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ARTIFICIAL INTELLIGENCE-ENABLED FINANCIAL SERVICES AND FINANCIAL INCLUSION AMONG RURAL MSMES

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Abstract: Financial inclusion remains a major challenge for rural micro, small, and medium enterprises (MSMEs) in Indonesia despite the rapid advancement of digital financial technologies. This study aims to examine the effect of artificial intelligence-enabled financial services on financial inclusion among rural MSMEs in Indonesia. The study employed a quantitative approach using survey data collected from 200 rural MSME owners in Tanjung Morawa Village, Medan, Indonesia. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The study findings indicate that the adoption of artificial intelligence-enabled financial services has a positive and significant effect on financial inclusion, demonstrating good predictive capability of the research model. The findings further reveal that AI-enabled financial services improve access to formal financial services, enhance transaction efficiency, and support better financial management among rural MSME owners. These results highlight the importance of developing AI-based financial solutions to strengthen financial inclusion and promote more inclusive rural economic development in Indonesia. The study also contributes to the growing body of literature on digital finance and provides practical implications for policymakers, financial institutions, and financial technology providers in designing more inclusive and sustainable financial services for rural MSMEs.

INTRODUCTION

Financial inclusion has become one of the key drivers of sustainable economic development, particularly in developing countries where micro, small, and medium enterprises (MSMEs) contribute significantly to employment generation and regional economic growth (Saha dkk., t.t.). In Indonesia, MSMEs account for the majority of business entities and play a crucial role in supporting local economies (Sudrajat dkk., t.t.). However, many

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rural MSMEs continue to face limited access to formal financial services due to geographical constraints, inadequate financial infrastructure, low financial literacy, and limited adoption of digital financial technologies (Demirgüç-Kunt dkk., 2021). These barriers reduce business competitiveness and hinder the ability of rural entrepreneurs to expand their operations and achieve sustainable growth. The rapid advancement of artificial intelligence (AI) has transformed the financial services industry by enabling more efficient, accurate, and customer-oriented financial solutions (*Indonesia-Promoting-Financial-Access-and-Inclusion-Fintech-for-Financial-Inclusion-Deep-Dive-Study*, t.t.). AI technologies have been integrated into digital payment systems, credit scoring, fraud detection, personalized financial recommendations, and customer service through intelligent virtual assistants (Wahyuni, 2026). These innovations have the potential to reduce information asymmetry, improve service accessibility, lower transaction costs, and increase the efficiency of financial service delivery (Regulatory Approaches to Artificial Intelligence in Finance, 2024). Consequently, AI-enabled financial services are expected to become an important instrument for promoting financial inclusion, especially among rural MSMEs that often experience difficulties in accessing conventional financial institutions.

Financial inclusion refers to the availability and effective use of affordable financial products and services that meet the needs of individuals and businesses in a responsible and sustainable manner. Previous studies have demonstrated that greater financial inclusion contributes to business growth, productivity, and economic resilience by facilitating access to savings, credit, insurance, and digital payment systems . Nevertheless, empirical evidence regarding the contribution of AI-enabled financial services to financial inclusion among rural MSMEs in Indonesia remains limited (OECD, 2025b). Existing studies have primarily focused on financial technology adoption, digital payments, or financial literacy without specifically examining the role of AI-driven financial services in improving financial inclusion in rural areas. Theoretically, this study is grounded in the Technology Acceptance Model (TAM), which explains that individuals are more likely to adopt new technologies when they perceive them as useful and easy to use (OECD, 2025a). The study is also supported by the concept of financial inclusion, which emphasizes equal access to formal financial services as an essential component of inclusive economic development (*The Global Findex Database 2025: Connectivity and Financial Inclusion in the Digital Economy*, t.t.). The integration of these theoretical perspectives provides a framework for understanding how AI-enabled financial services may enhance financial inclusion among rural entrepreneurs by improving accessibility, efficiency, and trust in digital financial systems (OECD, 2025b).

Based on these conditions, this study addresses the following research question: Does the adoption of artificial intelligence-enabled financial services significantly influence financial inclusion among rural MSMEs in Indonesia? Accordingly, the objective of this study is to analyze the effect of artificial intelligence-enabled financial services on financial inclusion among rural MSMEs in Indonesia (Febriyani dkk., 2024). The findings are expected to enrich the literature on digital finance and financial inclusion while providing practical recommendations for policymakers, financial institutions, and financial technology providers in designing inclusive financial services that support sustainable rural economic development.

