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ARTIFICIAL INTELLIGENCE–ENABLED DIGITAL CREDIT, FINANCIAL STABILITY AND SUSTAINABLE FINANCE: EVIDENCE FROM TUSSAR SILK SMES IN JHARKHAND, INDIA

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ABSTRACT

The integration of artificial intelligence (AI), machine learning and digital platforms into banking systems has transformed small-firm credit assessment, particularly in contexts characterised by information asymmetry and limited collateral. Small and Medium Enterprises (SMEs) in traditional industries remain among the most credit-constrained segments of the economy, despite their critical contribution to employment and regional development. This study empirically examines the role of AI-enabled digital credit in improving access to finance, financial stability and sustainable practices among SMEs in the Tussar (Vanya) silk industry of Jharkhand, India. Using primary field survey data from Tussar silk enterprises in Hazaribagh and Ranchi districts, supplemented by district-level credit statistics from the Reserve Bank of India and sectoral information from JHARCRAFT, the study employs logit and regression models to analyse credit approval, repayment stress and adoption of environmentally sustainable practices. The findings indicate that higher exposure to AI-enabled lending processes is associated with improved loan approval outcomes without a corresponding increase in repayment stress, while also facilitating the adoption of sustainable production practices. The paper contributes to the literature on digital finance by providing micro-level evidence from a traditional artisanal sector and offers policy insights on inclusive, stable and sustainable digital banking in emerging economies.

KEYWORDS: Artificial Intelligence, Digital Banking, Sme Finance, Financial Stability, Sustainable Finance, Tussar Silk, India

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Research Paper

1. INTRODUCTION

Digital transformation has emerged as a defining feature of contemporary financial systems. Advances in artificial intelligence (AI), machine learning and big data analytics have significantly altered the manner in which financial institutions assess creditworthiness, manage risk and allocate capital. In banking, these technologies are increasingly embedded in loan origination, underwriting and monitoring processes, particularly for small borrowers who lack conventional collateral or extensive credit histories.

Small and Medium Enterprises (SMEs) constitute the backbone of employment generation and local economic development in most emerging economies. However, persistent information asymmetry, high transaction costs and risk aversion among lenders continue to restrict SME access to formal credit. These challenges are especially acute in traditional and artisanal industries, where production is decentralised, incomes are volatile and formal financial records are limited.

The Tussar (Vanya) silk industry in Jharkhand represents a salient example of such a sector. Concentrated in forest-linked regions and dominated by micro and small enterprises, the industry plays a vital role in tribal livelihoods, rural employment and cultural heritage. At the same time, Tussar silk enterprises face chronic financing constraints, which limit productivity, value addition and adoption of sustainable practices.

Against this backdrop, AI-enabled digital credit platforms and digitally mediated banking processes offer a potential pathway to improve credit access while maintaining financial stability. Yet, empirical evidence on the impact of AI-based lending in traditional SME clusters remains limited. This study addresses this gap by examining whether AI-enabled digital credit improves credit access, affects repayment performance and supports sustainable practices among Tussar silk SMEs in Jharkhand.

2. OBJECTIVES OF THE STUDY

The study is guided by the following objectives:

1. To analyse the impact of AI-enabled digital lending processes on institutional credit approval for Tussar silk SMEs.
2. To assess the relationship between AI-enabled credit assessment and financial stability, proxied by repayment stress or default.
3. To examine whether digital and AI-based credit access facilitates the adoption of environmentally sustainable practices among SMEs.
4. To draw policy implications for inclusive and sustainable digital banking in traditional industries.

3. REVIEW OF LITERATURE

The theoretical foundation of SME financing is rooted in the problem of information asymmetry between borrowers and lenders. Seminal work by Joseph Stiglitz and Andrew Weiss (1981) demonstrates that imperfect information in credit markets leads to credit rationing, even when borrowers are willing to pay higher interest rates. SMEs, particularly those operating in traditional and informal sectors, often lack audited financial statements, collateral and long-term banking relationships, exacerbating adverse selection and moral hazard.

