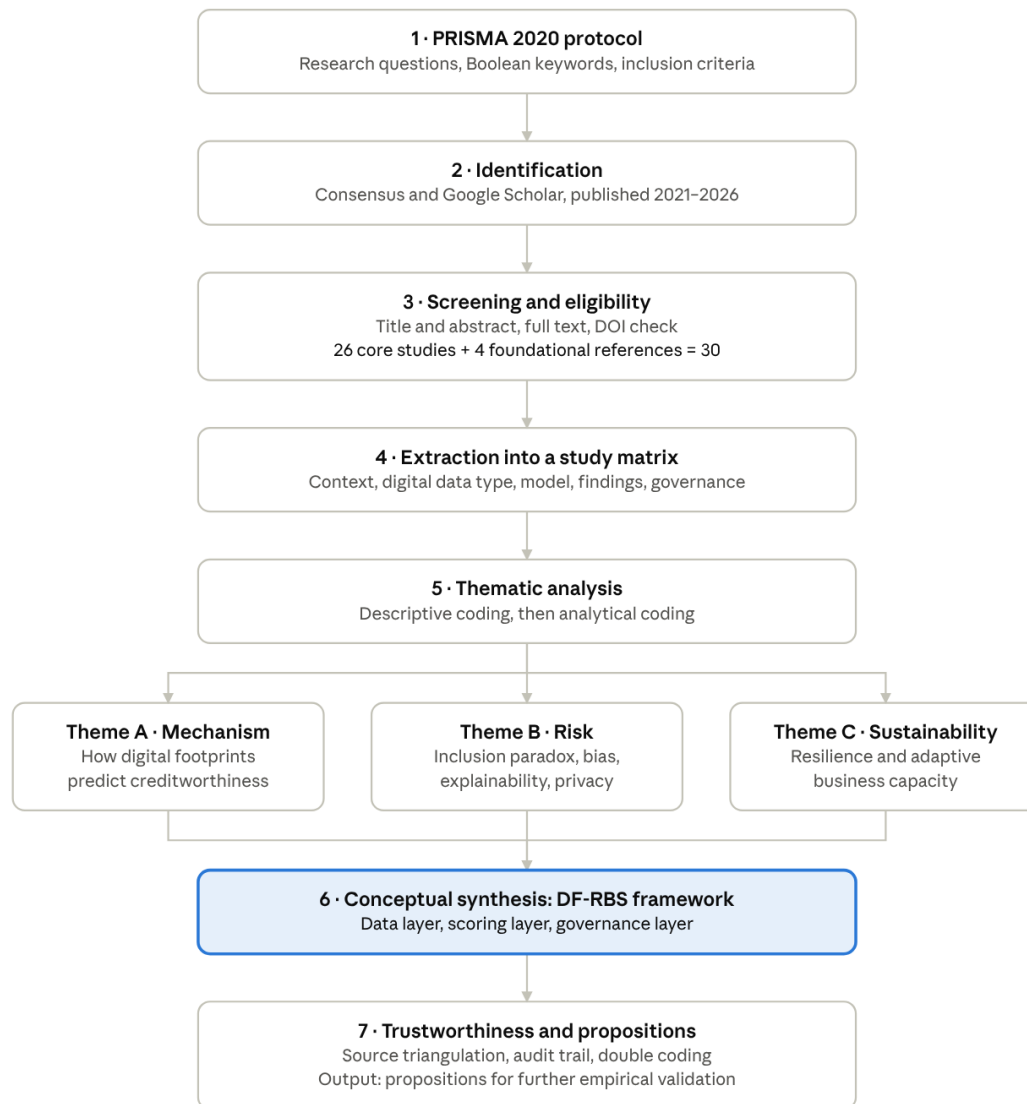
This study employs a qualitative Systematic Literature Review (SLR) guided by the PRISMA 2020 protocol (Page et al., 2021), followed by thematic analysis and conceptual synthesis. This design was chosen because the aim is not to test a single model on a single dataset but to consolidate evidence across countries, methods, and disciplines into an assessment framework that can be tested empirically.

