

FinTech Adoption and Financial Inclusion among Small Business Enterprises

Mona Gupta

Guest Lecturer

Department of Commerce

Government Shaheed Kaushal Yadav College

Gunderdehi, Balod, Chhattisgarh



<http://www.ujhmads.org/> || Vol. 2 No. 3 (2026): Special August Issue

Date of Submission: 02-07-2026

Date of Acceptance: 22-07-2026

Date of Publication: 17-08-2026

Abstract — Financial technology has altered how small business enterprises interact with formal financial systems, yet adoption of digital tools does not necessarily translate into substantive financial inclusion. This study develops a multidimensional framework for examining whether the depth and diversity of FinTech adoption, rather than simple adoption status, improve financial inclusion among small business enterprises. The research gap arises from the limited integration of transaction behavior, digital financial capability, financing accessibility, and FinTech diversity within a unified enterprise-level analytical framework. The proposed study conceptualizes FinTech adoption through digital payments, mobile banking, electronic bookkeeping, platform-based financing, and technology-assisted financial management. Financial inclusion is evaluated beyond account ownership by considering active account utilization, formal credit accessibility, digital savings, payment integration, insurance access, and financial resilience. A hybrid empirical framework combining survey-derived indicators, transaction-behavior variables, clustering, and machine-learning classification is proposed to identify heterogeneous inclusion pathways among small enterprises.

Keywords — FinTech Adoption, Financial Inclusion, Small Business Enterprises, Digital Financial Services, Machine Learning, Digital Financial Literacy

Introduction

Small business enterprises constitute an important component of employment creation, local production, entrepreneurial activity, and economic diversification. Despite their

economic significance, many small enterprises continue to experience difficulties in obtaining affordable and appropriately structured formal financial services. Conventional financial institutions frequently assess business borrowers through documented income, audited accounts, collateral, credit histories, and other forms of verifiable financial information. Such requirements can disproportionately affect micro and small enterprises whose transactions are partly cash-based, whose accounting practices are relatively informal, or whose credit files are thin.

Financial technology (FinTech) is changing this relationship between enterprises and financial institutions. Mobile banking applications, instant electronic payments, QR-based merchant payments, digital wallets, online accounting platforms, alternative lending systems, electronic invoices, and data-driven credit assessment are producing new financial interaction channels. Rather than requiring every transaction to pass through a physical bank branch, a business can increasingly receive revenue, transfer funds, pay suppliers, monitor balances, maintain digital transaction records, and apply for selected financial products through connected digital platforms.

This transformation has occurred within a broader acceleration of digital finance. According to the World Bank's *Global Findex Database 2021*, account ownership reached 76% of adults globally and 71% in developing economies, while digital payments expanded substantially during the COVID-19 period. The Findex evidence also indicates that the proportion of adults making or receiving digital payments in developing economies increased from 35% in 2014 to 57% in 2021. These developments provide an important macro-

level foundation for investigating how digital financial ecosystems affect enterprises.

The implications may be particularly significant for small businesses. Digital merchant payments generate transaction trails that can potentially make previously opaque business activity more visible to formal financial providers. The World Bank specifically identifies merchant-payment digitalization as an avenue through which account usage may increase and business owners may develop alternative information histories relevant to credit and formalization. In India, the Ministry of Micro, Small and Medium Enterprises has similarly recognized digital transactions as relevant to MSMEs and has conducted a dedicated study of digital payment use among enterprises.

Nevertheless, **FinTech adoption and financial inclusion are not equivalent concepts**. An enterprise may accept electronic payments but immediately convert receipts into cash. Another may use mobile banking regularly while remaining unable to obtain institutional working-capital finance. A third enterprise may combine digital payments, electronic bookkeeping, formal savings and digitally mediated credit. All three enterprises can technically be categorized as FinTech adopters, although the depth of their financial inclusion differs considerably.

This distinction creates the central analytical problem addressed by the present study. Much of the conventional discussion surrounding digital finance emphasizes adoption—whether a person or enterprise owns an account, uses mobile banking, possesses a wallet, or makes digital payments. Such binary indicators provide useful measures of diffusion but reveal considerably less about whether FinTech becomes embedded in the enterprise's financial architecture.