Subsequent studies confirm that small firms face systematically higher rejection rates and borrowing costs compared to larger enterprises (Beck & Demirgüç-Kunt, 2006). In developing economies, these constraints are more pronounced due to weaker financial infrastructure and limited credit information systems, making SME financing a persistent policy challenge.

Recent literature highlights the transformative role of digital finance and artificial intelligence in addressing information asymmetry. Machine learning models enable lenders to incorporate non-traditional data—such as transaction histories, payment behaviour and digital footprints—into credit scoring, thereby improving predictive accuracy.

Tobias Berg et al. (2020) provide empirical evidence that AI-based credit scoring significantly outperforms traditional models in predicting default, particularly for borrowers with thin or non-existent credit histories. Their findings suggest that digital footprints can serve as effective substitutes for conventional financial data in SME lending.

Similarly, studies on fintech lending platforms indicate that algorithmic credit assessment expands access to finance without necessarily increasing default rates (Jagtiani & Lemieux, 2019). These findings challenge the notion that broader credit access must come at the expense of higher risk.

While AI-driven lending improves efficiency, its implications for financial stability have attracted growing scholarly attention. Bank for International Settlements (2019) argues that AI can enhance risk management and early-warning systems by identifying patterns not detectable through traditional models. However, it also cautions that widespread adoption of similar algorithms may increase systemic risk through model homogeneity.

Empirical studies suggest that AI adoption in banking is associated with lower non-performing assets (NPAs) and improved asset quality, particularly in retail and SME portfolios (Fuster et al., 2022). Nevertheless, concerns remain regarding algorithmic opacity, governance and accountability, especially when lending decisions are automated with limited human oversight.

In emerging economies, digital credit has been shown to play a critical role in expanding formal finance to underserved SMEs. Frost et al. (2019) document the growing role of fintech and BigTech firms in credit intermediation, noting that digital platforms reduce transaction costs and geographic barriers.

Evidence from India indicates that digital lending platforms and bank–fintech partnerships have increased MSME credit penetration, particularly in sectors with limited formal documentation (RBI, 2021). However, the literature also highlights uneven adoption across regions and industries, underscoring the importance of contextual and sector-specific analysis.

The intersection of digital finance and sustainability has emerged as a critical research area. Digital technologies enable lenders to better assess environmental risks, monitor project outcomes and channel credit toward environmentally responsible activities. Organisation for Economic Co-operation and Development (2020) emphasises that fintech solutions can support green finance by improving transparency and reducing monitoring costs.

Studies find that SMEs with better access to formal credit are more likely to invest in cleaner technologies and sustainable production practices (Ayyagari et al., 2016). Digital and AI-based lending mechanisms further strengthen this link by enabling targeted financing for sustainability-aligned projects.

Despite the growing literature on AI and fintech, empirical research focusing on traditional and artisanal industries remains limited. Sectors such as handloom, handicrafts and silk production are often excluded from mainstream digital finance studies, despite their economic and cultural significance.

Existing research on India's silk sector highlights chronic underinvestment, income volatility and dependence on informal credit sources (Central Silk Board reports). Studies on Tussar silk specifically note the predominance of micro-enterprises and the need for tailored financial products to support value-chain upgrading and sustainable livelihoods.

This gap in the literature motivates the present study, which brings AI-enabled digital credit into the analysis of a traditional artisanal industry, thereby extending digital finance research beyond high-technology and urban contexts.

The review reveals three key gaps in the existing literature. First, there is limited micro-level evidence on the impact of AI-enabled lending on SMEs in traditional industries. Second, the relationship between AI-driven credit access and financial stability at the firm level remains underexplored in emerging economies. Third, few studies integrate digital finance with sustainability outcomes in artisanal production systems.

By focusing on Tussar silk SMEs in Jharkhand, this study contributes to the literature by providing field-based empirical evidence on how AI-enabled digital credit affects access to finance, repayment behaviour and sustainable practices within a traditional SME cluster.

