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Digital Financial Literacy, Digital Business Strategy, And Ai Innovation in Msmes: Performance Pathways and Implications for Sustainable Environmental Health Practices

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Abstract. Digital transformation offers micro, small, and medium enterprises (MSMEs) opportunities to improve business performance while supporting more resource-efficient and environmentally responsible operations. This study examines the effects of digital financial literacy and digital business strategy on MSME performance, with AI innovation as a mediating variable. A quantitative cross-sectional design was employed using data from 100 MSME owners in Manado, North Sulawesi, Indonesia. The proposed relationships were tested using partial least squares structural equation modeling. The results show that digital financial literacy ($\beta = 0.731$, $p < 0.001$) and digital business strategy ($\beta = 0.712$, $p < 0.001$) significantly influence AI innovation. AI innovation has a strong positive effect on MSME performance ($\beta = 0.843$, $p < 0.001$) and partially mediates the effects of digital financial literacy ($\beta = 0.616$, $p < 0.001$) and digital business strategy ($\beta = 0.601$, $p < 0.001$) on performance. The model explains 68.3% of the variance in AI innovation and 75.6% of the variance in MSME performance. These findings indicate that AI innovation serves as an important mechanism through which digital capabilities enhance MSME performance. The results also suggest potential applications of AI for energy and water monitoring, inventory optimization, waste management, food safety, occupational health, and lower-emission distribution. However, these environmental-health outcomes were not directly measured and should be interpreted as practical implications rather than confirmed effects.

Keywords: Artificial intelligence innovation; Digital business strategy; Digital financial literacy; Environmental health; MSME performance

INTRODUCTION

Micro, small, and medium enterprises (MSMEs) are central to local employment, household income, production, and economic resilience. However, their activities are also closely connected to environmental health through the consumption of water, energy, and raw materials; the generation of food and solid waste; the use of packaging and potentially hazardous substances; workplace sanitation; food handling; and transportation activities. This intersection is particularly relevant in North Sulawesi, Indonesia. Within the manufacturing segment, BPS-Statistics of Sulawesi Utara Province estimated that 48,902 micro and small industrial establishments were operating in the province in 2024. Food-processing industries accounted for 74.37% of these establishments, equivalent to approximately 36,366 businesses. The sector employed approximately 96,850 workers, of whom 76.35% were engaged in food industries (BPS Sulawesi Utara, n.d.). The dominance of food-related enterprises suggests that improvements in MSME management could have broader implications for food safety, sanitation, waste prevention, occupational health, and the responsible use of natural resources.

Despite their economic importance, the digital readiness of micro and small enterprises in North Sulawesi remains uneven. BPS data indicate that only 36.41% of micro and small industrial establishments used the internet in managing their businesses in 2024. Among businesses using the internet, marketing was the dominant application, accounting for 58.16% of reported uses, whereas ordering raw materials represented 13.96%, transaction payments 12.83%, and financial-technology borrowing only 0.96% (BPS Sulawesi Utara, n.d.). This pattern indicates that digital technologies are still primarily employed for communication and

market access rather than for integrated financial, production, resource, safety, and environmental management. At the national level, evidence from 5,035 ultra-micro, micro, and small enterprises across 17 Indonesian provinces shows that digital adoption is associated with business performance and that financial literacy forms an important component of successful digital engagement (Affandi et al., 2024).

Digital transformation is not limited to the acquisition of individual technological applications. It involves changes in organizational processes, strategies, capabilities, resource allocation, and relationships with customers and other stakeholders (Heredia et al., 2022; Plekhanov et al., 2023; Skare et al., 2023). Research across firms in different economies indicates that digital capabilities can improve performance by strengthening technological capabilities and enabling enterprises to respond more effectively to market disruption (Heredia et al., 2022). Among SMEs, digital transformation may improve access to customers, financing, operational information, and external markets, although its outcomes depend on managerial knowledge, organizational readiness, firm size, and the availability of appropriate human resources (Clemente-Almendros et al., 2024; Plekhanov et al., 2023; Skare et al., 2023). Consequently, MSMEs require more than internet connectivity; they need complementary capabilities that allow them to evaluate, select, finance, and integrate digital technologies into their business processes.

Two capabilities are especially relevant in this context: digital financial literacy and digital business strategy. Digital financial literacy refers to an entrepreneur's ability to access, understand, assess, and appropriately use digitally delivered financial information, services, platforms, and instruments. It includes the capacity to manage digital payments, evaluate technology-related expenditure, identify cybersecurity and fraud risks, compare financing alternatives, and estimate the financial feasibility of technology investments. Evidence suggests that digital financial literacy facilitates the effective use of digital financial services and can strengthen financial inclusion among entrepreneurs (Hasan et al., 2023). In Indonesia, financial literacy is also associated with variation in the scope and effectiveness of digital adoption among micro and small enterprises (Affandi et al., 2024). Thus, digital financial literacy may enable MSME owners to make better-informed decisions concerning subscriptions to cloud applications, automated accounting systems, digital monitoring devices, and artificial intelligence services.

Digital business strategy complements financial literacy by providing an organizational framework within which technologies are aligned with business objectives, operational processes, customer needs, and available resources. A coherent digital strategy allows an enterprise to move beyond fragmented adoption toward the integration of e-commerce, digital payments, cloud services, data analytics, inventory systems, and customer-management applications. Recent evidence demonstrates that managerial education and organizational knowledge influence the capacity of SMEs to pursue digital transformation (Clemente-Almendros et al., 2024). Digital transformation also contributes to firm performance when technological investment is translated into business-model innovation and meaningful organizational change (Arroyabe et al., 2024; Merín-Rodrigáñez et al., 2024). In this sense, digital financial literacy supports the evaluation and financing of technology, whereas digital business strategy determines where and how that technology will be deployed to generate value.