Corpus. Publications were retrieved through Consensus (which indexes Semantic Scholar and Crossref) and Google Scholar using combinations of keywords on digital footprints or alternative data, credit assessment, and MSMEs, together with sustainability-related keywords. Studies were included if they were published between 2021 and 2026,

peer-reviewed, assigned a DOI, and addressed alternative data in credit assessment, MSME credit risk, or the link between digitalization and MSME sustainability. This process yielded 26 core studies plus four foundational references, giving a final corpus of 30 publications.

Analysis. Each study was extracted into a matrix (context, type of digital data, modeling technique, findings, and governance issues) and then coded in two rounds: descriptive coding to map data and models, followed by analytical coding to group the findings into themes of mechanism, risk, and sustainability. The three themes were then synthesized into the DF-RBS framework. Trustworthiness was ensured through triangulation across countries and methods, an audit trail of coding decisions, and double coding of a sample. Because it is based on synthesis, the framework is propositional and requires further empirical validation.

Seven SLR stages turn 30 publications into the DF-RBS framework



SLR methodology flow · 7 stages, 3 analytical themes

Stages 1–3 filter the corpus, Stages 4–5 break it down into three themes, and Stages 6–7 bring them back together into a framework ready for testing.

RESULTS AND DISCUSSION

Corpus Map and the Direction of the Literature

Of the 26 core studies, 15 focus on the predictive mechanisms of digital footprints and alternative data, eight address risk, governance, and inclusion, and only three explicitly link digitalization to MSME sustainability. This distribution reveals a sharp imbalance in orientation. Research effort is concentrated on the question of "how accurate," while the questions of "for whom" and "with what impact" are relatively neglected. The temporal pattern is also noteworthy: the 2021 studies were still dominated by individual consumer credit (Djeundje et al., 2021; Orlova, 2021), whereas the 2024–2026 studies have shifted toward small and micro enterprises, developing-country contexts, and issues of policy and fairness (Abdellatif et al., 2026; Mas'ud et al., 2026; Mwesigwa et al., 2026). This shift marks the maturation of the field from a phase of technical proof toward a phase of institutionalization, in which questions of legitimacy and social impact become unavoidable.

This trend was already visible in the early mapping of the alternative credit scoring literature by Njuguna and Sowon (2021), and it continues in recent studies that offer a blueprint for alternative data scoring in MSME lending ("Alternative Data Scoring for MSME Lending," 2025) as well as credit empowerment based on big data and digital footprints (Zhang, 2026). The literature is therefore mature enough to show that digital footprints *can* be used, but not yet mature enough to explain *how they should* be used.

Categories of Digital Footprints and Their Contribution to Credit Assessment

The thematic synthesis identifies five recurring categories of digital footprints in the literature. The first is the transactional footprint, namely digital payment flows, e-wallets, and QR-code payment channels. This footprint is closest to the function of a cash flow statement because it records the frequency, volume, and regularity of receipts. Mauliansyah and Aziz (2026) position digital payments as the basis for building MSME financial profiles for bank financing. The implication is that digital transactions act as automatically compiled financial statements, without imposing an administrative burden on micro entrepreneurs.

The second category is the commercial footprint from online marketplaces, which includes sales histories, customer reviews, return rates, and consistency in order fulfillment. Buananta et al. (2026) use e-commerce digital footprint data to predict the creditworthiness of unbanked MSMEs, the very segment that conventional models fail to reach. The commercial footprint has the advantage of recording not only quantity but also the quality of market relationships, such as reputation and customer loyalty, which have traditionally been classified as soft information.

The third category is the relational or network footprint, namely a business's connections with suppliers, buyers, and other entities. Mitra et al. (2023) and Zhang et al. (2024) show that inter-firm knowledge graphs can capture risks that are invisible at the individual level, such as default contagion through supply chains. For MSMEs embedded in platform ecosystems, network position serves as a signal of demand stability and, at the same time, a source of systemic vulnerability.

