Bulletin of Community Engagement
Vol. 6, No. 3, December 2026
https://attractivejournal.com/index.php/bce//index

Artificial Intelligence-Based Business Model Transformation in MSMEs of Kendari City: The Role of Dynamic Capabilities in Business Sustainability

Muhammad Syaiful Saehu[1*], Tuti Dharmawati [2], Kemal Idris Balaka[1], Agustiawan [3]
[1] *Politeknik Bina Husada Kendari, Indonesia*
[2] *Universitas Halu Oleo, Indonesia*
[4] *Universitas Muhammadiyah Kendari, Indonesia*

syaiful_saehu@yahoo.co.id*

ARTICLE INFO
Article history:
Received
July 08, 2026
Revised
October 13, 2026
Accepted
November 01, 2026

Abstract

Artificial intelligence (AI) is reshaping how micro, small, and medium enterprises (MSMEs) create, deliver, and capture value, yet evidence from secondary cities in eastern Indonesia remains scarce. This study examines the effect of dynamic capabilities on AI-based business model transformation and business sustainability and tests the mediating role of AI-based business model transformation among MSMEs in Kendari City, Southeast Sulawesi. A quantitative explanatory design was employed through a survey of 203 MSME owners or managers selected purposively from a population of 42,210 MSMEs. Data was analysed using partial least squares structural equation modelling (PLS-SEM) with 5,000 bootstrap subsamples. The results show that dynamic capabilities have a positive and significant effect on AI-based business model transformation ($\beta = 0.613$; $p < 0.001$) and business sustainability ($\beta = 0.216$; $p = 0.003$), while AI-based business model transformation significantly enhances business sustainability ($\beta = 0.513$; $p < 0.001$) and partially mediates the relationship between dynamic capabilities and sustainability (indirect $\beta = 0.315$; $p < 0.001$). The model explains 44.5% of the variance in business sustainability. These findings extend the dynamic capabilities view to AI-driven business model change in resource-constrained MSMEs and suggest that local governments should prioritise capability-building programmes, rather than mere technology provision, to secure the long-term sustainability of MSMEs.

Keywords: Artificial Intelligence, Business Model Transformation, Business Sustainability, Dynamic Capabilities, MSMEs

Published by CV. Creative Tugu Pena
ISSN 2774-7077
Website https://attractivejournal.com/index.php/bce/
This is an open access article under the CC BY SA license
https://creativecommons.org/licenses/by-sa/4.0/

@ 2026 by the authors

INTRODUCTION

Creating sustainable value from artificial intelligence (AI)-enabled technologies is an unresolved theoretical challenge. AI can process large volumes of data, identify patterns, automate decisions, and personalise customer interactions, thereby opening new opportunities for value creation, delivery, and capture (Dwivedi et al., 2021; Mikalef & Gupta, 2021). However, technological capability is merely a potential, not an outcome. The issue is how that potential becomes lasting value rather than short-term efficiency. This issue is pressing for micro, small, and medium enterprises (MSMEs) in Indonesia, which account for approximately 99% of business units, 60.5% of gross domestic product, and 96.9% of national employment (Kementerian Koordinator Bidang Perekonomian Republik Indonesia, 2022), yet face low productivity, restricted market access, limited technological capabilities, and vulnerability to shocks, as seen during the COVID-19 pandemic (Priyono et al., 2020; Putritamara et al., 2023).

Access to technology, and even its adoption, is insufficient to resolve this issue. In this study, AI adoption is defined as whether and how a firm uses AI-enabled tools. Tools such as generative AI, chatbots, recommendation engines, and AI-assisted bookkeeping are now increasingly accessible to small businesses (Schwaeke et al., 2025). Existing evidence links AI adoption to the operational and economic performance of SMEs (Baabdullah et al., 2021; Badghish & Soomro, 2024), customer experience and loyalty (Wardoyo & Rizana, 2026), and content production and consumer interaction among local MSMEs (Putra & Azizah, 2026). Studies of digital transformation in Indonesia report similar associations (Affandi et al., 2024; Anatan & Nur, 2023; Setiawan et al., 2025). However, these findings mainly show the benefits of using technology and do not explain why firms with the same access obtain different outcomes. The strategic value of technology depends on how firms integrate it into their routines, decision-making, and business models (Sjödin et al., 2021; Wamba-Taguimdje et al., 2020). Adoption is therefore necessary but insufficient for sustainable value.

Dynamic capabilities theory explains how technological opportunities are converted into organisational change. According to Teece et al. (1997), dynamic capabilities are a firm's ability to integrate, build, and reconfigure internal and external competences in response to changing environments. Teece (2007) breaks them down into three interrelated processes: sensing opportunities and threats, seizing opportunities through resource mobilisation and strategic investment, and transforming organisational structures and routines. Within this framework, advantage does not stem from the technology itself, but from the organisation's ability to recognise its relevance, allocate resources to it, and reconfigure itself. This matters for MSMEs because owner-managers often make strategic decisions under substantial resource constraints (Helfat & Peteraf, 2015; Li et al., 2018). Firms with stronger dynamic capabilities are therefore better able to identify relevant AI applications, allocate resources to their implementation, and reorganise their business models.

Business model transformation is a plausible mechanism linking dynamic capabilities to sustainability. A business model describes how an organisation creates, delivers, and captures value (Teece, 2018), so it is where the reconfiguration produced by dynamic capabilities becomes concrete. In this study, AI-based business model transformation is defined as whether AI changes the firm's value proposition, value creation and delivery, or value capture, for example through personalised offerings, data-driven operations, predictive decision-making, and alternative mechanisms of value capture (Åström et al., 2022; Jorzik et al., 2024; Lee et al., 2019). This concept differs from adoption: a firm can use AI to accelerate existing tasks without changing any of these dimensions. Business model innovation has been consistently associated with SME performance (Anwar, 2018; Bouwman et al., 2019; Latifi et al., 2021; Pucihar et al., 2019). The link to sustainability is conceptual: economic, social, and environmental outcomes depend on how value is configured, delivered, and captured, not on the tools used [citation: sustainable business model literature]. Business sustainability here is defined as whether the firm achieves economic viability alongside social and environmental outcomes, a scope broader than financial performance or short-term competitiveness (Yacob et al., 2021). The chain of argument is as follows: dynamic capabilities determine whether AI use leads to business model change, and business model change determines whether the value created is sustainable.

AI adoption, business model transformation, and sustainability have each been widely studied, but the relationships among the three have not been fully explained. Existing studies tend to test the effect of technology adoption or business model innovation on performance, treat dynamic capabilities as a conceptual backdrop rather than a tested mechanism, and use economic performance as the end outcome rather than sustainability. The unresolved problem is how and under what conditions dynamic capabilities convert AI adoption into business model transformation, and whether that transformation explains MSME business sustainability. This study addresses it by testing (1) the role of dynamic capabilities in translating AI adoption into AI-based business model transformation, and (2) the role of business model transformation as the mechanism linking dynamic capabilities to MSME business sustainability. Kendari City is chosen as the testing ground because its MSME sector has grown rapidly (from 8,694 units in 2012 to 42,210 entrepreneurs in December 2024; Pemerintah Kota Kendari, 2017; Pemerintah Provinsi Sulawesi Tenggara, 2024) while its institutional and technological readiness remains uneven, making it possible to test whether capabilities, rather than mere access, determine business model change. Here is the English translation. The three-concept bullet list was missing from your pasted text

(after "Argumen ini menuntut tiga konsep yang dibedakan secara tegas:"), so the colon leads straight into the next paragraph. I reproduced it as is and did not add the list back.

The dynamic capabilities view offers a theoretical explanation of why firms with the same access to technology can obtain different outcomes, by explaining how technological opportunities are converted into organisational change. According to Teece et al. (1997), dynamic capabilities refer to a firm's ability to integrate, build, and reconfigure internal and external competences in response to changing environments. Teece (2007) breaks them down into three interrelated processes: sensing opportunities and threats, seizing opportunities through resource mobilisation and strategic investment, and transforming organisational structures and routines. Within this framework, advantage does not stem from the technology itself, but from the organisation's ability to recognise its relevance, mobilise resources for it, and reconfigure itself. In MSMEs, these capabilities are particularly important because owner-managers often make strategic decisions under substantial resource constraints (Helfat & Peteraf, 2015; Li et al., 2018). Firms with stronger dynamic capabilities are therefore better able to identify relevant AI applications, allocate resources to their implementation, and reorganise their business models to accommodate technological change.

This reorganisation of the business model is what serves as the mechanism linking dynamic capabilities to sustainability. A business model describes how an organisation creates, delivers, and captures value (Teece, 2018), so it is where the reconfiguration produced by dynamic capabilities becomes concrete. Economic, social, and environmental outcomes depend on how value is configured, delivered, and captured, not on the tools used. A firm can adopt AI to accelerate existing tasks without changing any dimension of its business model, in which case adoption has occurred but transformation has not. Likewise, business model transformation does not automatically mean sustainability, because sustainability also requires social and environmental outcomes, not only economic performance.

The unresolved theoretical problem is how and under what conditions dynamic capabilities convert AI adoption into business model transformation, and whether that transformation explains MSME business sustainability. The conditions that test this problem are found in regional economies where MSME development is characterised by rapid expansion but uneven institutional and technological readiness. Kendari City, the capital of Southeast Sulawesi Province, is a suitable setting. The number of MSMEs in the city rose from 8,694 units in 2012 to 11,837 units in 2016 (Pemerintah Kota Kendari, 2017), exceeded 18,000 units in 2019, and reached 41,939 units after the pandemic (Antara Sultra, 2023). By December 2024, the city recorded 42,210 MSME entrepreneurs, about 45% of the 93,874 MSME entrepreneurs registered in Southeast Sulawesi Province (Pemerintah Provinsi Sulawesi Tenggara, 2024). Under such conditions, access to technology is relatively open, so differences in outcomes are more likely to be explained by organisational capabilities than by access alone.

Despite this expansion, quantitative growth does not necessarily indicate equivalent improvements in organisational capacity or business sustainability. In 2023, only 982 businesses held permits through the city's one-stop licensing office (Antara Sultra, 2023). This disparity between the number of operating enterprises and formal business registration raises important questions concerning institutional readiness, managerial capacity, and the ability of MSMEs to adapt to an increasingly technology-driven competitive environment. As competition increasingly shifts towards AI-enabled digital platforms, understanding the capabilities that enable MSMEs to transform technological opportunities into sustainable business practices becomes an important research priority.