RESEARCH METHODS

This study employed a quantitative research approach using a cross-sectional survey design to examine the relationship between artificial intelligence-enabled financial services, digital financial literacy, and financial inclusion among rural micro, small, and medium enterprises (MSMEs) in Indonesia. The study aims to analyze the direct effect of artificial intelligence-enabled financial services on financial inclusion as well as the mediating role of digital financial literacy (Lailiyah dkk., 2025). The research was conducted in Desa Dalu Sepuluh B, Kecamatan Tanjung Morawa, Kabupaten Deli Serdang, Sumatera Utara, Indonesia, an area characterized by the presence of rural MSMEs engaged in trade, agriculture, food processing and household industries.

The research population consists of all rural MSME owners operating in the study area. The research sample comprises 200 MSME owners, selected using purposive sampling. Respondents were selected based on the following criteria:

1. Own or manage an MSME.
2. Operate the business for at least one year.
3. Have experience using digital financial services.
4. Are willing to participate voluntarily.

A sample size of 200 respondents is considered adequate for Partial Least Squares Structural Equation Modeling (PLS-SEM), exceeding the recommended minimum sample size for structural model estimation.

Primary data were collected using a structured questionnaire distributed directly to MSME owners. The questionnaire employed a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Prior to full-scale data collection, the questionnaire was reviewed by experts and pilot-tested to ensure clarity and content validity.

The study measured three latent variables :

1. The independent variable was Artificial Intelligence-Enabled Financial Services (AIFS), reflecting respondents' perceptions of AI-based financial technologies in facilitating business financial activities.
2. The mediating variable was Digital Financial Literacy (DFL), representing respondents' ability to understand, evaluate, and effectively utilize digital financial services (Tandilino dkk., 2025) .
3. The dependent variable was Financial Inclusion (FI), reflecting the accessibility and utilization of formal financial products and services.

Each construct was measured using multiple indicators adapted from previous international studies and modified to suit the Indonesian rural MSME context. Data analysis was performed using SmartPLS 4 through Partial Least Squares Structural Equation Modeling (PLS-SEM). The analysis consisted of two stages :

The first stage evaluated the measurement model by assessing:

1) Indicator reliability (Outer Loading)
2) Internal consistency reliability (Cronbach's Alpha and Composite Reliability)
3) Convergent validity (Average Variance Extracted)
4) Discriminant validity (HTMT Ratio)

The second stage evaluated the structural model by examining:

1) Path coefficients (β)
2) Bootstrapping t-statistics

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3) p-values
4) Coefficient of determination (R^2)
5) Effect size (f^2)
6) Predictive relevance (Q^2)
7) Standardized Root Mean Square Residual (SRMR)

RESULTS AND DISCUSSION

RESULTS

This section presents the research findings and discusses them in an integrated manner. It not only reports the analytical results but also explains their implications, relates them to the underlying theories, and compares them with previous studies.

1. Respondent Characteristics

This section presents the demographic profile of the respondents, including gender, age, education level, business experience, and business type. A total of 200 respondents participated in this simulated dataset.

Table 1. Respondent Characteristics (Simulated)

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	86	43.0
	Female	114	57.0
Age	20–30 years	42	21.0
	31–40 years	71	35.5
	41–50 years	56	28.0
	>50 years	31	15.5
Education Level	Elementary School	12	6.0
	Junior High School	27	13.5
	Senior High School	96	48.0
	Diploma	29	14.5
	Bachelor's Degree	36	18.0
Business Experience	<1 year	18	9.0
	1–3 years	54	27.0
	4–6 years	68	34.0
	>6 years	60	30.0
Business Type	Retail Trade	61	30.5
	Food and Beverage	54	27.0
	Agriculture	29	14.5
	Home Industry / Handicrafts	33	16.5
	Services	23	11.5

2. Measurement Model Evaluation

The measurement model was evaluated by assessing indicator reliability and construct validity through Outer Loadings, Cronbach's Alpha, Composite Reliability, Average Variance Extracted (AVE), and the Heterotrait–Monotrait Ratio (HTMT).

Table 2. Reliability and Convergent Validity Assessment (Simulated)

Construct	Indicator	Outer Loading
Artificial Intelligence-Enabled Financial Services	AI1	0.842
	AI2	0.867
	AI3	0.884
	AI4	0.851
	AI5	0.879
Digital Financial Literacy	DFL1	0.816
	DFL2	0.853
	DFL3	0.891
	DFL4	0.864
	DFL5	0.845
Financial Inclusion	FI1	0.861
	FI2	0.882
	FI3	0.848
	FI4	0.873
	FI5	0.857

All indicators achieved outer loading values greater than 0.70, indicating satisfactory indicator reliability. Therefore, all indicators were retained in the measurement model.

Table 3. Construct Reliability and Validity (Simulated)

Construct	Cronbach's Alpha	Composite Reliability	AVE
Artificial Intelligence-Enabled Financial Services	0.903	0.928	0.721
Digital Financial Literacy	0.889	0.918	0.693
Financial Inclusion	0.911	0.934	0.740

The simulated measurement model satisfies the recommended criteria:

Cronbach's Alpha > 0.70

Composite Reliability > 0.70

Average Variance Extracted (AVE) > 0.50

These results indicate satisfactory internal consistency reliability and convergent validity.

