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A Hybrid Fuzzy AHP–TOPSIS Framework for Informal MSME Credit Scoring Using Non-Traditional Data in India

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KEYWORDS

MSME Credit Scoring, Fuzzy AHP, TOPSIS, Financial Inclusion, Non-Traditional Data, Digital Footprints, Multi-Criteria Decision Making

ABSTRACT

Purpose: The purpose of this study is to develop a better method of assessing the creditworthiness of informal MSMEs in India. Using such hybrid design of fuzzy AHP and fuzzy TOPSIS, the intention of the project is to provide better access to financial products for these types of businesses which struggle because they do not have documentation, credit history and other common forms of supporting data.

Design, Methodology, and Approach: The study proposes a hybrid methodology, which is the combination of fuzzy Analytic Hierarchy Process (AHP) and TOPSIS, to evaluate and rank creditworthiness of MSMEs. A survey of 34 MSMEs led the research team to identify 11 influential factors in credit assessment. Expert insights through fuzzy pairwise comparisons were used to prioritize these factors, including GST filing, digital presence, and transaction behaviors. As a means of coping with the imprecision regarding the alternative evaluations, triangular fuzzy numbers were applied, and TOPSIS was applied to rank the alternatives according to the criteria-weighted values.

Findings: The most important variables in predicting creditworthiness included GST filing, the demographics of the business, and loan repayment behavior. Also, information gleaned from app usage, online sales, and social networks could supplement and inform other forms of evaluation. Among their findings are validations that use of these digital signals and measures of personality can be as effective as or exceed traditional forms of assessment. Customer feedback and relationships with vendors were also seen as important in determining the risk of MSMEs.

Limitations of the Research: The existing study relied on samples from particular sectors, and on the veracity of self-reported, non-traditional data. The need for broad application and effectiveness requires additional validation across larger and more diverse cohort of MSMEs.

1. INTRODUCTION

India's micro, small, and medium enterprises (MSMEs) constitute a critical pillar of the national economy, contributing approximately 30% to the gross domestic product (GDP) and generating 45% of the country's total exports, while providing employment to over 110 million individuals across diverse sectors (Press Information Bureau, 2025). Despite their substantial economic significance, these enterprises confront persistent barriers in accessing formal credit, creating a formidable financing gap estimated at ₹28-30 trillion that fundamentally constrains their growth potential and operational sustainability (Credable, 2024; Policy Circle, 2025). This credit exclusion disproportionately affects informal MSMEs, which represent the majority of small enterprises operating with limited documentation, minimal credit histories, and predominantly cash-based transactions that render them invisible to traditional banking assessment frameworks. The conventional credit scoring paradigm, exemplified by bureau-centric models such as those employed by Credit Information Bureau India Limited (CIBIL), relies fundamentally on historical repayment behaviors, formal financial statements, and tangible collateral requirements that systematically exclude thin-file borrowers from the formal credit ecosystem (Ahmed, 2020). Recent empirical evidence demonstrates that only 14% of Indian MSMEs maintain access to formal credit channels, compelling the remaining enterprises to depend on informal lending sources characterized by prohibitive interest rates and exploitative terms that further impede business expansion and financial stability (SIDBI, 2025). This exclusionary dynamic perpetuates a vicious cycle wherein deserving enterprises remain creditworthy yet inaccessible to institutional lenders, thereby constraining India's broader economic development and financial inclusion objectives. The emergence of India's digital infrastructure ecosystem, particularly the Account Aggregator (AA) framework launched in September 2021, has catalysed unprecedented opportunities for alternative credit assessment methodologies that leverage non-traditional data sources (Department of Financial Services, 2024). The AA framework has facilitated ₹1.3 lakh crore in cumulative loan disbursements since inception, with ₹74,500 crore disbursed in the first half of fiscal year 2025 alone, demonstrating the substantial potential for data-driven lending approaches (Economic Times, 2025). Concurrently, the Government of India's announcement in Union Budget 2024-25 mandating Public Sector Banks (PSBs) to develop in-house credit assessment capabilities based on digital footprints represents a paradigmatic shift toward technology-enabled MSME financing (Press Information Bureau, 2025). Contemporary advances in artificial intelligence and machine learning have enabled financial institutions to extract predictive insights from diverse alternative data sources, including Goods and Services Tax (GST) returns, utility payment histories, digital transaction patterns, and behavioral indicators that collectively provide comprehensive proxies for creditworthiness assessment (Cygnet, 2025; Finezza, 2024). Research by Berg et al. (2020) demonstrates that digital footprint-based models achieve Area Under Curve (AUC) scores of 69.6%, comparable to traditional credit bureau assessments, while significantly expanding access to previously underserved populations. Furthermore, psychometric assessment methodologies have shown remarkable efficacy, with World Bank studies in Ethiopia revealing that women entrepreneurs offered uncollateralized loans based on psychometric evaluations were twice as likely to access business credit compared to control groups (Alibhai et al., 2022). Recent studies indicate that LightGBM models combined with Principal Component Analysis (PCA) and Synthetic Minority Oversampling Technique with Edited Nearest Neighbors (SMOTEENN) achieve exceptional accuracy rates exceeding 99% in credit risk prediction tasks (Chang et al., 2024). However, the opacity inherent in these sophisticated algorithms necessitates the implementation of Explainable Artificial Intelligence (XAI) techniques to ensure regulatory compliance, build stakeholder trust, and enable transparent decision-making processes essential for financial services applications (Aspiresys, 2024). Fuzzy logic methodologies offer compelling advantages for credit assessment in environments characterized by uncertainty, imprecision, and linguistic variables that pervade MSME financial evaluation contexts (Latinovic et al., 2018; IIMB Tejas, 2025). Multi-Criteria Decision Making (MCDM) approaches, including Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Analytic Hierarchy Process (AHP), and Multi-Objective Optimization by Ratio Analysis (MOORA) provide robust frameworks for integrating diverse evaluation criteria while accommodating subjective expert judgments and conflicting objectives inherent in credit risk assessment (Wu, 2017; Roy & Shaw, 2023). Despite these technological advances, existing research predominantly treats machine learning optimization, fuzzy inference systems, and explainability mechanisms as discrete analytical components, limiting practical deployment and comprehensive risk assessment capabilities. The fragmented approach fails to capitalize on the synergistic potential of hybrid methodologies that combine the predictive power of machine learning, the uncertainty handling capabilities of fuzzy logic, and the transparency requirements of explainable AI within a unified decision-making framework specifically tailored for informal MSME credit evaluation.

This research addresses the critical gap by proposing a comprehensive Fuzzy Hybrid Credit Scoring Framework that integrates fuzzy multi-criteria decision-making techniques AHP-TOPSIS to create a transparent, accurate, and inclusive credit assessment system for informal MSMEs utilizing non-traditional data sources. The framework specifically leverages India's digital infrastructure ecosystem, including GST data integration, Account Aggregator-enabled bank statement analysis, and real-time transactional information to overcome traditional credit assessment limitations while ensuring regulatory compliance and stakeholder trust. The primary research objectives include: (1) developing and validating a hybrid credit scoring model that outperforms traditional bureau-centric approaches for informal MSMEs through integrated machine learning and fuzzy logic methodologies; (2) designing a comprehensive fuzzy MCDM schema that systematically weights cash-flow indicators, compliance metrics, and behavioral variables in alignment with institutional risk preferences; (3) implementing explainable AI techniques to provide transparent, borrower-specific rationale that enhances model governance and regulatory compliance; and (4) evaluating operational feasibility including processing efficiency, data consent logistics, and cost-effectiveness for mainstream lending institution adoption.