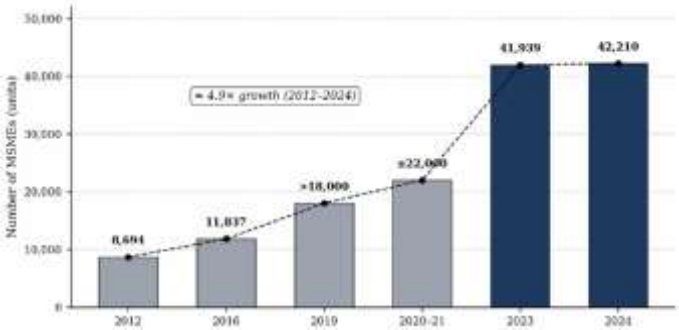


Figure 1. Growth of MSMEs in Kendari City, 2012–2024

A review of previous studies reveals several limitations that motivate the present research. First, empirical research on AI in SMEs remains predominantly focused on technology adoption, technological readiness, and the antecedents of adoption intention or actual use, including studies employing the technology–organisation–environment framework (Badghish & Soomro, 2024; Chatterjee et al., 2021). Although this research stream provides important insights into the determinants of AI adoption, it offers comparatively limited explanation of how AI transforms the business model itself. Recent studies have begun to examine AI-driven business model innovation (Burström et al., 2021; Jorzik et al., 2024), but the organisational capabilities facilitating this transformation among resource-constrained MSMEs remain insufficiently explored.

Second, although dynamic capabilities have been associated with SME performance (Hernández-Linares et al., 2021), digital transformation (Matarazzo et al., 2021; Putritamara et al., 2023), and sustainability performance (Eikelenboom & de Jong, 2019), the mechanism linking dynamic capabilities to sustainability through AI-based business model transformation has not been adequately examined. This limitation is theoretically significant because the dynamic capabilities perspective suggests that organisational capabilities influence performance not only through their direct effects but also through the resource configurations and strategic changes they enable (Eisenhardt & Martin, 2000). Investigating AI-based business model transformation as a mediating mechanism may therefore provide a more comprehensive explanation of how organisational capabilities are converted into sustainable business outcomes.

Third, the geographical distribution of empirical evidence remains uneven. Research on digital transformation and MSME development in Indonesia has largely concentrated on Java and major metropolitan areas (Jalaludin et al., 2026; Setiawan et al., 2025; Sundari et al., 2026). Studies conducted in Sulawesi remain relatively limited and have primarily addressed general digital transformation rather than AI-specific business model innovation (Yusuf et al., 2023). This geographical imbalance restricts the contextual understanding of how technological and organisational capabilities operate in different regional environments. Moreover, access to technology alone does not necessarily guarantee innovation among MSMEs (Zainuddin et al., 2026), reinforcing the importance of investigating the organisational capabilities required to transform technological access into sustainable value creation.

To clarify the position of the present study within the existing scholarship, Table 1 synthesises relevant previous research and identifies the specific gaps addressed by this investigation.

Table 1. Summary of prior studies and research gap

Study	Context	Method	Key finding	Gap addressed
Sjödin et al. (2021)	AI-providing industrial firms	Qualitative case study	AI capabilities enable business model innovation through co-evolution with customers and ecosystems	Not MSMEs; no sustainability outcome
Mikalef & Gupta (2021)	Firms	Survey	AI capability raises organisational creativity and firm performance	Business model change not examined
Badghish & Soomro (2024)	SMEs, Saudi Arabia	Survey, TOE framework	AI adoption improves operational and economic performance	Adoption focus; no dynamic capabilities
Eikelenboom & de Jong (2019)	SMEs	Survey	Dynamic capabilities improve economic, environmental and social sustainability	AI not examined
Putritamara et al. (2023)	388 beekeeping MSMEs, Indonesia	SEM	Dynamic capabilities → digital transformation → resilience	General digitalisation, not AI
Setiawan et al. (2025)	510 MSMEs, Java	PLS-SEM	Digital transformation and dynamic capabilities raise performance	Java-centred; performance, not sustainability

Yusuf et al. (2023)	100 SMEs, Makassar	Quantitative	Digital transformation and innovation predict business agility	No AI and no dynamic capabilities
Rhamdhani & Riptiono (2026)	380 batik SMEs, Central Java	SEM-AMOS	Entrepreneurial capability affects performance via digital marketing and innovation	No AI-based business model
This study	MSMEs, Kendari City	Survey, PLS-SEM	DC → AI-based business model transformation → business sustainability	Eastern Indonesia; AI-specific business model; triple bottom line

The present study addresses these limitations by integrating the dynamic capabilities view with the literature on AI-driven business model innovation and business sustainability. Rather than treating AI adoption as an isolated technological decision, this study conceptualises AI-based business model transformation as an organisational mechanism through which dynamic capabilities may generate sustainable outcomes. This approach extends existing research in three ways. First, it shifts the analytical focus from technology adoption towards the transformation of value creation, delivery, and capture processes. Second, it examines the mediating role of AI-based business model transformation in explaining the relationship between dynamic capabilities and business sustainability, thereby providing a more integrated account of the underlying organisational mechanism. Third, it extends empirical evidence to MSMEs in Kendari City, contributing a regional perspective from eastern Indonesia to a literature that has predominantly examined firms in Java and other major economic centres.

The conceptual foundation of this research is based on the assumption that dynamic capabilities enable MSMEs to identify technological opportunities, mobilise resources, and reconfigure organisational processes. These capabilities are expected to facilitate AI-based business model transformation, which subsequently contributes to business sustainability. In this framework, business sustainability encompasses three interrelated dimensions: economic viability, social responsibility, and environmental performance. AI-based business model transformation is positioned as a mediating mechanism that explains how organisational capabilities may be translated into sustainable business outcomes. The proposed conceptual relationships are illustrated in Figure 2.

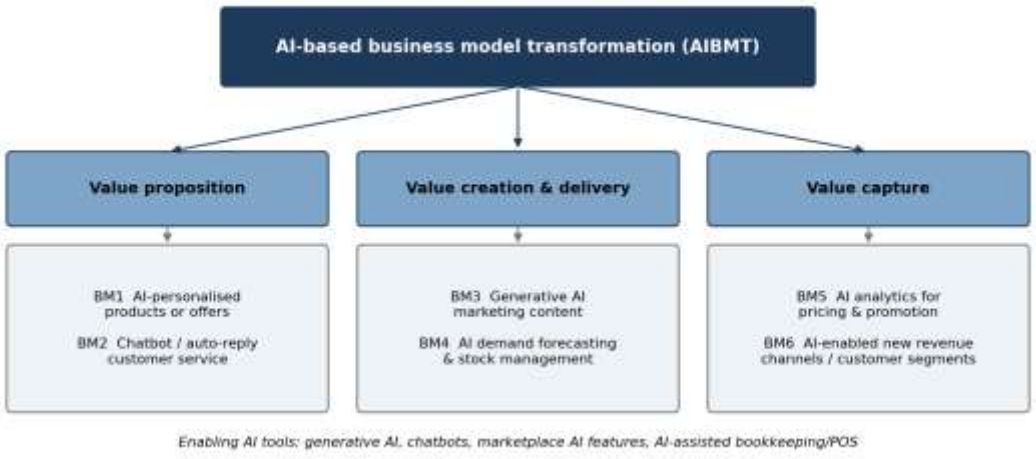


Figure 2. Conceptual Framework of the Study

The conceptual framework consists of three principal constructs: (1) Dynamic Capabilities, represented by sensing, seizing, and transforming; (2) AI-Based Business Model Transformation, encompassing value proposition, value creation and delivery, and value capture; and (3) Business Sustainability, comprising economic, social, and environmental dimensions. The framework

proposes direct relationships between dynamic capabilities and AI-based business model transformation (H1), AI-based business model transformation and business sustainability (H2), and dynamic capabilities and business sustainability (H3). It also proposes an indirect relationship in which AI-based business model transformation mediates the effect of dynamic capabilities on business sustainability (H4).

Based on this conceptual framework, the study proposes four hypotheses:

H1: Dynamic capabilities have a positive and significant effect on AI-based business model transformation.

H2: AI-based business model transformation has a positive and significant effect on business sustainability.

H3: Dynamic capabilities have a positive and significant effect on business sustainability.

H4: AI-based business model transformation mediates the effect of dynamic capabilities on business sustainability.

Accordingly, this study aims to analyse (1) the effect of dynamic capabilities on AI-based business model transformation, (2) the effect of AI-based business model transformation on business sustainability, (3) the direct effect of dynamic capabilities on business sustainability, and (4) the mediating role of AI-based business model transformation in the relationship between dynamic capabilities and business sustainability among MSMEs in Kendari City. By addressing these objectives, the study seeks to advance the theoretical understanding of AI-enabled organisational transformation while providing empirical insights for developing capability-oriented MSME development programmes in eastern Indonesia.

METHOD

Research Design and Procedure

This study employed a quantitative approach with an explanatory (causal) survey design to examine the hypothesised relationships among dynamic capabilities, AI-based business model transformation, and business sustainability. The explanatory design was selected because it enables the systematic examination of theoretically established relationships among latent constructs and the assessment of both direct and indirect effects within a unified structural model. The study focused on micro, small, and medium enterprises (MSMEs) operating in Kendari City, Southeast Sulawesi, Indonesia. The unit of analysis was the firm, represented by its owner or manager as the key informant, given their strategic decision-making authority and direct involvement in business operations (Li et al., 2018).

The research was conducted through five sequential stages to ensure methodological consistency and alignment between the research objectives, data collection procedures, and analytical techniques. The first stage involved developing the conceptual framework and research hypotheses based on a systematic review of relevant theoretical and empirical literature. The second stage involved adapting the measurement instruments from previously validated studies, translating them into Indonesian, obtaining expert assessments, and conducting a pilot test to evaluate the clarity and relevance of the questionnaire items. The third stage involved identifying eligible MSMEs and selecting respondents through purposive sampling based on predetermined inclusion criteria. The fourth stage consisted of collecting primary data using a structured questionnaire administered to eligible business owners or managers. The final stage involved data screening, preparation, and statistical analysis using partial least squares structural equation modelling (PLS-SEM) with SmartPLS 4.

Each stage was designed to ensure that the research procedures were appropriate for the study objectives and that the collected data could be used to evaluate the proposed relationships among the constructs. The overall research procedure is illustrated in Figure 4.



Figure 4. Research procedure

Population and Sample

The target population comprised 42,210 MSME entrepreneurs registered in Kendari City as of December 2024 (Pemerintah Provinsi Sulawesi Tenggara, 2024). Kendari City was selected as the research setting because its MSME sector provides an empirical context for examining the relationship between technological adoption, organisational capabilities, and business sustainability within an emerging digital economy.

Given the absence of a comprehensive sampling frame specifically identifying MSMEs that had adopted artificial intelligence (AI)-enabled technologies, this study employed purposive sampling. This non-probability sampling technique was considered appropriate because the research required respondents with specific organisational characteristics and direct experience of AI adoption. To ensure that the selected respondents could provide relevant and reliable information, four inclusion criteria were established: (1) the business must be located and actively operating in Kendari City; (2) it must have been in operation for at least two years to ensure sufficient operational experience; (3) the respondent must be the business owner or manager with authority over strategic and operational decisions; and (4) the business must have used at least one AI-enabled tool during the preceding 12 months.

Eligible AI-enabled applications included generative AI for marketing content creation, chatbots or automated messaging systems for customer communication, AI-based recommendation or advertising features on digital marketplaces, and AI-assisted bookkeeping or point-of-sale analytics. These criteria were established to ensure that respondents possessed direct experience of AI utilisation rather than merely having general awareness of the technology.

