International Journal of Scientific Research in Engineering and Management (IJSREM)
Conference - Volume 10 ICMEX -2026 SJIF Rating: 8.659 ISSN: 2582-3930

Banking the Unbanked : Sustainable AI as a Tool for MSME Financial Inclusion

Pooja Allure [1], **Prof. Shivkumar Deene** [2],

[1]Research Scholar, Dept. of Commerce, Central University of Karnataka
[2] Professor, Dept. of Commerce, Central University of Karnataka Email: poojaallure2002@gamil.com , shivakumardeene@cuk.ac.in

ABSTRACT

Despite employing over 110 million people and contributing approximately 30% to India's GDP, Micro, Small and Medium Enterprises (MSMEs) face a formal credit gap estimated at USD 300 billion, with only 14% having access to formal bank credit (IFC, 2017; RBI, 2023; Ministry of MSME, 2023). This paper examines how Sustainable Artificial Intelligence (AI) can bridge this gap within the Indian banking ecosystem. Through thematic synthesis of secondary data from institutional reports, policy documents, and peer-reviewed literature, the study maps AI tools to MSME credit needs, evaluates their Environmental, Social, and Governance (ESG) sustainability dimensions, and analyzes case studies from Lendingkart, SBI YONO, and M-Pesa Fuliza. Key findings include a strong positive correlation (r = +0.97) between AI adoption maturity and MSME credit access, a 4.8 percentage-point NPA advantage of AI-driven lending over traditional models, and a composite sustainability score of 5.4/10 against a target of 8.1/10. The paper proposes an integrated ESG-based framework and a four-stage implementation roadmap for responsible, inclusive, and green AI-driven MSME banking.

Keywords: *MSME, Financial Inclusion, Sustainable AI, ESG*

I. INTRODUCTION

The Micro, Small and Medium Enterprise (MSME) sector is a cornerstone of the Indian economy. According to the Ministry of MSME (2023), over 63.4 million MSMEs collectively employ more than 110 million people and contribute approximately 30% to India's GDP and 45% to exports. However, despite this significance, the sector remains severely underserved by formal financial institutions.

Traditional lending models built on rigid collateral requirements, audited financial statements, and established credit histories are fundamentally misaligned with the operational realities of most MSMEs, which often operate informally, maintain incomplete financial records, and lack tangible assets. The Reserve Bank of India (RBI, 2023) and International Finance Corporation (IFC, 2017) estimate India's formal MSME credit gap at over USD 300 billion, leaving an estimated 86% of MSMEs dependent on informal credit at interest rates of 24–36% per annum compared to formal banking rates of 10–14% (CRISIL, 2021).

Artificial Intelligence (AI) presents a transformative opportunity to bridge this financing gap through alternative credit scoring, automated loan processing, and personalized financial products (Cao, 2022; McKinsey Global Institute, 2023). However, rapid AI adoption raises critical sustainability concerns—environmental energy consumption, social equity risks, and ethical governance gaps—that demand careful attention (OECD, 2022; NITI Aayog, 2021).

A. Research Objectives

This paper aims to:

1. Examine the scale and causes of MSME financial exclusion in India.
2. Analyze AI-driven tools addressing MSME credit access.
3. Evaluate ESG sustainability dimensions of AI adoption in MSME banking.
4. Identify opportunities and challenges through case study analysis.
5. Propose an integrated ESG framework and policy roadmap for sustainable AI-driven MSME financial inclusion.

II. LITERATURE REVIEW

A. Financial Inclusion and MSMEs

Financial inclusion—defined as meaningful access to and active use of formal financial services— is an established driver of economic development in emerging economies (Demirguc-Kunt & Klapper, 2013). Beck, Demirguc-Kunt, and Levine (2005) demonstrated, using 44-country panel data, that more developed financial systems accelerate MSME growth and poverty reduction. Ayyagari, Beck, and Demirguc-Kunt (2007) identified the 'MSME paradox': enterprises that contribute disproportionately to employment and output consistently face greater financing constraints than large corporations—a paradox acutely felt in India's USD 300 billion credit gap (IFC, 2017; RBI, 2023). SIDBI and IFC (2022) further demonstrated that traditional collateral- based models are inherently ill-suited to India's predominantly informal MSME segment.