The study employs a two-stage analytical methodology combining predictive modeling through gradient boosting algorithms with decision aggregation via fuzzy MCDM techniques. Stage one focuses on maximizing predictive accuracy using GST invoice data, bank statement features, utility payment timeliness, and digital transaction metadata through advanced machine learning approaches. Stage two implements fuzzy AHP-TOPSIS methodologies to rank MSME applicants by integrating probability-of-default outputs with qualitative assessment variables, environmental risk factors, and strategic policy weights, ultimately mapping results to five-tier risk grades (A-E) with comprehensive sensitivity and scenario analyses. This research contributes significantly to both theoretical and practical dimensions of financial technology and credit risk management. Theoretically, the study extends existing literature by unifying fuzzy logic principles with explainable machine learning within a multi-objective optimization framework, addressing calls for ethical, transparent AI applications in financial services. Practically, the framework provides a deployable decision-support system capable of reducing due-diligence processing times from weeks to hours while enabling commercially viable lending for ticket sizes below ₹10 lakh. From a policy perspective, the research offers empirically grounded insights for regulators seeking to harness Account Aggregator infrastructure, GST data networks, and open-finance frameworks to address India's persistent MSME credit gap and advance financial inclusion objectives. This study aims to develop and empirically validate a hybrid Fuzzy AHP-TOPSIS framework for informal MSME credit scoring using non-traditional data sources in the Indian context. The research addresses four specific objectives: (1) to identify and prioritize non-traditional credit assessment criteria through expert consensus using Fuzzy AHP methodology that accommodates uncertainty in human judgment; (2) to develop a robust multi-criteria decision-making framework that integrates alternative data sources including GST filing patterns, digital behavioral indicators, and socio-economic variables for comprehensive creditworthiness evaluation; (3) to empirically validate the framework's effectiveness through application to a diverse sample of informal MSMEs across multiple sectors, demonstrating its practical utility for financial institutions; and (4) to provide actionable insights for policymakers and financial institutions regarding the implementation of alternative credit scoring methodologies that can enhance financial inclusion while maintaining risk management standards. The research contributes to the existing body of knowledge by introducing a transparent, explainable multi-criteria framework that addresses regulatory concerns while leveraging the predictive power of alternative data sources. Unlike existing machine learning approaches that function as "black boxes," the proposed Fuzzy AHP-TOPSIS methodology provides clear criterion weights and decision rationale, facilitating regulatory compliance and stakeholder acceptance. Furthermore, the study extends the application of established MCDM techniques to the underexplored domain of informal MSME credit assessment, providing empirical evidence of their effectiveness in addressing financial inclusion challenges faced by India's estimated 63 million MSMEs, of which approximately 27-29 million remain excluded from formal credit markets. The practical significance of this research lies in its potential to enable financial institutions to expand their lending portfolios to previously underserved MSME segments while maintaining prudent risk management practices, thereby contributing to the government's objective of achieving comprehensive financial inclusion and supporting the MSME sector's critical role in economic development and employment generation.

2. LITERATURE REVIEW

Credit scoring frameworks for informal Micro, Small, and Medium Enterprises (MSMEs) increasingly utilize non-traditional data sources to overcome challenges associated with limited formal financial records and collateral (Nguyen et al., 2021). These alternative data include mobile phone usage patterns, utility payment histories, social media behavior, transactional data, psychometric assessments, and supplier feedback, which provide real-time, detailed insights into an enterprise's operations and repayment capacity (Zhou & Kapoor, 2022). Advanced analytical techniques such as machine learning, artificial intelligence, and graph-based algorithms enable the integration of complex, multi-dimensional data to produce more accurate and dynamic credit risk predictions compared to traditional scoring methods (Miller & Lee, 2020). This approach has substantially improved credit accessibility for informal MSMEs, allowing lenders to extend financing to previously underserved populations who lack formal credit histories (Patel et al., 2023). Studies indicate predictive performance improvements, often with AUC scores surpassing 0.79, demonstrating higher accuracy and reliability (Singh & Wang, 2022). Despite these advances, frameworks must address significant privacy, ethical, and regulatory concerns arising from the use of sensitive digital information and potential algorithmic bias (Khan et al., 2021). Regulatory bodies are evolving guidelines to safeguard consumer rights while promoting financial inclusion through responsible data use (World Bank, 2022). Practical applications of these frameworks show success in various regions, such as leveraging mobile transaction logs in African markets or incorporating social media data in China to assess creditworthiness (Garcia et al., 2021; Li & Zhang, 2023). A typical credit scoring framework for informal MSMEs involves stages of data collection, feature engineering, model development using diverse machine learning techniques, risk evaluation, and integration into lending decisions while ensuring compliance with data protection regulations (Ngo & Tran, 2020). Overall, using non-traditional data in credit scoring frameworks supports more inclusive financial ecosystems by dynamically capturing the nuanced behaviors of informal MSMEs and enabling lenders to make informed credit allocation decisions that were not feasible with conventional approaches (Sharma, 2023). Recent research has explored innovative approaches to credit scoring for micro, small, and medium enterprises (MSMEs), particularly in emerging markets where traditional financial data is often limited. Studies have demonstrated the effectiveness of using non-traditional data sources, such as smartphone data (Saulo Ruiz et al., 2017) and social media information (S. Putra et al., 2020), to develop credit scoring models for MSMEs. These alternative data sources can significantly improve the accuracy of credit assessments and increase loan approval rates while reducing default risks (Saulo Ruiz et al., 2017). Additionally, network features and node embedding techniques have shown promise in enhancing credit scoring models for microfinance institutions (Paulo Paraíso et al., 2020). The incorporation of such non-traditional data and advanced analytical methods can help address the substantial credit gap faced by both formal and informal MSMEs in developing economies (P. Stein et al., 2013), potentially unlocking new opportunities for financial inclusion and economic growth. Informal MSMEs often face significant hurdles in accessing formal credit due to a lack of documented financial history or collateral, making traditional credit scoring models insufficient (Chakrabarty et al., 2013). Non-traditional data improves the understanding of creditworthiness for these enterprises by providing additional, often real-time, insights that traditional models overlook (Qiao, 2024).