The minimum sample size was estimated using Slovin's formula with a 7% margin of error, resulting in a minimum requirement of 203 respondents. The formula was applied as follows:

$$n = \frac{N}{1 + Ne^2}$$

where n represents the minimum sample size, Ndenotes the population size (42,210), and $e$represents the margin of error (0.07). Based on this calculation, the minimum sample size was established at 203 respondents. This figure served as the minimum target for data collection, while the purposive selection process ensured that all respondents met the substantive inclusion criteria of the study.

The sampling procedure was implemented by screening prospective respondents against the four inclusion criteria before their participation in the survey. Only responses from eligible business owners or managers were considered for subsequent analysis. This approach was intended to improve the relevance of the collected data and ensure that responses reflected actual organisational experiences with AI-enabled technologies.

Research Instrument and Measurement

Primary data were collected using a structured questionnaire developed from measurement instruments established in previous empirical studies. All research constructs were operationalised using multi-item scales measured on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). This response format was selected to capture respondents' perceptions of organisational capabilities, AI-related business model transformation, and sustainability performance in a consistent and quantifiable manner.

Dynamic capabilities were conceptualised as a second-order construct comprising three dimensions: sensing, seizing, and transforming. These dimensions reflect an organisation's ability

to identify emerging opportunities and threats, mobilise resources to exploit opportunities, and reconfigure organisational processes in response to changing environmental conditions (Kump et al., 2019; Teece, 2007).

AI-based business model transformation was operationalised through three dimensions: value proposition, value creation and delivery, and value capture. These dimensions represent the extent to which AI-enabled technologies are integrated into the ways businesses develop customer value, organise operational activities, deliver products or services, and generate revenue (Åström et al., 2022; Sjödin et al., 2021).

Business sustainability was also modelled as a second-order construct comprising economic, social, and environmental dimensions. The economic dimension captures business continuity and financial performance, the social dimension reflects contributions to employees and the surrounding community, and the environmental dimension assesses resource efficiency and the reduction of operational waste (Eikelenboom & de Jong, 2019; Munandar et al., 2025).

To ensure linguistic equivalence and contextual relevance, the questionnaire was translated into Indonesian using a back-translation procedure. The translated instrument was subsequently reviewed by three academic experts to assess the relevance, clarity, and representativeness of the measurement items. A pilot test involving 30 MSMEs outside the final research sample was then conducted to identify potential ambiguities and assess the comprehensibility of the questionnaire before the main data collection. Feedback from the pilot test was used to refine the wording and presentation of the items without altering their underlying conceptual meaning.

The operational definitions, measurement dimensions, indicators, and corresponding sources are presented in Table 2.

Table 2. Operational definitions and measurement indicators

Variable	Dimension	Indicators (code)	Source
Dynamic capabilities (DC)	Sensing	SE1 Regularly monitors AI and digital trends relevant to the business; SE2 Identifies changing customer needs from digital data; SE3 Recognises new opportunities from technological developments	Kump et al. (2019); Teece (2007)
	Seizing	SZ1 Quickly decides to invest in promising AI or digital tools; SZ2 Allocates time, funds, and skills to new opportunities; SZ3 Converts new ideas into concrete business actions	
	Transforming	TR1 Adjusts work routines when technology changes; TR2 Rearranges tasks and roles to use new tools; TR3 Continuously learns and implements new ways of working	
AI-based business model transformation (AIBMT)	Value proposition	BM1 Uses AI to personalise products or offers; BM2 Uses AI (chatbot/auto-reply) to serve customers	Sjödin et al. (2021); Åström et al. (2022)
	Value creation & delivery	BM3 Uses generative AI to create marketing content; BM4 Uses AI to forecast demand or manage stock	
	Value capture	BM5 Uses AI analytics to set prices and promotions; BM6 Uses AI to open new revenue channels or customer segments	Jorzik et al. (2024); Lee et al. (2019)
Business sustainability (BS)	Economic	EC1 Sales have grown steadily in the last two years; EC2 Profitability has improved; EC3 The business can withstand competition and shocks	Eikelenboom & de Jong (2019); Munandar et al. (2025)
	Social	SO1 The business creates or maintains local	

	jobs; SO2 Improves employee welfare and skills; SO3 Contributes to the local community
Environmental	EN1 Reduces waste of raw materials; EN2 Uses energy and resources efficiently; EN3 Reduces paper and plastic use through digitalisation

Data Collection Procedure

Data collection was conducted among eligible MSME owners or managers in Kendari City using a structured questionnaire. The questionnaire served as the primary data collection instrument because it enabled the standardised measurement of respondents' perceptions across the three principal constructs: dynamic capabilities, AI-based business model transformation, and business sustainability.

Before completing the questionnaire, prospective respondents were screened to confirm that their businesses satisfied the established inclusion criteria. Respondents were informed about the purpose of the study, the voluntary nature of their participation, and the confidentiality of the information provided. Anonymity was maintained to minimise potential response bias and encourage participants to provide accurate assessments of their business practices and performance.

The questionnaire consisted of measurement items corresponding to the dimensions and indicators presented in Table 2. Respondents were instructed to evaluate each statement based on their actual business experiences, particularly their utilisation of AI-enabled technologies during the preceding 12 months. Responses were recorded using the five-point Likert scale, with higher scores indicating stronger agreement with the statements.

Following data collection, the responses were examined for completeness and eligibility before being prepared for statistical analysis. Responses that did not satisfy the inclusion criteria or contained incomplete information were subject to screening. The eligible responses were subsequently organised and coded according to their respective measurement indicators before being imported into SmartPLS 4 for further analysis.

These procedures were implemented to maintain consistency in data collection, reduce the potential influence of measurement errors, and ensure that the final dataset was suitable for evaluating the proposed research model.

Data Analysis Technique

The collected data were analysed using partial least squares structural equation modelling (PLS-SEM) with SmartPLS 4. This technique was selected because the study aims to explain and predict relationships among multiple latent constructs, including higher-order constructs, while accommodating complex structural relationships and data that may not satisfy multivariate normality assumptions (Hair et al., 2019). The higher-order constructs were estimated using a two-stage approach to facilitate the assessment of their underlying dimensions and structural relationships.

The analytical procedure consisted of two principal stages: measurement model assessment and structural model evaluation.

First, the measurement model was assessed to establish the reliability and validity of the constructs. Indicator reliability was examined through outer loadings, while internal consistency reliability was evaluated using Cronbach's alpha and composite reliability (ρc). Convergent validity was assessed using the average variance extracted (AVE), and discriminant validity was examined using both the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT) (Fornell & Larcker, 1981; Henseler et al., 2015). These procedures were conducted to establish whether the measurement items adequately represented their respective theoretical constructs and were empirically distinguishable from other constructs in the research model.

Second, the structural model was evaluated by examining collinearity, explanatory power, effect size, and predictive relevance. Collinearity was assessed using variance inflation factors (VIF), while the coefficient of determination (R^2) was used to evaluate the proportion of variance explained in the endogenous constructs. The effect size (f^2) was calculated to determine the relative contribution of each exogenous construct to the explained variance. Predictive performance was

further examined using PLSpredict, which compares the predictive errors of the PLS-SEM model with those of a linear regression benchmark (Shmueli et al., 2019).

Hypotheses were tested using a bootstrapping procedure with 5,000 subsamples to estimate the significance of the path coefficients and indirect effects. A hypothesis was considered supported when the t-statistic exceeded 1.96, the p-value was below 0.05, and the 95% bias-corrected confidence interval did not include zero. Mediation effects were evaluated by examining the statistical significance of the specific indirect effects, thereby determining whether AI-based business model transformation mediated the relationship between dynamic capabilities and business sustainability.

To minimise the potential influence of common method bias, procedural remedies were implemented during questionnaire administration, including respondent anonymity and the separation of predictor and criterion items (Podsakoff et al., 2003). In addition, a full collinearity assessment was conducted using a VIF threshold of 3.3 to identify potential common method bias (Kock, 2015).

The evaluation criteria and corresponding methodological references are summarised in Table 3.

Table 3. Evaluation criteria of the PLS-SEM analysis

Assessment	Criterion	Threshold	Reference
Indicator reliability	Outer loading	≥ 0.708	Hair et al. (2019)
Internal consistency	Cronbach's α; composite reliability (ρc)	0.70–0.95	Hair et al. (2019)
Convergent validity	Average variance extracted (AVE)	≥ 0.50	Fornell & Larcker (1981)
Discriminant validity	Fornell–Larcker criterion	√AVE > inter-construct correlations	Fornell & Larcker (1981)
Discriminant validity	HTMT ratio	< 0.85 (conservative); < 0.90	Henseler et al. (2015)
Common method bias	Full collinearity VIF	< 3.3	Kock (2015)
Explanatory power	R^2	0.25 weak; 0.50 moderate; 0.75 substantial	Hair et al. (2019)
Effect size	f^2	0.02 small; 0.15 medium; 0.35 large	Hair et al. (2019)
Predictive power	Q^2predict; PLSpredict RMSE vs. LM	$Q^2 > 0$; PLS-SEM RMSE < LM for most indicators	Shmueli et al. (2019)
Hypothesis testing	t-statistic; p-value; 95% CI	t > 1.96; p < 0.05; CI excludes zero	Hair et al. (2019)

RESULT AND DISCUSSION

Respondent Profile

Table 4 presents the profile of the 203 respondents. Most respondents were female (53.7%) and aged 26–35 years (41.9%), followed by the 36–45 age group (33.0%). The culinary sector dominated the sample (40.9%), followed by retail and trade (19.7%). Nearly half of the businesses had operated for 2–5 years (48.8%), and the great majority were micro-scale enterprises (71.9%), with small (22.2%) and medium enterprises (5.9%) forming the remainder. Generative AI for content creation was the most frequently used AI tool (41.4%), followed by marketplace AI features (23.6%), chatbots or automated messaging (21.2%), and AI-assisted bookkeeping or POS (13.8%). This profile, visualised in Figure 5, indicates that AI use among Kendari MSMEs is still concentrated on front-end marketing applications rather than on back-office and value-capture functions.

Table 4. Respondent profile

Characteristic	Category	Frequency	%
Gender	Male	94	46.3
	Female	109	53.7
Age (years)	≤ 25	21	10.3
	26–35	85	41.9

	36–45	67	33.0
	> 45	30	14.8
Business sector	Culinary	83	40.9
	Fashion	26	12.8
	Retail and trade	40	19.7
	Services	26	12.8
	Crafts and creative	28	13.8
Business age (years)	2–5	99	48.8
	6–10	65	32.0
	> 10	39	19.2
Business scale	Micro	146	71.9
	Small	45	22.2
	Medium	12	5.9
Main AI tool used	Generative AI content	84	41.4
	Chatbot or automated messaging	43	21.2
	Marketplace AI features	48	23.6
	AI-assisted bookkeeping or POS	28	13.8

Source: Simulated dataset processed by the authors (2026).