B. Artificial Intelligence in Banking

Cao (2022), surveying over 300 studies, identified machine learning (ML), natural language processing (NLP), and predictive analytics as dominant technologies reshaping banking— particularly in credit assessment, fraud detection, and customer personalization. Jagtiani and Lemieux (2019) provided landmark empirical evidence from the LendingClub platform: alternative data-driven ML models significantly outperform traditional credit scoring for borrowers with thin credit files, directly relevant to MSME lending. The McKinsey Global Institute (2023) estimated that generative AI could add USD 2.6–4.4 trillion annually across industries, with financial services among the highest-value sectors. However, Fuster, Goldsmith- Pinkham, Ramadorai, and Walther (2022) caution that AI models risk perpetuating systemic biases against marginalized borrowers, including women-led and rural enterprises.

C. Sustainable AI: Ethical, Environmental, and Social Dimensions

The OECD (2022) introduced sustainability as a core evaluative dimension for AI systems, requiring performance to be assessed alongside environmental impact, social equity outcomes, and governance structures. UNEP (2023) highlighted the dual nature of AI in sustainable finance: while AI can accelerate green lending and ESG compliance, large-scale models entail substantial energy costs. NITI Aayog's (2021) Responsible AI for All framework outlined national ethical AI principles of fairness, accountability, transparency, and inclusion. Lipton (2018) argued that the opacity of black-box ML models poses significant risks to borrower rights, a concern incorporated into the RBI's (2022) discussion paper on AI governance.

D. Research Gap

No existing study simultaneously addresses sustainable AI's role in bridging the MSME financial inclusion gap within the Indian banking context—integrating technical, ethical, environmental, and policy dimensions into a unified framework. This paper fills this gap.

III. METHODOLOGY

This study adopts a descriptive-analytical, qualitative research design based on systematic secondary data synthesis. The approach is consistent with established practice in financial inclusion research (Demirguc-Kunt & Klapper, 2013; Huang, 2021) and is well-suited to examining the complex interplay between technological adoption, sustainability imperatives, and policy.

Data was drawn from: (1) institutional and policy reports including RBI (2022, 2023), IFC (2017), SIDBI & IFC (2022), World Bank (2022), Ministry of MSME (2023), NITI Aayog (2021), BIS (2022), OECD (2022), UNEP (2023), McKinsey Global Institute (2023), Deloitte (2022), PwC (2023), and CRISIL (2021); and (2) peer-reviewed journals including Cao (2022), Fuster et al. (2022), Jagtiani & Lemieux (2019), Beck et al. (2005), Bussmann et al. (2021), and Huang (2021). Analysis was structured around five thematic areas derived from the research objectives. The sustainability dimension was evaluated using an adapted ESG framework consistent with Schoenmaker and Schramade (2019) and the OECD (2022).

IV. MSME FINANCIAL EXCLUSION IN INDIA

A. Scale and Sectoral Distribution

The financial exclusion of MSMEs in India is documented through substantial empirical evidence. As shown in Table 1, only 14% of India's 63.4 million MSMEs access formal bank credit, leaving 86% dependent on informal sources. The formal credit gap amounts to USD 300 billion (IFC, 2017; RBI, 2023).

Table 1: MSME Contribution vs. Credit Access — The Paradox

Indicator	Value	Source
Total MSMEs in India	63.4 million	Ministry of MSME (2023)
MSME Contribution to GDP	~30%	Ministry of MSME (2023)
MSME Contribution to Exports	~45%	RBI (2023)
MSME Employment	110+ million	Ministry of MSME (2023)
MSMEs with Formal Bank Credit	14%	IFC (2017)
Formal Credit Gap	USD 300 billion	RBI (2023); IFC (2017)
MSMEs on Informal Credit	~86%	SIDBI & IFC (2022)
Informal Interest Rate	24–36% p.a.	CRISIL (2021)
Formal Banking Interest Rate	10–14% p.a.	RBI (2023)

Source: Compiled from Ministry of MSME (2023); IFC (2017); SIDBI & IFC (2022); CRISIL (2021); RBI (2023).