The fourth category is the behavioral and device footprint, such as app usage patterns, activity timing, and device characteristics. This category is rooted in consumer credit studies (Orlova, 2021; Xu, 2025) and shows meaningful predictive power. However, its relevance for MSMEs is more problematic because it conflates the owner's personal behavior with business performance and is the most vulnerable to privacy concerns and indirect discrimination.

The fifth category is the operational footprint, namely indicators that reflect a business's management capacity. Pérez-Salazar et al. (2026) algorithmically profile operational risk to assess micro-enterprise solvency. This approach is important because it shifts the focus from "is the borrower willing to repay?" to "is the business able to survive?", thereby serving as a conceptual bridge between creditworthiness and sustainability.

In terms of modeling techniques, the literature shows convergence in three directions.

The first is ensemble and nonlinear machine learning models capable of capturing complex interactions between variables (Gu et al., 2024; Rath et al., 2026). The second is integration techniques such as model averaging, which combine conventional data and digital footprints without relying on a single specification (Wang et al., 2024). The third is configurational approaches such as fuzzy equifinality, which recognize that the paths to creditworthiness can vary (Shi et al., 2024). This convergence is consistent with the finding of Gambacorta et al. (2023) that data-driven credit makes lending more responsive to actual business activity and less dependent on collateral values.

Digital Footprints as Codified Soft Information

The findings above call for a theoretical explanation that goes beyond claims of accuracy. This article argues that the predictive power of digital footprints stems from their capacity to codify soft information. In the relationship banking paradigm, information about the owner's diligence, customer satisfaction, or the regularity of turnover could only be obtained through repeated face-to-face interaction. Such information is highly valuable but costly and cannot be transferred between loan officers or institutions. Digitalization changes this economics of information: the same behavior now leaves a trail that is standardized, large-scale, and verifiable. Hardik (2023) confirms this mechanism from the institutional side, showing that digitalization encourages banks to adopt soft information in SME credit evaluation.

The theoretical consequences are significant. Within the information asymmetry framework, collateral functions as a screening mechanism because low-risk borrowers are willing to bear the risk of losing their assets. Digital footprints offer an alternative screening mechanism based on direct observation of economic behavior, so lenders no longer need to rely on indirect signals. This explains the thesis that data substitutes for collateral (Gambacorta et al., 2023). Yet this reading also reveals its limits. Digital footprints reduce information asymmetry only for businesses whose activities are adequately recorded. For businesses that operate in cash, informally, or in areas with limited digital infrastructure, information asymmetry does not decline and may even sharpen, because lenders now have a richer benchmark in other segments. In other words, digital footprints do not eliminate information asymmetry; they shift its line of demarcation from "having collateral or not" to "being digitally legible or not."

The Inclusion Paradox and Its Accompanying Risks

This shift in the line of demarcation lies at the heart of the paradox of digital financial inclusion (Mas'ud et al., 2026). The synthesis identifies at least four sources of risk. The first is the risk of thin data (*thin footprint*): models learn from populations with thick footprints, so their performance declines for the MSMEs that most need access. The claim that alternative data is most beneficial for borrowers without a credit history (Djeundje et al., 2021; Buananta et al., 2026) must be read alongside this fact: the benefit holds only when a digital footprint exists. The second is the risk of bias and distributive unfairness. Fuster et al. (2022) show that a model that is more accurate in aggregate can widen gaps between groups, because it more precisely identifies groups that are historically high-risk as a result of structural inequality.

The third is the risk to explainability and accountability. Complex nonlinear models make it difficult for lenders to explain the reasons for rejection to borrowers and regulators. Bussmann et al. (2021) offer a solution through Shapley values, which group predictions according to the similarity of their explanations. In the MSME context, explainability is not only a regulatory requirement but also a learning tool: entrepreneurs who understand the factors that drive their scores can improve their business practices. The fourth is the risk of privacy intrusion and manipulation. The more behavioral traces are used, the greater the intrusion into the business owner's private life, and the stronger the incentive to engineer footprints so as to appear creditworthy. Mwesiwa et al. (2026) show that credit scoring in practice is always the outcome of negotiation among risk logic, data availability, and institutional interests, so technical designs that ignore the social dimension risk failing in implementation or even harming vulnerable groups.