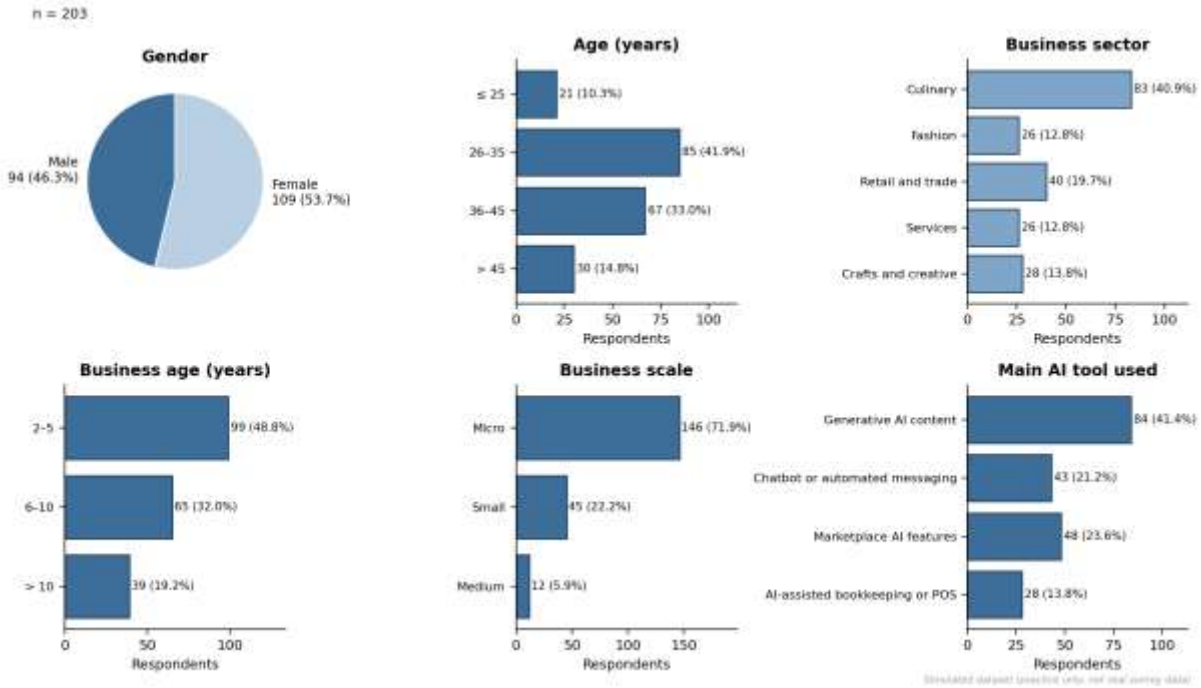


Figure 5. Respondent profile by gender, age, business sector, business age, business scale, and main AI tool used

Source: Simulated dataset processed by the authors (2026).

Descriptive Statistics of the Research Variables

Table 5 reports the descriptive statistics of the 24 indicators. Item means ranged from 3.30 (EN1) to 3.72 (SO3). Using the interval criterion for a five-point scale (1.00–1.80 very low; 1.81–2.60 low; 2.61–3.40 moderate; 3.41–4.20 high; 4.21–5.00 very high), dynamic capabilities (M = 3.59), AI-based business model transformation (M = 3.61), and business sustainability (M = 3.54) were all in the high category. Among the dimensions, transforming (M = 3.61) scored highest within dynamic capabilities, whereas the environmental dimension (M = 3.35) was the only dimension in the moderate category and the lowest of all. Skewness values ranged from -0.57 to -0.20 and excess kurtosis from -0.73 to -0.11, indicating mildly left-skewed but not severely non-normal distributions; PLS-SEM does not require multivariate normality (Hair et al., 2019). Figure 6 shows

the response distribution of each indicator, Figure 7 compares the dimension means, and Figure 8 presents the density curves of the three construct scores.

Table 5. Descriptive statistics of the indicators and dimensions

Dimension	Item	Mean	SD	Skewness	Kurtosis
Sensing (M = 3.57; SD = 0.90; high)	SE1	3.61	1.08	-0.45	-0.34
	SE2	3.53	1.06	-0.26	-0.64
	SE3	3.58	1.00	-0.52	-0.11
Seizing (M = 3.58; SD = 0.89; high)	SZ1	3.63	1.08	-0.39	-0.59
	SZ2	3.57	1.02	-0.50	-0.25
	SZ3	3.54	1.06	-0.32	-0.60
Transforming (M = 3.61; SD = 0.92; high)	TR1	3.63	1.11	-0.57	-0.43
	TR2	3.65	1.02	-0.27	-0.70
	TR3	3.57	1.11	-0.33	-0.71
AIBMT (value proposition, creation & delivery, capture) (M = 3.61; SD = 0.87; high)	BM1	3.67	1.05	-0.43	-0.60
	BM2	3.58	1.12	-0.49	-0.50
	BM3	3.61	1.08	-0.42	-0.62
	BM4	3.62	1.02	-0.38	-0.45
	BM5	3.63	1.10	-0.54	-0.45
	BM6	3.58	1.12	-0.41	-0.63
Economic (M = 3.63; SD = 0.87; high)	EC1	3.62	1.02	-0.40	-0.45
	EC2	3.60	1.01	-0.45	-0.15
	EC3	3.68	1.02	-0.33	-0.68
Social (M = 3.64; SD = 0.92; high)	SO1	3.59	1.09	-0.46	-0.50
	SO2	3.60	1.07	-0.39	-0.58
	SO3	3.72	1.07	-0.50	-0.64
Environmental (M = 3.35; SD = 0.91; moderate)	EN1	3.30	1.06	-0.20	-0.48
	EN2	3.34	1.14	-0.32	-0.73
	EN3	3.41	1.09	-0.33	-0.57

Note: Kurtosis = excess kurtosis. Source: Simulated dataset processed by the authors (2026).

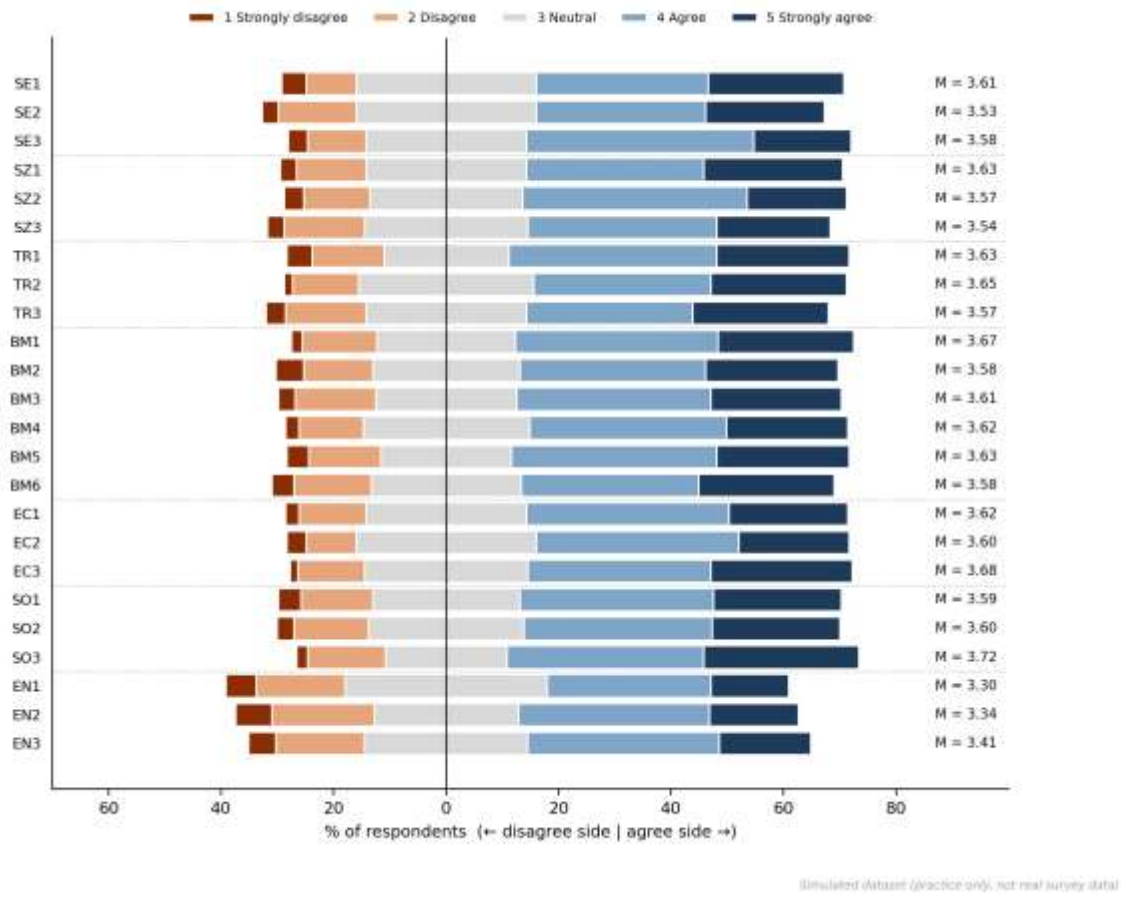


Figure 6. Distribution of responses for each indicator (diverging Likert chart)
Source: Simulated dataset processed by the authors (2026).

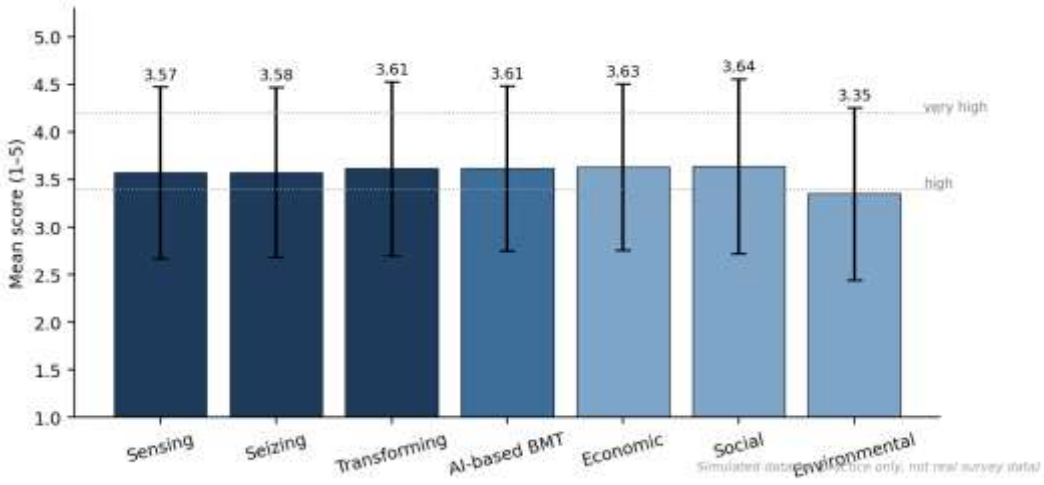


Figure 7. Mean scores of the research dimensions (error bars = SD)
Source: Simulated dataset processed by the authors (2026).

