

Scaling Up Micro Enterprises Key Success Factors and AI-Driven Development Model

Hanung Eka Atmaja^{1*} , Sofyan Ashari Nur² , Dinar Melani Hutajulu³ , Khairul Ikhwan⁴ ,

Suddin Lada⁵ , Raina Dewi Aldianti⁶ 

^{1,2,4,6}Department of Management, Tidar University, Indonesia

³Department of Economic Development, Tidar University, Indonesia

⁵Faculty of Business, Economics & Accountancy, Universiti Malaysia Sabah, Malaysia

¹hanung.ekaatmaja@untidar.ac.id, ²sofyan.ashari@untidar.ac.id, ³dinarmelani@untidar.ac.id, ⁴khairulikhwan@untidar.ac.id,

⁵suddin@ums.edu.my, ⁶raina.dewi@students.untidar.ac.id

*Corresponding Author

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ABSTRACT

In the development of MSMEs, there is a gap: micro businesses dominate in terms of quantity, but there has been no significant increase in those that have scaled up to become small or medium-sized businesses. Therefore, this **study aims** to analyze key factors for increasing the scalability of micro businesses and to examine an artificial intelligence-based micro business development model for upgrading to small and medium-sized businesses. This **study employs** a mixed-method approach with an explanatory sequential design. The population includes micro-enterprises in four regions with the highest number of SMEs: West Java, Central Java, East Java, and Jakarta, totalling 2,387,288 micro enterprises. A **sample** of 385 respondents was selected using a sampling technique. Proportionate stratified random sampling was used to ensure a representative sample distribution across each province. Qualitative data were collected through purposive sampling with two groups of micro businesses: those that successfully scaled up and those that did not. The analysis results indicate that sustainable leadership and absorptive capacity significantly influence the scalability of micro businesses, while innovation capacity does not. Furthermore, it was found that AI adoption can strengthen the influence of innovation capacity on the scalability of micro businesses. Additionally, the **findings** indicate that there are six strategic steps to enhance the scalability of AI-based micro businesses awareness, digital readiness assessment, simple AI pilot project, scaling up digital systems, partnerships and ecosystems, and monitoring and feedback loops.

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1. INTRODUCTION

Scaling up is one of the most challenging stages of business growth [1]. The Resource-Based View (RBV) emphasizes that scalability requires strategic resources that are valuable, rare, and difficult to imitate [2]. However, resources that function effectively at a small scale do not automatically translate into scalable capabilities at a larger scale [3]. That scaling requires mindset transformation, behavioural shifts, and organi-

zational commitment to adapt processes and invest in new capabilities [4]. Thus, scaling up is a complex and often “painful process” that businesses must undergo to grow. In the context of micro enterprises, scalability is not merely a strategy but a requirement for business continuity [5, 6]. Indonesia has more than 65 million MSMEs, which contribute 61% to GDP and employ 97% of the workforce [7]. However, the MSMEs structure is stagnant, with increasing numbers of microenterprises but a slow transition into the small and medium categories between 2020 and 2022. This stagnation reduces MSMEs economic impact and limits their contribution to national competitiveness [8]. Strengthening MSMEs scalability directly supports the United Nations Sustainable Development Goals (SDGs), specifically SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation and Infrastructure), where MSMEs are expected to drive inclusive economic acceleration through innovation and digitalization.

Prior studies consistently identify innovation and technology adoption as enablers of scalability [9]. Innovation expands market opportunities and enhances competitiveness, while technology accelerates efficiency and decision making [10]. Two capabilities that influence these aspects are innovation capacity and absorptive capacity, which reflect the ability to absorb and utilize external knowledge [11, 12]. However, innovation and technology alone do not guarantee scalability if not orchestrated through leadership [13]. Sustainable leadership encourages long term strategic thinking, empowers people, and builds adaptive systems that foster continuous innovation [14]. Although innovation and knowledge absorption are recognized as important drivers of growth, micro-enterprises often lack digital readiness and resources to convert these capabilities into scalability [15, 16]. In developing economy contexts, scalability challenges are not only caused by internal capability limitations but also by broader structural constraints, including limited access to finance, uneven digital infrastructure, low technological literacy, inadequate data management practices, and disparities in ecosystem support across regions and sectors. These constraints may reduce the ability of micro-enterprises to adopt AI effectively, even when leadership, innovation capacity, and absorptive capacity are present. Artificial Intelligence (AI) can offer strategic support by enabling data-driven leadership, automating innovation processes, and improving knowledge absorption speed and accuracy, but its effectiveness depends on the readiness of micro-enterprises and the availability of supportive external conditions [17]. The adoption of AI in MSMEs also contributes to SDG 9 through digital transformation and strengthens SDG 17 (Partnerships for the Goals) through collaboration among MSMEs, technology providers, and ecosystem enablers [18].