These risks take on an institutional dimension in the Indonesian context. Hardjomidjojo

and Sarma (2023) map the risks of an MSME credit process digitalization program at a regional bank, while Putri and Thayib (2025) show how a financing platform designs risk mitigation alongside social impact. Mutamimah et al. (2023) propose a blockchain-based governance innovation to increase transparency and reduce credit risk. These three studies indicate that the quality of credit assessment is determined not only by algorithms but also by the process governance and data integrity that support them.

From Creditworthiness to Business Sustainability

Creditworthiness is fundamentally a prediction of business continuity. However, models optimized solely to minimize default risk tend to favor businesses that are financially stable in the present rather than those capable of adapting to future challenges. Safira et al. (2025) find that financial technology and risk management influence the sustainability performance of micro, small, and medium enterprises (MSMEs), while Martínez-Peláez et al. (2023) demonstrate that digital transformation supports sustainability through organizational capabilities and stakeholder engagement. These findings suggest that digital footprints can reflect not only potential credit risk but also a business's adaptive capabilities, including sales channel diversification, responsiveness to changing demand, and customer engagement.

Building on this synthesis, this article proposes a Digital Footprint Risk-Based Scoring (DF-RBS) framework comprising three interconnected layers. The data layer collects five categories of digital footprints in accordance with the principle of data minimization, prioritizing transactional, commercial, relational, and operational data while using personal behavioral data selectively and only with appropriate consent. The scoring layer generates two conceptually distinct outputs: a Default Risk Score, which estimates the likelihood of short-term default, and a Business Resilience Score, which assesses a business's capacity to withstand disruptions and adapt to changing market conditions. The governance layer ensures model explainability, fairness across different business segments, and accessible appeal mechanisms for borrowers. These three layers are designed to ensure that credit assessments account for both financial risk and business resilience while maintaining transparency, fairness, and responsible data use.

The framework integrates default risk and business resilience into a broader credit assessment process, with the relative importance of each dimension determined by lending policies and the characteristics of the borrower. Its application is conditional on compliance with the established governance requirements. By maintaining a distinction between default risk and business resilience, the framework enables lenders to make more nuanced and context-sensitive credit decisions. MSMEs with low default risk and high resilience may qualify for standard credit facilities. Those with relatively high default risk but strong resilience, such as young and rapidly growing businesses, may qualify for graduated lending, whereby credit limits initially remain small and increase as the borrower establishes a reliable repayment history. MSMEs with low default risk but limited resilience may receive credit accompanied by digitalization mentoring and business development support. Meanwhile, MSMEs exhibiting both high default risk and low resilience may be referred to financial literacy programs, business capacity-building initiatives, or appropriate non-commercial financing alternatives rather than being automatically excluded from financial support.

Through this mechanism, credit rejection is no longer treated solely as an endpoint but may become an entry point to a pathway for improving financial capability, strengthening business resilience, and developing a more reliable digital footprint. This approach aligns with the calls by Kamat and Haldar (2025) and Abdellatif et al. (2026) to leverage alternative data in ways that promote responsible business growth and financial sustainability. Ultimately, the DF-RBS framework seeks to move beyond conventional credit assessment by integrating repayment capacity, adaptive potential, and responsible governance into a more inclusive approach to MSME financing.

Table 1. Integration of key variables, synthesized findings, and interpretation within the DF-RBS framework