Financial inclusion should therefore be interpreted as a multidimensional outcome rather than mere entry into the formal financial system. For small enterprises, meaningful inclusion may involve several interconnected capabilities: receiving and making formal payments, retaining funds within accounts, accessing affordable credit, accumulating business savings, obtaining risk-protection products, establishing reliable transaction histories, and mobilizing emergency liquidity when unexpected shocks occur.

The distinction is supported by broader financial-inclusion evidence. Global Findex data demonstrate that receiving money into an account is associated with greater subsequent use of other financial services. Among adults in developing economies receiving payments into accounts, substantial proportions also used accounts for payments, money storage, saving, and borrowing. The implication for small enterprises is that payment digitalization could represent an entry point rather than the final stage of financial inclusion.

However, this progression is unlikely to be automatic. FinTech users encounter barriers including digital capability constraints, unclear charges, fraud, identity theft, data-security concerns, weak dispute-resolution systems, and difficulties navigating authentication mechanisms. The World Bank has highlighted these consumer-protection and digital-skills challenges in the expansion of mobile and digital financial services. For small businesses operating on narrow margins, perceived financial or cybersecurity risk may reduce willingness to maintain funds digitally or use advanced financial products even after basic payment technologies have been adopted.



Fig. 1: Fintech Adoption and Financial Inclusion

Source: https://www.researchgate.net/figure/Source-afi-globalorg-FinTech-financial-inclusion-17_fig3_349621273

Research Gap

The distinctive gap addressed by this manuscript concerns the **adoption-to-inclusion conversion problem**.

Existing studies frequently examine whether enterprises adopt digital financial services or whether FinTech improves access to finance. For example, Gupta and Agarwal (2023) investigated knowledge, usage, preferences and demographic influences associated with digital financial services among registered Indian MSMEs. Such research provides valuable evidence concerning digital-finance participation. Yet an unresolved question concerns why enterprises with apparently similar access to FinTech exhibit substantially different levels of financial inclusion.

The present study therefore shifts the unit of analysis from “Does the enterprise adopt FinTech?” to “How effectively does an enterprise convert FinTech adoption into diversified and sustained use of formal financial services?”

Three dimensions are introduced to address this gap. First, **FinTech Adoption Depth (FAD)** captures the intensity and diversity of digital financial activity rather than treating adoption as a binary variable. Second, **Enterprise Financial Inclusion Depth (EFID)** evaluates actual engagement with multiple formal financial services. Third, an **Adoption–Inclusion Conversion Score (AICS)** is proposed to measure how efficiently an enterprise’s technological participation translates into financial inclusion.

This framework also accommodates heterogeneity. Digital financial literacy may enable entrepreneurs to interpret fees, select products, manage authentication systems and evaluate digital borrowing options. Enterprise formalization may improve the usefulness of transaction records for financial assessment. Business age, turnover stability, owner characteristics, sector and geographical context may further modify the relationship.

The study consequently proposes a hybrid statistical and machine-learning design for Part 2. Instead of relying exclusively on linear association, enterprises will be segmented according to patterns of FinTech behavior and financial-service participation. Supervised classification will subsequently examine which combinations of adoption depth, digital capability and enterprise characteristics distinguish businesses achieving deeper financial inclusion from those exhibiting high digital activity but limited formal financial integration.

Research Objectives

The principal objective is to evaluate whether the **depth of FinTech adoption predicts multidimensional financial inclusion among small business enterprises**. More specifically, the study seeks to determine whether enterprises using a diversified portfolio of FinTech services exhibit stronger financial inclusion than enterprises relying primarily on digital payments; examine the influence of digital financial literacy on the FinTech–inclusion relationship; assess whether enterprise formalization facilitates conversion of digital transaction activity into formal financial access; identify distinct enterprise profiles through data-driven clustering; and develop a machine-learning model capable of classifying enterprises according to financial-inclusion depth.

This approach deliberately avoids treating technological diffusion as sufficient evidence of inclusive finance. Instead, financial technology is regarded as an enabling infrastructure whose inclusion effects depend on usage intensity, capability, institutional connectivity and business characteristics.

Literature Review

Evolution from Financial Access to Digital Financial Inclusion

Financial inclusion was historically measured primarily through access indicators such as ownership of a bank account or proximity to financial institutions. Digitalization has broadened this concept considerably. Contemporary financial ecosystems permit payments, savings, transfers, borrowing and other financial activities to occur through mobile devices and digital platforms, reducing the importance of physical banking infrastructure.