B. Geographic Disparities and Root Causes

Geographic barriers represent a critical dimension of MSME financial exclusion. Rural MSMEs— constituting 42% of the MSME population—access formal credit at only 6% compared to 28% in urban areas, while bank branch density in rural areas is approximately six times lower (World Bank Global Findex, 2022; RBI, 2023). Synthesis of the literature reveals eight primary structural causes of exclusion: lack of credit history (severity score: 9.2/10), absence of collateral (8.9/10), informal business operations (8.4/10), geographic remoteness (7.8/10), high transaction costs for banks (7.5/10), inadequate financial literacy (6.9/10), excessive documentation (6.7/10), and gender bias in lending (6.2/10) (IFC, 2017; RBI, 2023; Beck et al., 2005; World Bank, 2022).

Despite a modest decline in the credit gap as a proportion of demand—from 75.6% in 2015 to 58.8% in 2023—the absolute gap has widened from USD 242 billion to USD 300 billion as MSME credit demand has outpaced supply, reinforcing the urgency of scalable AI-driven solutions (SIDBI & IFC, 2022; CRISIL, 2021; RBI, 2023).

V. AI AS A TOOL FOR MSME FINANCIAL INCLUSION

A. AI Technologies and Banking Applications

Cao (2022) identifies machine learning, NLP, predictive analytics, and robotic process automation as the four foundational technology categories reshaping banking. Table 2 maps each technology to its specific MSME banking application.

Table 2: AI Technologies and Their Applications in MSME Banking

AI Technology	Application in MSME Banking	Key Benefit	India Adoption Stage
Machine Learning	Alternative credit scoring	Eliminates collateral dependence	Growing FinTech's leading
NLP	Document verification, e-KYC	Reduces documentation burden	Emerging
Predictive Analytics	Cash flow forecasting	Improves loan structuring	Early stage
Robotic Process Automation	Automated loan processing	Reduces turnaround time	Moderate
Conversational AI / Chatbots	Customer onboarding	Improves accessibility	Moderate
Fraud Detection Algorithms	Real-time transaction monitoring	Reduces NPA risk	Well established

Source: Compiled from Cao (2022); McKinsey Global Institute (2023); Deloitte (2022); RBI (2022).

B. Alternative Credit Scoring: The Core AI Value Proposition

The most transformative AI application in MSME banking is alternative credit scoring. As Table 3 illustrates, AI-driven models reduce loan assessment costs by over 85%—from INR 8,000– 15,000 to INR 500–2,000—making small-ticket lending economically viable. Default prediction accuracy improves from 65–70% to 82–89%, while loan processing time reduces from 15–30 days to 24–72 hours (Jagtiani & Lemieux, 2019; SIDBI & IFC, 2022; RBI, 2022).

Table 3: Traditional vs. AI-Driven Credit Scoring — Comparative Analysis

Parameter	Traditional Credit Scoring	AI-Driven Alternative Scoring
Data Sources	Bank statements, ITR, collateral documents	GST data, UPI transactions, utility bills, e-commerce sales
Loan Processing Time	15–30 days	24–72 hours
Cost per Assessment	INR 8,000–15,000	INR 500–2,000
Borrower Coverage	Formally documented MSMEs only	Informal and semi-formal MSMEs

Default Prediction Accuracy	65–70%	82–89%
Scalability Potential	Low	Very High
Regulatory Maturity (India)	Well established	Evolving – RBI guidelines emerging

Source: Compiled from Jagtiani & Lemieux (2019); SIDBI & IFC (2022); RBI (2022); Fuster et al. (2022).

C. Growth of Digital MSME Lending

Digital MSME lending in India has grown at a CAGR of approximately 42.3% (2018–2023), from INR 180 billion to INR 1,050 billion, with fintech lenders' market share rising from 4% to 29%. Crucially, the NPA rate for AI-underwritten loans has declined from 6.8% (2019) to 4.9% (2023), compared with 9.7% for traditional lending—a 4.8 percentage-point divergence that provides compelling evidence of superior AI risk assessment (RBI, 2023; SIDBI & IFC, 2022; CRISIL, 2021).

VI. SUSTAINABILITY DIMENSIONS OF AI IN MSME BANKING

A. Environmental Sustainability

AI-driven digital banking significantly reduces environmental impact relative to traditional branch-based models: paper usage per loan decreases by approximately 95%, branch visits by 85%, and per-loan carbon footprint by 77.4%—from 12.4 kg CO_2 to 2.8 kg CO_2 (UNEP, 2023; PwC, 2023). However, OECD (2022) and UNEP (2023) caution that large AI models can be energy-intensive, creating a sustainability tension that institutions must manage through energy- efficient AI architectures and green AI certification.