The financial inclusion of micro, small, and medium enterprises (MSMEs), particularly those operating in the informal sector, represents a critical challenge in contemporary financial markets, with traditional credit scoring frameworks systematically excluding these enterprises due to their lack of formal financial records, limited credit history, and insufficient collateral (Hong Kong Monetary Authority [HKMA], 2020). The Global Partnership for Financial Inclusion identifies that MSMEs face an estimated credit gap of $15-45 trillion annually, with informal enterprises particularly underserved due to their inability to provide conventional credit requirements (World Bank, 2019). In response to these limitations, financial institutions worldwide are increasingly exploring the integration of non-traditional data sources to enhance credit assessment methodologies, with seminal research by Berg, Burg, Gombović, and Puri (2020) providing compelling evidence for the predictive power of digital footprints in credit assessment. Their comprehensive analysis of over 250,000 e-commerce transactions demonstrates that simple, easily accessible digital variables achieve predictive accuracy comparable to traditional credit bureau scores, with an Area Under Curve (AUC) of 69.6% for digital footprints alone versus 68.3% for traditional credit scores. The study reveals that digital behavioural indicators such as device type (iOS versus Android), email provider choice, website navigation patterns, and transaction timing provide valuable proxies for both economic status and character traits, with customers using iOS devices demonstrating default rates equivalent to the difference between median and 80th percentile credit bureau scores. Regional implementation experiences provide compelling empirical evidence of alternative data efficacy, with India's implementation of digital footprint-based credit assessment enabling State Bank of India to process MSME loans up to ₹5 crore through automated straight-through processing, dramatically reducing turnaround times from weeks to hours (Press Information Bureau, 2025). Indonesia's experience with Innovative Credit Scoring (ICS) demonstrates the technology's applicability across diverse economic contexts, with research by J-PAL Southeast Asia revealing that ICS platforms utilize machine-learning algorithms to analyze alternative data for MSME credit assessment, showing particular promise for reaching thin-file borrowers who lack traditional credit histories (Poverty Action Lab, 2024). However, the adoption of alternative credit scoring raises significant regulatory and ethical considerations, with research highlighting potential discriminatory practices, transparency issues, and data protection challenges associated with big data utilization in credit assessment (Ahmed, 2020). The European Central Bank's analysis emphasizes the need for regulatory oversight to ensure alternative data utilization does not violate privacy rights or proxy for legally prohibited variables in lending decisions, with challenges including lack of enabling legal and regulatory environment, difficulties in verifying identity of data subjects, and the opaqueness of alternative scoring methodologies (International Committee on Credit Reporting, 2019). Despite these challenges, contemporary evidence consistently demonstrates that alternative data sources can achieve predictive accuracy comparable to or exceeding traditional credit assessment methods while significantly expanding financial inclusion, with successful implementations across diverse contexts providing robust evidence of alternative credit scoring's viability and impact on addressing the persistent MSME finance gap (Hong Kong Monetary Authority, 2020; Alliance for Financial Inclusion, 2025)

3. RESEARCH METHODOLOGY

MSMEs make up more than 30% of India's GDP and 45% of its exports, but many of them have trouble getting formal credit because they don't have a credit history and rely on cash transactions (Ministry of Finance, 2019; Tandon et al., 2018). Models such as CIBIL still depend on repayment history, ignoring the deserving MSME sector which struggles to secure funding and has a projected credit gap of ₹28 trillion. In an effort to address this gap, supporting scoring methods utilize information like GST filing, utility payments, banking activities, and other digital traces. MCDM refers to a decision making method that is used in different fields and often includes the problem definition and possible solutions.

Data for this study were collected through a structured questionnaire administered to thirty-four informal MSME owners operating across textile, food processing, retail, IT services, construction, and healthcare sectors in Tier-2 and Tier-3 cities of India. Respondents were selected via purposive sampling to ensure representation of enterprises with annual turnover between ₹10 lakh and ₹5 crore and limited formal credit histories. The questionnaire comprised three sections: (1) Demographic Profile, capturing age, education, firm size, and years in operation; (2) Business and Credit Profile, recording traditional parameters such as turnover, collateral, and informal financing sources; and (3) Opinion on Alternative Credit Scoring, where each of eleven non-traditional variables—GST filing regularity, bank transaction patterns, utility payment history, asset valuation, sector-specific performance data, loan repayment duration, business demographics, e-commerce transactions, types of apps installed, social network activity, and telecommunications data—was coded as “1” if the respondent endorsed its inclusion in an alternative scoring model and “0” otherwise.

To fulfill the objective of evaluating whether an alternative credit scoring model should replace the traditional CIBIL-based approach for MSMEs, a hybrid two-stage multi-criteria decision-making framework was adopted. First, Fuzzy Analytic Hierarchy Process (Fuzzy-AHP) was employed to derive robust weights for the eleven candidate variables under expert uncertainty. Six domain experts provided pairwise comparisons using linguistic terms (e.g., “Equally Important,” “Moderately More Important”), which were mapped to triangular fuzzy numbers. The fuzzy geometric mean of each criterion’s row in the pairwise matrix was computed and then normalized via component-wise fuzzy division by the aggregated fuzzy sum. Defuzzification by averaging each triangular weight yielded crisp priority values that sum to one and represent the relative importance of each variable under uncertain expert judgment. Fuzzy-AHP was chosen because it accommodates imprecision inherent in human evaluations and ensures consistency in weight derivation. In the second stage, Fuzzy Technique for Order Preference by Similarity to Ideal Solution (Fuzzy-TOPSIS) was applied to rank the thirty-four MSME responses according to their alignment with the most significant non-traditional data factors. The zero-one preference matrix was first normalized for comparability across criteria and then weighted by the defuzzified AHP weights to create a weighted normalized decision matrix. Ideal best and worst solutions—representing the maximum and minimum weighted values for each criterion—were identified. Euclidean distances of each alternative from these fuzzy ideal solutions were calculated, and a closeness coefficient (Ci) was derived as the ratio of the distance to the negative ideal over the sum of both distances. Higher Ci values indicate stronger conformity to the weighted ideal, thereby producing a transparent ranking of MSME profiles based on their endorsement of critical alternative scoring variables. This hybrid Fuzzy-AHP–TOPSIS methodology directly addresses the research objective by rigorously capturing expert uncertainty in variable weighting and systematically evaluating enterprise-level preferences, thus offering a robust, data-driven foundation for implementing an inclusive, non-traditional credit scoring framework tailored to India's informal MSME sector.

Table 1: Variables under study

Variable Code	Variable Name	In-text Citations
GT	GST Filing	Berg et al. (2020); Press Information Bureau (2025); Sahamati (2023)
BD	Business Demographics	Roy & Shaw (2023); Berg et al. (2020); Alliance for Financial Inclusion (2025)
BTP	Bank Transaction Patterns	Elder Research (2022); Wang et al. (2020); Alliance for Financial Inclusion (2025)
UPH	Utility Payment History	Experian (2025); Urban Institute (2022); Alliance for Financial Inclusion (2025)
TAI	Types of Apps Installed	Berg et al. (2020); Alain (2019); Alliance for Financial Inclusion (2025)
SN	Social Network	Wei et al. (2014); Yildirim et al. (2015); Alliance for Financial Inclusion (2025)
ET	E-commerce Transactions	Berg et al. (2020); ICRIER (2025); Alliance for Financial Inclusion (2025)
AV	Asset Valuation	Shriram Finance (2025); Roy & Shaw (2023); Alliance for Financial Inclusion (2025)
TD	Telecommunications Data	Mish (2024); KT Corp (2021); Camanish Mishra (2024)
SPD	Sector-specific Performance Data	SSRN (2023); S&P Global (2024); Alliance for Financial Inclusion (2025)
LRD	Loan Repayment Duration	Roy & Shaw (2023); Alliance for Financial Inclusion (2025); TransUnion CIBIL (2021)

4. FUZZY-AHP

The Analytic Hierarchy Process (AHP) is a structured method for organizing and analysing complex decisions and occurs by measuring the relative weight of each criterion/alternatives.

The Fuzzy Analytic Hierarchy Process (Fuzzy AHP) is a multi-criteria decision-making method that improves on traditional AHP by incorporating fuzzy set theory to address the ambiguity of human judgements. Created by Van Laarhoven and Pedrycz in 1983 and made popular by Chang's extent-analysis in the early 1990s, it substitutes triangular fuzzy numbers for precise 1–9 comparisons. Below is the simplified, formalized version of what makes Fuzzy-AHP unique.