Artificial intelligence innovation may serve as a technological bridge through which these digital capabilities are converted into operational and performance improvements. AI-based applications can analyze transaction records, forecast customer demand, automate routine administration, identify inventory patterns, support pricing decisions, personalize marketing,

and improve customer interaction. However, AI adoption among SMEs is influenced by financial readiness, digital skills, data availability, managerial support, technological compatibility, and regulatory considerations (Ayinaddis, 2025). Evidence from more than 12,000 European SMEs further demonstrates that digital and innovation capabilities are significant drivers of AI adoption, whereas external support is less effective when firms lack sufficient internal capabilities (Arroyabe et al., 2024). Therefore, MSMEs with stronger digital financial literacy and more coherent digital business strategies are theoretically better positioned to evaluate AI investments, prepare the necessary data and infrastructure, and incorporate AI-supported decisions into everyday operations.

The relationship between digital transformation and sustainability provides an important basis for connecting AI-supported MSME performance with environmental health. A review of sustainable digital transformation in SMEs found that performance assessments frequently emphasize economic outcomes while insufficiently integrating environmental and social dimensions (Costa Melo et al., 2023). Empirical evidence also indicates that digital transformation does not automatically produce environmental improvements. Its relationship with environmental performance may be nonlinear and dependent on organizational capabilities, market conditions, and the intensity of digital implementation (L. Li, 2022). Nevertheless, when digital strategies and capabilities are properly integrated, they can support eco-process innovation, eco-product innovation, eco-management innovation, and sustainable performance (Xu et al., 2023). The alignment of digital technology with business strategy similarly strengthens sustainability-oriented innovation and performance by improving information processing and resource allocation (Lu et al., 2023).

AI expands these opportunities by allowing enterprises to convert operational data into predictions, alerts, classifications, and optimization recommendations. Research has shown that perceptive, predictive, and prescriptive AI capabilities can support circular business models and improve resource efficiency through data-driven automation and decision-making (Sjödin et al., 2023). Firm-level evidence indicates that AI applications can improve energy and resource efficiency through structural and efficiency effects (J. Li et al., 2023). AI adoption has also been associated with lower pollution-emission intensity and improved environmental performance through productivity enhancement, optimization of production inputs, and increased investment in pollution control (Cheng et al., 2024). Although much of this evidence originates from larger manufacturing enterprises, the underlying applications (monitoring, forecasting, classification, and optimization) can be adapted to the scale and operational requirements of MSMEs.

For MSMEs, these capabilities may support several practical environmental-health applications. AI-assisted demand forecasting can help food businesses estimate sales and purchasing requirements more accurately, potentially reducing overproduction, spoilage, and food waste. Digital inventories can record the type, quantity, and handling of raw materials, packaging, and business waste. Smart meters and analytical dashboards can identify unusual patterns in electricity or water consumption. Sensors and automated alerts can support the monitoring of refrigeration, storage temperatures, and food-processing conditions. Image-recognition applications may help identify defective products, visible contamination, damaged packaging, or unsafe workplace conditions. Digital documentation can reduce paper consumption, while route-planning systems may reduce unnecessary travel, fuel use, and distribution emissions. AI-supported learning platforms can also provide accessible guidance on sanitation, safe food handling, personal protective equipment, hazardous-material identification, and occupational health procedures.

These applications are supported by emerging environmental-health and safety research. Digital solutions can assist SMEs in recognizing and responding to hazardous workplace situations, although adoption is affected by implementation cost, perceived usefulness, data reliability, privacy concerns, and ease of use (Cagno et al., 2024). In the food sector, AI can support real-time monitoring, contaminant detection, shelf-life prediction, process optimization, traceability, and early identification of food-safety risks (Singh, 2025). Such applications are especially relevant to North Sulawesi because food processing constitutes the largest category of its micro and small industrial establishments (BPS Sulawesi Utara, n.d.). They illustrate how AI-related business capabilities could be directed toward cleaner, safer, and more resource-efficient operations while simultaneously contributing to productivity and operational performance.

Nevertheless, environmental-health improvements should not be interpreted as automatic consequences of AI adoption. A business may implement AI exclusively for marketing, customer communication, or sales forecasting without applying it to waste management, sanitation, energy efficiency, food safety, or occupational health. Digital technologies also require energy, infrastructure, data governance, employee adaptation, and financial investment, and poorly planned digital transformation may fail to generate the expected environmental outcomes (L. Li, 2022). SMEs may face additional constraints arising from limited technical expertise, implementation costs, insufficient data, privacy concerns, and regulatory uncertainty (Ayinaddis, 2025; Cagno et al., 2024; Singh, 2025). AI should therefore be understood as an enabling capability whose environmental-health contribution depends on strategic objectives, organizational readiness, and the specific operational problems to which it is applied.

An important methodological distinction must also be maintained in the present study. The primary survey measures digital financial literacy, digital business strategy, AI innovation, and MSME performance. It does not contain a separate environmental-health construct or direct indicators of water consumption, energy use, waste reduction, sanitation, food contamination, workplace exposure, or emissions. Consequently, sustainable environmental health is not treated as an empirically tested dependent variable in the PLS-SEM model. Instead, it is positioned as an applied domain in which the organizational and performance capabilities generated through digital financial literacy, digital business strategy, and AI innovation may subsequently be used. This positioning preserves the integrity of the original respondent data and avoids making causal claims that are not supported by the measurement instrument.

Despite growing interest in MSME digitalization, limited research has simultaneously examined digital financial literacy, digital business strategy, AI innovation, and business performance in secondary Indonesian cities. Previous studies commonly investigate digital capabilities, financial literacy, AI readiness, firm performance, or sustainability as separate issues. Research linking digital transformation with environmental performance has also predominantly focused on larger manufacturing enterprises or industries outside Indonesia. Evidence from Manado remains particularly limited, even though the city operates within a regional economy characterized by numerous micro and small food-processing enterprises and uneven levels of advanced digital utilization (BPS Sulawesi Utara, n.d.). This creates a need for context-specific evidence concerning how entrepreneurs' digital financial and strategic capabilities facilitate AI innovation and how such innovation contributes to MSME performance.

Accordingly, this study examines the effects of digital financial literacy and digital business strategy on AI innovation and MSME performance among MSME owners in Manado, North Sulawesi. It further evaluates the mediating role of AI innovation in the relationships

between the two digital capabilities and MSME performance. The study uses the original primary survey and PLS-SEM results, while official BPS statistics and recent Scopus-indexed literature are employed as secondary evidence for contextualization and interpretation. The secondary sources do not replace, modify, or become part of the respondent dataset.