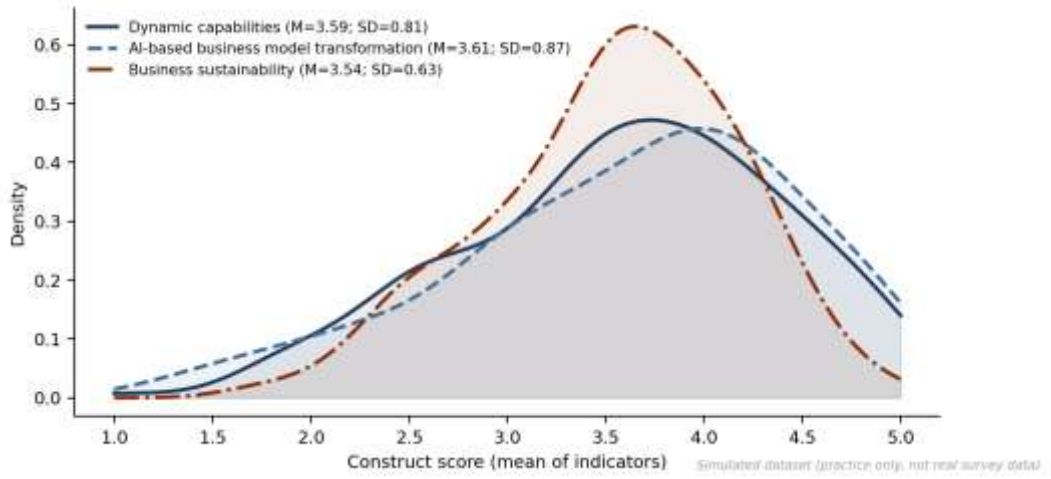


Figure 8. Density curves of the construct scores
Source: Simulated dataset processed by the authors (2026).

Measurement Model Evaluation

In the first stage, the measurement model of the lower-order constructs was assessed. Outer loadings ranged from 0.702 (BM4) to 0.899 (TR3), and all but 1 exceeded 0.708 (Figure 9). The only exception was BM4 (0.702), which was retained because the AVE and composite reliability of its construct exceeded the thresholds (Hair et al., 2019). Cronbach's alpha ranged from 0.770 to 0.889, composite reliability from 0.867 to 0.915, and AVE from 0.643 to 0.739, confirming internal consistency and convergent validity (Table 6).

In the second stage, the lower-order construct scores served as indicators of the higher-order constructs. Dynamic capabilities showed strong loadings of sensing, seizing, and transforming (0.887–0.906), with α = 0.879, ρc = 0.926, and AVE = 0.806. For business sustainability, the economic (0.765) and social (0.773) dimensions loaded satisfactorily, but the environmental dimension loaded only 0.524; consequently, α = 0.482, ρc = 0.734, and AVE = 0.486, which is marginally below the 0.50 benchmark.

Discriminant validity among the lower-order constructs was supported by the HTMT ratio (Table 7; Figure 10). All HTMT values were below 0.85 (maximum 0.686) except those among the three dimensions of dynamic capabilities (TR–SE = 0.870, TR–SZ = 0.894), which remained below the liberal 0.90 threshold and are expected because these dimensions reflect the same higher-order construct (Henseler et al., 2015). The Fornell–Larcker criterion was fully met (Table 8) (Fornell & Larcker, 1981). At the higher-order level (Table 9), the HTMT between AI-based business model transformation and business sustainability (0.937) exceeded 0.90, largely reflecting the low internal consistency of business sustainability, while the Fornell–Larcker criterion was met. The full collinearity VIF values ranged from 1.687 to 2.077, below 3.3, indicating that common method bias is not a concern (Kock, 2015).

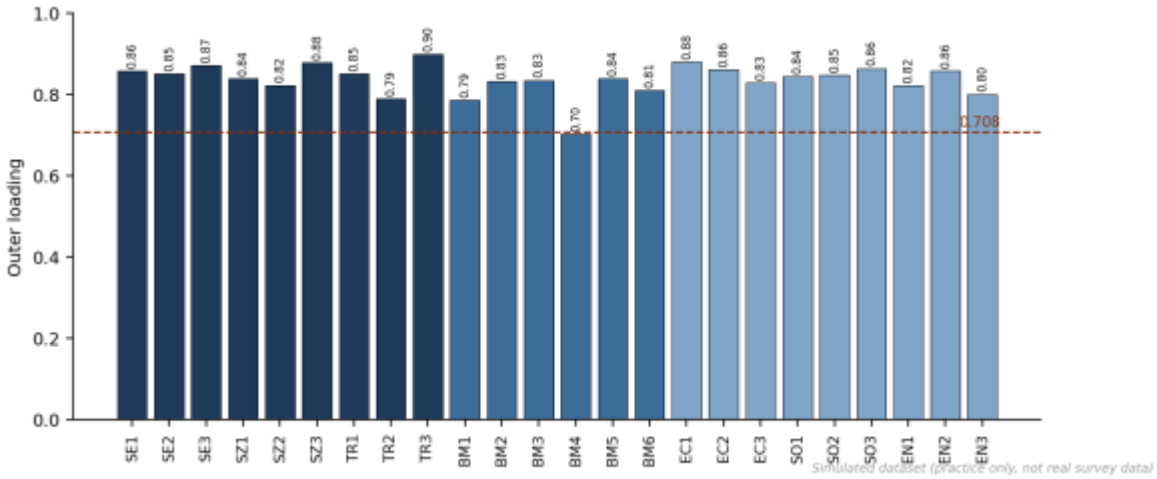


Figure 9. Outer loadings of the indicators (dashed line = 0.708 threshold)
Source: Simulated dataset processed by the authors (2026).

Table 6. Reliability and convergent validity

Construct	Dimension	Items	Loading range	Cronbach's α	CR (ρc)	AVE
DC	Sensing	SE1–SE3	0.851–0.871	0.823	0.895	0.739
	Seizing	SZ1–SZ3	0.823–0.878	0.803	0.884	0.718
	Transforming	TR1–TR3	0.790–0.899	0.804	0.884	0.719
AIBMT	AIBMT	BM1–BM6	0.702–0.839	0.889	0.915	0.643
BS	Economic	EC1–EC3	0.828–0.880	0.819	0.892	0.734
	Social	SO1–SO3	0.844–0.864	0.811	0.888	0.726
	Environmental	EN1–EN3	0.801–0.858	0.770	0.867	0.684
Dynamic capabilities (HOC)	Second-order	SE, SZ, TR	0.887–0.906	0.879	0.926	0.806
Business sustainability (HOC)	Second-order	EC, SO, EN	0.524–0.773	0.482	0.734	0.486

Note: HOC = higher-order construct (second stage of the two-stage approach). Source: Simulated dataset processed by the authors (2026).

Table 7. Heterotrait–monotrait ratio (HTMT)

Construct	SE	SZ	TR	AIBMT	EC	SO	EN
SE	–						
SZ	0.849	–					
TR	0.870	0.894	–				
AIBMT	0.597	0.686	0.654	–			
EC	0.423	0.473	0.402	0.587	–		
SO	0.497	0.486	0.527	0.610	0.344	–	
EN	0.198	0.234	0.294	0.325	0.294	0.237	–

Source: Simulated dataset processed by the authors (2026).

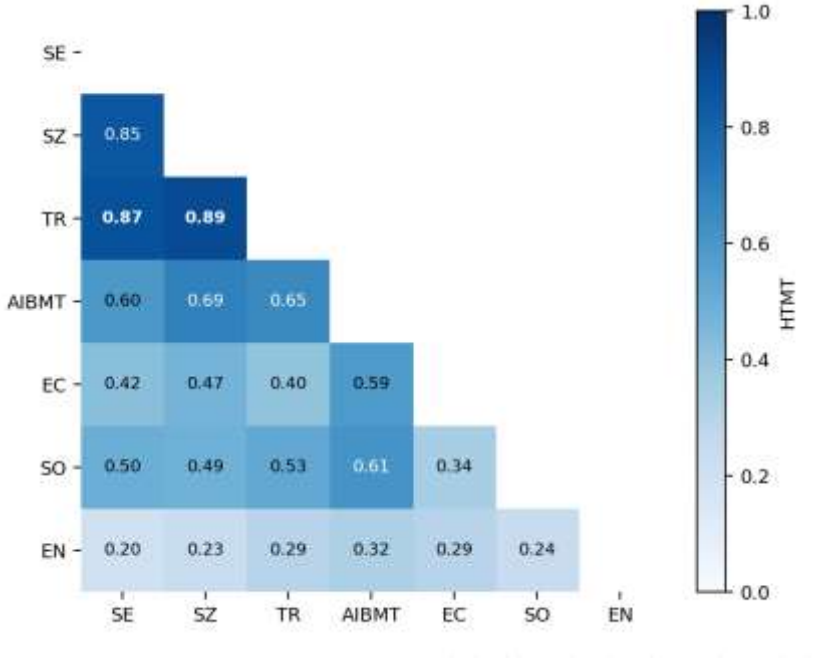


Figure 10. HTMT heatmap of the first-order constructs

Table 8. Fornell–Larcker criterion (first-order constructs)

Construct	SE	SZ	TR	AIBMT	EC	SO	EN
SE	[0.860]						
SZ	0.690	[0.847]					
TR	0.713	0.723	[0.848]				
AIBMT	0.513	0.579	0.557	[0.802]			
EC	0.347	0.383	0.329	0.506	[0.857]		
SO	0.406	0.392	0.426	0.521	0.280	[0.852]	
EN	0.156	0.182	0.231	0.271	0.242	0.187	[0.827]

Table 9. Discriminant validity at the higher-order level

Construct	DC	AIBMT	BS
DC	[0.898]	0.692	0.774
AIBMT	0.613	[0.802]	0.937
BS	0.530	0.645	[0.697]

Structural Model Evaluation

The inner VIF value for the predictors of business sustainability was 1.603, indicating no collinearity problem. AI-based business model transformation and business sustainability had R^2 values of 0.376 (adjusted R^2 = 0.373) and 0.445 (adjusted R^2 = 0.440), respectively, which exceed the 0.25 benchmark and are classified as weak-to-moderate explanatory power (Hair et al., 2019). The effect size of dynamic capabilities on AI-based business model transformation was large (f^2 = 0.603), that of AI-based business model transformation on business sustainability was medium (f^2 = 0.296), and the direct effect of dynamic capabilities on business sustainability was small (f^2 = 0.052). The construct-level Q^2predict values were positive (0.367 and 0.267), and PLSpredict showed that 9 of the 9 endogenous indicators had lower RMSE values than the linear model benchmark, indicating high predictive power (Shmueli et al., 2019). These results are summarised in Tables 10 and 11 and Figure 11.