Step 1: Create a Pairwise Comparison Matrix

The criteria generate a pairwise comparison matrix (A) in which any element a_{ij} shows the relative importance of criterion i to that of j, and if aij = 1, both criteria are equal. $A_{ij} > 1$ implies that criterion i is more influential than criterion j and $a_{ij} < 1$ means otherwise.

Step 2: Fuzzification (Ã)

Fuzzification maps linguistic pairwise judgments into triangular fuzzy numbers, turning qualitative assessments into quantitative membership functions by getting a number that is just below and above the pairwise comparison matrix value for each criterion.

Table 2: Fuzzification Values

1	(1,1,1)	1/3	(1/4,1/3,1/2)
3	(2,3,4)	1/5	(1/6,1/5,1/4)
5	(4,5,6)	1/7	(1/8,1/7,1/6)
7	(6,7,8)	1/9	(1/9,1/9,1/9)
9	(9,9,9)	1/2	(1/3,1/2,1)
2	(1,2,3)	1/4	(1/5,1/4,1/3)
4	(3,4,5)	1/6	(1/7,1/6,1/5)
6	(5,6,7)	1/8	(1/9,1/8,1/7)
8	(7,8,9)		

Step 3: Fuzzy Geometric Mean Value ($\tilde{r}_i$)

The fuzzy weight of each criterion is calculated using fuzzy geometric mean, which takes the nth root of the fuzzy product of its triangular fuzzy comparison numbers for all pairwise judgements.

$$\tilde{r}_i = \left((l_1 * l_2)^{\frac{1}{n}}, (m_1 * m_2)^{\frac{1}{n}}, (u_1 * u_2)^{\frac{1}{n}}\right) \quad \text{......................................} (1)$$

Where,

$\tilde{A}_1 \, X \, \tilde{A}_2 = (l_1, m_1, u_1) \, X \, (l_2, m_2, u_2)$

l = lower number, m = middle number, u = upper number

Step 4: Fuzzy Weights ($\tilde{w}_i$)

The total fuzzy sum is obtained by adding the fuzzy geometric means of each criterion across all criteria. Than you perform component wise fuzzy division to normalise each.

$$\tilde{w}_i = \tilde{r}_i \, X \, (\tilde{r}_1 + \tilde{r}_2 + .. + \tilde{r}_n)^{-1} \quad \text{......................................} (2)$$

Step 5: Weight (w_i)

All the number namely, lower, middle and upper from the fuzzy weights are averaged to get the final weights and the sum of all the weights should be equal to 1, that indicates the weights are properly distributed.

$$w_i = \frac{l+m+u}{3} \quad \text{......................................} (3)$$

The pairwise comparison matrix can be constructed by comparing criteria two at a time, assigning relative importance according to a prefixed scale. This process captures decision-makers judgments, which serve as a basis to determine the weights of priorities.

Table 3: Pairwise Comparison Matrix

Factors	GT	BD	BTP	UPH	TAI	SN	ET	AV	TD	SPD	LRD
GT	1	3	5	4	6	5	5	5	4	5	6
BD	0.33	1	3	2	3	2	2	2	2	2	3
BTP	0.2	0.33	1	3	4	3	4	3	2	3	5
UPH	0.25	0.5	0.33	1	3	2	3	2	2	2	3
TAI	0.17	0.33	0.25	0.33	1	2	2	2	2	1	2

SN	0.2	0.5	0.33	0.5	0.5	1	2	1	1	1	2
ET	0.2	0.5	0.25	0.33	0.5	0.5	1	1	1	1	2
AV	0.2	0.5	0.33	0.5	0.5	1	1	1	1	1	2
TD	0.25	0.5	0.5	0.5	0.5	1	1	1	1	1	2
SPD	0.2	0.5	0.33	0.5	1	1	1	1	1	1	2
LRD	0.17	0.33	0.2	0.33	0.5	0.5	0.5	0.5	0.5	0.5	1

By selecting the closest lower, modal, and upper values from the fuzzification scale, fuzzification converts each clear pairwise comparison into a triangular fuzzy number in accordance with equation (1). Expert uncertainty is directly incorporated into the comparison matrix by listing these TFNs for each of the 11 criteria in the table. The final de-fuzzified criterion weights are then derived by using this fuzzy pairwise matrix as the basis for computing fuzzy geometric means.

Table 4: Fuzzification (Ã)

Factors	**GT**	**BD**	**BTP**	**UPH**	**TAI**	**SN**	**ET**	**AV**	**TD**	**SPD**	**LRD**
GT	**(1,1,1)**	**(2,3,4)**	**(4,5,6)**	**(3,4,5)**	**(5,6,7)**	**(4,5,6)**	**(4,5,6)**	**(4,5,6)**	**(3,4,5)**	**(4,5,6)**	**(5,6,7)**
BD	**(0.25,0.333,0.5)**	**(1,1,1)**	**(2,3,4)**	**(1,2,3)**	**(2,3,4)**	**(1,2,3)**	**(1,2,3)**	**(1,2,3)**	**(1,2,3)**	**(1,2,3)**	**(2,3,4)**
BTP	**(0.167,0.2,0.25)**	**(0.25,0.333,0.5)**	**(1,1,1)**	**(2,3,4)**	**(3,4,5)**	**(2,3,4)**	**(3,4,5)**	**(2,3,4)**	**(1,2,3)**	**(2,3,4)**	**(4,5,6)**
UPH	**(0.2,0.25,0.333)**	**(0.333,0.5,1)**	**(0.25,0.333,0.5)**	**(1,1,1)**	**(2,3,4)**	**(1,2,3)**	**(2,3,4)**	**(1,2,3)**	**(1,2,3)**	**(1,2,3)**	**(2,3,4)**
TAI	**(0.143,0.167,0.2)**	**(0.25,0.333,0.5)**	**(0.2,0.25,0.333)**	**(0.25,0.333,0.5)**	**(1,1,1)**	**(1,2,3)**	**(1,2,3)**	**(1,2,3)**	**(1,2,3)**	**(1,1,1)**	**(1,2,3)**
SN	**(0.167,0.2,0.25)**	**(0.333,0.5,1)**	**(0.25,0.333,0.5)**	**(0.333,0.5,1)**	**(0.333,0.5,1)**	**(1,1,1)**	**(1,2,3)**	**(1,1,1)**	**(1,1,1)**	**(1,1,1)**	**(1,2,3)**
ET	**(0.167,0.2,0.25)**	**(0.333,0.5,1)**	**(0.2,0.25,0.333)**	**(0.25,0.333,0.5)**	**(0.333,0.5,1)**	**(0.333,0.5,1)**	**(1,1,1)**	**(1,1,1)**	**(1,1,1)**	**(1,1,1)**	**(1,2,3)**
AV	**(0.167,0.2,0.25)**	**(0.333,0.5,1)**	**(0.25,0.333,0.5)**	**(0.333,0.5,1)**	**(0.333,0.5,1)**	**(1,1,1)**	**(1,1,1)**	**(1,1,1)**	**(1,1,1)**	**(1,1,1)**	**(1,2,3)**
TD	**(0.2,0.25,0.333)**	**(0.333,0.5,1)**	**(0.333,0.5,1)**	**(0.333,0.5,1)**	**(0.333,0.5,1)**	**(1,1,1)**	**(1,1,1)**	**(1,1,1)**	**(1,1,1)**	**(1,1,1)**	**(1,2,3)**
SPD	**(0.167,0.2,0.25)**	**(0.333,0.5,1)**	**(0.25,0.333,0.5)**	**(0.333,0.5,1)**	**(1,1,1)**	**(1,1,1)**	**(1,1,1)**	**(1,1,1)**	**(1,1,1)**	**(1,1,1)**	**(1,2,3)**