This study makes three contributions. First, it examines digital financial literacy as an antecedent of AI innovation, thereby connecting entrepreneurs' financial capabilities with advanced technology adoption. Second, it integrates digital business strategy, AI innovation, and MSME performance within a single empirical model in the context of Manado. Third, it develops a cautious environmental-health interpretation of the findings by identifying how AI-supported operational capabilities may be applied to resource monitoring, waste prevention, food safety, sanitation, occupational health, and lower-emission distribution. Rather than claiming that environmental-health outcomes have been directly measured, the study identifies sustainable environmental health as a strategically important field for applying the performance and innovation capabilities investigated in the structural model.

MATERIAL AND METHODS

Research Design and Analytical Scope

This study employed a quantitative, cross-sectional, and explanatory research design to examine the relationships among digital financial literacy, digital business strategy, artificial intelligence innovation, and MSME performance. The analysis retained the four latent constructs and the original respondent-level dataset used in the initial study. No new primary variables, questionnaire items, or respondent observations were added during the environmental-health-oriented revision.

Partial least squares structural equation modeling (PLS-SEM) was selected because the study focused on estimating direct and indirect relationships among latent variables and explaining the variance in AI innovation and MSME performance. PLS-SEM is particularly suitable for prediction-oriented models involving multiple simultaneous relationships and does not require the assumption of multivariate normality (Hair & Alamer, 2022; Vaithilingam et al., 2024). Nevertheless, the use of PLS-SEM does not by itself eliminate concerns regarding statistical power, sampling limitations, or model robustness. Consequently, the analytical procedures and evaluation criteria were reported transparently to facilitate verification and replication (Adler et al., 2023; Ringle et al., 2023; Vaithilingam et al., 2024).

Sustainable environmental health practices were not specified as a latent variable or dependent variable in the structural model because the original questionnaire did not directly measure water consumption, energy consumption, waste generation, emissions, food contamination, occupational exposure, sanitation, or related environmental-health outcomes. Environmental health was therefore incorporated only as an interpretive application domain for the digital and AI capabilities examined in the model. Accordingly, the statistical results indicate relationships among digital capabilities, AI innovation, and MSME performance, but they do not constitute direct empirical evidence that AI adoption reduced environmental or health risks.

Study Area and Target Population

The study was conducted in Manado City, North Sulawesi, Indonesia. Manado was selected because it represents a growing secondary urban economy in eastern Indonesia in which MSMEs increasingly use digital payments, social media, online marketplaces, and other digital business applications. The unit of analysis was the individual MSME, represented by its owner or primary business decision-maker.

The target population consisted of MSMEs that were actively operating in Manado in 2024 and had adopted at least one digital tool in their business activities. Digital tools included, but were not limited to, e-commerce platforms, digital payment services, online banking, social media marketing, cloud-based applications, and digitally supported business administration.

Respondents were eligible to participate when they met the following criteria:

1. The enterprise was actively operating in Manado during the data-collection period.
2. The enterprise used at least one digital technology in its business activities.
3. The respondent was the owner or principal decision-maker responsible for financial or strategic decisions.
4. The submitted questionnaire contained sufficient information for analysis.

The inclusion criteria ensured that respondents had direct knowledge of the enterprise's financial decisions, digital strategy, technology adoption, and business performance.

Sampling and Data Collection

A purposive sampling technique was applied because the study required respondents who had decision-making authority and direct experience with digital business tools. The questionnaire was distributed between August and October 2024 through MSME associations, local government business networks, entrepreneurship communities, and digital communication channels in Manado.

Data were collected using both printed and online questionnaires. The use of the two distribution formats was intended to accommodate differences in respondents' access to and familiarity with online survey platforms. Questionnaires with incomplete responses to the principal measurement items were excluded. After data screening, 100 valid responses were retained for the PLS-SEM analysis.

Because the study used an existing fixed dataset of 100 respondents, no retrospective claim that the sample represented the entire MSME population of Manado was made. The sample was non-probabilistic and limited to enterprises that had already used at least one digital tool. Therefore, the findings should be interpreted as explanatory evidence concerning the observed relationships within the sampled digitally engaged MSMEs rather than as population estimates for all enterprises in Manado.

The revised manuscript should also avoid the statement that the sample size was determined by "ten observations per indicator." With 16 indicators, that statement would imply 160 observations rather than 100. Moreover, recent methodological literature cautions that simple rules such as the "10-times rule" should not be treated as definitive evidence of adequate statistical power (Adler et al., 2023; Hair & Alamer, 2022).

Questionnaire and Construct Measurement

The questionnaire consisted of respondent characteristics and measurement items for four latent constructs: digital financial literacy, digital business strategy, AI innovation, and MSME performance. Each construct was represented by four reflective indicators, producing a total of 16 measurement items.

All items were measured using a five-point Likert scale:

$1 =$ Strongly Disagree, $2 =$ Disagree, $3 =$ Neutral, $4 =$ Agree, $5 =$ Strongly Agree.

The operationalization of the constructs is presented in Table 1.

Table 1. Operationalization of the Study Constructs

Construct	Code	Operational focus
Digital Financial Literacy	DFL1	Ability to use digital payment platforms
	DFL2	Ability to use online or mobile banking
	DFL3	Understanding and use of digital financial or investment tools
	DFL4	Awareness of cybersecurity and digital financial risks
Digital Business Strategy	DBS1	Strategic use of e-commerce platforms
	DBS2	Use of cloud-based applications in business operations
	DBS3	Integration of digital marketing into business strategy
	DBS4	Use of business data and analytics in decision-making
AI Innovation	AII1	Use of AI-supported information in business decisions
	AII2	Use of AI in customer communication or interaction
	AII3	Use of AI in inventory or supply-chain activities
	AII4	Use of AI or intelligent automation in operational processes
MSME Performance	MP1	Improvement in revenue or sales performance
	MP2	Expansion of market reach
	MP3	Improvement in customer satisfaction
	MP4	Improvement in operational efficiency

From Table 1, Digital financial literacy represents the knowledge and ability required to use digital financial services, evaluate digitally mediated financial decisions, and recognize the associated risks. In the present model, it functions as an individual-level capability that may help MSME owners assess the affordability, risks, and potential returns of AI-based business applications.