Although previous studies have examined AI adoption in SMEs, most of them position AI mainly as a technological tool for automation, operational efficiency, or decision support. In contrast, this study advances the extended RBV by conceptualizing AI-enabled capability transformation as a higher-order dynamic capability that reconfigures the interaction among sustainable leadership, innovation capacity, absorptive capacity, and scalability [19]. AI is not treated merely as a technological support mechanism or a statistical moderator, but as a strategic meta-capability that enables micro-enterprises to convert fragmented resources and innovation potential into scalable business outcomes. Through data processing, learning acceleration, predictive insight, and digital experimentation, AI strengthens the way internal capabilities are coordinated and transformed into growth-oriented actions. Therefore, the proposed model differs from prior SME AI adoption studies by explaining not only whether AI is adopted, but also how AI structurally enhances capability orchestration and supports the transition of micro-enterprises toward higher scalability [20]. Therefore, this study integrates AI into sustainable leadership, innovation capacity, and absorptive capacity to explain their synergistic influence on microenterprise scalability [21]. However, the broader applicability of the proposed AI-driven scalability model depends on several contextual boundary conditions, including digital infrastructure, government policy support, ecosystem maturity, technological literacy, access to affordable AI tools, and MSME readiness for data-driven decision-making. This model is most relevant for developing economies where micro-enterprises already have basic digital exposure but still require structured capability development to achieve scalability. By clarifying these contextual conditions, this study provides a stronger SDG-aligned perspective on how AI enables capability development and accelerates MSMEs growth toward scalable and sustainable development [22].

2. RESEARCH METHODS

This study aims to analyze the key determinants influencing micro-enterprise scalability and to develop an AI enabled scalability model that supports micro businesses in upgrading into small and medium-sized enterprises [23]. Beyond testing existing constructs such as sustainable leadership, innovation capacity,

and absorptive capacity, this study advances theoretical contributions by positioning AI not merely as a technological tool but as an enabling capability that transforms innovation into measurable scalability outcomes [24]. Compared with recent AI-based MSME digital transformation studies published after 2022, which commonly emphasize AI adoption readiness, automation, operational efficiency, digital marketing support, or technology acceptance, the proposed framework provides a more integrated capability-based explanation of micro-enterprise scalability. This study differs from prior frameworks by placing AI as an enabling mechanism that connects innovation capacity, absorptive capacity, and sustainable leadership with scalability outcomes. Rather than only explaining whether MSMEs adopt AI, this model explains how AI strengthens internal capability orchestration and converts innovation potential into scalable business development. Therefore, the novelty of this study lies in introducing AI-enabled capability transformation as an extension of the RBV, where AI functions as a strategic capability enabler within micro-enterprise development [25, 26].

To achieve these objectives, this research employs a mixed methods approach with an explanatory sequential design [27]. The quantitative phase examines causal relationships among variables using PLS-SEM to identify which capabilities significantly drive scalability [28]. Sustainable leadership, innovation capacity, and absorptive capacity were tested as predictors, while AI adoption was examined as a moderator [29]. As highlighted by the reviewers, deeper analysis was conducted to explain why AI moderates only specific paths, particularly strengthening innovation capacity, while not significantly moderating leadership and absorptive capacity, which are more dependent on human decision-making rather than automated processes [30, 31].

This study contributes to SDG 9 (Industry, Innovation, and Infrastructure) through digital transformation, supporting the development and scaling of MSMEs via AI adoption. It also aligns with SDG 17 (Partnerships for the Goals) by fostering collaboration across stakeholders, including MSMEs, technology providers, and ecosystem enablers. The selection of respondents followed a proportionate stratified random sampling technique to ensure representation from regions with the highest concentrations of MSMEs: West Java, Central Java, East Java, and DKI Jakarta [32]. With a total population of 2,387,288 microenterprises [33], a minimum sample size of 385 respondents was determined using the formula [34]. Distribution across provinces was proportional to MSME density, ensuring external validity and enabling a more generalizable interpretation of scalability behavior in developing economies [35, 36].

The results of the sequential integration between the quantitative and qualitative phases produced an AI-based microenterprise development model comprising six strategic steps: awareness, digital readiness assessment, simple AI pilot projects, scaling up digital systems, partnership and ecosystem building, and monitoring and feedback loops [37]. This model offers managerial implications and demonstrates how AI adoption can be gradually operationalized across diverse sectors [38]. The methodological design ensures that the findings not only contribute to the theoretical literature on scalability and capability building but also offer actionable guidance for practitioners and policymakers [39]. With this sampling method, each province will receive a sample allocation based on the proportion of MSMEs present, as shown in the following Table 1.