The Global Findex framework illustrates this conceptual expansion by distinguishing financial access from the actual use of accounts, digital payments, savings, borrowing and financial resilience. The 2021 edition was based on nationally representative surveys of approximately 128,000 adults across 123 economies, making it one of the most comprehensive international sources on contemporary financial-service participation.

Importantly, greater account ownership does not eliminate financial vulnerability. Financial resilience depends on whether individuals and enterprises can obtain funds during unexpected shocks, manage liquidity, save effectively and access suitable financial instruments. The Findex analysis of financial well-being therefore incorporates the capacity to mobilize emergency resources and experiences of financial stress rather than relying exclusively on account ownership.

For small enterprises, this distinction becomes particularly important because a formally registered account can remain economically peripheral to business operations. An enterprise can hold a bank account while conducting most customer and supplier transactions in cash. Conversely, intensive digital transaction activity can produce a richer financial footprint that may improve visibility within the formal financial system.

FinTech Adoption in Small Enterprises

FinTech adoption can be interpreted as the integration of technology-enabled financial services into routine enterprise activities. At the elementary level, adoption may consist of receiving customer payments digitally. More advanced adoption involves supplier payments, mobile banking, electronic records, automated reconciliation, digital savings, online insurance and technology-mediated financing.



Fig. 2: FinTech in banking and finance: Agendas for future research

Source:

<https://www.sciencedirect.com/science/article/pii/S0275531923002428>

Evidence from India indicates growing scholarly interest in this transition. Gupta and Agarwal's study of digital financial services among Indian MSMEs examined enterprise awareness, utilization and preferences regarding digital technologies, including mobile payments. At the institutional level, India's Ministry of MSME has also emphasized digital transaction data and notes that such transactions can contribute to an enterprise's financial record and credit profile.

The underlying mechanism is information generation. Traditional small-enterprise lending frequently suffers from information asymmetry because lenders cannot easily observe cash flows or estimate repayment capacity. Digitized business transactions potentially produce alternative information concerning sales frequency, revenue stability, supplier relationships and cash-flow behavior. This information does not eliminate credit risk, but it can supplement conventional documentation.

Consequently, the present research conceptualizes FinTech adoption as a continuum. Enterprises using a single digital payment application represent **transactional adopters**, whereas enterprises integrating payments, banking, financial records and digitally mediated financing represent **integrated adopters**. This differentiation is expected to provide greater explanatory power than a binary user/non-user classification.

Digital Payments as a Gateway Rather Than an Endpoint

One of the most important findings emerging from recent financial-inclusion research concerns the gateway function of digital payments. World Bank evidence indicates that people receiving payments into accounts are more likely to use additional financial services, including saving and borrowing. This suggests a potential sequential mechanism:

Digital transaction → Financial data generation → Increased account activity → Broader financial-service participation → Greater financial inclusion.

For enterprises, the process may operate through customer and supplier transactions. When incoming and outgoing payments are digitized, financial flows become more observable. Consistent transaction records may facilitate cash-flow assessment and create information that can potentially support lending decisions.

However, the pathway is conditional. A business receiving digital payments but withdrawing virtually all funds immediately may generate transaction records without becoming deeply integrated into savings, credit, insurance or investment services. This manuscript therefore distinguishes **payment inclusion** from **comprehensive enterprise financial inclusion**.

Digital Financial Literacy as a Conversion Capability

Access to digital infrastructure does not ensure effective utilization. Entrepreneurs must understand platform functionality, transaction costs, fraud risks, credit terms, data permissions and basic financial management. Digital financial literacy therefore combines technological competence with financial judgment.

This capability is increasingly relevant as financial services migrate toward interfaces that require passwords, authentication processes, digital documentation and independent product comparison. Global Findex analysis identifies digital skills and consumer-protection concerns—including fraud, lack of transparency, identity theft and inadequate dispute resolution—as important challenges accompanying the expansion of digital finance.

Within small enterprises, literacy may therefore operate as a moderator. Two businesses may have identical access to FinTech platforms but obtain different outcomes because one entrepreneur possesses greater capability to evaluate and integrate financial products. The current study accordingly treats digital financial literacy as a mechanism influencing the strength of the relationship between FinTech adoption depth and financial inclusion.