Digital business strategy represents the extent to which digital technologies are incorporated into the enterprise's strategic and operational activities. It captures whether the enterprise uses digital tools as isolated applications or as part of a broader strategy involving customers, marketing, operations, data, and business development.

AI innovation measures the enterprise's application of AI-related or intelligent digital functions in decision-making, customer interaction, supply-chain management, and operational automation. The construct assesses business-oriented AI use rather than the technical sophistication of a particular algorithm.

MSME performance captures respondents' assessments of revenue development, market reach, customer satisfaction, and operational efficiency. It does not directly measure environmental or public-health performance. Consequently, an increase in the MSME performance construct cannot automatically be interpreted as an improvement in waste management, sanitation, resource efficiency, food safety, or occupational health.

Content relevance was evaluated through a review by three academics with expertise in digital management and quantitative research. All four constructs were modeled reflectively because the indicators were treated as manifestations of their respective underlying concepts. Current PLS-SEM literature emphasizes that reflective specification should be based on construct conceptualization and not selected solely for statistical convenience (Hair & Alamer, 2022; Ringle et al., 2023).

Structural Model Specification

The structural model assessed the effects of digital financial literacy and digital business strategy on AI innovation and MSME performance. It also examined whether AI innovation transmitted part of the effects of the two digital capabilities to MSME performance.

The structural relationships can be represented as follows:

$$AII = \beta_1 DFL + \beta_2 DBS + \zeta_1,$$

and

$$MP = \beta_3 DFL + \beta_4 DBS + \beta_5 AII + \zeta_2,$$

where:
DFL denotes digital financial literacy;
DBS denotes digital business strategy;
AII denotes AI innovation;
MP denotes MSME performance;
β represents the standardized path coefficient; and
ζ represents the residual variance.

The tested hypotheses were retained from the original model:
H1: Digital financial literacy has a positive effect on AI innovation.
H2: Digital business strategy has a positive effect on AI innovation.
H3: Digital financial literacy has a positive effect on MSME performance.
H4: Digital business strategy has a positive effect on MSME performance.
H5: AI innovation has a positive effect on MSME performance.
H6: AI innovation mediates the relationship between digital financial literacy and MSME performance.
H7: AI innovation mediates the relationship between digital business strategy and MSME performance.

The two specific indirect effects were calculated as:

$$\text{Indirect effect of DFL} = \beta_1 \times \beta_5,$$

And

$$\text{Indirect effect of DBS} = \beta_2 \times \beta_5.$$

No path from AI innovation to sustainable environmental health practices was estimated. Adding such a path would require a separate environmental-health construct supported by directly measured indicators and new respondent data.

PLS-SEM Analytical Procedure

The analysis was conducted using SmartPLS 4. The evaluation consisted of two principal stages: assessment of the reflective measurement model and assessment of the structural model. This sequence is consistent with contemporary PLS-SEM reporting recommendations (Hair & Alamer, 2022; Ringle et al., 2023).

Measurement Model Assessment

The reflective measurement model was evaluated using the following criteria:

1. **Indicator reliability:** Outer loadings were expected to be at least 0.70.
2. **Internal consistency:** Cronbach's alpha and composite reliability values were expected to exceed 0.70.
3. **Convergent validity:** Average variance extracted values were expected to exceed 0.50.

4. **Discriminant validity:** The heterotrait-monotrait ratio of correlations was evaluated using the conservative threshold of 0.85.

An outer loading of at least 0.70 indicates that a substantial proportion of the indicator's variance is explained by its corresponding construct. Composite reliability and Cronbach's alpha were reported together because they provide complementary information regarding internal consistency. Average variance extracted was used to determine whether each construct explained more than half of the variance in its indicators.

Discriminant validity was assessed through the HTMT criterion rather than relying exclusively on comparisons of construct correlations. HTMT was developed to identify whether theoretically distinct constructs exhibit excessive empirical overlap (Henseler et al., 2015).

Structural Model Assessment

After satisfactory measurement quality was established, the structural model was evaluated using:

1. standardized path coefficients (β);
2. standard errors;
3. t-statistics;
4. p-values;
5. coefficients of determination (R^2); and
6. effect sizes (f^2).

The R^2 values were used to assess the amount of variance in AI innovation and MSME performance explained by their predictors. The f^2 statistic was used to evaluate the contribution of each predictor to the explained variance of an endogenous construct. Effect sizes were interpreted using the conventional approximate values of 0.02, 0.15, and 0.35 for small, medium, and large effects, respectively.

The statistical significance of the direct and indirect effects was evaluated through nonparametric bootstrapping with 5,000 subsamples. Bootstrapping was appropriate because indirect-effect distributions are frequently asymmetric and should not be evaluated solely through assumptions of normality. Bias-corrected 95% confidence intervals were used to assess whether an indirect effect differed significantly from zero (Sarstedt & Moisescu, 2024).

Mediation was evaluated by first examining the significance of the indirect effect and then considering whether the corresponding direct effect remained significant. A significant indirect effect accompanied by a significant direct effect was interpreted as partial mediation. A significant indirect effect accompanied by a nonsignificant direct effect would indicate indirect-only mediation. The analysis did not require the direct effect to become nonsignificant before mediation could be established (Sarstedt & Moisescu, 2024).

Common Method Bias Assessment

Because all constructs were measured through the same self-reported questionnaire at one point in time, common method bias was considered a potential limitation. The original study used Harman's single-factor test as a preliminary statistical diagnostic. Under this procedure, all measurement items were entered into an exploratory factor analysis to determine whether one factor accounted for most of the total variance.

The result of this diagnostic is reported in the Results and Discussion section. However, Harman's single-factor test should not be presented as definitive proof that common method

bias is absent. It is more appropriately interpreted as an initial diagnostic that must be considered together with the distinctiveness of the constructs, the measurement-model results, respondent eligibility criteria, and the limitations of a single-source cross-sectional design. Transparent disclosure of such analytical decisions is recommended in recent PLS-SEM reporting literature (Adler et al., 2023; Vaithilingam et al., 2024).