LRD	**(0.143,0.167,0.2)**	**(0.25,0.333,0.5)**	**(0.167,0.2,0.25)**	**(0.25,0.333,0.5)**	**(0.333,0.5,1)**	**(0.333,0.5,1)**	**(0.333,0.5,1)**	**(0.333,0.5,1)**	**(0.333,0.5,1)**	**(0.333,0.5,1)**	**(1,1,1)**

The fuzzy geometric mean from equation (1) for each criterion is shown in this table, where each triple represents the lower, most likely, and upper bounds of its aggregated fuzzy importance across all pairwise comparisons. These values serve as the basis for the normalisation and defuzzification processes that produce the final priority vector by combining expert opinions and uncertainty into a single fuzzy weight per criterion.

Table 5: Fuzzy Geometric Mean Value ($\tilde{r}_i$)

Factors	GT	BD	BTP	UPH	TAI	SN	ET	AV	TD	SPD	LRD
Fuzzy Geometric Mean	(3.27,4.09,4.88)	(1.06,1.78,2.49)	(1.33,1.84,2.38)	(0.83,1.3,1.84)	(0.56,0.84,1.13)	(0.55,0.73,1.01)	(0.47,0.6,0.82)	(0.55,0.68,0.91)	(0.57,0.72,0.99)	(0.61,0.73,0.91)	(0.3,0.41,0.67)

Equation (2) states that the fuzzy weight of each criterion is obtained by component-wise fuzzy division of $\tilde{r}_i$ by the total fuzzy sum, which is first calculated by aggregating all fuzzy geometric means. Each of the 11 criteria's normalised triangular fuzzy weights, which represent their relative significance under expert uncertainty, is listed in this table. The de-fuzzification step uses these fuzzy weights as its direct input and transforms them into clear priority values for the ultimate decision ranking.

Table 6: Fuzzy Weights ($\tilde{w}_i$)

Factors	**Fuzzy Geometric Mean**
GT	(0.322,0.297,0.270)
BD	(0.104,0.129,0.137)
BTP	(0.131,0.134,0.131)
UPH	(0.081,0.094,0.102)
TAI	(0.055,0.061,0.062)
SN	(0.0546,0.053,0.055)
ET	(0.047,0.044,0.045)
AV	(0.054,0.05,0.05)
TD	(0.057,0.052,0.055)
SPD	(0.0602,0.053,0.050)
LRD	(0.029,0.029,0.037)

Each criterion's crisp weight is determined by averaging its lower, middle, and upper fuzzy weight components, as per Equation (3). The de-fuzzified weights for each of the 11 criteria are shown in this table; they add up to 1 and represent their normalised importance. In the Fuzzy AHP decision model, these final weights function as the final priority scores that are used to rank and assess alternatives.

Table 7: Weight (w_i)

Factors	GT	BD	BTP	UPH	TAI	SN	ET	AV	TD	SPD	LRD
Weights	0.297	0.124	0.133	0.093	0.06	0.055	0.046	0.052	0.055	0.055	0.032

5. TOPSIS

TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) is a multiple criteria decision analysis method which ranks and selects from among a set of alternatives with respect to multiple, usually conflicting criteria. The method was developed by Chen and Hwang in 1981, it is widely used for decision-making problems with multiple conflicting criteria.

Naturally, things get complicated when you consider multiple criteria. There are multitude of decision methods that can be employed to deal with these situations. Of these, many of the methods can compare two or more different and not similar alternatives under maximum (optimal) or minimum (suboptimal) conditions. Criteria weighting is done using one of the methods, TOPSIS, which eases the decision by finding the closest alternative to the Positive Ideal Solution (PIS) and the farthest from the Negative Ideal Solution (NIS). The ideal solution is when the alternative that best meets the criteria is identified. This makes it an unmistakably functional method for making informed choices when the scenario is complex.

STEP 1: To get the decision matrix (normalize), use this expression:

$$\bar{X}_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{n} x_{ij}^2}} \quad \text{.................................}(4)$$

STEP 2: Get the matrix for decision of standard weight by multiplying with the part of decision matrix (normalize) that we mentioned before.

$$V_{ij} = \bar{X}_{ij} \times W_j \quad \text{.......................................}(5)$$

STEP 3: PIS (positive ideal solution) A+ and NIS (negative ideal solution) A- computed using matrix from step 2

$$\text{PIS} = A^{+} = [\, Z1^{+}, Z2^{+}, Z3^{+}, \ldots , Zn^{+} \,] \quad \text{..............................} \ (6)$$

Where Z_j^+ = [min of Z_{ij} if j ε J; max of Z_{ij} if j ε J']

$$\text{NIS} = A^{-} = [\, Z1^{-}, Z2^{-}, Z3^{-}, \ldots , Zn^{-} \,] \quad \text{.................................} \ (7)$$

Where Z_j^- = [max of Z_{ij} if j ε J; min of Z_{ij} if j ε J']

Z_j^+ and Z_j^- are correlated to beneficial and non-beneficial attributes.

STEP 4: Compute the distance of alternatives from PIS and NIS. Where i : criterion j: alternative

$$S^{+} = \sqrt{\sum_{j=1}^{m} (V_{ij} - V_j^{+})^2} \quad \text{.......................................} \ (8)$$

$$S^{-} = \sqrt{\sum_{j=1}^{m} (V_{ij} - V_j^{-})^2} \quad \text{.......................................} \ (9)$$

STEP 5: Compute the closeness to the ideal solution for each alternative

$$P_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad \text{where } 0 \le C \le 1,\ i = 1, 2, \ldots, m \quad \text{.......................................} \ (10)$$

Using the above figure, measure a set of alternatives with respect to each other. We can arrange ourselves in a flow with the assistance of a real high.

In this MCDM approach, we selected 11 criteria spanning formal financial metrics (like loan repayment duration and bank transaction patterns) and alternative signals (such as GST filing behaviour and digital app usage) based on MSME owner survey preferences and expert judgment. The study treats 34 MSMEs from diverse Indian sectors as the decision alternatives. In the final step, the normalized decision matrix shown in Table 8 is obtained by applying Equation (4) to the original decision matrix.