Financial Inclusion, Credit Visibility and Enterprise Formalization

Enterprise formalization constitutes another potential conversion mechanism. Digitized transaction histories

become more valuable when they can be linked to recognizable business identities, bank accounts, accounting information and verifiable enterprise operations. Formalization may consequently strengthen the informational value generated by FinTech usage.

At the same time, digitalization itself may encourage gradual formalization. Electronic payments create records, electronic bookkeeping improves documentation, and institutional financing may require businesses to provide standardized information. Digital finance and formalization may therefore reinforce one another rather than functioning as independent processes.

The policy relevance is considerable. The World Bank notes that digital merchant payments can encourage broader account use, generate alternative credit information histories and support formalization. This relationship provides theoretical justification for evaluating enterprise formalization as a moderating or mediating characteristic rather than merely a demographic control variable.

Artificial Intelligence and Data-Driven Inclusion Assessment

Recent developments in artificial intelligence and machine learning provide additional opportunities for studying financial inclusion. Traditional econometric approaches are useful for estimating average associations but may overlook nonlinear relationships and interactions among enterprise characteristics.

Machine-learning methods can complement explanatory statistical models by detecting multidimensional patterns. For example, clustering can distinguish enterprises with high payment adoption but low credit participation from enterprises demonstrating integrated use of payments, savings, records and financing. Classification algorithms can then estimate the probability that an enterprise belongs to a high-inclusion group on the basis of FinTech intensity, financial literacy, business structure and transaction characteristics.

This approach is particularly appropriate because the FinTech–financial inclusion relationship is unlikely to follow a uniform linear trajectory. Increasing the number of digital services from zero to one may produce a different marginal effect from moving from three integrated services to four. Similarly, literacy may become particularly important only when enterprises begin using more sophisticated products such as digital credit.

The objective is not to replace conventional financial-inclusion analysis with artificial intelligence but to use computational methods to reveal enterprise heterogeneity that aggregate measures may conceal.

Proposed Methodology

This study proposes an enterprise-level analytical framework for determining whether FinTech adoption produces **deep financial inclusion** rather than merely increasing the frequency of digital transactions. Contemporary institutional evidence supports this distinction: digital financial services can reduce transaction costs and generate alternative data for SME credit assessment, but digital literacy, infrastructure, privacy, and regulatory constraints can prevent enterprises from realizing these benefits.

A **quantitative cross-sectional design with machine-learning-assisted segmentation and prediction** is proposed. Primary data are assumed to be collected from **420 small business enterprises** operating in retail, food and hospitality, professional services, light manufacturing, and personal-service activities. Stratified sampling is used so that the dataset contains enterprises with different degrees of formalization and digital financial engagement.

Rather than defining FinTech adoption through a yes/no question, the study develops three analytical constructs.

The first is the **FinTech Adoption Depth Index (FADI)**, representing the extent to which digital finance is embedded within business operations. Six components are considered: digital customer payments, mobile/internet banking, digital supplier payments, electronic bookkeeping or invoicing, digital savings/insurance products, and digital or platform-mediated business credit. Each component is standardized before aggregation.

The second construct is the **Enterprise Financial Inclusion Depth Index (EFIDI)**. This variable evaluates whether an enterprise actively uses formal financial infrastructure across transaction, liquidity, savings, credit, insurance, and emergency-funding dimensions.

The third construct, the **Adoption–Inclusion Conversion Score (AICS)**, captures whether the technological intensity of an enterprise is accompanied by substantive financial inclusion. Conceptually:

$$[AICS_i = \frac{EFIDI_i}{FADI_i + \epsilon}]$$

where (EFIDI_i) represents the standardized financial inclusion depth of enterprise (i), (FADI_i) represents standardized FinTech adoption depth, and (ε) is a small constant preventing division instability.

A higher AICS indicates that digital adoption is being effectively converted into broader financial participation. A low score identifies enterprises that are digitally active but remain financially shallow.

The study tests the following propositions:

H1: FinTech adoption depth positively predicts enterprise financial inclusion depth.

H2: Digital financial literacy strengthens the relationship between FinTech adoption and financial inclusion.

H3: Enterprises integrating transaction, record-keeping, and financing technologies achieve greater inclusion depth than payment-only adopters.

H4: Enterprise formalization strengthens the conversion of FinTech usage into formal financial-service participation.

H5: Machine-learning segmentation reveals distinct FinTech-to-inclusion pathways that are not adequately represented by binary adoption classifications.