Integration of Secondary Environmental-Health Evidence

Secondary data were used to provide contextual and interpretive support for the environmental-health orientation of the manuscript. The secondary sources consisted of official statistics from BPS-Statistics Indonesia and BPS-Statistics of Sulawesi Utara Province, together with recent Scopus-indexed journal articles addressing digital transformation, AI, sustainability, resource efficiency, food safety, occupational safety, and SME performance.

The secondary evidence was not combined with the questionnaire database, entered into SmartPLS, or used to modify the estimated path coefficients. It was used only for three purposes:

1. to describe the regional MSME and micro-industry context;
2. to explain why environmental health is relevant to MSMEs in North Sulawesi; and
3. to interpret potential applications of AI-supported business capabilities.

For the discussion, the secondary evidence was organized into eight potential application areas:

1. monitoring water and energy consumption;
2. optimizing inventories to prevent spoilage and food waste;
3. recording and separating business waste;
4. monitoring storage temperature and food safety;
5. identifying potentially hazardous materials or conditions;
6. reducing paper-based administration;
7. planning distribution routes to reduce fuel use and emissions; and
8. providing digital education on sanitation and occupational health.

These areas constitute an interpretive framework rather than additional variables in the PLS-SEM model. Any future claim that AI innovation causes improvements in these environmental-health outcomes would require new indicators, direct environmental measurements, and a revised research design.

RESULTS AND DISCUSSION

Respondent Characteristics

Table 2 presents the demographic and business characteristics of the 100 MSME owners included in the analysis. Female entrepreneurs constituted 70% of the respondents, while male entrepreneurs accounted for 30%. Most respondents were between 31 and 40 years of age (60%), followed by those aged 41–50 years (20%). Respondents aged 21–30 years and those older than 50 years each represented 10% of the sample.

Regarding educational attainment, 50% of the respondents had completed senior high school, 20% held a diploma, 20% held a bachelor's degree, and 10% held a master's degree. Half of the sampled businesses had operated for three to five years, while 20% had operated for one to two years, 20% for six to ten years, and 10% for more than ten years.

The respondents were predominantly micro-scale enterprises. Sixty percent reported monthly revenues between IDR 10 million and IDR 25 million, while 10% earned less than IDR

10 million, 20% earned between IDR 25 million and IDR 50 million, and 10% earned more than IDR 50 million. In terms of employment, 60% of the enterprises employed two workers and 20% employed only one worker. Enterprises with three to five employees accounted for 15%, while only 5% employed more than five workers.

Table 2. Demographic and Business Characteristics of Respondents

Characteristic	Category	Frequency	Percentage (%)
Gender	Female	70	70
	Male	30	30
Age	21–30 years	10	10
	31–40 years	60	60
	41–50 years	20	20
	More than 50 years	10	10
Education	Senior high school	50	50
	Diploma	20	20
	Bachelor's degree	20	20
	Master's degree	10	10
Business duration	1–2 years	20	20
	3–5 years	50	50
	6–10 years	20	20
	More than 10 years	10	10
Monthly revenue	Less than IDR 10 million	10	10
	IDR 10–25 million	60	60
	IDR 25–50 million	20	20
	More than IDR 50 million	10	10
Employees	1 employee	20	20
	2 employees	60	60
	3–5 employees	15	15
	More than 5 employees	5	5

Source: Primary data (2024).

From Tabel 2, the profile indicates that the study primarily represents small, owner-managed enterprises with limited human and financial resources. This characteristic is important when interpreting AI innovation. For businesses employing only one or two workers, AI adoption is more likely to involve accessible applications embedded in digital-payment systems, accounting software, e-commerce platforms, chatbots, inventory applications, or cloud services than the development of proprietary AI infrastructure.

The educational profile also emphasizes the importance of simple interfaces and practical digital training. AI solutions designed for this segment should not depend on advanced programming knowledge. Instead, they should translate operational data into understandable recommendations, alerts, forecasts, or automated actions. Indonesian evidence similarly shows that enterprise and owner characteristics, financial literacy, and internal business conditions affect the adoption and productive use of digital technologies among micro and small businesses (Affandi et al., 2024).

Because purposive sampling was employed, the respondent distribution should not be interpreted as representing the gender, educational, revenue, or employment composition of the entire MSME population in Manado. It describes the characteristics of the digitally engaged MSMEs participating in this study.

Reflective Measurement Model Assessment

The reflective measurement model was evaluated before examining the structural relationships. As presented in Table 3, all outer loadings exceeded the recommended value of 0.70, ranging from 0.798 to 0.876. This result indicates that every indicator had an adequate relationship with its corresponding latent construct.

The average variance extracted values ranged from 0.681 to 0.738, exceeding the minimum criterion of 0.50. Digital financial literacy had an AVE of 0.681, digital business strategy had an AVE of 0.697, AI innovation had an AVE of 0.738, and MSME performance had an AVE of 0.682. Therefore, each construct explained more than half of the variance in its indicators.

Composite reliability values ranged from 0.895 to 0.919, while Cronbach's alpha values ranged from 0.868 to 0.896. Both measures exceeded 0.70, indicating satisfactory internal consistency. These results support the reliability and convergent validity of all four constructs under commonly applied PLS-SEM evaluation criteria (Hair & Alamer, 2022).

Table 3. Measurement Model Assessment

Construct	Indicator	Outer loading	AVE	Composite reliability	Cronbach's α
Digital Financial Literacy	DFL1	0.821	0.681	0.895	0.868
	DFL2	0.836			
	DFL3	0.798			
	DFL4	0.845			
Digital Business Strategy	DBS1	0.834	0.697	0.903	0.879
	DBS2	0.847			
	DBS3	0.812			
	DBS4	0.856			
AI Innovation	AII1	0.876	0.738	0.919	0.896
	AII2	0.845			
	AII3	0.863			
	AII4	0.831			
MSME Performance	MP1	0.812	0.682	0.898	0.872
	MP2	0.837			
	MP3	0.823			
	MP4	0.856			

Note: AVE = average variance extracted. All outer loadings were significant at $p < 0.001$.

From Table 4, Among the four constructs, AI innovation had the highest AVE, composite reliability, and Cronbach's alpha. The result indicates that the four indicators concerning AI-supported decision-making, customer interaction, supply-chain management, and operational automation coherently represented the AI innovation construct in this sample.