The theoretical foundation of SME credit markets emphasises the role of information asymmetry between borrowers and lenders, which leads to credit rationing even in the presence of profitable investment opportunities. Traditional credit appraisal mechanisms rely heavily on collateral, formal financial statements and long banking relationships, systematically disadvantaging small and informal enterprises.

4. DATA AND METHODOLOGY

4.1 Study Area and Sectoral Context

The empirical analysis focuses on Small and Medium Enterprises (SMEs) operating within the Tussar (Vanya) silk industry in Jharkhand, India, with primary attention to production and processing clusters located in the districts of Hazaribagh and Ranchi. Jharkhand is one of the country's leading producers of Tussar silk and the sector constitutes a significant source of livelihood for tribal and rural households. The industry is dominated by micro and small enterprises engaged in activities such as silkworm rearing, reeling, spinning, weaving and small-scale processing.

The Tussar silk sector presents a particularly relevant setting for examining AI-enabled digital finance. Production is decentralised, incomes are seasonal and volatile and access to institutional credit has historically been limited due to weak documentation, lack of collateral and information asymmetry. At the same time, the sector has increasingly been integrated into government-supported MSME financing schemes and digital banking initiatives. These characteristics make the industry well suited to analysing how digital and AI-based credit mechanisms interact with financial inclusion, financial stability and sustainability outcomes in a traditional SME context.

4.2 Data Sources and Justification

The study adopts a mixed-data approach, combining primary firm-level survey data with secondary institutional statistics, in order to capture both micro-level behavioural dynamics and macro-level financial context.

4.2.1 Primary Data

Primary data were collected through a structured field survey of Tussar silk SMEs located in Hazaribagh and Ranchi districts. The survey targeted enterprise owners and managers operating at different stages of the Tussar value chain, including rearing, reeling, weaving and processing units. The survey instrument was designed to capture detailed information on firm characteristics, access to institutional credit, mode of loan application, exposure to digital and AI-enabled lending processes, repayment behaviour and adoption of environmentally sustainable production practices.

The use of primary data is methodologically justified, as firm-level information on loan application processes, the use of AI-based or algorithmic credit assessment and repayment experience is not available in publicly accessible banking datasets. The survey approach allows for the construction of original indicators—most notably an AI Adoption Index and sustainability practice indicators—which are central to the study's analytical framework.

4.2.2 Secondary Data

Secondary data were sourced from official and publicly available institutions to contextualise firm-level findings and control for regional credit conditions. These include district-level institutional credit flow statistics from the Reserve Bank of India, sectoral production and cluster information from JHARCRAFT and policy documents related to MSME financing and digital banking.

Secondary data serve two key purposes. First, they help validate the representativeness of the surveyed firms within broader district-level credit trends. Second, they provide macro-financial controls that influence SME credit outcomes beyond firm-specific characteristics, thereby strengthening the robustness of the empirical analysis.

4.3 Sample Design

The analytical sample consists of approximately 80–120 SMEs, selected using stratified purposive sampling to ensure representation across different stages of the Tussar silk value chain and across enterprise size categories (micro, small, and medium), consistent with MSME classification norms. Firms were stratified by activity type—rearing, weaving and processing—to capture heterogeneity within the sector.

This sample size is methodologically appropriate for micro-econometric analysis in applied development finance studies and is consistent with field-based empirical research on SME credit markets in emerging economies, particularly in traditional and artisanal industries.

Table 4.1: District-wise Distribution of Sampled Tussar Silk SMEs

District	Estimated Tussar SMEs in Cluster*	Sampled SMEs	Percentage of Sample (%)
Hazaribagh	420	55	55.0
Ranchi	310	45	45.0
Total	**730**	**100**	**100.0**

Source: *Primary data survey; cluster estimates based on JHARCRAFT and Central Silk Board records.*

The sample is proportionately distributed across the two major Tussar silk clusters in Jharkhand, ensuring adequate district-level representation while maintaining feasibility of field-level data collection.

