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AI-Powered Decision Support Systems for MSMEs Growth Strategies in Emerging Markets

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ABSTRACT

Micro, Small, and Medium Enterprises (MSMEs) in emerging markets face significant challenges in strategic decision-making due to limited resources and dynamic environments. This study aims to explore the role of AI-Powered Decision Support Systems (AI-DSS) in supporting growth strategies using the dynamic capabilities theory. The study involved 250 food processing business actors who have adopted or considered implementing AI-DSS, with data analysis conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that dynamic capabilities and dynamic environments significantly influence the adoption of AI-DSS, ultimately enhancing business performance. Furthermore, dynamic environments were found to moderate the relationship between dynamic capabilities and AI-DSS adoption, indicating that adaptability to external changes is crucial in maximizing the benefits of AI technology. This research contributes theoretically to the literature on dynamic capabilities and technology while offering practical implications for food processing entrepreneurs and policymakers in emerging markets. The study highlights the importance of developing adaptive capabilities and leveraging AI technology to improve competitiveness amidst ever-changing business dynamics.

1. Introduction

Micro, Small, and Medium Enterprises (MSMEs) play a critical role in the economy, especially in emerging markets (Gurney, 2022). MSMEs contribute significantly to job creation, local innovation, and poverty alleviation (Povolná, 2019). However, many food processing entrepreneurs in emerging markets face substantial challenges in terms of growth and competitiveness, including limited resources, lack of access to technology, and difficulties in making strategic decisions in a dynamic business environment, particularly in highly competitive industries such as food processing (Rachmawati et al., 2023). One effective approach to enhancing the efficiency and effectiveness of decisions made by food processing entrepreneurs is by utilizing Artificial Intelligence (AI)-based Decision Support Systems (DSS) (Soori et al., 2024). This study aims to analyze how AI-DSS can be applied to support MSMEs' growth strategies in the food processing sector based on Kaplan and Norton's growth strategy framework.

Most food processing entrepreneurs in emerging markets have not optimally utilized technology, even though AI can help personalize customer experiences through advanced data analysis, increase sales by offering relevant products, and support product innovation through market analysis and trend prediction (Ananias et al., 2024). Empirical data indicate that the adoption rate of AI-powered DSS (AI-DSS) among food processing entrepreneurs remains low (Hendrian et al., 2024). Factors such as limited organizational capabilities, low technological literacy, and adaptation challenges to changing business environments hinder the widespread implementation of AI-DSS (Pitelis, Teece, & Yang, 2024). This creates a significant gap between the potential of AI-DSS and its practical adoption.

AI-based Decision Support Systems (AI-DSS) integrate AI methods to optimize and support decision-making processes in complex and uncertain situations (Soori & Jough, 2024). Additionally, Srinivasan (2024) states that AI-DSS can reduce the time required to process data and make decisions, improve decision accuracy based on deeper data analysis, minimize human error, and better allocate resources, such as in production planning, inventory management, or financial management. This enables companies to respond more quickly to market changes or operational challenges.

Theoretically, the dynamic capabilities theory emphasizes the importance of an organization's ability to respond and adapt to environmental changes (Leemann & Kanbach, 2022). However, literature integrating the dynamic capabilities of food processing entrepreneurs with AI technology adoption, particularly AI-DSS, is still limited (Chege & Wang, 2020). According to Mammadov et al. (2024), barriers to organizational dynamic capabilities include a lack of technical competence in AI development and management, concerns about AI replacing human jobs, and organizations not fully understanding how to implement AI strategically. Similarly, Borges et al. (2021) found that food processing entrepreneurs face challenges in implementing AI, including limited technical skills and ethical risks, such as algorithmic bias and privacy concerns. Srinivasan et al. (2024) noted that a key challenge in implementing AI-DSS lies in the availability of trained human resources capable of integrating problems with existing systems.

The urgency of research on the role of AI-DSS is critical to address empirical and theoretical gaps. AI-DSS has the potential to enhance decision-making capabilities of food processing entrepreneurs through advanced data analysis, AI-based predictions, and adaptive strategy recommendations. These systems can help entrepreneurs tackle dynamic environmental challenges by providing accurate and responsive strategic insights. This study aims to fill these empirical and theoretical gaps by exploring the relationship between dynamic capabilities, AI-DSS adoption, and MSME performance in emerging markets. By adopting AI technology, food processing entrepreneurs can enhance knowledge management and improve innovation ambidexterity (Acosta et al., 2018).