Nevertheless, the high reliability of the AI innovation scale should not be interpreted as evidence that the participating enterprises used technically advanced or autonomous AI systems. The indicators capture respondents' perceptions of AI-related business applications and operational innovation, rather than the algorithmic sophistication, investment value, or maturity of the technology used.

Discriminant Validity

Discriminant validity was examined using the heterotrait-monotrait ratio. As shown in Table 4, all HTMT values were below the conservative threshold of 0.85. The values ranged

from 0.643 to 0.756, indicating that the constructs were related but remained empirically distinguishable.

Table 4. Heterotrait-Monotrait Ratio Matrix

Construct	DFL	DBS	AII	MP
Digital Financial Literacy	—			
Digital Business Strategy	0.724	—		
AI Innovation	0.698	0.712	—	
MSME Performance	0.643	0.671	0.756	—

Note: DFL = digital financial literacy; DBS = digital business strategy; AII = AI innovation; MP = MSME performance.

From Table 4, The highest HTMT value was observed between AI innovation and MSME performance (0.756). This association is theoretically reasonable because AI innovation is expected to be closely related to improvements in decision-making, customer interaction, market activities, and operational efficiency. However, the value remained below 0.85, indicating that respondents did not perceive AI innovation and business performance as the same concept.

The HTMT value between digital financial literacy and digital business strategy was 0.724. This result indicates that entrepreneurs' ability to use digital financial services was associated with their broader digital strategic orientation, but the two constructs captured different organizational capabilities. Digital financial literacy primarily represents the owner's capacity to understand and evaluate digital financial activities, whereas digital business strategy reflects the integration of digital tools into the overall direction and operation of the enterprise.

Structural Model and Direct Effects

The structural model explained 68.3% of the variance in AI innovation and 75.6% of the variance in MSME performance. Thus, digital financial literacy and digital business strategy jointly demonstrated considerable in-sample explanatory power for AI innovation. Digital financial literacy, digital business strategy, and AI innovation also explained a large proportion of the observed variation in MSME performance.

Table 5 presents the direct-effect results. All five direct relationships were positive and statistically significant at $p < 0.001$.

Table 5. Direct Effects and Hypothesis Testing

Hypothesis	Structural relationship	β	SE	t-statistic	p-value	f^2	Decision
H1	DFL - AII	0.731	0.06	12.17	<0.001	0.312	Supported
H2	DBS - AII	0.712	0.05	14.2	<0.001	0.298	Supported
H3	DFL - MP	0.649	0.07	9.29	<0.001	0.187	Supported
H4	DBS - MP	0.682	0.06	11.33	<0.001	0.203	Supported
H5	AII - MP	0.843	0.05	16.8	<0.001	0.521	Supported

Note: β = standardized path coefficient; SE = standard error; f^2 = effect size; R^2 for AII = 0.683; R^2 for MP = 0.756. Statistical significance was assessed using 5,000 bootstrap subsamples.

Digital Financial Literacy and AI Innovation

Digital financial literacy had a positive and significant effect on AI innovation ($\beta = 0.731$, $p < 0.001$), supporting H1. Its effect size was 0.312, which can be interpreted as a moderate-to-substantial contribution under conventional PLS-SEM benchmarks (Hair & Alamer, 2022).

The finding indicates that MSME owners who are more capable of using digital payments, online banking, digital financial applications, and cybersecurity-related information are also more likely to implement AI-related innovations. Digital financial literacy may reduce

uncertainty surrounding technology costs, subscription payments, digital transactions, expected financial benefits, and the risks of adopting new applications.

The result is consistent with evidence from Indonesian micro and small enterprises showing that financial literacy and digital adoption are interconnected with business performance (Affandi et al., 2024). It also complements European SME evidence showing that internal digital capabilities are important predictors of AI adoption (Arroyabe et al., 2024).

Digital financial literacy is therefore not limited to the performance of online financial transactions. In the context of AI adoption, it represents an evaluative capability that enables entrepreneurs to compare technological alternatives, estimate costs and benefits, assess subscription commitments, identify fraud and data-security risks, and determine whether an AI-supported service is financially appropriate for their enterprise.

Digital Business Strategy and AI Innovation

Digital business strategy had a positive and significant effect on AI innovation ($\beta = 0.712$, $p < 0.001$), supporting H2. The effect size of 0.298 indicates that digital business strategy made an important contribution to the explained variance in AI innovation.

MSMEs with an established strategy for e-commerce, cloud-based operations, digital marketing, and data analytics are more likely to have the organizational foundation required for AI implementation. AI applications generally depend on existing digital processes and data. An enterprise that already records sales digitally, manages inventory using an application, communicates with customers online, or uses electronic payments can integrate AI more easily than an enterprise whose activities remain entirely manual.

This interpretation is consistent with research demonstrating that digital capabilities and innovation capacity facilitate AI adoption in SMEs (Arroyabe et al., 2024). It also aligns with evidence that digital transformation improves SME performance when it is translated into organizational and business-model innovation rather than treated merely as the acquisition of isolated technological tools (Merín-Rodrigáñez et al., 2024).

The similarity between the DFL-to-AII coefficient (0.731) and the DBS-to-AII coefficient (0.712) indicates that both financial capability and strategic digital orientation are relevant to AI innovation. AI readiness among MSMEs should therefore not be approached exclusively as a technical issue. It also requires the ability to finance digital adoption and the strategic capacity to identify suitable areas of application.

Digital Financial Literacy and MSME Performance

Digital financial literacy positively affected MSME performance ($\beta = 0.649$, $p < 0.001$), supporting H3. The effect size was 0.187, indicating a moderate contribution to MSME performance.

Entrepreneurs with stronger digital financial literacy may be better able to monitor cash flow, manage digital payments, assess financing alternatives, identify transaction risks, and allocate funds to productive business activities. These abilities can directly support revenue development, market expansion, customer satisfaction, and operational efficiency, even without considering the additional role of AI.

The result is consistent with Indonesian evidence showing meaningful relationships among financial literacy, digital adoption, and the performance of ultra-micro, micro, and small enterprises (Affandi et al., 2024).