Table 1. Respondent Stratification

Province	Sample	Proportion	Provincial Sample
West Java	385	25%	94
Central Java	385	34%	131
DKI Jakarta	385	5%	21
East Java	385	36%	139
Total	385	-	385

The qualitative research data were selected from two groups of micro business owners. The first group consisted of micro businesses that had successfully upgraded to small businesses (as evidenced by increases in assets, turnover, or the number of employees). During the search for informants and the dissemination of survey data, five informants were identified in this category. The second group consists of microenterprises that have not yet succeeded in upgrading, despite having operated for the same period or longer. During the process of identifying informants, five informants were found in the second category.

3. RESULTS AND DISCUSSION

3.1. Respondent Characteristics

The target sample in this study comprised 385 MSMEs across four provinces: West Java, Central Java, East Java, and DKI Jakarta. In distributing the questionnaire, 405 responses were obtained, and data selection was carried out to ensure the final sample matched the target, namely, 385 respondents. To gain a deeper understanding of the study respondents, they will be classified based on several characteristics, including gender, age, duration of MSME operation, MSME industry, and MSME location.

To enrich the theoretical and empirical contribution, this study aligns its sampling approach with the diversity of Indonesia's MSME landscape by involving respondents from culinary, fashion, handicraft, services, and other business sectors. However, as shown in Table 2, the sample is predominantly represented by culinary and fashion micro-enterprises. Therefore, the cross-sector applicability of the proposed AI-driven scalability model should be interpreted carefully. This study does not conduct sectoral comparison analysis, such as multi-group analysis in PLS-SEM, to examine whether the effects of AI adoption differ across sectors. AI adoption dynamics may vary between culinary, fashion, services, agribusiness, and technology-based enterprises due to differences in digital infrastructure, data availability, customer interaction patterns, and technological literacy. Thus, future research is encouraged to conduct sector-specific analysis or multi-group comparison to validate the model across broader MSME sectors.

Table 2. Respondent Characteristics

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	210	54.5%
	Female	175	45.5%
Age	< 30 years	78	20.3%
	31 – 40 years	132	34.3%
	41 – 50 years	103	26.8%
	> 50 years	72	18.7%
Years of SME Operation	1 – 3 years	95	24.7%
	4 – 6 years	122	31.7%
	7 – 10 years	98	25.5%
	> 10 years	70	18.2%
Type of SME Industry	Culinary	148	38.4%
	Fashion	92	23.9%
	Handicraft	65	16.9%
	Services	50	13.0%
	Others	30	7.8%
SME Location	West Java	96	24.9%
	Central Java	94	24.4%
	DKI Jakarta	98	25.5%
	East Java	97	25.2%
Total		385	100%

As presented in Table 2, a total of 385 SME respondents from four provinces participated in this study, providing a diverse representation of SME characteristics across Indonesia. Based on gender distribution, male respondents dominated with 54.5%, while female respondents accounted for 45.5%, indicating relatively balanced participation between male and female SME operators. In terms of age, the majority of respondents were within the productive working-age category of 31–40 years (34.3%), followed by those aged 41–50 years (26.8%), suggesting that most SME actors are in a mature and economically active phase with considerable business experience and operational responsibility. Regarding the duration of business operation, most SMEs had been operating for 4–6 years (31.7%), followed by 7–10 years (25.5%), indicating that many businesses are currently in the business growth and expansion stage rather than the establishment stage. Only 18.2% of SMEs had operated for more than 10 years, reflecting that long-term business sustainability remains a challenge for many SMEs. From the industry perspective, the culinary sector dominated the sample with 38.4%, followed by fashion businesses (23.9%) and handicrafts (16.9%), demonstrating that creative and consumer-oriented industries continue to play a significant role in SME development. Furthermore, the geographical distribution of respondents was relatively balanced across West Java (24.9%), Central Java (24.4%), DKI Jakarta (25.5%),

and East Java (25.2%), which indicates that the respondent distribution was proportionally representative and capable of supporting broader generalization of SME conditions across the targeted regions [40].

3.2. Quantitative Analysis Using Smart-PLS

Structural Equation Modeling (PLS-SEM) was performed using SmartPLS in two main stages, Outer model analysis, which evaluates the measurement model through convergent validity, discriminant validity, and reliability based on factor loadings (> 0.5) and AVE criteria; and Inner model analysis, which examines the structural relationships among variables using path coefficients, t -values, and p -values to assess significance. These steps help assess whether the measurement items are valid and reliable for further analysis.