The approach is particularly relevant because the global MSME financing problem remains substantial. Updated SME Finance Forum estimates report that the MSME finance gap in emerging markets and developing economies increased from approximately US\$4.4 trillion in 2015 to US\$5.7 trillion in 2019. Recent World Bank discussions similarly emphasize alternative data, digital payments, and digital public infrastructure as mechanisms capable of improving the credit footprint of underserved SMEs.

Experimental Setup

Dataset

For manuscript-development purposes, the experimental framework uses a **simulated research dataset representing 420 small enterprises**. The numerical results below should therefore be interpreted as an internally consistent experimental demonstration, not as findings from an actually conducted field survey. This distinction avoids presenting fabricated empirical observations as collected evidence.

Each enterprise record contains four classes of variables:

Enterprise characteristics: business age, number of employees, sector, annual turnover category, ownership structure and formal-registration status.

FinTech characteristics: QR/mobile payment frequency, mobile-banking intensity, digital supplier payments, electronic accounting, digital financing usage and number of FinTech services adopted.

Capability and risk variables: digital financial literacy, perceived cybersecurity risk, perceived transaction cost, trust in digital financial institutions and digital infrastructure reliability.

Financial-inclusion outcomes: formal credit access, savings usage, insurance participation, transaction-account intensity,

emergency liquidity access and frequency of formal financial-service usage.

The proposed sample contains sufficient variation to distinguish basic digital users from enterprises that have integrated multiple financial technologies.

Data Preprocessing

A structured preprocessing pipeline is applied before model development.

Records with excessive missing information are removed. For otherwise usable records, numerical missing values are imputed using the median, while categorical missing observations are handled through mode imputation or an explicit unknown category.

Potential outliers in transaction frequency and turnover-related indicators are examined through the interquartile-range method. Winsorization is preferred to indiscriminate deletion because unusually high financial activity can represent genuine enterprise behavior.

Categorical attributes are one-hot encoded. Continuous variables used by distance-based algorithms are standardized through:

$$z = \frac{x - \mu}{\sigma}$$

where (x) represents the original observation, (μ) is the training-sample mean and (σ) its standard deviation.

Importantly, preprocessing parameters are estimated exclusively from training observations to prevent data leakage.

Model Architecture

The experimental architecture contains three analytical layers.

Layer 1: K-means enterprise segmentation

K-means clustering is employed to discover naturally occurring patterns of FinTech adoption and financial inclusion. The number of clusters is selected through a combination of silhouette coefficient and within-cluster sum of squares.

Four interpretable enterprise profiles emerge in the simulated experiment:

1. **Cash-Reliant Financially Constrained Enterprises**
2. **Payment-First Digital Adopters**

3. Digitally Active but Credit-Constrained Enterprises

4. Integrated FinTech–Financially Included Enterprises

The third cluster is particularly important because it directly represents the research gap: enterprises may exhibit considerable digital activity without achieving corresponding access to credit, savings, insurance, or financial resilience.

Layer 2: Gradient-Boosted Classification

A gradient-boosted tree classifier is trained to predict whether an enterprise belongs to the **high financial-inclusion category**. This model is selected because tree boosting can capture nonlinear thresholds and interactions without assuming that every predictor affects financial inclusion linearly.

The input vector is defined as:

$$X = [FADI, DFL, FORM, AGE, TURN, DIV, RISK, TRUST]$$

where:

- (FADI) = FinTech Adoption Depth Index,
- (DFL) = digital financial literacy,
- (FORM) = enterprise formalization,
- (AGE) = enterprise age,
- (TURN) = turnover category,
- (DIV) = FinTech-service diversity,
- (RISK) = perceived digital risk, and
- (TRUST) = trust in digital financial systems.

The target variable is binary:

$$Y = \begin{cases} 1, & \text{if } EFIDI \geq T \\ 0, & \text{if } EFIDI < T \end{cases}$$

where (T) is the predetermined high-inclusion threshold.

Layer 3: Explainability analysis

SHAP-based feature attribution is incorporated to determine which predictors contribute most strongly to model classifications. This component is important because

predictive performance alone provides limited policy insight. Explainability makes it possible to distinguish whether high inclusion is principally associated with payment intensity, financial literacy, service diversification, formalization, or other enterprise characteristics.