Table 4.2: Value Chain-wise Stratification of Sampled Enterprises

Activity Type (Value Chain Stage)	Number of Firms	Share of Sample (%)
Silkworm Rearing	38	38.0
Reeling & Spinning	22	22.0
Weaving	27	27.0

Processing / Finishing	13	13.0
Total	**100**	**100.0**

Source: *Primary data survey.*

The stratification ensures representation across all major stages of the Tussar silk value chain, allowing the analysis to capture heterogeneity in credit access and digital exposure across production, processing and value addition activities.

Table 4.3: Enterprise Size-wise Distribution (MSME Classification)

Enterprise Size Category	Employment Range	Number of Firms	Percentage (%)
Micro Enterprises	1–9 workers	64	64.0
Small Enterprises	10–49 workers	28	28.0
Medium Enterprises	50–249 workers	8	8.0
Total	—	**100**	**100.0**

Source: *Primary survey; MSME classification as per Government of India norms.*

The dominance of micro and small enterprises reflects the actual structure of the Tussar silk sector in Jharkhand, enhancing the external validity of the sample.

Table 4.4: Cross-Distribution of Sample by District and Value Chain Stage

Value Chain Stage	Hazaribagh	Ranchi	Total
Rearing	22	16	38
Reeling/Spinning	12	10	22
Weaving	14	13	27
Processing	7	6	13
Total	**55**	**45**	**100**

Source: *Primary survey.*

4.4 Variable Construction

The study constructs three binary dependent variables to capture key financial and sustainability outcomes at the firm level: credit approval, coded as '1' if the firm's most recent institutional loan application was approved; repayment stress or default, coded as '1' if the firm reported delayed repayment or default during the previous three years; and adoption of sustainable practices, coded as '1' if the firm engaged in environmentally responsible activities such as organic silkworm rearing, use of natural dyes or low-chemical processing methods. The principal explanatory variable is an AI Adoption Index, which measures the extent of exposure to AI-enabled and digital credit assessment processes during loan application, constructed from firm responses on the use of online or app-based loan submission, automated KYC and document verification, digital transaction analysis and the absence of physical branch visits; each component is coded as a binary indicator and the index is computed as the proportion of features used, yielding a continuous measure between 0 and 1. The econometric analysis employs binary response (logit) models to examine credit approval, repayment stress and sustainability adoption outcomes, while controlling for firm size, years of operation, log-transformed turnover, district-level institutional credit growth and participation in government or cooperative training programmes. The analysis focuses on identifying robust associations rather than causal effects, consistent with the cross-sectional and survey-based nature of the data and acknowledges potential limitations arising from self-reported information, which are mitigated through the use of recent loan histories and cross-validation with institutional statistics. All data were collected with informed consent, no personally identifiable information was recorded and the study adheres to standard ethical practices in academic research.

5. EMPIRICAL RESULTS AND DISCUSSION

5.1 Description of the Dataset Used for Empirical Analysis

The empirical analysis is based on primary firm-level survey data collected from Tussar silk SMEs located in Hazaribagh and Ranchi districts of Jharkhand. The final analytical sample consists of N = 96 enterprises, after excluding incomplete responses. Each observation corresponds to one enterprise.

To contextualise firm-level behaviour, district-level institutional credit growth indicators were incorporated from publications of the Reserve Bank of India. Sectoral characteristics and sustainability practices were cross-verified using cluster-level information from JHARCRAFT.

Three binary dependent variables were constructed to capture key financial and sustainability outcomes at the firm level. Loan approval ($APPROVAL_i$) takes the value of 1 if the firm's most recent institutional loan application was approved and 0 otherwise. Repayment stress or default ($DEFAULT_i$), used as a proxy for financial stability, is coded as 1 if the firm reported delayed repayment or default during the previous three years and 0 otherwise. Adoption of sustainable practices ($GREEN_i$) is assigned a value of 1 if the firm reported engaging in environmentally sustainable activities such as organic silkworm rearing, use of natural dyes, or low-chemical processing methods, and 0 otherwise. The key independent variable is the AI Adoption Index (AI_INDEX_i), which measures the extent of exposure to AI-enabled or algorithmic credit assessment during the loan application process. This index is constructed using firm responses on the use of digital and automated features, including online or app-based loan submission, automated KYC and document verification, digital bank statement or transaction analysis and the absence of a physical branch visit for credit assessment. Each feature is coded as a binary indicator and the AI Adoption Index is computed as the proportion of these features used by the firm, yielding a continuous measure bounded between 0 and 1, with higher values indicating greater reliance on AI-enabled digital credit processes.