Next is the construct validity analysis, which tests the validity of the research variables. This test refers to the AVE values for each variable. The construct validity criterion is $AVE > 0.5$, and if this criterion is met, the variable is deemed valid [41]. The analysis results show that the AVE values range from 0.612 to 0.792, thus meeting the minimum criterion of 0.5. Therefore, it can be concluded that the variables in this study meet the construct validity criteria and are deemed valid.

The construct validity analysis tests the overall validity of the research variables by evaluating the Average Variance Extracted (AVE) for each construct. The construct validity criterion is that the AVE value must exceed 0.5 for each variable. If this criterion is met, the variable is deemed valid. The analysis results show that the AVE values for all constructs in this study range from 0.612 to 0.792, thereby satisfying the minimum requirement of 0.5, confirming the validity of the variables.

The results from the outer model analysis and construct validity analysis show that the variables used in this study meet the criteria for convergent validity, discriminant validity, and reliability. The AVE values for all variables exceed the threshold of 0.5, confirming that the constructs are valid and reliable for further analysis. Thus, the measurement model is deemed to be robust, allowing for accurate testing of the structural relationships in the next phase of the analysis.

Table 3. Convergent Validity

Variable	Indicator	Outer Loadings	Validity	Indicator	Outer Loadings
Sustainable Leadership	SL1	0.777	Valid	AIA1	0.846
	SL10	0.812	Valid	AIA2	0.898
	SL2	0.841	Valid	AIA3	0.897
	SL3	0.852	Valid	AIA4	0.899
	SL4	0.794	Valid	AIA5	0.927
	SL5	0.800	Valid	AIA6	0.877
	SL6	0.787	Valid	AIA7	0.884
	SL7	0.698	Valid	AVE	0.792
	SL8	0.663	Valid	ES1	0.873
	SL9	0.779	Valid	ES2	0.815
	AVE	0.612	Valid	ES3	0.726
Absorptive Capacity	AC1	0.818	Valid	ES4	0.838
	AC2	0.791	Valid	ES5	0.842
	AC3	0.848	Valid	ES6	0.827
	AC4	0.868	Valid	AVE	0.675
	AC5	0.875	Valid	IC1	0.837
	AC6	0.787	Valid	IC2	0.846
	AVE	0.692	Valid	IC3	0.881
	–	–	–	IC4	0.852
	–	–	–	AVE	0.730

Table 3 shows the results of the convergent validity analysis, which indicates the factor loadings for each indicator [42]. The results show that the indicators in this study have outer loadings on the Sustainable Leadership variable ranging from 0.663 to 0.852, indicating moderate variation among the indicators [43, 44]. For the Absorptive Capacity variable, the values range from 0.787 to 0.875.

While AI Adoption has the highest range, from 0.846 to 0.927, indicating very strong consistency among the indicators [45]. The MSE Scalability variable ranges from 0.726 to 0.873, and the Innovation

Capacity variable ranges from 0.837 to 0.881. Overall, all variables demonstrate adequate construct validity, as supported by AVE values above 0.5 for each. It is concluded that all indicators have met the convergent validity criteria with factor loadings > 0.5 and are deemed valid [46].

Table 4. Reliability Analysis

Variable	Cronbach's Alpha	Composite Reliability
AI Adoption	0.956	0.960
Absorptive Capacity	0.911	0.912
Innovation Capacity	0.877	0.880
Scalability	0.903	0.913
Sustainable Leadership	0.929	0.934

The next analysis is shown in Table 4, which shows the reliability values of the variables. These measurements were used to test the reliability of the instruments and research data. The criteria for reliability testing were Cronbach's alpha and composite reliability values > 0.7 .

Table 5. HTMT (Heterotrait-Monotrait Ratio)

Construct Relationship	HTMT Value
Absorptive Capacity $\leftrightarrow$ AI Adoption	0.508
Innovation Capacity $\leftrightarrow$ AI Adoption	0.662
Innovation Capacity $\leftrightarrow$ Absorptive Capacity	0.850
Scalability $\leftrightarrow$ AI Adoption	0.431
Scalability $\leftrightarrow$ Absorptive Capacity	0.874
Scalability $\leftrightarrow$ Innovation Capacity	0.763
Sustainable Leadership $\leftrightarrow$ AI Adoption	0.452
Sustainable Leadership $\leftrightarrow$ Absorptive Capacity	0.823
Sustainable Leadership $\leftrightarrow$ Innovation Capacity	0.884
Sustainable Leadership $\leftrightarrow$ Scalability	0.893

The HTMT results in Table 5 show that most of the relationships between constructs are below the threshold of 0.90, indicating that the discriminant validity in this model is fulfilled. The lowest HTMT values are found in the relationships between Scalability and AI Adoption (0.431) and Sustainable Leadership and AI Adoption (0.452), indicating clear conceptual differences. The relationship between Innovation Capacity and Absorptive Capacity (0.850) and Sustainable Leadership and Innovation Capacity (0.884) is close to the threshold but still within the acceptable range. Meanwhile, the highest value is between Sustainable Leadership and Scalability (0.893).