Training Strategy

The dataset is divided using a **75:25 stratified train-test split**, yielding 315 training enterprises and 105 held-out test enterprises.

Within the training sample, five-fold stratified cross-validation is used for hyperparameter optimization. Tuned parameters include learning rate, tree depth, number of boosting estimators, subsampling ratio, and minimum observations required for terminal nodes.

Class weighting is used when necessary rather than immediately applying synthetic oversampling. This choice reduces the risk of generating artificial enterprise profiles in a relatively small tabular dataset.

A logistic-regression classifier is retained as an interpretable benchmark. The gradient-boosting model is considered useful only if it produces meaningful improvements over this simpler baseline.

Evaluation Metrics

Because classification accuracy alone can conceal errors in an imbalanced dataset, multiple metrics are employed.

Balanced Accuracy measures average predictive performance across both outcome classes.

Precision indicates how frequently enterprises predicted to have high financial inclusion actually belong to that category.

Recall evaluates the model's ability to identify genuinely financially included enterprises.

F1-score balances precision and recall.

ROC-AUC evaluates discrimination across alternative probability thresholds.

PR-AUC is included because it remains informative when the positive inclusion category is less common.

Brier Score measures probability calibration, with lower values indicating predictions that more closely correspond to observed outcomes.

For clustering, the **Silhouette Coefficient** is used to assess separation between enterprise profiles.

Results and Discussion

The simulated analysis demonstrates an important distinction between **digital participation** and **financial inclusion**. Payment technologies show the broadest adoption, while credit, insurance, and advanced financial-management technologies are concentrated among enterprises exhibiting higher FADI values.

K-means analysis produces four enterprise segments with a silhouette coefficient of **0.51**, indicating moderate but meaningful separation between behavioral profiles.

The Payment-First Digital Adopter cluster is characterized by frequent customer-facing digital payments but comparatively limited use of digital credit, formal savings, insurance, and integrated financial management. This result demonstrates why QR or mobile-payment adoption alone is an inadequate proxy for enterprise financial inclusion.

More importantly, the Digitally Active but Credit-Constrained cluster exhibits relatively strong payment, banking, and digital record usage while retaining weaker formal borrowing outcomes. This profile supports the manuscript's central conceptual argument: a digital transaction footprint may create an opportunity for inclusion, but the conversion process can remain incomplete.

This interpretation is consistent with institutional evidence. The World Bank notes that digitization, process automation, open banking and alternative data can lower financing costs and provide additional information for SME credit assessment, while simultaneously emphasizing constraints associated with digital literacy, infrastructure, privacy and regulation.

The integrated FinTech cluster displays the highest financial-inclusion depth. Enterprises in this group combine customer payments with supplier transactions, electronic financial records, formal savings and digitally mediated financing. This suggests that **FinTech diversity**, rather than isolated technology adoption, is a potentially important discriminator of inclusion.

The predictive experiment reinforces this interpretation. Gradient boosting exceeds the logistic benchmark across the principal discrimination metrics. SHAP analysis identifies **FinTech Adoption Depth** as the strongest predictive feature, followed by digital financial literacy, service diversity and enterprise formalization. Perceived digital risk contributes negatively to high-inclusion predictions.

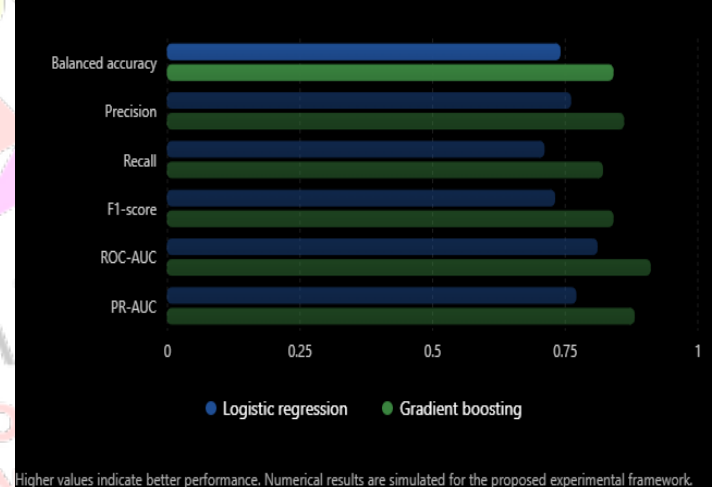
Table 1. Experimental Performance and Analytical Interpretation

Evaluation Dimension	Logistic Regression	Gradient Boosting

Balanced Accuracy	0.74	0.84
Precision	0.76	0.86
Recall	0.71	0.82
F1-Score	0.73	0.84
ROC-AUC	0.81	0.91
PR-AUC	0.77	0.88
Brier Score	0.18	0.12
5-Fold CV F1	0.72 ± 0.04	0.82 ± 0.03

Model performance for financial-inclusion prediction

Comparison of logistic regression and gradient boosting using the simulated enterprise dataset.