Theoretical Framework and Hypotheses

Theoretical Adoption of AI in Business Processes

Russell & Norvig (2021) stated that the adoption of Artificial Intelligence (AI) in businesses is the process of implementing AI-based technology to improve operational efficiency, support decision-making, and create new value. AI-DSS enables companies to analyze large amounts of data, identify hidden patterns, and provide real-time, data-driven solutions. Mukherjee & Chang (2024) highlighted that AI helps businesses address complex problems through algorithms designed for optimal decision-making, such as providing data-based recommendations for marketing strategies. Additionally, AI allows businesses to deliver more personalized services to customers.

The use of AI in businesses has its benefits and challenges. Huang & Rust (2021) noted benefits such as improving efficiency through process automation, enhancing customer experience, and driving service innovation. However, challenges include technological limitations understood by human resources, concerns over data privacy, and potential resistance from employees due to changes in job dynamics. This underscores the need for a balance between AI and human interaction to complement each other rather than entirely replace human tasks (Choi et al., 2021).

The adoption of AI technology can help companies improve operational efficiency, reduce costs, and generate valuable customer data insights about the products or services offered (Soni et al., 2020). Although many companies have adopted AI, its adoption among MSMEs remains relatively low (Hulme, 2020). Factors such as limited understanding of AI functions (Borger et al., 2021), fear of jobs being replaced by machines (Choi et al., 2021), resource constraints (Duan et al., 2019), and the lack of technological and regulatory ecosystems supporting AI usage in businesses (Gresee et al., 2022) contribute to this gap.

AI-powered Decision Support Systems (AI-DSS) support strategic and operational decision-making processes based on data, enabling MSMEs to efficiently manage challenges and seize opportunities (Rana et al., 2022). AI-DSS significantly enhances decision efficiency and quality by processing large volumes of data, providing more precise analytics-based recommendations, saving time, identifying patterns and trends invisible to humans, minimizing decision-making risks, and leveraging data-driven insights for better long-term decisions (Gangwar et al., 2024).

Dynamic Capabilities

The dynamic capabilities theory, first developed by Teece & Pisano (1994), relates to an organization’s ability to create, reshape, assimilate knowledge and skills, and maintain a competitive edge in rapidly changing environments. Teece (2014) described dynamic capabilities as the key to long-term business success. Dynamic capabilities enable organizations to continually adapt and evolve in dynamic business environments. Simply put, it is the ability of businesses to 'learn' and 'grow' over time, ensuring they remain relevant and competitive.

Dynamic capabilities view companies as strategic assets for developing productive knowledge. The theory represents an evolution of the resource-based view, emphasizing the importance of an organization’s ability to manage and develop unique and valuable resources to achieve sustainable competitive advantages (Barney, 1991). According to Barney (1991), the resource-based view of the firm suggests that a company’s competitive advantage is determined by its heterogeneous and integrated resources.

Dynamic capabilities refer to an organization’s ability to integrate, build, and distribute resources and competencies to respond to market changes and dynamic business environments (Teece, 2018). Research by Olan et al. (2022) showed that AI, by enhancing knowledge sharing, can strengthen a company’s dynamic capabilities. Organizations that integrate AI technology into knowledge management are better equipped to adapt to market and environmental changes, which lie at the core of dynamic capabilities. Thus, applying AI in knowledge sharing can be a critical factor in strengthening an organization’s dynamic capabilities, enhancing operational efficiency, innovation, and competitiveness (Chatterjee et al., 2022).

Growth Strategies

Wheelen and Hunger (2018) stated that the strategy framework consists of four stages: environmental analysis, strategy formulation, strategy implementation, and evaluation and control, which sequentially form a strategic planning cycle. Grant (2021) viewed strategy as a process of directing and coordinating resources to achieve an organization’s long-term goals, making strategy a tool for creating competitive advantages in the market through decisions involving all aspects of the business. David & David (2016) emphasized that strategy in management is one of the primary efforts for organizations to achieve long-term goals through fundamental planning and decision-making.

Agarwal et al. (2003) explained that business performance can be measured through financial performance analysis, such as utilization rates, profitability, and market share, as well as non-financial or subjective performance, which complement each other to provide a comprehensive picture. Business performance is influenced by both internal and external factors (Layoo & Rahman, 2019). Teece, Pisano, & Shuen (1997) stated that internal factors influence business performance by integrating, building, and adapting internal resources to respond to market and technological changes.