This is very close to the 0.90 threshold, so it requires further attention, even though it is still considered statistically valid. Thus, all constructs in the model can be said to have good discriminant validity, supporting the reliability and conceptual separation between the variables tested. The next stage is inner model analysis, which involves testing the relationships among research variables. In this context, several aspects are examined, namely the coefficient of determination, path analysis, and hypothesis testing results. The first stage in inner model analysis is the coefficient of determination with an R-Square value.

The results in Table 5 indicate that all variables met the reliability criteria, so this study is considered reliable. To test the discriminant validity of the constructs in this research model, the Heterotrait Monotrait Ratio (HTMT) was used. HTMT is a recommended method for assessing whether a construct is truly different from other constructs in the model. An HTMT value below 0.90 indicates adequate discriminant validity, meaning that each variable measures distinct concepts and that there is no overlap in meaning between constructs.

Table 6. Coefficient of Determination

Variable	R-square
Absorptive Capacity	0.733
Innovation Capacity	0.651
Scalability	0.725

Table 6 R-squared (R^2) value indicates how well the independent variables explain the dependent variable in a structural model. Based on the research results, the R-square value for Absorptive Capacity is 0.733, indicating that 73.3% of the variance in absorptive capacity is explained by the independent variables in the model. Furthermore, Innovation Capacity has an R-square of 0.651, indicating that 65.1% of its variance is explained by the constructs that influence it. Meanwhile, Scalability has an R-square of 0.725, indicating that the model's variables explain 72.5% of the variation in SME scalability. To test the relationships among the variables in the structural model, path analysis was conducted using Partial Least Squares Structural Equation Modelling (PLS-SEM). The main outputs obtained include the original sample values (path coefficients), t-statistics, and p-values. A relationship is considered statistically significant if the t-value is greater than 1.96 and the p-value is less than 0.05 (at a 5% significance level).

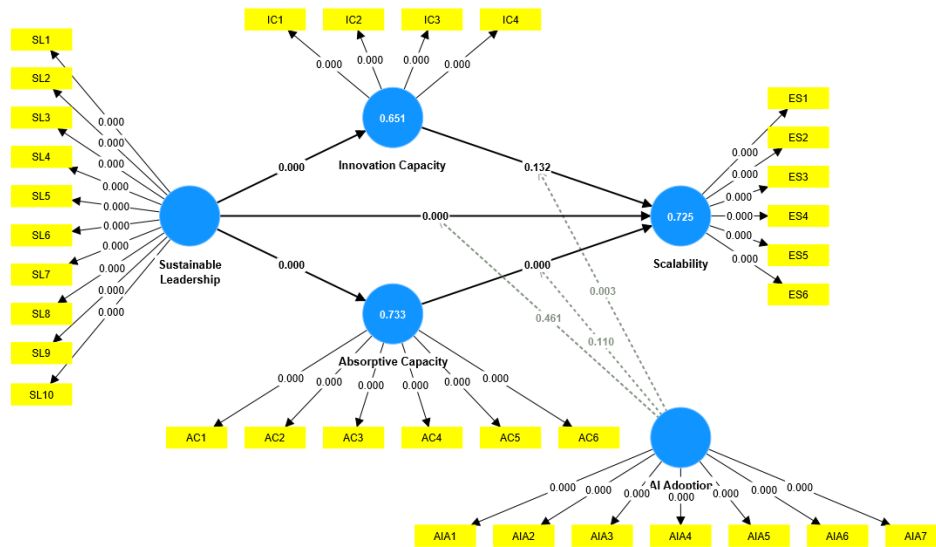


Figure 1. Inner Model

As illustrated in Figure 1, the structural relationships among constructs are presented in an enlarged and higher-resolution format to improve readability and visual clarity. The revised figure now uses larger font sizes, clearer path coefficient labels, and enhanced graphical quality to ensure that the relationships among sustainable leadership, absorptive capacity, innovation capacity, AI adoption, and scalability can be clearly interpreted in the final publication format. In addition, the conceptual framework and structural model diagrams have been refined to comply with journal presentation standards and to improve overall manuscript readability. A relationship is considered statistically significant when the t -statistic is greater than 1.96 and the p -value is lower than 0.05 at a significance level of 5%. In addition, the moderating effect of AI adoption was examined using the interaction term within the structural model, allowing the analysis to identify whether the presence of AI strengthens or weakens the relationship between sustainable leadership, absorptive capacity, innovation capacity, and scalability.