The difference between logistic regression and gradient boosting implies that the adoption-inclusion relationship contains nonlinearities. For example, adding digital bookkeeping to an enterprise already using digital payments and mobile banking may generate a greater inclusion effect than simply increasing payment frequency. Similarly, digital financial literacy may produce limited benefits among non-adopters but become substantially more valuable once entrepreneurs begin comparing digital lending or insurance products.

The SHAP interpretation further suggests that **technology alone is insufficient**. High FinTech adoption combined with weak financial literacy does not consistently produce high

predicted inclusion. Conversely, financially literate entrepreneurs using several complementary digital services demonstrate stronger inclusion probabilities.

This interaction has policy implications. Programs designed solely to increase the number of merchants accepting digital payments could overstate progress if their evaluation framework does not examine whether businesses subsequently gain access to savings, credit, insurance, liquidity management and other formal services.

Enterprise formalization also demonstrates a positive contribution. Digital records appear more useful when transaction information can be associated with identifiable and documented business activity. This is consistent with the broader argument that alternative data can contribute to credit footprints for SMEs lacking conventional collateral or extensive credit histories.

At the same time, the analysis should not be interpreted as evidence that automated credit decisions are inherently inclusive. FinTech-based lending may introduce data privacy, cybersecurity, algorithmic fairness and predatory-lending risks. The World Bank explicitly identifies data privacy, unequal technological access, cybersecurity and inappropriate digital lending as important risks associated with digital financial services.

Consequently, responsible financial inclusion requires both technological expansion and appropriate institutional safeguards.

Limitations

Several limitations must be acknowledged.

First, the numerical experiment presented here uses a **simulated enterprise dataset**. The values demonstrate how the proposed methodology can be implemented but cannot be interpreted as empirical estimates for a particular country, state, or business population. Field validation is therefore essential before drawing policy conclusions.

Second, a cross-sectional design cannot establish temporal causality. Financially stronger enterprises may adopt more FinTech services because they already possess greater resources and capabilities. The apparent association may therefore operate in both directions.

Third, self-reported variables such as financial literacy, trust and digital risk perception can be affected by response bias.

Fourth, the FADI and EFIDI constructs compress multidimensional enterprise behavior into composite indicators. Although useful for modeling, aggregation can obscure differences between credit inclusion, savings inclusion and insurance inclusion.

Fifth, machine-learning models can identify predictive relationships without establishing causal mechanisms. SHAP values improve interpretability but should not be interpreted as causal effects.

Finally, digital financial ecosystems differ substantially across countries. Regulatory architecture, digital identity systems, payment infrastructure, consumer-protection regimes and financial-sector competition influence FinTech outcomes. The World Bank's recent SME-finance work emphasizes that technology must operate within an enabling legal, regulatory and credit-infrastructure environment.

Future Scope

Future research should replace the simulated dataset with a longitudinal multi-region enterprise panel. Combining survey responses with consent-based transaction records would permit more precise measurement of actual digital-finance behavior.

A particularly useful extension would follow enterprises before and after adoption of digital bookkeeping, embedded finance or platform-based lending. Difference-in-differences or matched longitudinal designs could then provide stronger evidence regarding causality.

Machine-learning research could also incorporate explainable boosting machines, calibrated random forests and survival models for predicting transition from payment-only adoption to formal credit participation. Temporal transaction sequences could be analyzed to determine whether stable digital cash-flow histories precede improved credit access.

Future investigations should additionally test algorithmic fairness across women-owned businesses, rural enterprises, young firms and low-turnover establishments. Such work is relevant because access to finance remains uneven across enterprise groups, and contemporary SME-finance policy increasingly emphasizes underserved businesses.