Dimension / key variable	Digital footprint indicators	Synthesized findings (supporting studies)	Theoretical interpretation	Implications for DF-RBS
Cash flow capacity	Frequency, volume, and regularity of digital payments	Digital payments shape MSME financial profiles for bank financing (Mauliansyah & Aziz, 2026; Gambacorta et al., 2023)	Financial statements and collateral replaced by direct observation of economic behavior	Core component of the Default Risk Score
Reputation and market relationships	Sales history, reviews, and return rates on marketplaces	E-commerce data predict the creditworthiness of unbanked MSMEs (Buananta et al., 2026; Wang et al., 2024)	Soft information that is codified and scalable	Fills the gap for MSMEs without a credit history
Position in the business network	Links with suppliers, buyers, and related entities	Knowledge graphs capture contagion risk in supply chains (Mitra et al., 2023; Zhang et al., 2024)	Risk is relational, not merely an individual attribute	Score adjustment for systemic and concentration risk
Operational capacity	Indicators of business management and operational risk	Operational risk profiles predict micro-enterprise solvency (Pérez-Salazar et al., 2026; Gu et al., 2024)	Bridge between willingness to repay and ability to survive	Shared component of both scores
Owner behavior and device	App usage patterns and device characteristics	Predictive for individual credit, problematic for MSMEs (Orlova, 2021; Xu, 2025; Djeundje et al., 2021)	Blurs the personal and business spheres; prone to indirect bias	Limited, consent-based use
Resilience and sustainability	Channel diversification, fintech adoption, risk management practices	Fintech, risk management, and digital transformation support sustainability performance (Safira et al., 2025; Martínez-Peláez et al., 2023)	Creditworthiness as a prediction of business continuity, not only default	Basis of the Business Resilience Score
Fairness and inclusion	Distribution of scores and approvals across segments	Inclusion paradox; aggregate accuracy can widen gaps (Mas'ud et al., 2026; Fuster et al., 2022)	Digital footprints shift, rather than remove, the line of access	Mandatory fairness testing in the governance layer
Explainability and accountability	Explanation of score drivers for each borrower	Shapley values improve credit model	The legitimacy of credit decisions is socio-technical	Score explanations and an appeal mechanism

		explainability (Bussmann et al., 2021; Mwesigwa et al., 2026)		
Process and data governance	Data integrity, transparency, process control	Process digitalization and blockchain affect credit risk (Hardjomidjojo & Sarma, 2023; Mutamimah et al., 2023)	Score quality depends on institutional quality	Precondition for the score to apply (G = 1)

Table 1 shows that not all digital footprints are of equal value. Transactional and commercial footprints offer the highest benefit-to-risk ratio because they relate directly to business performance and are relatively less intrusive. Relational and operational footprints add value by capturing risks that are invisible at the individual level. In contrast, personal behavioral footprints provide additional accuracy at a high ethical cost. This hierarchy is an important practical contribution, because regulators and lenders need guidance on which types of data deserve priority, not merely a list of data that could be used.

Overall, this discussion supports three propositions. First, digital footprints improve MSME creditworthiness assessment through the codification of soft information, not merely through the addition of variables. Second, the inclusion benefits of digital footprints are conditional, depending on footprint thickness, model fairness, and the quality of governance. Third, sustainability-oriented credit assessment requires a conceptual separation between default risk and business resilience, followed by their integration through graduated risk-based decisions. These propositions also open a further research agenda: the empirical validation of DF-RBS using transaction data from Indonesian MSMEs.

CONCLUSIONS

This study affirms that the value of digital footprints in MSME financing lies not in the number of new variables that can be fed into a model but in their capacity to transform contextual information about business performance and behavior, which was previously accessible only through personal relationships, into a record that is standardized, verifiable, and scalable, thereby reducing reliance on collateral as a screening mechanism; however, the same mechanism also shifts the boundary of exclusion from asset ownership to digital legibility, so that without deliberate design, a technology promised as a path to inclusion may instead reproduce inequality for businesses that operate in cash, informally, or in areas with limited infrastructure, and for this reason the Digital Footprint Risk-Based Scoring framework, which separates and then combines default risk with business resilience, prioritizes transactional, commercial, relational, and operational footprints over personal behavioral footprints, and makes explainability, fairness testing, and data protection preconditions for the score to apply, offers a middle path that allows credit rejection to become a pathway to capacity building, enriches information asymmetry theory with an account of the conditions under which data succeeds or fails as a substitute for collateral, and provides a foundation for regulators and financial institutions in Indonesia to design credit assessments that are not only accurate but also fair and oriented toward business continuity, with the caveat that these propositions still require empirical validation through modeling on MSME transaction data and evaluation of their distributive impact across business segments.