Table 10. Explanatory and predictive power of the structural model

Endogenous construct	R^2	Adjusted R^2	Q^2predict	f^2
AI-based business model transformation	0.376	0.373	0.367	DC → AIBMT: 0.603
Business sustainability	0.445	0.440	0.267	DC → BS: 0.052; AIBMT → BS: 0.296

Table 11. PLSpredict results at the indicator level

Indicator	Q^2predict	RMSE (PLS-SEM)	RMSE (LM)	MAE (PLS-SEM)	MAE (LM)
BM1	0.232	0.919	0.921	0.752	0.754
BM2	0.274	0.960	0.969	0.782	0.791
BM3	0.274	0.925	0.934	0.752	0.758
BM4	0.180	0.929	0.937	0.764	0.765
BM5	0.222	0.971	0.981	0.745	0.756
BM6	0.228	0.983	0.993	0.790	0.799
EC	0.149	0.929	0.938	0.769	0.779
SO	0.196	0.902	0.910	0.745	0.753
EN	0.032	0.989	0.996	0.788	0.790

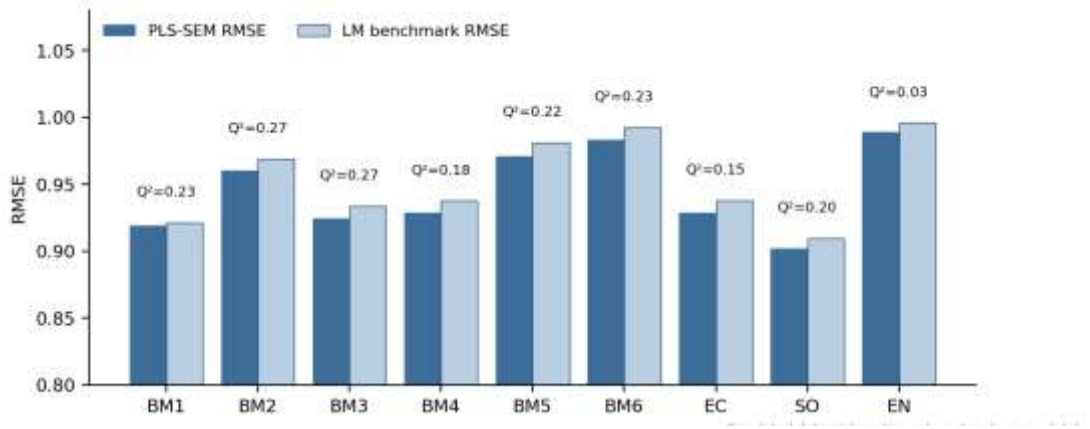


Figure 11. PLSpredict comparison of RMSE between the PLS-SEM model and the linear model benchmark

Hypothesis Testing

The bootstrapping results in Table 12 and Figures 12 and 13 show that dynamic capabilities have a positive and significant effect on AI-based business model transformation ($\beta = 0.613$; $t = 13.009$; $p < 0.001$), supporting H1. AI-based business model transformation has a positive and significant effect on business sustainability ($\beta = 0.513$; $t = 8.008$; $p < 0.001$), supporting H2, and dynamic capabilities have a positive and significant direct effect on business sustainability ($\beta = 0.216$; $t = 3.051$; $p = 0.003$), supporting H3. The specific indirect effect of dynamic capabilities on business sustainability through AI-based business model transformation is also significant ($\beta = 0.315$; $t = 7.248$; 95% CI [0.231; 0.398]), supporting H4. Because the direct effect remains significant and has the same sign as the indirect effect, AI-based business model transformation acts as a partial (complementary) mediator; the indirect effect accounts for 59.3% of the total effect (total $\beta = 0.530$). Figure 13 shows that none of the bootstrap distributions of the path coefficients includes zero within its 95% confidence interval.

Table 12. Results of hypothesis testing

Hypothesis	Path	β	SD	t-statistic	p-value	95% CI	Decision
H1	DC → AIBMT	0.613	0.047	13.009	< 0.001	[0.512; 0.695]	Supported
H2	AIBMT → BS	0.513	0.064	8.008	< 0.001	[0.373; 0.628]	Supported
H3	DC → BS	0.216	0.071	3.051	0.003	[0.079; 0.356]	Supported
H4	DC → AIBMT → BS	0.315	0.043	7.248	< 0.001	[0.231; 0.398]	Supported
–	Total effect DC → BS	0.530	0.054	9.762	< 0.001	[0.415; 0.627]	–

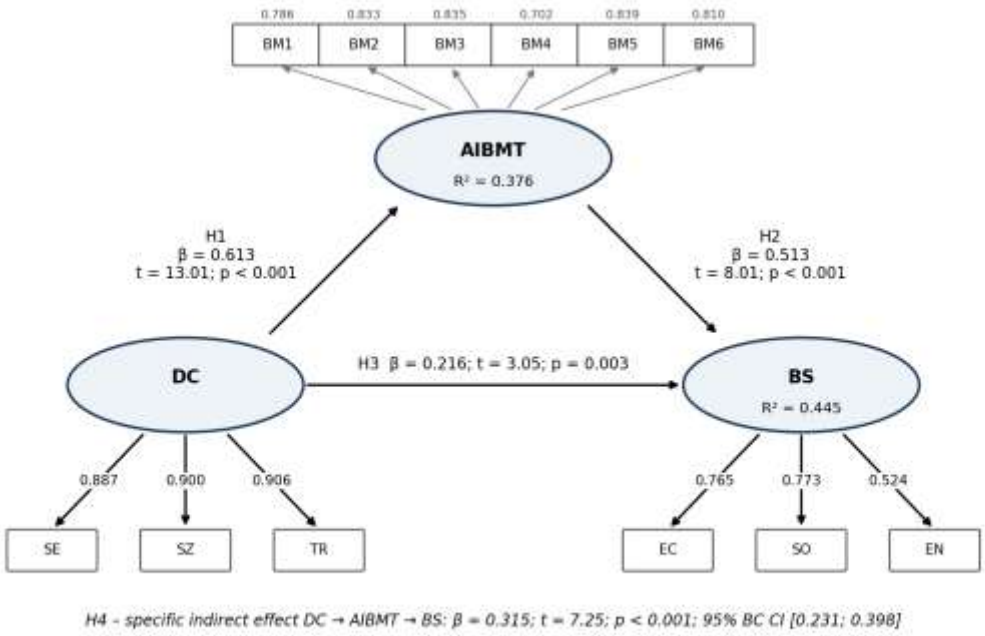


Figure 12. Structural model results
Source: Simulated dataset processed by the authors (2026).

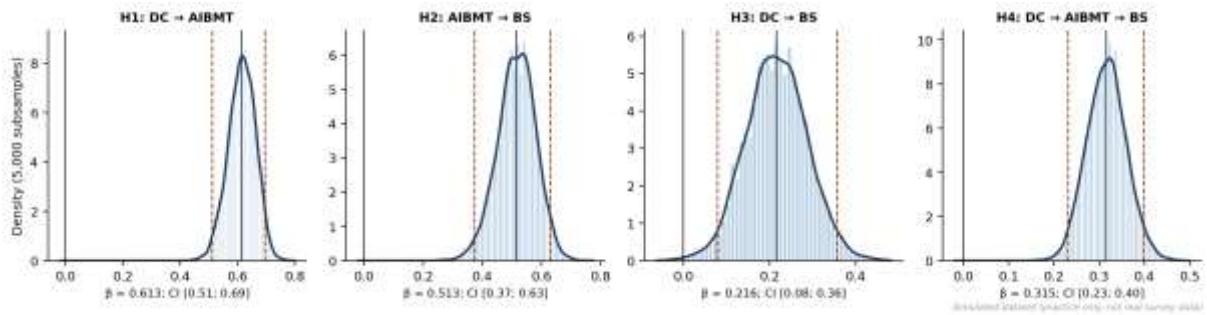


Figure 13. Bootstrap distributions of the path coefficients (dashed lines = 95% bias-corrected CI)

DISCUSSION

The findings of this study demonstrate that dynamic capabilities play a fundamental role in enabling AI-based business model transformation and strengthening business sustainability among MSMEs in Kendari City. The results reveal that dynamic capabilities positively influence AI-based business model transformation ($\beta = 0.613$; $p < 0.001$), which subsequently enhances business sustainability ($\beta = 0.513$; $p < 0.001$). Dynamic capabilities also exert a significant direct effect on business sustainability ($\beta = 0.216$; $p = 0.003$), while AI-based business model transformation partially mediates this relationship ($\beta = 0.315$; 95% CI [0.231; 0.398]). Taken together, these findings suggest that the sustainability benefits of AI adoption do not arise merely from technological availability but depend on the organisational capabilities that enable MSMEs to recognise technological opportunities, mobilise resources, and translate AI applications into meaningful changes in their business models.

The positive relationship between dynamic capabilities and AI-based business model transformation confirms that AI does not automatically reshape MSME business models. Rather, business owners who systematically sense technological and market signals, make timely investment decisions, and reorganise operational routines are better positioned to integrate AI into value creation, delivery, and capture. This finding reinforces Teece's (2018) argument that business model design and renewal depend on strong dynamic capabilities and is consistent with evidence that digital sensing, seizing, and transforming capabilities facilitate business model change in SMEs (Matarazzo et al., 2021; Warner & Wäger, 2019). It also corroborates Indonesian studies demonstrating that dynamic capabilities drive digital transformation (Putritamara et al., 2023; Setiawan et al., 2025). In the context of Kendari, where many MSMEs operate at a micro scale with limited financial and technological resources, the owner's cognitive ability to interpret AI-related opportunities constitutes a critical micro-foundation of organisational adaptation (Helfat & Peteraf, 2015; Li et al., 2018). This finding further explains why access to technology alone may be insufficient to generate innovation among Indonesian MSMEs (Zainuddin et al., 2026). Accordingly, AI adoption should be understood not as an isolated technological investment but as a capability-dependent process through which firms identify, exploit, and institutionalise technological opportunities.

The significant effect of AI-based business model transformation on business sustainability ($\beta = 0.513$; $p < 0.001$) further indicates that integrating AI into core business model components is associated with improved economic, social, and environmental outcomes. By personalising customer offers, automating customer service, generating marketing content, and optimising pricing decisions, MSMEs can enhance operational responsiveness and create greater value from existing resources. This finding aligns with previous research showing that business model innovation contributes to SME performance (Anwar, 2018; Latifi et al., 2021; Pucihar et al., 2019) and that AI adoption can improve the operational and economic performance of SMEs (Baabdullah et al., 2021; Badghish & Soomro, 2024). Beyond economic performance, AI-enabled personalisation and customer engagement may strengthen customer experience, loyalty, and business scalability, thereby supporting the social dimension of sustainability (Sundari et al., 2026; Wardoyo & Rizana, 2026). Environmental improvements may also emerge from more accurate demand forecasting, efficient resource allocation, and the digital substitution of physical materials (Dwivedi et al., 2021). Nevertheless, the empirical results indicate that environmental sustainability remains a relatively less developed dimension, as reflected in its loading on the higher-order business sustainability construct (0.524) and mean score (3.35). This suggests that environmental considerations have not yet become a primary motivation for AI adoption among the sampled MSMEs. The finding is consistent with Munandar et al. (2025), who reported that economic and social considerations tend to dominate the competitiveness priorities of micro-enterprises. Thus, although AI-based business model transformation contributes to multidimensional sustainability, the realisation of environmental benefits may require more explicit managerial commitment and targeted institutional support.