Table 4. Heterotrait–Monotrait Ratio (HTMT) (Simulated)

Construct	AIFS	DFL	FI
Artificial Intelligence-Enabled Financial Services	—		
Digital Financial Literacy	0.683	—	
Financial Inclusion	0.611	0.725	—

All HTMT values are below 0.85, indicating that discriminant validity has been established.

3. Structural Model Evaluation

The structural model was evaluated using Path Coefficients (β), t-statistics, p-values, Coefficient of Determination (R^2), Effect Size (f^2), Predictive Relevance (Q^2), and the Standardized Root Mean Square Residual (SRMR).

Table 5. Path Coefficients (Simulated)

Hypothesis	Relationship	Path Coefficient (β)	t-statistic	p-value	Decision
H1	Artificial Intelligence-Enabled Financial Services → Digital Financial Literacy	0.618	9.421	<0.001	Supported
H2	Digital Financial Literacy → Financial Inclusion	0.453	6.782	<0.001	Supported
H3	Artificial Intelligence-Enabled Financial Services → Financial Inclusion	0.298	4.015	<0.001	Supported

Table 6. Coefficient of Determination (R^2) (Simulated)

Endogenous Construct	R^2
Digital Financial Literacy	0.382
Financial Inclusion	0.567

The simulated model indicates that Artificial Intelligence-Enabled Financial Services explain 38.2% of the variance in Digital Financial Literacy. Furthermore, the model explains 56.7% of the variance in Financial Inclusion.

Table 7. Effect Size (f^2) (Simulated)

Relationship	f^2	Interpretation
AIFS → DFL	0.618	Large
DFL → FI	0.287	Medium
AIFS → FI	0.118	Small

The simulated results indicate a large effect of Artificial Intelligence-Enabled Financial Services on Digital Financial Literacy, a medium effect of Digital Financial Literacy on Financial Inclusion, and a small direct effect of Artificial Intelligence-Enabled Financial Services on Financial Inclusion.

Table 8. Predictive Relevance (Q^2) (Simulated)

Construct	Q^2

Digital Financial Literacy	0.251
Financial Inclusion	0.401

All Q^2 values are greater than zero, indicating that the simulated model possesses predictive relevance.

Table 9. Model Fit Assessment (SRMR) (Simulated)

Model Fit Index	Value	Recommended Threshold
SRMR	0.061	<0.08
NFI	0.912	>0.90

The simulated model demonstrates an acceptable level of model fit, as indicated by an SRMR value of 0.061, which is below the recommended threshold of 0.08.

Table 10. Structural Model Evaluation Summary (Simulated)

Evaluation	Criterion	Simulated Result	Conclusion
Path Coefficient (β)	Positive relationship	0.298–0.618	Acceptable
t-statistic	>1.96	4.015–9.421	Acceptable
p-value	<0.05	<0.001	Acceptable
R^2	>0.25	0.382–0.567	Moderate
f^2	0.02 / 0.15 / 0.35	0.118–0.618	Small to Large
Q^2	>0	0.251–0.401	Predictive Relevance
SRMR	<0.08	0.061	Good Fit

Important note: All tables and statistical values presented above are simulated examples intended solely for demonstrating SEM-PLS reporting and interpretation. They are not empirical research findings and should not be presented as actual results in a scientific publication.

CONCLUSION

The simulated findings suggest that Artificial Intelligence-Enabled Financial Services (AIFS) have a positive relationship with Digital Financial Literacy (DFL) among rural micro, small, and medium enterprises (MSMEs). The relatively stronger path coefficient between AIFS and DFL indicates that the adoption of AI-based financial services may enhance entrepreneurs' understanding and utilization of digital financial technologies. This finding is consistent with the Technology Acceptance Model (TAM), which proposes that individuals are more likely to adopt new technologies when they perceive them as useful and easy to use (Davis, 1989). AI-powered financial services, such as intelligent payment systems, automated financial recommendations, and digital lending platforms, may encourage MSME owners to become more familiar with digital financial products and improve their financial capabilities. The simulated model also indicates that Digital Financial Literacy has a positive relationship with Financial Inclusion. This suggests that entrepreneurs with stronger digital financial knowledge and skills are more capable of accessing and utilizing formal financial products and services. Digital financial literacy enables MSME owners to understand financial information, evaluate financial products, and make informed financial decisions. These observations are in line with previous studies showing that financial literacy is an important determinant of financial inclusion because it reduces information asymmetry and increases confidence in using digital financial services.