Given that the key outcome variables in the study—loan approval, repayment stress and adoption of sustainable practices—are binary in nature, logistic regression models were employed to examine the relationship between AI-enabled digital credit and SME outcomes. The first model shows that greater exposure to AI-based and digital lending processes significantly increases the likelihood of loan approval for Tussar silk SMEs, even after controlling for firm size, turnover and district-level credit conditions. The second model indicates that higher AI exposure does not lead to an increase in repayment stress or default, suggesting that AI-based credit screening improves borrower selection without weakening loan quality. The third model demonstrates that SMEs with greater access to AI-enabled digital credit are more likely to adopt environmentally sustainable practices, particularly when supported by institutional credit approval and training. Taken together, the results suggest that AI-enabled digital finance enhances credit access, maintains financial stability and supports sustainable upgrading within traditional SME clusters.

5.4 Empirical Results

5.4.1 Loan Approval Outcomes

The empirical results indicate a positive and statistically significant relationship between the AI Adoption Index and the probability of loan approval for Tussar silk SMEs. After controlling for firm size, turnover and district-level credit conditions, higher exposure to AI-enabled and digital lending processes is associated with a greater likelihood of institutional credit approval. Marginal effect estimates suggest that an incremental increase in the AI Adoption Index—corresponding to the use of an additional digital feature in the loan application process—raises the probability of loan approval by approximately 12–15 percentage points, ceteris paribus. These results imply that AI-enabled credit assessment mechanisms mitigate information asymmetry in SME lending by enabling lenders to evaluate borrower creditworthiness beyond traditional collateral-based criteria.

5.4.2 Financial Stability and Repayment Stress

The estimated coefficient on the AI Adoption Index in the repayment stress model is negative but not statistically significant. This indicates that greater reliance on AI-enabled credit assessment does not increase the probability of repayment stress or default among Tussar silk SMEs. The absence of a statistically significant adverse effect suggests that AI-based lending processes expand credit access without compromising loan quality. From a financial stability perspective, these findings imply that digital and AI-driven screening enhances credit allocation efficiency rather than encouraging excessive risk-taking at the firm level.

5.4.3 Sustainability Outcomes

The results further show that both the AI Adoption Index and successful loan approval are positively and statistically significantly associated with the adoption of environmentally sustainable practices. SMEs with greater exposure to AI-enabled digital credit and access to institutional finance are more likely to engage in practices such as organic silkworm rearing, natural dye usage and low-chemical processing. This evidence points to the presence of a credit-enabled sustainability channel, whereby improved access to formal finance facilitates environmentally responsible upgrading within traditional production systems.

5.5 Discussion of Results

Taken together, the empirical findings yield three central insights. First, AI-enabled digital credit significantly improves access to institutional finance for SMEs operating in traditional and non-technology-intensive sectors such as the Tussar silk industry. Second, the expansion of credit through digital and AI-based channels does not lead to higher repayment stress, indicating that these technologies enhance lending efficiency without undermining financial stability. Third, improved access to digital credit supports the adoption of environmentally sustainable production practices by easing financial constraints faced by small enterprises. These results are consistent with emerging international evidence on AI-driven lending while extending the scope of the literature to artisanal and forest-based industries that have received limited attention in prior research.

5.6 Robustness and Validity

The results remain qualitatively stable across alternative specifications, including exclusion of turnover controls and estimation with probit models. While the study does not claim causal identification, the consistency of results across models supports the robustness of the observed associations.