B. Social Sustainability

AI adoption has produced measurable social inclusion improvements: women-led MSMEs with formal credit access rose from 8% (2015) to 16% (2023), average loan processing time fell from 21 days to 3 days, and minimum loan size decreased from INR 5 lakh to INR 10,000, enabling micro-lending at scale (World Bank Global Findex, 2022; RBI, 2023; SIDBI & IFC, 2022). However, a critical gender gap persists: women-led MSMEs face an 18 percentage-point higher rejection rate than male-led enterprises, even when using AI-assisted applications (Fuster et al., 2022; World Bank, 2022)—confirming that AI trained on historical data replicates existing biases unless corrected by fairness-aware techniques.

C. Governance, Sustainability, and Composite Scorecard

Governance sustainability encompasses regulatory, ethical, and accountability frameworks. India's current framework shows significant gaps in algorithmic transparency, mandatory bias auditing, and AI explainability requirements for borrowers—all rated 'High Gap' against ideal standards (RBI, 2022); NITI (Aayog, 2021; OECD, 2022; Lipton, 2018). Table 4 presents the composite ESG sustainability scorecard.

Table 4: Composite Sustainability Scorecard — AI in MSME Banking in India

Sustainability Dimension	Key Indicators	Current Score (/10)	Target (/10)	Priority
Environmental	Energy efficiency, paperless banking, and carbon reduction	6.8	8.5	Medium
Social Financial Inclusion	Credit access rate, rural reach, processing speed	5.2	8.0	Very High
Social Gender Equity	Gender gap, bias reduction, vernacular access	4.1	7.5	Critical
Governance Transparency	Explainability, disclosure, accountability	4.8	8.0	High
Governance Regulation	Policy framework, enforcement, sandbox	5.5	8.5	High
Economic Sustainability	Long-term viability, NPA management, MSME resilience	6.2	8.0	Medium
Overall Composite Score	**Weighted average of the above dimensions**	**5.4**	**8.1**	**High**

Source: Author's synthesis using ESG scoring methodology; informed by Schoenmaker & Schramade (2019); OECD (2022); RBI (2022); NITI Aayog (2021).

D. AI Adoption and Financial Inclusion: Statistical Correlation

Table 5 presents Pearson correlation coefficients computed from cross-institutional data. The correlation between AI maturity score and MSME credit access is $r = +0.97$; NPA rate, $r = -0.96$; and customer satisfaction, $r = +0.98$. While these correlations do not establish causation, they provide strong statistical support for the claim that AI adoption is a critical enabler of inclusive, efficient, and sustainable MSME banking (Cao, 2022; Jagtiani & Lemieux, 2019)

Table 5: Correlation Between AI Adoption Intensity and Financial Inclusion Indicators

Institution Type	AI Maturity Score	MSME Credit Access (%)	NPA Rate (%)	Customer Satisfaction (/10)
Fintech Lenders	9.1	71%	4.9%	8.4
Large Private Banks	8.2	43%	5.8%	7.6
NBFCs	7.8	38%	6.2%	7.1
Public Sector Banks	5.6	22%	8.4%	6.2
Small Finance Banks	4.3	18%	7.9%	5.8
Regional Rural Banks	2.4	6%	10.2%	4.9
Pearson Correlation (r)	**—**	**+0.97**	**−0.96**	**+0.98**

Source: Compiled from RBI (2023); SIDBI & IFC (2022); Deloitte (2022). The author computed Pearson's r.

VII. CASE STUDIES

A. Lendingkart (India): AI-Driven MSME Credit

Established in 2014, Lendingkart analyzes over 3,000 alternative data points per application, including GST returns and e-commerce transaction histories, and generates credit decisions within 72 hours (versus the 21-day industry average). Serving over 200,000 MSMEs across 27 states, including Tier 3 and Tier 4 cities, with a minimum loan of INR 50,000, it demonstrates the scalability and geographic reach of AI-powered lending. Its NPA rate below 5% compares favorably with the public sector bank average of 9.7% (CRISIL, 2021; SIDBI & IFC, 2022; RBI, 2023). A critical limitation is that women borrowers constitute only 22% of its customer base, well below the 30% government target—reflecting the replication of AI bias (Ministry of MSME, 2023; Fuster et al., 2022)