The moderation analysis shows that AI adoption significantly moderates the relationship between innovation capacity and scalability, while its moderating effects on the relationships between sustainable leadership and scalability, as well as absorptive capacity and scalability, are not statistically supported. The significant interaction between AI adoption and innovation capacity indicates that AI strengthens the conversion of innovative ideas into scalable business outcomes, particularly when micro-enterprises use AI for digital experimentation, customer insight analysis, product improvement, and market responsiveness. However, the non-significant moderation effects on sustainable leadership and absorptive capacity suggest that AI adoption has not yet reached a level where it can substantially transform leadership practices or knowledge absorption processes. This condition may reflect variance limitations in the AI adoption construct, where most micro-enterprises still apply AI at a basic operational level rather than as an integrated strategic capability. Therefore, the moderation finding should be interpreted as evidence of selective interaction strength, meaning that AI adoption contributes more strongly to innovation-related scalability pathways than to leadership- or knowledge-based pathways. To improve methodological rigor, the discussion also considers the need for future analysis

using interaction effect size assessment, such as f^2 , and further evaluation of AI adoption variance to determine the practical magnitude of moderation effects in micro-enterprise scalability models.

Table 7. Path Analysis

Path	Original Sample	T Statistics	P Values
Sustainable Leadership → Scalability	0.545	6.812	0.000
Sustainable Leadership → Innovation Capacity	0.807	37.037	0.000
Sustainable Leadership → Absorptive Capacity	0.856	46.742	0.000
Absorptive Capacity → Scalability	0.394	4.970	0.000
Innovation Capacity → Scalability	0.068	1.118	0.132
AI Adoption × Sustainable Leadership → Scalability	0.010	0.097	0.461
AI Adoption × Absorptive Capacity → Scalability	0.112	1.228	0.110
AI Adoption × Innovation Capacity → Scalability	0.116	2.802	0.003

Based on the Table 7 results of the path analysis using PLS-SEM, most hypotheses in this study are empirically supported. Hypothesis 1 (H1), which proposes that Sustainable Leadership influences Scalability, is supported ($\beta = 0.545$, $t = 6.812$, $p = 0.000$). Likewise, Hypothesis 2 (H2), stating that Sustainable Leadership influences Innovation Capacity, is supported ($\beta = 0.807$, $t = 37.037$, $p = 0.000$), and Hypothesis 3 (H3), regarding the influence of Sustainable Leadership on Absorptive Capacity, is supported ($\beta = 0.856$, $t = 46.742$, $p = 0.000$). Furthermore, Hypothesis 4 (H4), which examines the effect of Absorptive Capacity on Scalability, is also supported ($\beta = 0.394$, $t = 4.970$, $p = 0.000$).

However, Hypothesis 5 (H5), which states that Innovation Capacity influences Scalability, is not supported ($\beta = 0.068$, $t = 1.118$, $p = 0.132$). For the moderating effects, both Hypothesis 6 (H6), which examines whether AI Adoption moderates the relationship between Sustainable Leadership and Scalability ($\beta = 0.010$, $t = 0.097$, $p = 0.461$), and Hypothesis 7 (H7), which examines the moderating effect of AI Adoption on the relationship between Absorptive Capacity and Scalability ($\beta = 0.112$, $t = 1.228$, $p = 0.110$), are not supported. Only Hypothesis 8 (H8), stating that AI Adoption moderates the relationship between Innovation Capacity and Scalability is supported ($\beta = 0.116$, $t = 2.802$, $p = 0.003$). Overall, these results indicate that Sustainable Leadership and Absorptive Capacity serve as key determinants in enhancing the scalability of micro and small enterprises, while AI Adoption strengthens the effect of Innovation Capacity for scalability, but it does not significantly influence other relationships within the model [47].

3.3. Qualitative Analysis

This study adopts a mixed-method explanatory sequential design, which integrates both quantitative and qualitative approaches to provide a comprehensive understanding of how and why AI influences micro-enterprise scalability. The quantitative phase presents initial findings, while the qualitative phase builds upon these results to explore the deeper nuances of AI adoption. By using qualitative methods, this stage specifically delves into the moderating role of AI adoption, highlighting how AI strengthens the relationship between innovation capacity and scalability. Furthermore, the qualitative analysis investigates why AI has a limited or non-existent moderating effect on leadership and absorptive capacity, contrasting its impact on different organizational factors. This two-phase approach allows for a more thorough examination of the dynamics at play, bridging the gap between the observed statistical relationships and the underlying mechanisms, thereby offering valuable insights into the complex role of AI in enhancing microenterprise growth. The combination of both methods enriches the understanding of AI's influence, providing not only evidence of its impact but also an explanation of why its effects vary across different organizational capabilities.