However, the result should not be interpreted as demonstrating that digital financial literacy directly improves environmental health. The performance indicators used in the present

study concern revenue, market reach, customer satisfaction, and operational efficiency. No direct indicator of resource use, environmental exposure, or sanitation was included.

Digital Business Strategy and MSME Performance

Digital business strategy had a positive effect on MSME performance ($\beta = 0.682$, $p < 0.001$), supporting H4. Its effect size was 0.203, indicating a moderate contribution.

A coherent digital strategy can improve business performance through several mechanisms. E-commerce can expand market access; digital marketing can improve customer communication; cloud-based systems can support business continuity and information availability; and data analytics can strengthen operational decision-making. The result indicates that the benefits of digitalization depend not only on access to technology but also on its strategic integration.

The finding is consistent with recent SME research demonstrating that digital transformation can support firm performance through organizational adaptation and business-model innovation (Merín-Rodrigáñez et al., 2024). It is also compatible with evidence that digital capability and digital strategy can support eco-innovation when they are integrated with production and management processes (Xu et al., 2023).

AI Innovation and MSME Performance

AI innovation had the strongest direct association in the structural model ($\beta = 0.843$, $p < 0.001$), supporting H5. Its effect size was 0.521, which falls within the large-effect category under conventional interpretation.

The result suggests that AI-supported decision-making, customer interaction, supply-chain management, and operational automation are strongly associated with the performance perceived by the sampled MSME owners. AI may help enterprises process information faster, identify customer patterns, respond to inquiries, estimate demand, manage inventory, and reduce repetitive administrative work.

The coefficient should nevertheless be interpreted within the design limitations of the study. The cross-sectional data establish an association rather than a temporal causal sequence. High-performing MSMEs may possess greater resources to adopt AI, while AI adoption may also contribute to performance. Longitudinal data would be required to determine how these relationships evolve over time.

The result is broadly consistent with recent evidence that internal digital and innovation capabilities support AI adoption in SMEs (Arroyabe et al., 2024) and that digital transformation generates performance benefits when technologies are embedded in organizational innovation (Merín-Rodrigáñez et al., 2024).

Mediating Role of AI Innovation

The mediation analysis examined whether digital financial literacy and digital business strategy influenced MSME performance indirectly through AI innovation. As shown in Table 6, both indirect effects were positive and statistically significant.

Table 6. Indirect Effects Through AI Innovation

Hypothesis	Indirect relationship	β	SE	t-statistic	95% confidence interval	p-value	Mediation
H6	DFL - AII -- MP	0.616	0.05	12.2	0.518, 0.714	<0.001	Partial
H7	DBS - AII - MP	0.601	0.045	13.5	0.513, 0.689	<0.001	Partial

Note: Confidence interals were obtained using bias-corrected bootstrapping with 5,000 subsamples.

From Table 6, the indirect effect of digital financial literacy on MSME performance through AI innovation was 0.616, with a 95% confidence interval from 0.518 to 0.714. Since the confidence interval did not contain zero, H6 was supported. The direct relationship between digital financial literacy and performance also remained significant, indicating partial mediation.

Similarly, digital business strategy had a significant indirect effect on MSME performance through AI innovation (β = 0.601), with a 95% confidence interval from 0.513 to 0.689. Therefore, H7 was supported. Because the direct DBS-to-performance relationship remained statistically significant, AI innovation also partially mediated this relationship.

As both the direct and indirect effects were positive, the findings can be described more specifically as complementary partial mediation. Digital financial literacy and digital business strategy contribute directly to MSME performance while also producing additional performance benefits through AI innovation. Contemporary PLS-SEM guidance emphasizes the confidence interval of the indirect effect when evaluating mediation, rather than relying only on whether the direct relationship becomes nonsignificant (Sarstedt & Moisescu, 2024).

The results demonstrate that AI innovation does not replace the need for basic digital capabilities. Financial literacy and business strategy continue to influence performance independently. AI functions as an additional mechanism that converts these capabilities into data-supported decisions, automation, customer responsiveness, and operational improvement.

Common Method Bias Diagnostic

Harman's single-factor diagnostic showed that one factor accounted for 29.4% of the total variance, below the commonly used 50% reference value. This result indicates that the indicators did not collapse into a single dominant factor.

Nevertheless, this diagnostic does not prove that common method bias was completely absent. All variables were obtained from the same respondents, through the same questionnaire, and during the same data-collection period. The possibility of self-reporting bias, consistency motives, and socially desirable responses should therefore remain acknowledged when interpreting the strength of the structural relationships.

The available original results did not report inner variance inflation factors or out-of-sample predictive measures such as PLSpredict. Accordingly, the present interpretation is limited to the reported measurement properties, path coefficients, R^2 values, effect sizes, and bootstrap confidence intervals. No unreported diagnostic values were reconstructed or assumed.

Implications for Sustainable Environmental Health Practices

The structural model did not directly test sustainable environmental health practices. However, the results provide a basis for discussing how the digital and AI capabilities associated with MSME performance could be applied to environmental-health management.

The significant relationships between DFL, DBS, and AI innovation indicate that financial and strategic digital readiness may provide the organizational foundation for adopting applications that support resource monitoring, waste prevention, food safety, occupational safety, and sanitation. The strong relationship between AI innovation and performance further suggests that such applications are more likely to be accepted by MSMEs when they simultaneously provide clear operational or financial value.

Research outside the present dataset indicates that digital transformation can facilitate eco-process, eco-product, and eco-management innovation (Xu et al., 2023). AI use has also been associated with improved energy and resource efficiency and better enterprise environmental performance (Cheng et al., 2024; J. Li et al., 2023). However, these findings originate mainly from manufacturing firms outside the Manado MSME context and should

therefore be treated as supporting literature rather than as direct confirmation of the environmental effects of the present model.