Kaplan & Norton (2001) described business performance as a method to evaluate the success of a business, measured through four perspectives: financial, customer, internal business processes, and learning and growth. Business performance can be assessed using the Balanced Scorecard (BSC), which evaluates business performance holistically, encompassing financial results, customer satisfaction, internal processes, and employee development and innovation. This approach helps companies focus not only on short-term outcomes but also prepare for long-term success (Kaplan &

Norton, 2001). The Balanced Scorecard emphasizes the connection between performance measurement and strategic management (Kaplan & Norton, 2001).

The financial perspective focuses on how well an organization generates profitable financial outcomes, reflecting value creation for shareholders and other stakeholders (Brignall, 2007). Kaplan & Norton (2001) noted that the financial perspective within the BSC offers advantages such as enhancing profitability, increasing shareholder value, managing costs, improving operational efficiency, supporting long-term financial strategies, and providing balanced financial performance measurements. Martínez et al. (2024) emphasized that customer satisfaction is one of the key factors affecting a company's long-term results, especially in industries heavily reliant on customer loyalty. Additionally, service quality, particularly in terms of reliability and responsiveness, significantly influences satisfaction, while the physical aspects of applications have a lesser impact (Kalantarzadeh, 2024). Thus, customer satisfaction leads to increased customer loyalty, which in turn supports the sustainability and growth of an organization (Islam et al., 2021).

The internal business process perspective evaluates organizational performance, focusing on the efficiency and effectiveness of internal processes. Its goal is to ensure the organization can produce innovative products (Argawa et al., 2003). Therefore, the internal perspective assesses how effective and efficient internal processes contribute to improving business performance (Kawiana et al., 2020). By focusing on internal processes, companies can achieve sustainable efficiency, effectiveness, and competitive advantages.The learning perspective involves enhancing skills and knowledge by combining individual and group learning with organizational learning strategies (Cung et al., 2012). It is a strategy that supports continuous innovation to sustain business performance. The learning perspective aims to adapt to market changes and improve operational efficiency (Terziovski, 2020).

This study builds on Kaplan and Norton's (1996) growth strategy theory, which identifies four main perspectives for developing growth strategies: financial, customer, internal processes, and learning and growth. AI-DSS can support these perspectives by improving data-driven decision-making and facilitating more effective strategic planning. Based on this theory, several hypotheses are proposed:

Dynamic capabilities refer to an organization's ability to identify external opportunities and threats and reconfigure internal assets and resources to respond to dynamic business environments (Teece, 2018). For MSMEs operating in environments of high uncertainty and resource constraints, dynamic capabilities enable businesses to remain competitive by fostering innovation, formulating adaptive strategies, and exploiting new market opportunities (Eisenhardt & Martin, 2000). These capabilities encompass three main processes: sensing (identifying opportunities), seizing (capitalizing on opportunities), and transforming (restructuring assets and operations to support growth strategies) (Teece et al., 1997). In the context of MSMEs in emerging markets, challenging environments demand high flexibility and adaptability to cope with changing market demands, regulations, and technological advancements (Zahra et al., 2006).

Previous studies have shown that dynamic capabilities play a crucial role in driving business growth by facilitating product innovation, operational efficiency, and long-term strategy development (Barreto, 2010). Therefore, it is assumed that food processing entrepreneurs with high dynamic capabilities are better equipped to develop sustainable growth strategies compared to those with lower capabilities. Based on the explanation above, the first hypothesis of this study is as follows:

H_1: Dynamic capabilities (X_1) have a positive and significant influence on growth strategies (Y).

Artificial intelligence (AI)-based technology has become one of the primary drivers of digital transformation in business, including the MSME sector. AI power refers to an organization's ability to utilize AI technology in various business processes, such as data analysis, decision-making, and operational automation (Jarrahi, 2018). With the proper implementation of AI, food processing entrepreneurs can enhance efficiency, reduce operational costs, and accelerate innovation processes (Dwivedi et al., 2021). In the context of growth strategies, the use of AI enables MSMEs to utilize market data more effectively to detect trends, understand customer needs, and formulate more personalized and adaptive marketing strategies (Ransbotham et al., 2017). Additionally, AI-powered decision support systems help businesses identify previously undetected growth opportunities and accelerate evidence-based decision-making processes (Wamba-Taguimdje et al., 2020).