B. SBI YONO Platform (India): Public Sector AI Adoption

Launched in 2017, SBI's YONO platform onboarded over 1.8 million MSMEs digitally and processed INR 480 billion in digital MSME loans in 2022–23, with a turnaround time of 59 minutes for pre-approved loans (SBI Annual Report, 2022–23; RBI, 2023). However, YONO's outreach remains concentrated among existing SBI customers with established banking relationships, limiting its ability to serve the 86% of the unbanked MSME population (SIDBI & IFC, 2022)—illustrating the critical distinction between digital efficiency and genuine financial inclusion (Demirguc-Kunt & Klapper, 2013)

International Journal of Scientific Research in Engineering and Management (IJSREM)
Conference - Volume 10 ICMEX -2026 SJIF Rating: 8.659 ISSN: 2582-3930

C. M-Pesa Fuliza (Kenya): International Evidence

Launched in 2019, M-Pesa Fuliza serves over 18 million users with real-time micro-credit averaging USD 8–50 per transaction without collateral, maintaining a default rate of only 3.2% (Safaricom Annual Report, 2022; World Bank Global Findex, 2022). Using mobile transaction history as a credit proxy provides a direct template for India's UPI ecosystem. Huang (2021) cites this platform as a benchmark for fintech-driven financial inclusion, demonstrating that AI credit models can simultaneously be inclusive, profitable, and environmentally efficient when designed with mobile-first, constrained-data principles.

D. Comparative Analysis

Table 6 synthesizes key findings across the three case studies. Fintech-led models consistently outperform public-sector AI in terms of depth and sustainability of financial inclusion. All three share a weakness in gender equity, confirming that algorithmic bias against women is a systemic challenge requiring deliberate policy intervention (Fuster et al., 2022; World Bank, 2022).

Table 6: Cross-Case Comparison — Key Lessons for Sustainable AI in MSME Banking

Dimension	Lendingkart (India)	SBI YONO (India)	M-Pesa Fuliza (Kenya)
Target Segment	Semi-formal MSMEs	Existing bank customers	Unbanked micro-enterprises
AI Maturity Level	Very High	Moderate-High	Very High
Loan Processing Time	72 hours	59 minutes	Real-time (seconds)
Minimum Loan Size	INR 50,000	INR 10,000	USD 8
NPA / Default Rate	Below 5%	Moderate	3.2%
Sustainability Score (/10)	7.1	6.7	8.2
Gender Equity Gap	Women = 22% of borrowers	Limited data	Moderate – improving
Key Limitation	Gender equity gap	Serves mainly existing customers	Tiny loan size

Source: Author's synthesis from CRISIL (2021); SIDBI & IFC (2022); RBI (2023); SBI Annual Report (2022–23); World Bank Global Findex (2022); Safaricom Annual Report (2022); Huang (2021).

VIII. OPPORTUNITIES AND CHALLENGES

A. Key Opportunities

India's digital public infrastructure presents a uniquely favorable ecosystem. The Account Aggregator Framework (Ministry of Finance, 2023) enables consent-based financial data sharing, providing AI credit models with rich alternative data. The UPI ecosystem—processing over 10 billion monthly transactions (RBI, 2023)—generates an unprecedented stream of real-time transactional data for MSME creditworthiness assessment. Jan Dhan Yojana's 500 million accounts provide baseline financial identities for previously unbanked populations. CRISIL (2021) estimates these infrastructure initiatives, when harnessed through AI, could unlock USD 600 billion in MSME lending, while McKinsey Global Institute (2023) projects full AI adoption could reduce the credit gap by 67–73% and unlock USD 150–200 billion in annual economic value.

B. Key Challenges

The three most severe and least easily resolved barriers—constituting what this study terms the 'Sustainability Trilemma' of AI-driven MSME inclusion—are: digital literacy gaps among MSME owners (severity 8.4/10, ease of resolution 5.2/10); data quality and availability issues (8.1/10; 6.1/10); and algorithmic bias against marginalised borrowers (8.0/10; 5.8/10) (NITI Aayog, 2021; RBI, 2022; Fuster et al., 2022). Additional high-severity challenges include high AI implementation costs for smaller banks (7.6/10), regulatory uncertainty (7.4/10), cybersecurity risks (7.2/10), risk of over-indebtedness (6.8/10), and institutional resistance in public sector banks (6.8/10) (Deloitte, 2022; PwC, 2023; SIDBI & IFC, 2022).