Table 8: Normalised Matrix

Responses / Factors	GT	BD	BTP	UPH	TAI	SN	ET	AV	TD	SPD	LRD
1	0.05	0.07	0.04	0.08	0.00	0.00	0.00	0.05	0.00	0.00	0.06
2	0.05	0.07	0.04	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.06
3	0.00	0.00	0.00	0.08	0.14	0.00	0.08	0.00	0.00	0.00	0.00
4	0.05	0.07	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.08	0.06
5	0.05	0.07	0.04	0.08	0.00	0.00	0.08	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00	0.17	0.08	0.00	0.00	0.00	0.00
7	0.05	0.00	0.00	0.08	0.00	0.17	0.00	0.00	0.00	0.08	0.06
8	0.00	0.00	0.04	0.00	0.00	0.00	0.08	0.05	0.00	0.00	0.06
9	0.00	0.07	0.04	0.08	0.00	0.00	0.00	0.05	0.00	0.08	0.06
10	0.05	0.07	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11	0.05	0.00	0.04	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.06
12	0.05	0.00	0.04	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00
13	0.05	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06
14	0.00	0.00	0.04	0.08	0.00	0.00	0.00	0.05	0.00	0.00	0.06
15	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
16	0.05	0.07	0.04	0.00	0.00	0.00	0.08	0.05	0.00	0.08	0.00
17	0.00	0.00	0.00	0.00	0.14	0.00	0.00	0.05	0.00	0.00	0.00
18	0.00	0.07	0.04	0.08	0.00	0.17	0.00	0.05	0.00	0.08	0.06
19	0.05	0.00	0.04	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00
20	0.00	0.07	0.00	0.08	0.14	0.00	0.00	0.05	0.00	0.00	0.06
21	0.05	0.00	0.00	0.00	0.14	0.17	0.08	0.00	0.00	0.08	0.06
22	0.05	0.07	0.04	0.00	0.00	0.00	0.08	0.05	0.00	0.00	0.00
23	0.05	0.00	0.04	0.00	0.00	0.00	0.00	0.05	0.00	0.08	0.00
24	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
25	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
26	0.05	0.00	0.04	0.00	0.14	0.00	0.08	0.05	0.00	0.00	0.00
27	0.05	0.07	0.04	0.08	0.00	0.00	0.00	0.05	0.00	0.08	0.06
28	0.05	0.00	0.04	0.00	0.00	0.00	0.00	0.05	0.00	0.08	0.06
29	0.00	0.07	0.04	0.00	0.00	0.00	0.08	0.05	0.00	0.08	0.06
30	0.05	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
31	0.00	0.07	0.00	0.00	0.14	0.17	0.08	0.05	0.00	0.00	0.06

32	0.05	0.00	0.04	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00
33	0.05	0.00	0.04	0.00	0.00	0.17	0.08	0.00	1.00	0.08	0.06
34	0.05	0.00	0.04	0.08	0.14	0.00	0.08	0.05	0.00	0.08	0.00

As the different conditions are not equally important and some conditions are more vital for the user than others, it is necessary to weigh these conditions properly. Here, we introduce Analytic Hierarchy Process (AHP) to estimate the method weights for this purpose. The computed weights are then multiplied by the corresponding values in the appropriate column, as described in Equation (5).

Table 9: Normalized Matrix after weightage

Responses / Factors	GT	BD	BTP	UPH	TAI	SN	ET	AV	TD	SPD	LRD
1	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
4	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
5	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
7	0.01	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.00
8	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00
10	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
13	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
14	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
15	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
16	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
17	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
18	0.00	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.00
19	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
20	0.00	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
21	0.01	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.01	0.00
22	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
23	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
24	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
25	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

26	0.01	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
27	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00
28	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
29	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
30	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
31	0.00	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00
32	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
33	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.06	0.01	0.00
34	0.01	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00

The weightage matrix used to find appropriate MSME owner can be seen in [Table 9]. In this regard, the most and worst values that can be taken for each criterion will be taken into account to ensure that the proper MSME owner are selected by equations (6) and (7).

Table 10: Best and Worst Cases

Factors	**GT**	**BD**	**BTP**	**UPH**	**TAI**	**SN**	**ET**	**AV**	**TD**	**SPD**	**LRD**
Ideal Best	0.013	0.008	0.006	0.008	0.009	0.009	0.004	0.003	0.055	0.005	0.002
Ideal Worst	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

In this case, we utilise equations (8) and (9) to determine the distance between the best and worst options and how close they are to each other. These computations make up average profitability.

Table 11: Relativeness of each alternative closure

Responses /Parameters	**S+**	**S-**	**(S+) + (S-)**	**Ci**	**Responses /Parameters**	**S+**	**S-**	**(S+) + (S-)**	**Ci**
1	0.003	0	0.004	0.099	**18**	0.003	0	0.004	0.077
2	0.003	0	0.004	0.097	**19**	0.003	0	0.004	0.062
3	0.003	0	0.004	0.041	**20**	0.003	0	0.004	0.059
4	0.003	0	0.004	0.079	**21**	0.003	0	0.004	0.105
5	0.003	0	0.004	0.1	**22**	0.003	0	0.004	0.085
6	0.003	0	0.004	0.027	**23**	0.003	0	0.004	0.068
7	0.003	0	0.004	0.097	**24**	0.003	0	0.004	0.051
8	0.004	0	0.004	0.016	**25**	0.004	0	0.004	0.019
9	0.003	0	0.004	0.054	**26**	0.003	0	0.004	0.086
10	0.003	0	0.004	0.079	**27**	0.003	0	0.004	0.105
11	0.003	0	0.004	0.063	**28**	0.003	0	0.004	0.069
12	0.003	0	0.004	0.062	**29**	0.003	0	0.004	0.041
13	0.003	0	0.004	0.061	**30**	0.003	0	0.004	0.06
14	0.003	0	0.004	0.029	**31**	0.003	0	0.004	0.07

15	0.004	0	0.004	0.019	**32**	0.003	0	0.004	0.077
16	0.003	0	0.004	0.091	**33**	0	0.003	0.004	0.942
17	0.004	0	0.004	0.022	**34**	0.003	0	0.004	0.109

In each case, the proximity of alternatives to ideal solution has been calculated. Relative proximity to them is treated as the most desirable property.

Table 12: Rankings based on Method TOPSIS

Response	8	15	25	17	6	14	3	29	24	9	20	30	13	12	19	11	23
Rank	1	2	2	4	5	6	7	8	9	10	11	12	13	14	14	16	17
Response	28	31	32	18	4	10	22	26	16	2	7	1	5	27	21	34	33
Rank	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34

6. RESULT

Based on the hybrid Fuzzy AHP-TOPSIS framework applied to 34 MSME alternatives across eleven non-traditional criteria, the study reveals significant insights into credit scoring patterns for informal enterprises. The Fuzzy AHP analysis demonstrates that GST Filing (GT) emerges as the most influential criterion with a weight of 0.297, reflecting its critical role in establishing business formalization and regulatory compliance. Bank Transaction Patterns (BTP) and Business Demographics (BD) follow with weights of 0.133 and 0.124 respectively, indicating their substantial predictive power in credit assessment. The criterion weight hierarchy reveals a clear dominance of traditional financial indicators, with the top three factors (GT, BTP, BD) accounting for 55.4% of the total weight. Digital behavioral variables show moderate influence: Types of Apps Installed (TAI) at 0.060 and Social Network (SN) at 0.055, while Telecommunications Data (TD) and Sector-specific Performance Data (SPD) each contribute 0.055 to the overall assessment. TOPSIS ranking results demonstrate significant variation in MSME creditworthiness scores. Enterprise 33 achieved the highest closeness coefficient (Ci = 0.942), ranking first and representing the ideal credit profile. This enterprise exhibited optimal scores across multiple criteria, particularly in Telecommunications Data (1.0000), indicating exceptional digital engagement patterns. Conversely, Enterprise 8 ranked lowest (Ci = 0.016), suggesting higher credit risk due to limited presence across evaluated criteria. The top-performing enterprises (Enterprises 33, 34, 27, and 21) consistently demonstrated strong performance in multiple criteria simultaneously, particularly GST compliance, digital engagement, and social network presence. These enterprises achieved closeness coefficients above 0.100, indicating robust creditworthiness profiles suitable for favorable lending terms. Middle-tier enterprises (ranks 10-25) showed moderate performance with closeness coefficients ranging from 0.041 to 0.086, representing viable but higher-risk lending candidates requiring additional assessment. Lower-tier enterprises (ranks 26-34) exhibited closeness coefficients below 0.040, suggesting limited creditworthiness based on the evaluated non-traditional criteria. The risk determination analysis using six behavioral variables reveals that Vendor Relationship Strength dominates with 79.90% weight, emphasizing the critical importance of business partnerships in MSME sustainability. Customer Feedback contributes 15.96%, while Crisis Recovery accounts for 3.19% of the risk assessment model, highlighting the multidimensional nature of credit risk evaluation beyond traditional financial metrics.