Research indicates that organizations that successfully integrate AI technology into their business strategies have the potential to accelerate growth by enhancing flexibility, agility, and innovation capabilities (Bughin et al., 2018). Therefore, it is hypothesized that AI power has a positive and significant influence on supporting MSME growth strategies in increasingly competitive markets. Based on the explanation above, the second hypothesis of this study is as follows:

H_2: AI power (X_2) has a positive and significant influence on growth strategies (Y).

Dynamic capabilities play a crucial role in facilitating the adoption and utilization of advanced technologies, including AI. These capabilities involve a company's ability to quickly respond to technological changes and market environments by identifying, leveraging, and integrating relevant innovations (Teece et al., 1997). In this context, organizations with high dynamic capabilities are better equipped to adopt AI power and integrate it into strategic decision-making processes (Zahra et al., 2006). The sensing capability in dynamic capabilities helps organizations detect technological trends and opportunities related to AI adoption, while the seizing capability facilitates strategic steps in investing and developing AI technology (Kindermann et al., 2020). Furthermore, the transforming capability enables companies to adapt their internal structures and business processes to ensure effective AI adoption that supports long-term business goals (Teece, 2018).

Previous research shows that organizations with strong dynamic capabilities are better positioned to utilize AI as a strategic tool to enhance innovation, efficiency, and organizational flexibility (Garrido-Moreno et al., 2021). Therefore, it is hypothesized that dynamic capabilities have a positive and significant influence on a company's ability to use AI effectively. Based on the explanation above, the third hypothesis of this study is as follows:

H_3: Dynamic capabilities (X_1) have a positive and significant influence on AI power (X2).

The ability of MSMEs to effectively utilize AI power does not solely depend on the availability of technology but also on the dynamic capabilities of the organization to recognize, adopt, and integrate this technology into their business strategies (Teece, 2018). Dynamic capabilities enable companies to navigate market changes, identify technological opportunities, and develop processes and structures that support AI as a tool for growth and innovation (Zahra et al., 2006). In this context, AI power can mediate the relationship between dynamic capabilities and growth strategies by accelerating data-driven decision-making processes, identifying relevant market trends, and supporting the development of new products or services that better meet customer needs (Garrido-Moreno et al., 2021). Companies with strong dynamic capabilities are better positioned to leverage AI for competitive advantages through innovative and adaptive growth strategies (Dwivedi et al., 2021).

Research shows that companies that can effectively integrate AI technology with their dynamic capabilities are better equipped to respond to market challenges and create sustainable growth (Wamba-Taguimdje et al., 2020). Thus, AI power serves as a mediating mechanism that strengthens the positive relationship between dynamic capabilities and growth strategies. Based on the explanation above, the fourth hypothesis of this study is as follows:

H_4: AI power (X_2) mediates the relationship between dynamic capabilities (X1) and growth strategies (Y).

These hypotheses reflect the expected causal relationships and emphasize that integrating AI-based technology with a company's dynamic capabilities can provide sustainable competitive advantages and support effective growth strategies in dynamic business environments.

2. Method

This study adopts a quantitative approach using a case study method to explore in-depth the relationship between AI-DSS adoption and growth strategies of micro and small businesses in West Java. The sample consists of 250 food processing business respondents. The data analysis method used is Partial Least Squares Structural Equation Modeling (PLS-SEM), which offers advantages by not requiring strict data normality assumptions, making it more flexible when working with non-normally distributed data or varying sample sizes (Hair et al., 2019).

2.1 Research Method

The research model employs descriptive and inferential approaches. Data were collected from micro and small enterprises operating in the food processing sector in West Java. The primary focus of this study is to measure the extent to which AI-DSS is used to support growth strategies within Kaplan & Norton's (2021) four perspectives. PLS-SEM is used to examine the impact of AI-DSS on growth strategies in various aspects.

2.2 Data Collection

Data were collected through a questionnaire consisting of two main parts: the first, questions about the adoption of AI-DSS by food processing businesses; the second, questions about business growth strategies based on Kaplan and Norton's perspectives. The questionnaire was distributed to 250 food processing businesses across various districts and cities in West Java. Responses from these businesses were processed to evaluate how AI-DSS adoption influences their growth strategies.

2.3 Data Analysis

The collected data were analyzed using PLS-SEM to test the relationships between variables in the model. The first step involved conducting validity and reliability tests on the research instruments to ensure the questionnaire accurately measured the desired variables. Subsequently, the PLS-SEM model was analyzed to test the previously proposed hypotheses. The analysis was performed using SmartPLS software.