IX. RECOMMENDATIONS AND IMPLEMENTATION ROADMAP

A. Integrated Stakeholder Recommendations

Based on gaps identified in the governance analysis, challenge severity matrix, and case study findings, Table 7 presents targeted policy and institutional recommendations grounded in NITI Aayog (2021), RBI (2022), OECD (2022), Fuster et al. (2022), and Schoenmaker and Schramade (2019).

Table 7: Integrated Recommendations — Stakeholder Action Matrix

Recommendation	Stakeholder	Priority	Timeline
Mandate periodic bias audits for all AI credit models	RBI / Regulators	Critical	6 months
Expand the Account Aggregator Framework to all MSME sectors	Ministry of Finance	Critical	12 months
Establish a shared cloud AI infrastructure for rural and small banks	RBI / IBA	High	18 months

Launch national MSME digital literacy mission via Jan Dhan network	Government	High	12 months
Mandate multilingual AI banking interfaces in 22 scheduled languages	Banks / Fintechs	High	18 months
Require gender-sensitive training datasets for AI credit models	Banks / Fintechs	Critical	12 months
Issue mandatory explainability requirements for AI credit decisions	RBI	High	12 months
Introduce green AI certification standards for banking AI systems	OECD / RBI	Moderate	24 months

Source: Author's synthesis from NITI Aayog (2021); RBI (2022); Fuster et al. (2022); MoF (2023); CRISIL (2021); OECD (2022); UNEP (2023); Lipton (2018); World Bank (2022).

B. Four-Stage Implementation Roadmap

The roadmap progresses from foundational infrastructure development to complete sustainability optimisation: Stage 1 (0–12 months): Expand Account Aggregator Framework, launch digital literacy programs, and establish AI governance guidelines per RBI (2022). Stage 2 (12–24 months): Deploy shared AI cloud for rural banks, mandate multilingual interfaces, and pilot green AI certification per OECD (2022). Stage 3 Scale fintech-bank co-lending, mandate bias audits, and target women's MSME credit at 25% per Fuster et al. (2022). Stage 4 (36–60 months): Achieve full ESG compliance per Schoenmaker and Schramade (2019), implement post-credit monitoring, and mandate green AI certification—targeting an improvement in composite sustainability score from 5.4 to 8.0 (Ministry of Finance, 2023; RBI, 2022; NITI Aayog, 2021).

X. Conclusion

This paper examined sustainable AI as a transformative tool for MSME financial inclusion in India. The evidence demonstrates that AI adoption is strongly correlated with improved financial inclusion outcomes ($r = +0.97$), superior credit risk management (a 4.8 percentage-point NPA advantage), and significant cost efficiencies (an 85% reduction in assessment costs). However, India's composite sustainability score of 5.4/10 against a target of 8.1/10 reveals substantial room for improvement, with gender equity (4.1/10) and governance transparency (4.8/10) as the most critical gaps.

Three theoretical contributions emerge: (1) an integrated ESG framework for evaluating sustainable AI adoption in banking, extending Schoenmaker and Schramade (2019) to the MSME financial inclusion context; (2) empirical establishment of a strong correlation between AI adoption intensity and inclusion outcomes; and (3) synthesis and mapping of the research gap at the intersection of sustainable AI, MSME banking, and emerging market finance.

India stands at a historic inflection point. The convergence of a vast MSME sector, sophisticated digital public infrastructure, a growing fintech ecosystem, and an increasingly progressive regulatory environment (Ministry of Finance, 2023; RBI, 2022; NITI (Aayog, 2021) creates a unique window to deploy AI in ways that could fundamentally transform the financial lives of millions of small business owners. Full potential, however, demands not just more innovative algorithms but wiser governance—ensuring AI intelligence is matched by institutional wisdom. Sustainable AI represents both a powerful tool and a moral imperative for India's financial inclusion mission.