In the AI Adoption framework, the analysis identifies how AI readiness through data availability, digital mindset, and agility shapes the scalability path. Coding analysis was conducted to derive actionable strategies, resulting in a practical AI-driven scalability model for micro-enterprises. For example, a culinary micro-enterprise in Indonesia can begin by recording daily sales, customer preferences, and menu demand using a simple digital spreadsheet or cashier application. After the data become more structured, the business owner can apply a simple AI tool to identify best-selling products, predict peak selling times, generate promotional content, and improve customer response through chatbot assistance. The results of this pilot stage can then be used to scale up digital systems, such as integrating sales dashboards, inventory monitoring, and customer feedback analysis. This illustration shows how the proposed AI-driven model moves from awareness

and digital readiness assessment toward simple AI pilot projects, system scaling, partnership development, and continuous monitoring, making the model more applicable for real-world micro-enterprise transformation.

Table 8. Summary of Coding Analysis

Aspect	Interview Summary	Interview Quote	Recommended Strategic Flow
Data	Many MSMEs are still unaware of the importance of data inventory, even though data is the main fuel for AI.	“I still record everything manually in a notebook.” (Informant 1) “Many MSMEs don’t realize daily transactions are data assets.” (Informant 8)	1) Awareness → Educate on the importance of business data. 2) Digital Readiness Assessment → Survey on data recording habits and digital data potential.
Intelligent	Most MSMEs lack a clear digital strategy and adequate technical skills.	“Some entrepreneurs follow trends without long-term planning.” (Informant 5) “I don’t understand how to start or why it matters.” (Informant 1)	1) Awareness → Provide training on AI-based digital strategy. 2) Digital Readiness Assessment → Map skills and human resource readiness.
Grounded	A gradual, needs-based approach makes MSMEs more open to AI adoption.	“Started with copywriting, then moved to analyzing menu performance.” (Informant 7) “If there’s a step-by-step approach, I’m very open.” (Informant 1)	3) Simple AI Pilot Projects → Practical AI use such as chatbots, product recommendations, or scheduling.
Integral	Digital system integration is uneven, but great potential exists among digitally active MSMEs.	“I’m integrating AI-based inventory management now.” (Informant 9) “Manual records make AI connection difficult.” (Informant 6)	4) Scale Up Digital Systems → Digitize core processes, centralized dashboards, AI-based sales analytics.
Teaming	Collaboration with tech communities, startups, or government supports AI adoption.	“We partner with tech communities and platforms.” (Informant 10) “I’m active in a digital MSMEs group, we share tools.” (Informant 7)	5) Partnership & Ecosystem → Join AI communities, business incubators, and collaborative trainings.
Agile	MSMEs have high flexibility to adapt and quickly change strategies.	“I can change promo strategies in a day, even the menu weekly.” (Informant 7) “MSMEs adapt faster than big companies.” (Informant 5)	6) Monitoring & Feedback Loop → Build data-driven evaluation systems to detect trends and respond quickly.
Leadership	Business owner leadership plays a key role in digital and AI transformation success.	“If the owner believes in tech, the whole team follows.” (Informant 6) “Leaders must become change agents.” (Informant 8)	1) Awareness → Develop leadership awareness as a digital change driver. 5) Partnership → Strengthen digital leadership exposure.

Based on the Table 8, the coding analysis shows that micro businesses can scale more effectively when they follow a gradual and structured digital transformation process Table 8. After that, they assess their

readiness, whether they already have digital data, basic systems, and the skills needed to support the transition [48].

Once the foundation is clear, they begin with simple AI pilot projects such as using chatbots to respond to customers faster [49]. As confidence increases, digital systems are gradually upgraded and integrated, for example, through sales dashboards or small AI analytics that help predict demand and guide planning [47, 50]. Collaboration also plays a key role, where businesses join digital communities or incubators to learn from others and gain support [51].

The process ends with continuous monitoring and evaluation, so decisions are made based on data rather than intuition. These qualitative insights strengthen the study's quantitative findings, showing that innovation drives scalability only when supported by readiness and the right AI adoption strategy.

4. MANAGERIAL IMPLICATIONS

The study's findings offer essential advice for small business owners: before attempting to "scale up," ensure your digital foundation is strong. Many small businesses want to use digital tools like WhatsApp or advanced technologies, but they mostly rely on paper to store data. Technology won't help if the data isn't accurate. As a result, the first thing business owners can do is use easy-to-use digital tools, such as spreadsheets or cashier applications. Decision-making becomes more objective and less intuitive when business owners focus on analyzing data and numbers. This supports SDG 9 (Industry, Innovation, and Infrastructure) by encouraging digital transformation and SDG 17 (Partnerships for the Goals) through collaborative actions with partners and stakeholders.