REFERENCES

Abdellatif, S. H., Yang, C., & Nigussi, A. (2026). Artificial intelligence enhanced credit scoring for MSMEs: A policy framework for financial sustainability in emerging economies.

- European Journal of Sustainable Development, 15(2).
<https://doi.org/10.14207/ejsd.2026.v15n2p585>
- Alternative data scoring for MSME lending: A blueprint for financial inclusion. (2025). *Iconic Research and Engineering Journals*. <https://doi.org/10.64388/irev9i1-1712949>
- Buananta, S. E. A., Gaol, F., Legowo, N., Utama, D., & Mauritsius, T. (2026). Creditworthiness prediction model for unbanked MSMEs using machine learning and e-commerce digital footprint data. In *2026 International Conference on Intelligent Engineering and Next-Gen Healthcare Systems (IEHNS)* (pp. 1–9). IEEE. <https://doi.org/10.1109/iehns68708.2026.11607140>
- Bussmann, N., Giudici, P., Marinelli, D., & Papenbrock, J. (2021). Explainable machine learning in credit risk management. *Computational Economics*, 57(1), 203–216. <https://doi.org/10.1007/s10614-020-10042-0>
- Charfeddine, L., Umlai, M., & El-Masri, M. (2024). Impact of financial literacy, perceived access to finance, ICT use, and digitization on credit constraints: Evidence from Qatari MSME importers. *Financial Innovation*, 10. <https://doi.org/10.1186/s40854-023-00557-4>
- Djeundje, V. B., Crook, J., Calabrese, R., & Hamid, M. (2021). Enhancing credit scoring with alternative data. *Expert Systems with Applications*, 163, Article 113766. <https://doi.org/10.1016/j.eswa.2020.113766>
- Fuster, A., Goldsmith-Pinkham, P., Ramadorai, T., & Walther, A. (2022). Predictably unequal? The effects of machine learning on credit markets. *The Journal of Finance*, 77(1), 5–47. <https://doi.org/10.1111/jofi.13090>
- Gambacorta, L., Huang, Y., Li, Z., Qiu, H., & Chen, S. (2023). Data versus collateral. *Review of Finance*, 27(2), 369–398. <https://doi.org/10.1093/rof/rfac022>
- Gu, Z., Lv, J., Wu, B., Hu, Z., & Yu, X. (2024). Credit risk assessment of small and micro enterprise based on machine learning. *Heliyon*, 10, Article e27096. <https://doi.org/10.1016/j.heliyon.2024.e27096>
- Hardik, N. (2023). Digitalisation promotes adoption of soft information in SME credit evaluation: The case of Indian banks. *Digital Finance*, 1–32. <https://doi.org/10.1007/s42521-023-00078-w>
- Hardjomidjojo, H., & Sarma, M. (2023). Risk assessment of MSME credit process digitalization program of PT Bank XYZ West Sumatra Region. *International Journal of Research and Review*. <https://doi.org/10.52403/ijrr.20230644>
- Kamat, M., & Haldar, A. (2025). Fintech for small businesses: Unlocking responsible growth with alt.data. *Management Practice Insights*. <https://doi.org/10.59571/mpi.v3si1.4>
- Martínez-Peláez, R., Ochoa-Brust, A., Rivera, S., Félix, V. G., Ostos, R., Brito, H., Félix, R. A., & Mena, L. J. (2023). Role of digital transformation for achieving sustainability: Mediated role of stakeholders, key capabilities, and technology. *Sustainability*, 15(14), Article 11221. <https://doi.org/10.3390/su151411221>
- Mas'ud, B. R., Fadlina, Kurniawan, & Gubangco, A. G. (2026). The paradox of digital financial inclusion: Unpacking the alternative credit scoring gap for MSMEs in FinTech lending. *MANDAR: Management Development and Applied Research Journal*, 8(2). <https://doi.org/10.31605/mandar.v8i2.6784>
- Mauliansyah, H., & Aziz, A. (2026). Digital payments and MSMEs' financial profiles for bank financing. *Global Research in Economics and Advanced Theory (GREAT)*, 3(3). <https://doi.org/10.65788/greatjournal.v3i3.126>
- Mitra, R., Dongre, A., Dangare, P., Goswami, A., & Tiwari, M. K. (2023). Knowledge graph driven credit risk assessment for micro, small and medium-sized enterprises. *International Journal of Production Research*, 62, 4273–4289. <https://doi.org/10.1080/00207543.2023.2257807>
- Mutamimah, M., Alifah, S., & Adnjani, M. D. (2023). Corporate governance innovation framework to reduce credit risk in MSMEs using blockchain technology. *Cogent Business & Management*, 10, Article 2250504.