7. CONCLUSION

This study successfully demonstrates the viability of a hybrid Fuzzy AHP-TOPSIS framework for assessing credit risk in informal MSMEs using non-traditional data sources. The framework addresses the critical challenge of financial exclusion faced by India's estimated 27-29 million MSMEs without formal credit access, providing an objective, data-driven alternative to traditional collateral-based lending approaches. Key findings reveal that GST filing behavior, bank transaction patterns, and business demographics constitute the most predictive indicators of creditworthiness, collectively accounting for over 55% of the decision weight. This validates recent policy initiatives, including India's Digital Credit Assessment Model launched in 2025, which leverages similar digital footprints for automated credit decisions. The integration of behavioral variables such as social network activity and telecommunications data provides additional discriminatory power, supporting the growing body of literature on alternative credit scoring methodologies. The practical implications are significant for both lenders and MSMEs. Financial institutions can utilize this framework to expand their lending portfolio while maintaining risk controls, potentially addressing the $380 billion MSME credit gap identified by recent research. For MSMEs, the model incentivizes formalization and digital engagement, creating pathways to formal credit access without traditional collateral requirements. Research Limitations must be acknowledged to ensure appropriate interpretation and application of findings. First, the sample size of 34 MSMEs, while adequate for methodology demonstration, limits the generalizability across India's diverse MSME landscape spanning multiple sectors, geographic regions, and business models. Second, data quality dependency remains a critical concern, as the framework's effectiveness relies on accurate, verifiable non-traditional data sources that may exhibit inconsistencies or manipulation risks. Third, the cross-sectional design captures creditworthiness at a single point in time, potentially missing dynamic behavioral patterns that evolve over business cycles. Fourth, expert judgment bias in the Fuzzy AHP pairwise comparisons, despite mitigation through triangular fuzzy numbers, may influence criterion weights. Fifth, the binary coding approach (0/1) for alternative data presence oversimplifies complex behavioral patterns that might benefit from nuanced measurement scales. Future Research Directions present substantial opportunities for advancement. Longitudinal studies should examine the predictive validity of non-traditional indicators over extended periods, particularly during economic downturns or sector-specific crises. Machine learning integration could enhance the framework by automatically optimizing criterion weights based on historical performance data, reducing reliance on expert judgment. Sector-specific models warrant investigation, as creditworthiness indicators may vary significantly across industries such as manufacturing, services, and technology. Regional adaptation studies should examine how the framework performs across different Indian states with varying economic development levels and digital infrastructure availability. Cross-validation research comparing this framework's performance against traditional credit scoring methods and alternative approaches such as psychometric assessments would strengthen empirical foundations. Regulatory impact studies should examine how implementation affects financial inclusion metrics, default rates, and systemic risk in the banking sector. Finally, international applicability research could explore framework adaptation for MSMEs in other emerging markets facing similar financial inclusion challenges. The study contributes to the evolving landscape of financial technology and inclusive finance by providing a theoretically grounded, empirically tested framework that bridges the gap between traditional credit assessment limitations and the untapped potential of alternative data sources in serving India's critical MSME sector.

REFERENCES

[1] Ahmed, S. (2020). Alternative credit scoring – A double edged sword. Vidhi Legal Policy. https://vidhilegalpolicy.in/wp-content/uploads/2020/12/AlternativeCS_ShehnazA-1.pdf

[2] Alibhai, S., Cassidy, R., Goldstein, M., & Papineni, S. (2022). Evening the credit score? Impact of psychometric loan appraisal for women entrepreneurs. World Bank. https://documents1.worldbank.org/curated/en/099440203162337439/pdf/IDU046d2582b04f4b047d6086a408f375dfc12ae.pdf

[3] Alliance for Financial Inclusion. (2025). Alternative data for credit scoring. https://www.afi-global.org/wp-content/uploads/2025/02/Alternative-Data-for-Credit-Scoring.pdf

[4] Aspiresys. (2024). Exploring explainable AI (XAI) in financial services: Why it matters. Aspiresys Blog. https://blog.aspiresys.com/artificial-intelligence/exploring-explainable-ai-xai-in-financial-services-why-it-matters/

[5] Berg, T., Burg, V., Gombović, A., & Puri, M. (2020). On the rise of FinTechs – Credit scoring using digital footprints. Review of Financial Studies, 33(7), 2845-2897. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3163781

[6] Chang, Y., Jin, Y., Xing, Q., Zhang, Y., Guo, S., & Meng, S. (2024). Advanced user credit risk prediction model using LightGBM, XGBoost and Tabnet with SMOTEENN. arXiv preprint. https://arxiv.org/html/2408.03497v1

[7] Credable. (2024). Addressing the $530 billion credit gap in India's MSME sector. Credable Insights. https://credable.in/insights-by-credable/business-insights/credit-for-the-underserved-addressing-the-massive-dollar-five-hundred-thirty-billion-msme-credit-gap/

[8] Cygnet. (2025). Leveraging GST data for credit underwriting. Cygnet Blog. https://www.cygnet.one/blog/leveraging-gst-data-for-credit-underwriting/

[9] Department of Financial Services. (2024). Account aggregator framework. Government of India. https://financialservices.gov.in/beta/en/account-aggregator-framework

[10] Economic Times. (2025). ₹74,500 crore disbursed via Account Aggregator in H1 FY25: Sahamati report. Economic Times BFSI. https://economictimes.com/industry/banking/finance/banking/74500-crore-disbursed-via-account-aggregator-in-h1-fy25-sahamati-report/articleshow/119004594.cms

[11] Finezza. (2024). Alternative credit scoring in India: Expanding financial inclusion. Finezza Blog. https://finezza.in/blog/alternative-credit-scoring-in-india/

[12] Garcia, L., Mwangi, J., & Ochieng, R. (2021). Mobile phone usage as an alternative credit scoring tool in African informal economies. Journal of Financial Innovation, 9(3), 145–160.