Furthermore, the simulated results indicate that Artificial Intelligence-Enabled Financial Services are directly associated with Financial Inclusion. This relationship suggests that AI-based financial technologies may simplify access to financial services through faster transactions, automated customer support, personalized financial recommendations, and more efficient credit assessment. Such innovations may reduce traditional barriers faced by rural entrepreneurs, including limited geographical access to financial institutions and lengthy administrative procedures. The coefficient of determination obtained in the simulated structural model indicates that Artificial Intelligence-Enabled Financial Services explain a meaningful proportion of the variance in Digital Financial Literacy, while the combined model explains more than half of the variation in Financial Inclusion. These simulated findings imply that AI-enabled financial services and digital financial literacy together may play an important role in expanding financial inclusion among rural MSMEs. However, because a substantial proportion of the variance remains unexplained, additional factors such as financial infrastructure, internet accessibility, institutional support, trust in digital technology, and government policy may also influence financial inclusion.

The simulated effect size analysis further suggests that Artificial Intelligence-Enabled Financial Services have a large effect on Digital Financial Literacy, whereas Digital Financial Literacy has a moderate effect on Financial Inclusion. The direct relationship between Artificial Intelligence-Enabled Financial Services and Financial Inclusion appears comparatively smaller, indicating that digital financial literacy may serve as an important mechanism through which AI-based financial services contribute to greater financial inclusion. This pattern highlights the importance of complementing technological innovation with capacity-building initiatives that improve users' digital financial competencies. From a practical perspective, these simulated findings indicate that policymakers, financial institutions, and financial technology providers should not only expand AI-enabled financial services but also strengthen digital financial literacy programs for rural MSMEs. Training programs, financial education initiatives, and user-friendly AI-based financial applications may improve entrepreneurs' ability to adopt digital financial services effectively and increase their participation in the formal financial system. Such efforts may ultimately contribute to inclusive and sustainable rural economic development in Indonesia.

Overall, the simulated findings provide a conceptual illustration of how Artificial Intelligence-Enabled Financial Services, supported by Digital Financial Literacy, may contribute to strengthening Financial Inclusion among rural MSMEs. Future empirical studies using real survey data are required to validate these relationships and to examine additional determinants that may influence financial inclusion in rural communities.

REFERENCE

Demirgüç-Kunt, A., Klapper, L., Singer, D., & Ansar, S. (2021). Financial Inclusion, Digital Payments, and Resilience in the Age of. *The Global*.

Febriyani, W., Supratman, N. A., & Witjaksono, R. W. (2024). Exploring the Contribution of Fintech to Digital Transformation in Indonesian MSMEs: A Literature Review. *SISTEMASI*, *13*(6), 2564. https://doi.org/10.32520/stmsi.v13i6.4638

Indonesia-Promoting-Financial-Access-and-Inclusion-Fintech-for-Financial-Inclusion-Deep-Dive-Study. (t.t.).

Lailiyah, E. H., Zulyanti, N. R., Fajri, M. B., Syah, I., & Abdullah, A. H. (2025). Digital Financial Inclusion and Access to Financing for MSMEs: A Case Study of MSMEs in the Creative Sector in Lamongan. *RIGGS: Journal of Artificial Intelligence and Digital Business*, *4*(4), 2292–2298. https://doi.org/10.31004/riggs.v4i4.3705

OECD. (2025a). *Africa Capital Markets Report 2025*. OECD Publishing. https://doi.org/10.1787/7d26e1d3-en

OECD. (2025b). *Artificial intelligence in Asia's financial sector: A review of country* *policies* (50 ed., OECD Artificial Intelligence Papers) [OECD Artificial Intelligence Papers]. https://doi.org/10.1787/3385bbd8-en

Regulatory approaches to Artificial Intelligence in finance (OECD Artificial Intelligence Papers No. 24; OECD Artificial Intelligence Papers, Vol. 24). (2024). https://doi.org/10.1787/f1498c02-en

Saha, B., Rani, N., & Shukla, S. K. (t.t.). *Generative AI in Financial Institution: A Global Survey of Opportunities, Threats, and Regulation*.

Sudrajat, B., Johan, D. I., & Kusumawardhani, A. (t.t.). *The Utilization of Artificial Intelligence for Financial Inclusion and Business Sustainability Among MSME Operators: Literature Review*.

Tandilino, C., Pontoh, G. T., Darmawati, D., & Indrijawati, A. (2025). Digital Financial Inclusion as a Mediator of Digital Financial Literacy and Government Support in MSME Performance. *International Journal of Financial Studies*, *13*(4), 199. https://doi.org/10.3390/ijfs13040199

The Global Findex Database 2025: Connectivity and Financial Inclusion in the Digital Economy. (t.t.).

Wahyuni, S. (2026). Artificial Intelligence and Digital Competence in Digital HRM: How Educational Collaboration Moderates HR Effectiveness. *Jurnal Manajemen Pendidikan*, *07*(01).