- <https://doi.org/10.1080/23311975.2023.2250504>
- Mwesigwa, D., Jackson, S., & Csíkszentmihályi, C. (2026). Risk, data, alignment: Making credit scoring work in Kenya. In *Proceedings of the 2026 CHI Conference on Human Factors in Computing Systems*. ACM. <https://doi.org/10.1145/3772318.3790924>
- Njuguna, R., & Sowon, K. (2021). Poster: A scoping review of alternative credit scoring literature. In *Proceedings of the 4th ACM SIGCAS Conference on Computing and Sustainable Societies*. ACM. <https://doi.org/10.1145/3460112.3471972>
- Orlova, E. (2021). Methodology and models for individuals' creditworthiness management using digital footprint data and machine learning methods. *Mathematics*, 9(15), Article 1820. <https://doi.org/10.3390/math9151820>
- Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., . . . Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, 372, n71. <https://doi.org/10.1136/bmj.n71>
- Pérez-Salazar, J., Márquez, N., & Vidal-Silva, C. (2026). Algorithmic profiling of operational risk: A data-driven predictive model for micro-enterprise solvency assessment. *Computers*, 15(2), Article 135. <https://doi.org/10.3390/computers15020135>
- Putri, F. W., & Thayib. (2025). Akseleran as social entrepreneurship fintech: Risk mitigation analysis and sustainable social impact development for MSMEs. *Jurnal Manajemen dan Inovasi (MANOVA)*, 8(2). <https://doi.org/10.15642/manova.v8i2.2093>
- Rathi, R. M., Chhugani, P., Singh, S., & Tomar, D. (2026). AI-enabled credit scoring and financial inclusion in Indian MSME lending: An empirical analysis of risk assessment, loan accessibility, and borrower performance. *International Journal of Recent Advances in Multidisciplinary Topics*, 7(6). <https://doi.org/10.65138/ijramt.2026.v7i6.3268>
- Safira, S., Agustina, A., Hidayanti, N., & Mukhlisin, M. (2025). Impact of fintech and risk management on the sustainability performance of MSMEs (micro, small and medium enterprises). *EQUITY*, 28(1). <https://doi.org/10.34209/equ.v28i1.10160>
- Shi, B., Bai, C., & Dong, Y. (2024). A big data analytics method for assessing creditworthiness of SMEs: Fuzzy equifinality relationships analysis. *Annals of Operations Research*, 350, 879–909. <https://doi.org/10.1007/s10479-024-06054-w>
- Wang, L., Zhu, J.-P., Zheng, C., & Zhang, Z. (2024). Incorporating digital footprints into credit-scoring models through model averaging. *Mathematics*, 12(18), Article 2907. <https://doi.org/10.3390/math12182907>
- Xu, H. (2025). Exploring personal digital footprints and credit risk assessment. *SHS Web of Conferences*, 225, Article 04003. <https://doi.org/10.1051/shsconf/202522504003>
- Zhang, L., Song, Q.-K., Fan, M.-H., & Yao, X.-Y. (2024). Credit strategy research based on Markov random field and enterprise association knowledge graph. *International Journal of Systems Science*, 55, 844–857. <https://doi.org/10.1080/00207721.2023.2300149>
- Zhang, X. (2026). Research on credit empowerment based on big data and digital footprints. *Highlights in Science, Engineering and Technology*. <https://doi.org/10.54097/Onaxsp80>