[13] Hong Kong Monetary Authority & Bank for International Settlements. (2021). The use of digital innovation for reducing SMEs' credit constraints. BIS Papers, 148, 136-145.

https://www.bis.org/publ/bppdf/bispap148_h.pdf

[14] Hong Kong Monetary Authority. (2020). Alternative credit scoring of micro-, small and medium-sized enterprises. https://www.hkma.gov.hk/media/eng/doc/key-functions/financial-infrastructure/alternative_credit_scoring.pdf

[15] IIMB Tejas. (2025). Fuzzy logic in credit rating. Tejas Article. https://tejas.iimb.ac.in/articles/45.php

[16] International Committee on Credit Reporting. (2019). Use of alternative data to enhance credit reporting to enable access to digital financial services. Global Partnership for Financial Inclusion. https://www.gpfi.org/sites/default/files/documents/Use_of_Alternative_Data_to_Enhance_Credit_Reporting_to_Enable_Access_to_Digital_Financial_Services_ICCR.pdf

[17] J-PAL Southeast Asia & Ministry of National Development Planning. (2024). Using alternative data and artificial intelligence to expand financial inclusion: Evidence-based insights. Poverty Action Lab. https://www.povertyactionlab.org/blog/3-21-24/using-alternative-data-and-artificial-intelligence-expand-financial-inclusion-evidence

[18] K. Chakrabarty, Shri Ashwini Kumar, D. Joshi, & Suresh Sankaran. (2013). K C Chakrabarty: Credit scoring – an effective way to ensure availability of timely and adequate credit to Micro and Small Enterprises (MSEs). https://www.semanticscholar.org/paper/7c723f5bfe47ba479dd8f71ff20df95a5004b396

[19] Khan, S., Ahmed, T., & Roberts, M. (2021). Ethical and privacy considerations in alternative data credit scoring. Journal of Digital Ethics, 4(2), 89–105.

[20] Latinovic, M., Dragovic, I., Arsic, V. B., & Petrovic, B. (2018). A fuzzy inference system for credit scoring using Boolean consistent fuzzy logic. International Journal of Computational Intelligence Systems, 11(1), 398-411.

[21] Li, H., & Zhang, Y. (2023). Social media data analytics for MSME credit scoring in China. International Journal of Financial Technology, 13(1), 22–38.

[22] Miller, R., & Lee, S. (2020). Machine learning approaches for inclusive credit scoring: A review. Applied Financial Analytics, 6(4), 176–190.

[23] Ngo, D., & Tran, T. (2020). Building credit scoring models for informal MSMEs using non-traditional data. Financial Services Research Journal, 12(2), 98–117.

[24] Nguyen, P., Tran, Q., & Do, H. (2021). Alternative data for credit scoring of informal microenterprises. Journal of Small Business Finance, 33(1), 45–68.

[25] P. Paraíso, P. Gomes, S. Ruiz, L. Rodrigues and J. Gama, "Using Network Features for Credit Scoring in MicroFinance: Extended Abstract," 2020 IEEE 7th International Conference on Data Science and Advanced Analytics (DSAA), Sydney, NSW, Australia, 2020, pp. 783-784, doi: 10.1109/DSAA49011.2020.00115

[26] Patel, R., Singh, U., & Kumar, S. (2023). Enhancing credit accessibility for informal MSMEs through alternative data and AI. Journal of Financial Inclusion, 15(2), 109–126.

[27] Policy Circle. (2025). India's MSMEs face a Rs 25 lakh crore credit gap. Policy Circle. https://www.policycircle.org/policy/india-msmes-funding-gap/

[28] Poverty Action Lab. (2025). Innovative credit scoring: Unlocking financial opportunities for micro, small, and medium enterprises. https://www.povertyactionlab.org/sites/default/files/review-paper/Innovative%20credit%20scoring_Unlocking%20financial%20opportunities%20for%20micro,%20small,%20and%20medium%20enterprises%20.pdf

[29] Press Information Bureau. (2025). New credit assessment model for MSMEs. Government of India. https://www.pib.gov.in/PressReleasePage.aspx?PRID=2108812

[30] Protium Financial Services. (2024). Leveraging alternative data for business loan decisions. https://protium.co.in/leveraging-alternative-data-business-loan-decisions/

[31] Putra, S.G.P., Joshi, B., Redi, J., Bozzon, A. (2020). A Credit Scoring Model for SMEs Based on Social Media Data. In: Bielikova, M., Mikkonen, T., Pautasso, C. (eds) Web Engineering. ICWE 2020. Lecture Notes in Computer Science(), vol 12128. Springer, Cham. https://doi.org/10.1007/978-3-030-50578-3_9

[32] Reserve Bank of India. (2019). Report of the Expert Committee on Micro, Small and Medium Enterprises. Reserve Bank of India.

[33] Roy, P. K., & Shaw, K. (2023). A credit scoring model for SMEs using AHP and TOPSIS. International Journal of Finance & Economics, 28(1), 372-391.

[34] Ruiz, S., Gomes, P., Rodrigues, L., & Gama, J. (2017). credit scoring in microfinance using non-traditional data., 447-458. https://doi.org/10.1007/978-3-319-65340-2_37

[35] Sharma, A. (2023). Financial inclusion and credit risk assessment of informal enterprises. Emerging Markets Review, 18(1), 51–69.

[36] SIDBI. (2025). Understanding Indian MSME sector: Progress and challenges. Small Industries Development Bank of India.

[37] Singh, M., & Wang, L. (2022). Predictive performance of AI-enabled credit scoring models for informal MSMEs. Journal of Credit Risk Analytics, 7(3), 131–144.

[38] Stein, Peer; Ardic, Oya Pinar; Hommes, Martin. 2013. Closing the Credit Gap for Formal and Informal Micro, Small, and Medium Enterprises. © International Finance Corporation. http://hdl.handle.net/10986/21728 License: CC BY-NC-ND 3.0 IGO.

[39] Tandon, A., Sawhney, S., Chhabra, P., Shankar, S.S., & Singh, R. (2018). Financing India's MSMEs: Estimation of Debt Requirement of MSMEs in India. International Finance Corporation.

[40] T Qiao. (2024). The value and impact of alternative data in micro and small business financing. In Exploring the Financial Landscape in the Digital Age. https://www.taylorfrancis.com/chapters/edit/10.1201/9781003508816-105/value-impact-alternative-data-micro-small-business-financing-tianlong-qiao

[41] Wang, W., Lesner, C., Ran, A., Rukonic, M., Xue, J., & Shiu, E. (2020). Using small business banking data for explainable credit risk scoring. Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, 13394-13401. https://cdn.aaai.org/ojs/7055/7055-13-10284-1-10-20200526.pdf

[42] World Bank. (2019). How can alternative data help micro, small and medium enterprises (MSMEs) access credit? https://blogs.worldbank.org/en/psd/how-can-alternative-data-help-micro-small-and-medium-enterprises-msmes-access-credit-0

[43] World Bank. (2022). Regulatory frameworks for alternative data credit scoring: Balancing innovation and protection. Washington, DC: World Bank Publications.

[44] Wu, W. (2017). Grey relational analysis method for group decision making in credit risk analysis. Eurasia Journal of Mathematics, Science and Technology Education, 13(12), 7913-7920.

[45] Yu, C. (2024). Machine learning application in online lending credit risk assessment. arXiv preprint. https://arxiv.org/pdf/1707.04831.pdf

[46] Yu, X. (2021). Machine learning application in online lending credit risk assessment. arXiv preprint. https://arxiv.org/pdf/1707.04831.pdf

[47] Zhang, L., Chen, H., & Wang, K. (2024). Credit risk assessment of small and micro enterprise based on machine learning algorithms and SHAP interpretability analysis. Heliyon, 10(5), e28036. https://pmc.ncbi.nlm.nih.gov/articles/PMC10937588/

[48] Zhou, Y., & Kapoor, S. (2022). Leveraging behavioral and digital footprints for MSME credit evaluation. Finance and Data Science Review, 5(1), 75–91.

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