Table 7. Potential Environmental-Health Applications of AI Innovation in MSMEs

Application area	Possible digital or AI application	Potential environmental-health relevance	Status in this study
Energy management	Smart-meter dashboards, anomaly alerts, consumption forecasting	Reduced unnecessary energy use and indirect emissions	Not directly measured
Water management	Digital meter records and unusual-consumption alerts	Improved water efficiency and earlier detection of leakage	Not directly measured
Food inventory	Demand forecasting and expiry-date alerts	Reduced spoilage, organic waste, and unsafe food storage	Not directly measured
Waste management	Digital waste records and automated classification support	Improved identification, separation, and handling of waste	Not directly measured
Food safety	Temperature sensors, predictive alerts, and image recognition	Improved storage control and earlier identification of contamination risks	Not directly measured
Hazard identification	Image-based detection and digital safety checklists	Earlier recognition of unsafe materials or workplace conditions	Not directly measured
Paper reduction	Digital invoices, records, and financial reporting	Reduced paper consumption and physical document storage	Not directly measured
Distribution	Data-supported route planning	Reduced travel distance, fuel use, and transport emissions	Not directly measured
Sanitation education	AI-assisted digital training and reminders	Improved access to sanitation and occupational-health information	Not directly measured

Within Table 7, for food-related MSMEs, AI-supported demand forecasting could reduce excessive purchasing and overproduction. Temperature monitoring and automated alerts could strengthen storage control, while image recognition could assist with identifying damaged packaging or visible product defects. Recent food-safety research identifies real-time monitoring, contaminant detection, shelf-life prediction, and predictive analytics as important AI applications (Singh, 2025).

In occupational-health management, digital systems may support hazard identification, safety checklists, training records, equipment-maintenance reminders, and reporting of unsafe conditions. Evidence from SMEs indicates that digital safety solutions can assist the management of workplace risks, although adoption remains affected by cost, technical readiness, perceived usefulness, and organizational capacity (Cagno et al., 2024).

The DFL result is relevant because entrepreneurs must be capable of assessing whether environmental-health technologies are affordable and financially beneficial. For example, the adoption of a temperature sensor, digital inventory platform, or energy-monitoring system requires an evaluation of acquisition costs, subscription charges, expected waste reduction, possible energy savings, and operational benefits.

The DBS result is equally relevant because environmental-health applications must be integrated into daily procedures. A monitoring application will have limited value when the enterprise does not assign responsibility for reviewing alerts, recording corrective action, or using the resulting data in purchasing and production decisions. Digital business strategy can therefore connect the technology with operating procedures and measurable business objectives.

The strong AII-to-performance relationship suggests that environmental-health applications may achieve greater MSME acceptance when they generate simultaneous business benefits. Inventory optimization, for instance, may reduce food waste while lowering

purchasing losses. Temperature monitoring may strengthen food safety while protecting product quality and customer confidence. Route optimization may reduce emissions while lowering fuel costs. Digital records may reduce paper consumption while improving administrative efficiency.

These examples represent potential co-benefits, not outcomes demonstrated by the structural model. The present data cannot establish that the sampled MSMEs reduced energy use, waste, contamination, occupational risks, or emissions through AI. Such claims would require direct environmental-health indicators and preferably objective measurements collected over time.

Theoretical and Practical Implications

The findings make three principal theoretical contributions. First, they position digital financial literacy as an antecedent of AI innovation. This extends the role of financial literacy beyond financial-service use by showing its relationship with the enterprise's capacity to evaluate and adopt advanced digital applications.

Second, the findings demonstrate that digital business strategy and digital financial literacy represent complementary capabilities. The former establishes the organizational direction for digitalization, while the latter supports financially informed technology decisions. Both capabilities had significant direct effects on AI innovation and MSME performance.

Third, the mediation findings identify AI innovation as a mechanism through which foundational digital capabilities are translated into performance. The partial nature of the mediation indicates that AI is neither an isolated performance solution nor a complete substitute for financial knowledge and digital strategy.

Practically, MSME development programs in Manado should integrate financial literacy, business strategy, and AI application rather than offering them as unrelated training subjects. A practical sequence could begin with digital financial and cybersecurity competencies, continue with the mapping of business processes and operational problems, and subsequently introduce affordable AI-supported applications.

Environmental-health content can be embedded within this sequence. MSMEs could be trained to calculate the financial losses associated with energy waste, water leakage, food spoilage, poor stock rotation, unsafe storage, excessive packaging, and inefficient distribution. AI applications could then be introduced as tools for solving these specific business and environmental-health problems.

Policy interventions should prioritize accessible and low-cost applications suited to enterprises with one or two employees. Technology providers should offer interfaces in clear language, simple onboarding, transparent subscription costs, and compatibility with the payment, accounting, marketplace, and communication platforms already used by MSMEs.

Finally, the findings support a cautious interpretation of sustainable environmental health. Digital capabilities and AI innovation may create the financial, informational, and organizational capacity needed for safer and more resource-efficient business practices. However, environmental-health performance should remain an implication of the present results rather than an empirically confirmed outcome.

CONCLUSION

This study examined the relationships among digital financial literacy, digital business strategy, AI innovation, and MSME performance using data from 100 MSME owners in Manado, North Sulawesi. The findings show that digital financial literacy and digital business strategy significantly strengthen AI innovation and MSME performance. AI innovation

produced the strongest direct effect on MSME performance and partially mediated the effects of both digital capabilities. The model explained 68.3% of the variance in AI innovation and 75.6% of the variance in MSME performance, indicating substantial explanatory power.

These findings suggest that AI adoption is most effective when supported by adequate financial knowledge and a coherent digital strategy. For MSMEs, digital financial literacy supports the evaluation of technology costs, benefits, and risks, while digital business strategy facilitates the integration of AI into operational and managerial processes. AI innovation therefore acts as a complementary mechanism that converts foundational digital capabilities into improved business performance.

The results also provide practical implications for sustainable environmental health. AI-supported applications may assist MSMEs in monitoring energy and water use, improving inventory planning, reducing food waste, strengthening temperature control and food safety, recording business waste, supporting occupational safety, reducing paper use, and optimizing distribution routes. However, these environmental-health outcomes were not directly measured in the present study. They should therefore be interpreted as potential applications of the identified digital capabilities rather than as empirically confirmed effects.

Future studies should extend the present model by incorporating direct measures of sustainable environmental health practices, such as energy and water consumption, waste generation, food-safety compliance, sanitation quality, occupational safety, and transportation emissions. Longitudinal and mixed-method designs are also recommended to assess causal relationships and changes over time. Further research may compare different MSME sectors, regions, and levels of AI maturity to determine whether the relationships identified in this study remain consistent across different institutional and operational contexts.

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