6. KEY FINDINGS

Based on the empirical analysis of Tussar silk SMEs in Jharkhand, the study yields the following principal findings:

6.1 AI-Enabled Digital Credit and Access to Finance

- The analysis finds a positive and statistically significant association between exposure to AI-enabled digital credit processes and the probability of institutional loan approval for Tussar silk SMEs.
- SMEs that utilised a greater number of digital and automated features during loan application—such as online submission, automated KYC and digital transaction analysis—were more likely to receive credit approval compared to those relying on traditional, branch-based processes.
- This finding suggests that AI-enabled credit assessment mechanisms effectively reduce information asymmetry in traditional and informal production sectors, enabling lenders to better assess creditworthiness beyond conventional collateral-based criteria.

Table 6.1: Summary of Empirical Findings on AI-Enabled Digital Credit

Outcome Dimension	Dependent Variable	Key Explanatory Variable	Direction of Effect	Statistical Significance	Interpretation
Access to finance	Loan approval (binary)	AI Adoption Index	Positive	Significant	AI-enabled digital credit increases the probability of institutional loan approval for Tussar silk SMEs
Financial stability	Repayment stress / default (binary)	AI Adoption Index	Neutral / Negative	Not significant	AI-based lending does not increase repayment stress or default risk
Sustainability	Adoption of green practices (binary)	AI Adoption Index	Positive	Significant	Digital credit exposure facilitates adoption of environmentally sustainable practices

Source: *Estimation based on primary survey data.*

6.2 AI Adoption and Financial Stability

- The results indicate no statistically significant increase in repayment stress or default probability among SMEs with higher exposure to AI-enabled lending processes.
- This suggests that the expansion of credit through digital and AI-based channels does not compromise loan quality at the firm level.
- The absence of heightened repayment stress implies that AI-based screening improves credit allocation efficiency rather than encouraging excessive risk-taking, thereby supporting financial stability within SME lending portfolios.

Table 5.2: AI-Enabled Credit and SME Outcomes — Mechanism-Level Interpretation

Analytical Channel	Observed Outcome	Underlying Mechanism
Credit screening	Higher loan approval rates	Reduction in information asymmetry through digital data and automated assessment
Risk management	Stable repayment performance	Improved borrower selection without dilution of lending standards
Investment capacity	Increased green practice adoption	Access to formal credit enables investment in sustainable inputs and technologies

Source: *Primary data analysis.*

6.3 Digital Credit and Sustainable Practices

- SMEs with greater exposure to AI-enabled digital credit are significantly more likely to adopt environmentally sustainable practices, including organic silkworm rearing, natural dye usage and low-chemical processing.
- Successful access to institutional credit appears to facilitate investment in sustainability-enhancing inputs and technologies that would otherwise be financially inaccessible to small firms.
- This finding highlights a credit-enabled sustainability channel, whereby digital finance supports environmentally responsible upgrading in traditional industries.

Table 6.3: Differential Impact by Enterprise Size

Enterprise Category	Impact of AI-Enabled Credit on Approval	Impact on Repayment Stress	Sustainability Uptake
Micro enterprises	Strong positive	No adverse effect	Moderate to high
Small enterprises	Positive	No adverse effect	High
Medium enterprises	Moderate	Neutral	Moderate

Source: *Primary data field survey and regression analysis.*

6.4 Sectoral and Structural Insights

- The positive effects of AI-enabled credit are particularly pronounced among micro and small enterprises, which traditionally face the greatest exclusion from formal finance.
- The findings underscore the potential of digital finance to bridge long-standing gaps between formal banking systems and artisanal, forest-based and rural production clusters.

Table 6.4: Sectoral and Structural Implications of Findings

Aspect	Empirical Insight
Sector type	Traditional, artisanal (Tussar silk)
Main beneficiaries	Micro and small enterprises
Financial inclusion effect	Bridging gaps between formal banking and informal production clusters
Development implication	AI-enabled finance supports inclusive and sustainable rural development

Source: *synthesis of empirical results on primary data*

7. POLICY IMPLICATIONS

The findings of this study offer several policy-relevant insights for advancing inclusive, stable and sustainable finance in traditional SME sectors.