The direct effect of dynamic capabilities on business sustainability ($\beta = 0.216$; $p = 0.003$) provides further evidence that organisational adaptability contributes to sustainable business outcomes beyond its role in technological transformation. This result supports the perspective that sustainability is closely connected to an organisation's capacity to continuously reconfigure its

resources and respond to environmental changes (Amui et al., 2017). It also corroborates empirical evidence that dynamic capabilities improve the sustainability performance of SMEs (Eikelenboom & de Jong, 2019) and contribute to their overall performance (Hernández-Linares et al., 2021). For MSMEs in Kendari, which have experienced economic disruptions associated with the COVID-19 pandemic and increasing competition from national e-commerce platforms, the ability to reconfigure resources represents an important source of organisational resilience (Khurana et al., 2022). This interpretation is also consistent with Indonesian studies highlighting the contributions of dynamic human resource capabilities, entrepreneurial competence, and strategic capabilities to SME performance (Gunawan & Raspati, 2026; Jalaludin et al., 2026; Sari et al., 2026). However, the direct effect is smaller than the indirect effect, with a small effect size ($f^2 = 0.052$). This distinction suggests that although dynamic capabilities independently contribute to sustainability, a substantial proportion of their benefits is realised when organisational adaptability is translated into concrete business model renewal through AI integration.

The mediating role of AI-based business model transformation provides an important explanation of how dynamic capabilities generate sustainable outcomes. The significant indirect effect ($\beta = 0.315$; 95% CI [0.231; 0.398]), accounting for 59.3% of the total effect, confirms partial mediation. This means that dynamic capabilities contribute to business sustainability through two complementary pathways: a direct pathway involving the development and reconfiguration of organisational resources and an indirect pathway through the transformation of business models using AI. The finding reinforces Eisenhardt and Martin's (2000) proposition that dynamic capabilities create value through the resource configurations they generate and mirrors the indirect mechanisms identified in studies of IT-enabled dynamic capabilities (Mikalef & Pateli, 2017), entrepreneurial capability in batik SMEs (Rhamdhani & Riptiono, 2026), and strategic human resource management in digital startups (Nursi et al., 2026). However, this study extends these contributions by positioning AI-based business model transformation, rather than general digitalisation, as the specific mechanism through which dynamic capabilities are translated into multidimensional sustainability outcomes. The result therefore highlights the importance of distinguishing between possessing organisational capabilities and effectively converting those capabilities into new value creation, delivery, and capture mechanisms. In this respect, AI-based business model transformation represents not merely a technological outcome but a strategic transmission mechanism linking organisational adaptability with sustainable performance.

These findings offer several theoretical contributions. First, the study extends the dynamic capabilities view by demonstrating its relevance to AI-driven business model transformation in resource-constrained MSMEs located outside Indonesia's main economic centres. By examining the relationships among sensing, seizing, transforming, AI integration, and sustainability, the study provides empirical support for understanding AI adoption as an organisational transformation process rather than a purely technological phenomenon. Second, it advances the literature on AI-driven business model innovation by identifying business model transformation as a mediating mechanism connecting dynamic capabilities with sustainability. This contribution responds to calls for further research on AI-driven business model innovation and AI adoption in SMEs (Jorzik et al., 2024; Schwaeke et al., 2025). Third, the findings provide contextual evidence that the relationship between dynamic capabilities and sustainability operates through both direct and indirect mechanisms, thereby offering a more comprehensive explanation of how organisational adaptability generates value in emerging-market settings.

From a practical perspective, the findings suggest that MSME owners should approach AI not merely as a marketing instrument but as a strategic resource for redesigning their value propositions, operational processes, customer relationships, and revenue models. The adoption of AI should be accompanied by continuous learning, timely resource allocation, and the willingness to reorganise established business routines. For the Kendari City Government and the provincial cooperative and SME authorities, the results indicate the importance of shifting policy priorities from technology provision alone towards sustained capability development. Practical interventions may include AI clinics, peer-learning communities, and mentoring programmes designed to strengthen sensing, seizing, and transforming capabilities among MSME owners. These initiatives could be integrated with business formalisation programmes, particularly given the reported low proportion of licensed MSMEs (Antara Sultra, 2023). Financial literacy and governance training should also complement digital capability development because these competencies can strengthen the capacity to identify, evaluate, and implement innovation opportunities (Sayekti et al., 2026).

Similarly, digital access initiatives should be accompanied by human capital development to ensure that technological investments generate meaningful organisational outcomes (Saif & Santoso, 2026). Particular attention should also be given to the strategic role of women entrepreneurs in the digital economy to ensure that AI capability-building initiatives support inclusive participation in digital transformation (Nurhayani et al., 2025).

Overall, the findings establish that sustainable AI adoption among MSMEs requires the alignment of technological opportunities, organisational capabilities, and business model renewal. Dynamic capabilities provide the organisational foundation for recognising and exploiting AI opportunities, while AI-based business model transformation serves as the mechanism through which these capabilities generate economic, social, and environmental value. The relatively weaker environmental dimension further indicates that sustainability-oriented AI adoption requires deliberate managerial and policy interventions beyond the pursuit of immediate economic returns. By integrating these elements, the study offers a contextualised explanation of how MSMEs in emerging regional economies can move from basic technology adoption towards capability-driven business transformation and more sustainable development.

CONCLUSION

This study concludes that dynamic capabilities are a fundamental driver of AI-based business model transformation and business sustainability among MSMEs in Kendari City. MSMEs whose owners can sense AI-related opportunities, seize them through timely investment, and transform their routines are more likely to embed AI into their value proposition, value creation and delivery, and value capture. AI-based business model transformation, in turn, strengthens the economic, social, and environmental sustainability of MSMEs and partially mediates the effect of dynamic capabilities on sustainability. The main advantage of this study lies in integrating the dynamic capabilities view with the literature on AI-driven business model innovation in a secondary city of eastern Indonesia, a context rarely covered by previous research, and in offering an empirically tested model that can guide capability-based MSME development policies.

This study also has several limitations. The cross-sectional design limits causal inference, the purposive sample of AI-using MSMEs restricts generalisation to non-users, and self-reported sustainability measures may be subject to perception bias. In addition, the higher-order business sustainability construct showed limited internal consistency (AVE = 0.486), driven mainly by the environmental dimension, so its measurement should be refined. Future research is suggested to adopt longitudinal or mixed-method designs, compare AI users and non-users, include moderating variables such as digital literacy, government support, or firm size, and extend the model to other cities in Sulawesi and eastern Indonesia. MSME owners are advised to develop AI literacy and to experiment gradually with AI in core business processes, while local governments and universities are encouraged to design AI capability-building programmes that are linked to business formalisation and access to finance.

REFERENCES

Affandi, Y., Ridhwan, M. M., Trinugroho, I., & Hermawan Adiwibowo, D. (2024). Digital adoption, business performance, and financial literacy in ultra-micro, micro, and small enterprises in Indonesia. Research in International Business and Finance, 70, 102376. https://doi.org/10.1016/j.ribaf.2024.102376

Amui, L. B. L., Jabbour, C. J. C., de Sousa Jabbour, A. B. L., & Kannan, D. (2017). Sustainability as a dynamic organizational capability: A systematic review and a future agenda toward a sustainable transition. Journal of Cleaner Production, 142, 308–322. https://doi.org/10.1016/j.jclepro.2016.07.103

Anatan, L., & Nur. (2023). Micro, small, and medium enterprises' readiness for digital transformation in Indonesia. Economies, 11(6), 156. https://doi.org/10.3390/economies11060156

Annarelli, A., Battistella, C., Nonino, F., Parida, V., & Pessot, E. (2021). Literature review on digitalization capabilities: Co-citation analysis of antecedents, conceptualization and consequences. Technological Forecasting and Social Change, 166, 120635. https://doi.org/10.1016/j.techfore.2021.120635

Antara Sultra. (2023, April 8). Diseperdagkop sebut jumlah UMKM di Kendari meningkat usai pandemi. ANTARA News Sulawesi Tenggara.

https://sultra.antaranews.com/berita/442443/diseperdagkop-sebut-jumlah-umkm-di-kendari-meningkat-usai-pandemi
Anwar, M. (2018). Business model innovation and SMEs performance—Does competitive advantage mediate? International Journal of Innovation Management, 22(7), 1850057. https://doi.org/10.1142/S1363919618500573
Åström, J., Reim, W., & Parida, V. (2022). Value creation and value capture for AI business model innovation: A three-phase process framework. Review of Managerial Science, 16(7), 2111–2133. https://doi.org/10.1007/s11846-022-00521-z
Baabdullah, A. M., Alalwan, A. A., Slade, E. L., Raman, R., & Khatatneh, K. F. (2021). SMEs and artificial intelligence (AI): Antecedents and consequences of AI-based B2B practices. Industrial Marketing Management, 98, 255–270. https://doi.org/10.1016/j.indmarman.2021.09.003
Badghish, S., & Soomro, Y. A. (2024). Artificial intelligence adoption by SMEs to achieve sustainable business performance: Application of technology–organization–environment framework. Sustainability, 16(5), 1864. https://doi.org/10.3390/su16051864
Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. https://doi.org/10.1177/014920639101700108
Bocken, N. M. P., & Geradts, T. H. J. (2020). Barriers and drivers to sustainable business model innovation: Organization design and dynamic capabilities. Long Range Planning, 53(4), 101950. https://doi.org/10.1016/j.lrp.2019.101950
Bouwman, H., Nikou, S., & de Reuver, M. (2019). Digitalization, business models, and SMEs: How do business model innovation practices improve performance of digitalizing SMEs? Telecommunications Policy, 43(9), 101828. https://doi.org/10.1016/j.telpol.2019.101828
Burström, T., Parida, V., Lahti, T., & Wincent, J. (2021). AI-enabled business-model innovation and transformation in industrial ecosystems: A framework, model and outline for further research. Journal of Business Research, 127, 85–95. https://doi.org/10.1016/j.jbusres.2021.01.016
Buzzao, G., & Rizzi, F. (2021). On the conceptualization and measurement of dynamic capabilities for sustainability: Building theory through a systematic literature review. Business Strategy and the Environment, 30(1), 135–175. https://doi.org/10.1002/bse.2614
Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. Technological Forecasting and Social Change, 170, 120880. https://doi.org/10.1016/j.techfore.2021.120880 Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002
Eikelenboom, M., & de Jong, G. (2019). The impact of dynamic capabilities on the sustainability performance of SMEs. Journal of Cleaner Production, 235, 1360–1370. https://doi.org/10.1016/j.jclepro.2019.07.013
Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? Strategic Management Journal, 21(10–11), 1105–1121. https://doi.org/10.1002/1097-0266(200010/11)21:10/11<1105::AID-SMJ133>3.0.CO;2-E
Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.1177/002224378101800104
Gunawan, C., & Raspati, G. (2026). Linking entrepreneurial knowledge to business performance through competence. Indonesian Journal of Business and Entrepreneurship Research, 4(3), 62– 81. https://doi.org/10.62794/ijober.v4i3.234
Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hansen, E. B., & Bøgh, S. (2021). Artificial intelligence and internet of things in small and mediumsized enterprises: A survey. Journal of Manufacturing Systems, 58, 362–372. https://doi.org/10.1016/j.jmsy.2020.08.009

Helfat, C. E., & Peteraf, M. A. (2015). Managerial cognitive capabilities and the microfoundations of dynamic capabilities. Strategic Management Journal, 36(6), 831–850. https://doi.org/10.1002/smj.2247