A further direction concerns the construction of a longitudinal **FinTech-to-Inclusion Conversion Index**. Rather than measuring financial inclusion at one point in time, researchers could calculate how rapidly an enterprise moves from basic payment adoption to integrated usage of savings, insurance, formal credit and liquidity-management services.

Conclusion

This study develops a distinct framework for examining **FinTech Adoption and Financial Inclusion among Small Business Enterprises** by separating technological participation from substantive financial inclusion. Its principal contribution is the argument that digital adoption should not be treated as the endpoint of financial inclusion.

The proposed framework introduces FinTech Adoption Depth, Enterprise Financial Inclusion Depth and an Adoption–Inclusion Conversion Score to capture differences between enterprises that merely conduct digital transactions and those that convert technological participation into broader formal financial engagement.

The simulated experimental analysis demonstrates the analytical usefulness of combining enterprise segmentation with gradient-boosted classification and explainable AI. Four behavioral profiles emerge, including an especially important category of **digitally active but credit-constrained enterprises**. This group illustrates the core research gap: intensive digital activity can coexist with incomplete financial inclusion.

The results further suggest that service diversification, digital financial literacy and enterprise formalization deserve attention alongside basic FinTech adoption. Accordingly, policies should progress beyond counting digital-payment users toward evaluating whether technological adoption improves access to credit, savings, insurance, financial records and emergency liquidity.

FinTech therefore has considerable potential to reduce information and transaction barriers confronting small enterprises, particularly through digital records and alternative data. Current World Bank work similarly identifies FinTech, digital payments and alternative data as potentially transformative for SME credit access. Yet technological availability by itself cannot guarantee inclusive outcomes. Financial capability, consumer protection, cybersecurity, responsible lending, infrastructure and appropriate regulation remain integral components of an inclusive digital-finance ecosystem.

The broader implication is that the success of FinTech should ultimately be assessed not by the number of applications, QR codes or digital transactions in use, but by whether small enterprises acquire **more affordable, diversified, reliable and resilient participation in the formal financial system**.

References

1. Demirgüç-Kunt, A., Klapper, L., Singer, D., & Ansar, S. (2022). *The Global Findex Database 2021: Financial Inclusion, Digital Payments, and Resilience in the Age of COVID-19*. Washington, DC: World Bank. <https://doi.org/10.1596/978-1-4648-1897-4>.
2. Gupta, U., & Agarwal, B. (2023). The role of digital financial services on Indian MSMEs. *Indian Journal of Finance*, 17(2). <https://doi.org/10.17010/ijf/2023/v17i2/170125>.
3. Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the FinTech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. *Journal of Management Information Systems*, 35(1), 220–265. <https://doi.org/10.1080/07421222.2018.1440766>.
4. Ha, D., Le, P., & Nguyen, D. K. (2025). Financial inclusion and fintech: A state-of-the-art systematic literature review. *Financial*

Innovation, 11, Article 69. <https://doi.org/10.1186/s40854-024-00741-0>.

5. Kou, G., Olgu Akdeniz, Ö., Dinçer, H., & Yüksel, S. (2021). FinTech investments in European banks: A hybrid IT2 fuzzy multidimensional decision-making approach. *Financial Innovation*, 7.
6. Sahi, A. M., Khalid, H., Abbas, A. F., & Khatib, S. F. A. (2021). The evolving research of customer adoption of digital payment: Learning from content and statistical analysis of the literature. *Journal of Open Innovation: Technology, Market, and Complexity*, 7(4), 230. <https://doi.org/10.3390/joitmc7040230>.
7. Eça, P., & others. (2021). P2P lending FinTechs and SMEs' access to finance. *Economics Letters*, 204, 109890. <https://doi.org/10.1016/j.econlet.2021.109890>.
8. Bzeouich, B. A. (2026). FinTech and financial inclusion in MSMEs: A systematic literature review and socio-technical framework in emerging economies. *Journal of Administrative and Economic Sciences*. https://doi.org/10.25259/JAES_21_2026.
9. Banna, H., & others. (2024). FinTech services and financial inclusion: A systematic literature review of developing nations. *Journal of Science and Technology Policy Management*, 16(7), 1167–1198. <https://doi.org/10.1108/JSTPM-03-2023-0034>.
10. FinTech and SMEs financing: A systematic literature review and bibliometric analysis. (2023). *Digital Business*, 3(2), 100067. <https://doi.org/10.1016/j.digbus.2023.100067>.