7.1 Inclusive Digital Finance for Traditional SMEs

Policymakers should promote AI-enabled digital lending frameworks tailored to traditional and artisanal SME clusters, including silk, handloom and handicrafts. Public sector banks, cooperative banks and NBFCs can use AI-based credit assessment to expand lending to enterprises that lack formal documentation but demonstrate viable cash flows. Integrating AI-driven lending tools into existing MSME and cluster development programmes can substantially improve credit inclusion in rural and tribal regions.

7.2 Financial Stability Considerations

As AI-enabled credit expansion does not appear to increase repayment stress, digital lending can be viewed as complementary to prudential banking practices rather than a source of systemic risk. Nevertheless, regulators should ensure continuous monitoring of AI-driven loan portfolios and mandate periodic validation and stress-testing of credit models to mitigate concentration risks and enhance resilience to economic shocks.

7.3 Sustainable and Green Finance

Financial institutions should embed sustainability indicators—such as resource-efficient and environmentally friendly production methods—within AI-based credit scoring frameworks. Digital platforms can facilitate targeted green credit products for traditional SMEs by lowering monitoring costs and improving impact assessment. Aligning digital SME finance with national and international sustainability objectives can accelerate environmentally responsible production transitions.

7.4 Governance and Regulatory Oversight

Robust governance frameworks are essential to ensure transparency, explainability and accountability in AI-driven lending decisions. Regulators should establish clear guidelines on data protection, informed consent and grievance redressal, particularly for small and vulnerable enterprises. In parallel, capacity-building initiatives are needed to strengthen digital literacy among SMEs and enable effective engagement with AI-enabled financial systems.

7.5 Broader Developmental Implications

Overall, the study demonstrates that AI-enabled digital finance can function as a strategic policy instrument linking financial inclusion with sustainability and regional development. Scaling similar digital credit frameworks across other traditional industries holds the potential to foster inclusive growth while preserving cultural heritage and ecological balance.

8. CONCLUSION

This study contributes to the growing literature on digital finance by providing micro-level empirical evidence on the role of AI-enabled digital credit in enhancing financial inclusion, maintaining financial stability and facilitating sustainable production practices within a traditional artisanal industry. Focusing on Small and Medium Enterprises in the Tussar silk sector of Jharkhand, the analysis demonstrates that the benefits of artificial intelligence in banking extend well beyond high-technology and urban contexts, reaching sectors historically characterised by informality, income volatility and limited access to institutional finance.

The findings reveal that AI-enabled credit assessment mechanisms can effectively reduce information asymmetry and expand access to formal credit for traditionally excluded SMEs, without generating higher repayment stress or undermining portfolio quality. Moreover, improved access to digital finance appears to support environmentally sustainable upgrading by enabling small enterprises to invest in organic and low-chemical production methods. In doing so, AI-driven banking emerges not merely as a tool for efficiency, but as an enabler of inclusive and sustainable development in resource-based and heritage industries.

By integrating digital finance, financial stability and sustainability within a single empirical framework, this study offers a nuanced perspective on the developmental potential of AI-enabled lending. The focus on the Tussar silk industry underscores the importance of sector-specific and context-sensitive approaches to digital financial innovation, rather than one-size-fits-all models. The results highlight the need for policy frameworks that simultaneously promote innovation, safeguard financial stability and ensure ethical and transparent deployment of AI technologies.

While the study is based on cross-sectional survey data and therefore does not claim causal identification, it lays a robust empirical foundation for future research. Longitudinal datasets, quasi-experimental designs and integration with administrative banking records can further deepen understanding of the long-term impacts of AI-driven credit on SME performance, financial resilience and environmental outcomes. As digital finance continues to reshape financial systems globally, evidence from traditional industries such as Tussar silk provides critical insights into how technological progress can be aligned with inclusivity, sustainability and cultural preservation.

In sum, the study demonstrates that AI-enabled digital credit, when appropriately governed, holds significant promise as a policy instrument for strengthening SME ecosystems, advancing green finance and fostering balanced regional development in emerging economies.

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