REFERENCES

A. Institutional and Policy Reports

1. Bank for International Settlements [BIS]. (2022). Artificial intelligence and machine learning in central banking. BIS Working Paper No. 1040. https://www.bis.org/publ/work1040.htm
2. CRISIL. (2021). India's MSME sector: Unlocking the $600 billion lending opportunity. CRISIL Research, Mumbai.
3. Deloitte. (2022). AI and risk management in financial services. Deloitte Insights. https://www2.deloitte.com
4. International Finance Corporation [IFC]. (2017). MSME finance gap: Assessment of the shortfalls and opportunities in financing micro, small, and medium enterprises in emerging markets. World Bank Group, Washington, D.C.
5. McKinsey Global Institute. (2023). The economic potential of generative AI: The next productivity frontier. McKinsey & Company, New York.
6. Ministry of Finance, Government of India. (2023). Account aggregator framework: Enabling data empowerment for MSMEs. Ministry of Finance, New Delhi.
7. Ministry of MSME, Government of India. (2023). Annual report 2022–23. Ministry of Micro, Small & Medium Enterprises, New Delhi.
8. NITI Aayog. (2021). Responsible AI for all: Adopting the framework—A use case approach on AI in financial services. Government of India, New Delhi.
9. Organization for Economic Co-operation and Development [OECD]. (2022). OECD framework for the classification of AI systems. OECD Publishing, Paris. https://doi.org/10.1787/cb6d9eca-en
10. PricewaterhouseCoopers [PwC]. (2023). Financial services technology 2025 and beyond. PricewaterhouseCoopers Global Report.
11. Reserve Bank of India [RBI]. (2022). Discussion paper on governance of AI and ML models in the financial sector. RBI, Mumbai. https://www.rbi.org.in
12. Reserve Bank of India [RBI]. (2023). Report of the committee on MSME / Annual report 2022–23. RBI, Mumbai.
13. Safaricom PLC. (2022). Annual report and financial statements 2022. Safaricom PLC, Nairobi.
14. Small Industries Development Bank of India [SIDBI] & IFC. (2022). Digital lending for MSMEs in India: Landscape and the way forward. SIDBI, New Delhi.
15. State Bank of India [SBI]. (2023). Annual report 2022–23. SBI, Mumbai.
16. United Nations Environment Programme [UNEP]. (2023). Sustainable finance and AI: Opportunities and risks for emerging markets. UNEP Finance Initiative, Nairobi.

17. World Bank. (2022). Global Findex database 2021: Financial inclusion, digital payments, and resilience in the age of COVID-19. World Bank, Washington D.C. https://doi.org/10.1596/978-1-4648-1897-4

B. Peer-Reviewed Journal Articles and Books

18. Ayyagari, M., Beck, T., & Demirguc-Kunt, A. (2007). Small and medium enterprises across the globe. Small Business Economics, 29(4), 415–434. https://doi.org/10.1007/s11187-006-9002-5
19. Beck, T., Demirguc-Kunt, A., & Levine, R. (2005). SMEs, growth, and poverty: Cross- country evidence. Journal of Economic Growth, 10(3), 199–229. https://doi.org/10.1007/s10887-005-3533-5
20. Bussmann, N., Giudici, P., Marinelli, D., & Papenbrock, J. (2021). Explainable machine learning in credit risk management. Frontiers in Artificial Intelligence, 4, 618–644. https://doi.org/10.3389/frai.2021.618644
21. Cao, L. (2022). AI in finance: Challenges, techniques, and opportunities. ACM Computing Surveys, 55(3), 1–38. https://doi.org/10.1145/3502289
22. Demirguc-Kunt, A., & Klapper, L. (2013). Measuring financial inclusion: Explaining variation in use of financial services across and within countries. Brookings Papers on Economic Activity, Spring 2013, 279–321. https://doi.org/10.1353/eca.2013.0002
23. Fuster, A., Goldsmith-Pinkham, P., Ramadorai, T., & Walther, A. (2022). Predictably unequal? The effects of machine learning on credit markets. Journal of Finance, 77(1), 5–47. https://doi.org/10.1111/jofi.13090
24. Huang, H. (2021). Financial inclusion and innovation in developing economies. Journal of Financial Regulation, 7(1), 99–118. https://doi.org/10.1093/jfr/fjab003
25. Jagtiani, J., & Lemieux, C. (2019). The roles of alternative data and machine learning in fintech lending: Evidence from the LendingClub consumer platform. Financial Management, 48(4), 1009–1029. https://doi.org/10.1111/fima.12295
26. Lipton, Z. C. (2018). The mythos of model interpretability. Queue, 16(3), 31–57. https://doi.org/10.1145/3236386.3241340
27. Schoenmaker, D., & Schramade, W. (2019). Principles of sustainable finance. Oxford University Press, Oxford.