The next step is to conduct a comprehensive digital readiness analysis. Does the company already have data that can be analyzed? Can you explain how to use the application? Following this, businesses can experiment with simple, low-tech solutions, such as using chatbots to automatically handle customer feedback or AI templates to create promotional content. Smaller things will give you a sense of self-worth, and business owners can see their benefits before moving on to more complex technologies. By focusing on SDG 9, businesses strengthen their technological capabilities to accelerate growth and development.

This research also shows that micro-enterprise digital transformation cannot be achieved only through individual business efforts, but requires stronger ecosystem and policy-level support. From a technopreneurship perspective, AI adoption should be supported through collaboration among micro-enterprises, government institutions, digital platform providers, business incubators, universities, and technology communities. Policymakers can strengthen AI-based MSME scalability by providing digital infrastructure, affordable AI access, AI literacy programs, data governance guidance, and incentive schemes for technology adoption. Business incubators and technology partners also play a strategic role in assisting micro-enterprises to move beyond basic tools such as spreadsheets and chatbots toward more integrated AI-enabled business models. Therefore, the managerial implication of this study is not limited to operational digitalization, but also emphasizes the need for an inclusive technopreneurship ecosystem that enables micro-enterprises to transform capabilities, expand markets, and achieve sustainable scalability.

Finally, to maintain business growth, business owners need to conduct regular evaluations. This doesn't have to be complicated; simply evaluating weekly sales data or monitoring customer responses to promotions is sufficient. Regularly monitoring results allows business owners to quickly identify what's working and what needs to change. This finding also reinforces quantitative research findings that new innovations will lead to growth if supported by digital readiness and data-driven decision-making habits. With a phased approach, a focus on data, and consistent evaluation, digital transformation is not only possible but also achievable for anyone, even micro-businesses with limited resources.

5. CONCLUSION

This study aims to analyze the key factors in improving the scalability of micro businesses and analyze artificial intelligence-based micro business development models for upgrading to small and medium-sized businesses. The analysis results show that sustainable leadership and absorptive capacity have a significant effect on the scalability of micro businesses, while innovation capacity does not. Furthermore, it was found that AI adoption can strengthen the influence of innovation capacity on the scalability of micro businesses. Additionally, the findings indicate that there are six strategic steps in improving the scalability of AI-based micro businesses, namely awareness, digital readiness assessment, simple AI pilot project, scaling up digital systems,

partnerships and ecosystems, and monitoring and feedback loops.

This study provides important managerial implications for micro-businesses, policymakers, and institutions supporting MSMEs development. The findings that sustainable leadership and absorptive capacity have a significant effect on the scalability of micro-businesses indicate that strengthening leadership and the ability to absorb and manage external information are key to encouraging micro-businesses to move up the ladder. Meanwhile, although innovation capacity does not directly influence scalability, the research results show that AI adoption can enhance the positive impact of innovation, indicating that AI can function as a strategic enabler, not just an operational tool.

Practically speaking, micro businesses need to be guided to adopt technology gradually and contextually through six strategic steps: starting with building awareness, conducting a digital readiness assessment, implementing a simple AI pilot project, scaling up digital systems, building partnerships and ecosystems, and creating data-driven monitoring and feedback loops. Theoretically, this research enriches the study of digital transformation in the micro-enterprise sector by combining the perspectives of the RBV and technology adoption, and positioning AI as a moderating variable that strengthens the role of innovation in driving business growth. This approach is relevant for developing countries, where technology can play an accelerative role in expediting the transition of micro-enterprises toward larger scale and competitiveness.

6. DECLARATIONS

6.1. About Authors

Hanung Eka Atmaja (HE)  <https://orcid.org/0000-0002-5528-6857>

Sofyan Ashari Nur (SA)  <https://orcid.org/0009-0006-0116-1836>

Dinar Melani Hutajulu (DM)  <https://orcid.org/0000-0001-8825-7211>

Khairul Ikhwan (KI)  <https://orcid.org/0000-0003-1878-5355>

Suddin Lada (SL)  <https://orcid.org/0000-0002-9827-2033>

Raina Dewi Aldianti (RD)  <https://orcid.org/0009-0007-5588-9424>

6.2. Author Contributions

Conceptualization: HE; Methodology: SA; Software: DM; Validation: KI, SL and RD; Formal Analysis: HE, SA, DM; Investigation: KI; Resources: SL and RD; Data Curation: HE; Writing Original Draft Preparation: HE and SA; Writing Review and Editing: DM, KI and RD; Visualization: SL; All authors HE, SA, DM, KI, SL and RD. have read and agreed to the published version of the manuscript.

6.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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