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hernández-Linares, R., Kellermanns, F. W., & López-Fernández, M. C. (2021). Dynamic capabilities and SME performance: The moderating effect of market orientation. Journal of Small Business Management, 59(1), 162–195. https://doi.org/10.1111/jsbm.12474

Jalaludin, E., Ahman, E., Machmud, A., & Setiawan, Y. (2026). Strategic leadership and SMEs performance in Indonesia: The mediating role of dynamic human resource capability. Indonesian Journal of Business and Entrepreneurship Research, 4(3), 82–101. https://doi.org/10.62794/ijober.v4i3.329

Jorzik, P., Klein, S. P., Kanbach, D. K., & Kraus, S. (2024). AI-driven business model innovation: A systematic review and research agenda. Journal of Business Research, 182, 114764. https://doi.org/10.1016/j.jbusres.2024.114764

Kementerian Koordinator Bidang Perekonomian Republik Indonesia. (2022, October 1). Perkembangan UMKM sebagai critical engine perekonomian nasional terus mendapatkan dukungan pemerintah [Press release]. https://www.ekon.go.id/publikasi/detail/4593/perkembangan-umkm-sebagai-critical-engine-perekonomian-nasional-terus-mendapatkan-dukungan-pemerintah

Khurana, I., Dutta, D. K., & Singh Ghura, A. (2022). SMEs and digital transformation during a crisis: The emergence of resilience as a second-order dynamic capability in an entrepreneurial ecosystem. Journal of Business Research, 150, 623–641. https://doi.org/10.1016/j.jbusres.2022.06.048

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration, 11(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Kump, B., Engelmann, A., Kessler, A., & Schweiger, C. (2019). Toward a dynamic capabilities scale: Measuring organizational sensing, seizing, and transforming capacities. Industrial and Corporate Change, 28(5), 1149–1172. https://doi.org/10.1093/icc/dty054

Latifi, M.-A., Nikou, S., & Bouwman, H. (2021). Business model innovation and firm performance: Exploring causal mechanisms in SMEs. Technovation, 107, 102274. https://doi.org/10.1016/j.technovation.2021.102274

Lee, J., Suh, T., Roy, D., & Baucus, M. (2019). Emerging technology and business model innovation: The case of artificial intelligence. Journal of Open Innovation: Technology, Market, and Complexity, 5(3), 44. https://doi.org/10.3390/joitmc5030044

Li, L., Su, F., Zhang, W., & Mao, J.-Y. (2018). Digital transformation by SME entrepreneurs: A capability perspective. Information Systems Journal, 28(6), 1129–1157. https://doi.org/10.1111/isj.12153

Matarazzo, M., Penco, L., Profumo, G., & Quaglia, R. (2021). Digital transformation and customer value creation in Made in Italy SMEs: A dynamic capabilities perspective. Journal of Business Research, 123, 642–656. https://doi.org/10.1016/j.jbusres.2020.10.033

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & Management, 58(3), 103434. https://doi.org/10.1016/j.im.2021.103434

Mikalef, P., & Pateli, A. (2017). Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: Findings from PLS-SEM and fsQCA. Journal of Business Research, 70, 1–16. https://doi.org/10.1016/j.jbusres.2016.09.004

Munandar, J. M., Cahyadi, E. R., & Andrianto, M. S. (2025). The impacts of business sustainability factors on competitiveness and marketing performance: An exploratory approach to the case of Indonesian micro-, small, and medium enterprises. Sustainability, 17(10), 4593. https://doi.org/10.3390/su17104593

Nurhayani, Jumardi, & Haruna, H. (2025). The strategic role of millennial women in advancing MSMEs in the digital economy era. Indonesian Journal of Business and Entrepreneurship Research, 3(1), 50–62. https://journal.feb-unm.com/index.php/IJOBER/article/view/159

Nursi, M., Risnawati, H., Gustiawan, D., & Kurniawan, R. R. (2026). Strategic HRM, digital marketing capability, and startup performance: The mediating role of entrepreneurial orientation in Generation Z digital startups. Indonesian Journal of Business and Entrepreneurship Research, 4(2), 1–12. https://doi.org/10.62794/ijober.v4i2.224

Pemerintah Kota Kendari. (2017). [Strategic plan of the Kendari City office in charge of cooperatives and SMEs]. https://ppid.kemendagri.go.id/storage/dokumen/i2WtL4vfxkVQAA7FgHlxt99GSndeJEEpaZZ0lf9M.pdf

Pemerintah Provinsi Sulawesi Tenggara. (2024). [Number of MSME entrepreneurs by regency/city in Southeast Sulawesi Province, December 2024] [Data set]. SIMDATA Sultra. https://simdata.sultraprov.go.id/detail-tabel/tabel_74_654/2024

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Priyono, A., Moin, A., & Putri, V. N. A. O. (2020). Identifying digital transformation paths in the business model of SMEs during the COVID-19 pandemic. Journal of Open Innovation: Technology, Market, and Complexity, 6(4), 104. https://doi.org/10.3390/joitmc6040104

Pucihar, A., Lenart, G., Kljajić Borštnar, M., Vidmar, D., & Marolt, M. (2019). Drivers and outcomes of business model innovation—Micro, small and medium-sized enterprises perspective. Sustainability, 11(2), 344. https://doi.org/10.3390/su11020344

Putra, H. D., & Azizah, J. (2026). Generative AI in digital marketing strategy: Transforming brand communication and consumer engagement. Indonesian Journal of Business and Entrepreneurship Research, 4(1), 1–13. https://doi.org/10.62794/ijober.v4i1.23

Putritamara, J. A., Hartono, B., Toiba, H., Utami, H. N., Rahman, M. S., & Masyithoh, D. (2023). Do dynamic capabilities and digital transformation improve business resilience during the COVID-19 pandemic? Insights from beekeeping MSMEs in Indonesia. Sustainability, 15(3), 1760. https://doi.org/10.3390/su15031760

Rhamdhani, I. M., & Riptiono, S. (2026). A resource-based and dynamic capabilities perspective on batik SME performance: The sequential mediating roles of digital marketing and innovation capability. Indonesian Journal of Business and Entrepreneurship Research, 4(2), 52–67. https://doi.org/10.62794/ijober.v4i2.255

Saif, S. A. A., & Santoso, R. P. (2026). Push–pull factors and entrepreneurial activity: Digital access, human capital, and self-employment in Indonesia and the United Kingdom. Indonesian Journal of Business and Entrepreneurship Research, 4(3), 260–283. https://doi.org/10.62794/ijober.v4i3.273

Sari, N. S., Akbar, M., Iskandar, R., Utami, A. P., & Wulandari, E. P. (2026). Strategic capabilities and Muslim entrepreneurial behavior: The mediating role of competitive advantage on MSME performance. Indonesian Journal of Business and Entrepreneurship Research, 4(1), 26–44. https://doi.org/10.62794/ijober.v4i1.192

Sayekti, F., Resmi, S., & Pahlevi, R. W. (2026). Financial literacy, governance mechanisms, and innovation capability in explaining SME performance: The moderating role of organizational culture. Indonesian Journal of Business and Entrepreneurship Research, 4(2), 13–30. https://doi.org/10.62794/ijober.v4i2.268

Schilke, O., Hu, S., & Helfat, C. E. (2018). Quo vadis, dynamic capabilities? A content-analytic review of the current state of knowledge and recommendations for future research. Academy of Management Annals, 12(1), 390–439. https://doi.org/10.5465/annals.2016.0014

Schwaeke, J., Peters, A., Kanbach, D. K., Kraus, S., & Jones, P. (2025). The new normal: The status quo of AI adoption in SMEs. Journal of Small Business Management, 63(3), 1297–1331. https://doi.org/10.1080/00472778.2024.2379999

Setiawan, B., Pamungkas, B., Mekaniwati, A., & Kusuma, P. M. (2025). The strategic role of digital transformation, dynamic and agile capabilities for the performance of micro, small, and medium enterprises (MSMEs). The Bottom Line, 38(2), 130–153. https://doi.org/10.1108/BL-08-2024-0120

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. European Journal of Marketing, 53(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189

Sjödin, D., Parida, V., Palmié, M., & Wincent, J. (2021). How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. Journal of Business Research, 134, 574–587. https://doi.org/10.1016/j.jbusres.2021.05.009

Soluk, J., Decker-Lange, C., & Hack, A. (2023). Small steps for the big hit: A dynamic capabilities perspective on business networks and non-disruptive digital technologies in SMEs. Technological Forecasting and Social Change, 191, 122490. https://doi.org/10.1016/j.techfore.2023.122490

Sundari, A., Armanu, Indrasari, M., & Sukesi. (2026). Digital financial transformation on retail MSME scalability through customer engagement. Indonesian Journal of Business and Entrepreneurship Research, 4(1), 57–71. https://doi.org/10.62794/ijober.v4i1.364

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. Strategic Management Journal, 28(13), 1319–1350. https://doi.org/10.1002/smj.640

Teece, D. J. (2018). Business models and dynamic capabilities. Long Range Planning, 51(1), 40–49. https://doi.org/10.1016/j.lrp.2017.06.007

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. Journal of Business Research, 122, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. The Journal of Strategic Information Systems, 28(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003 Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AIbased transformation projects. Business Process Management Journal, 26(7), 1893–1924. https://doi.org/10.1108/BPMJ-10-2019-0411 Wardana, L. W., Ahmad, Indrawati, A., Maula, F. I., Mahendra, A. M., Fatihin, M. K., Rahma, A., Nafisa, A. F., Putri, A. A., & Narmaditya, B. S. (2023). Do digital literacy and business sustainability matter for creative economy? The role of entrepreneurial attitude. Heliyon, 9(1), e12763. https://doi.org/10.1016/j.heliyon.2022.e12763

Wardoyo, E., & Rizana, D. (2026). Customer experience as a mediator between AI personalization and consumer loyalty: Evidence from Shopee users. Indonesian Journal of Business and Entrepreneurship Research, 4(3), 16–31. https://doi.org/10.62794/ijober.v4i3.205

Warner, K. S. R., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. Long Range Planning, 52(3), 326–349. https://doi.org/10.1016/j.lrp.2018.12.001

Yacob, S., Sulistiyo, U., Erida, E., & Siregar, A. P. (2021). The importance of e-commerce adoption and entrepreneurship orientation for sustainable micro, small, and medium enterprises in Indonesia. Development Studies Research, 8(1), 244–252. https://doi.org/10.1080/21665095.2021.1976657

Yusuf, M., Surya, B., Menne, F., Ruslan, M., Suriani, S., & Iskandar, I. (2023). Business agility and competitive advantage of SMEs in Makassar City, Indonesia. Sustainability, 15(1), 627. https://doi.org/10.3390/su15010627

Zainuddin, Syah, A., & Nurfadilah. (2026). Public financial accountability, technological access, and innovation capability among digitally engaged MSMEs in Indonesia. Indonesian Journal of Business and Entrepreneurship Research, 4(3), 144–154. https://doi.org/10.62794/ijober.v4i3.386