This study uses PLS-SEM analysis as recommended by Hair et al. (2019), where indicator loadings are analyzed to test the reliability of each item. This can be observed in Table 2, Table 3, and Figure 1. Internal consistency is assessed based on the Construct Reliability (CR) values, which range between 0.70 and 0.90 and are considered to meet eligibility standards. All indicators used in this study are declared valid, as the loading factor values for each indicator exceed 0.7. As shown in Table 3, CR values range from 0.856 to 0.958, which are far above the minimum threshold of 0.50. Additionally, the Cronbach's alpha values for all constructs exceed 0.70, indicating that the items within the measurement model have adequate internal consistency (Hair et al., 2019). Furthermore, convergent validity is evaluated based on the Average Variance Extracted (AVE) values.

3 Results and Discussion

3.1 Descriptive Statistics and Outer Model Evaluation

This study uses PLS-SEM analysis as recommended by Hair et al. (2019), where indicator loadings are analyzed to test the reliability of each item. This is illustrated in Table 2, Table 3, and Figure 1. Internal consistency is assessed based on the Construct Reliability (CR) values, which range between 0.70 and 0.90 and are considered to meet eligibility standards. All indicators used in this study are declared valid, as the loading factor values for each indicator exceed 0.7. As shown in Table 3, CR values range from 0.856 to 0.958, which are significantly above the minimum threshold of 0.50. Furthermore, the Cronbach's alpha values for all constructs exceed 0.70, indicating that the items within the measurement model exhibit adequate internal consistency (Hair et al., 2019). Convergent validity is subsequently evaluated based on the Average Variance Extracted (AVE) values.

3.2 Inner Model Evaluation and Hypothesis Testing

According to Hair et al. (2019), convergent validity is considered satisfied if the AVE values reach 0.50 or higher. All AVE values presented in Table 3 surpass this threshold, indicating that all items used in this study have convergent validity in forming latent variables. Discriminant validity, which is also part of the measurement model evaluation, is shown in Table 3. This evaluation is based on a comparison between the square root of AVE and the correlations among latent variables. The analysis results show that all squared correlation coefficients among variables are smaller than the square root of the AVE, thus confirming acceptable discriminant validity (Hair et al., 2019). The relationship between variable dimensions and their indicators measures the construct validity used in the study, specifically how well the concept is represented by the selected indicators (Hair et al., 2013). Besides determining the accuracy of the measurement tools, reflective indicators are also evaluated. Constructs are noted for both convergent and discriminant validity. Convergent validity is considered good when each item has an AVE value of 0.50 or higher (Hair et al., 2019). Table 4 presents the data processing results using SmartPLS software, showing AVE values above 0.5

Table 1. Respondents' Characteristics in This Study

		Frequency	percent
Gender	Male	170	68,4%
	Female	80	31,6%
Age	> 30 years	8	3%
	30-50 years	232	93%
	> 50 years	10	6%
Type of business	Micro	65	26%
	Small	185	74%

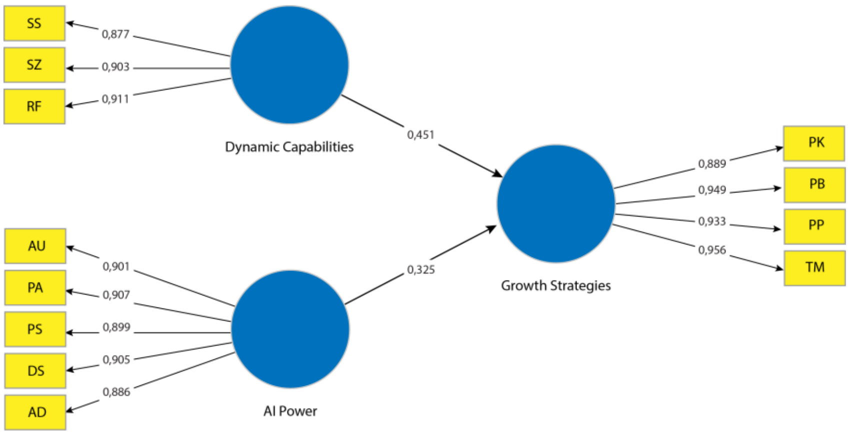

Fig. 1. SmartPLS 3 Results for the Measurement Model

Table 2. Lambda Estimation Values (*Loading Factors*)

Exogenous Variables	Dimensions	Value λ (Loading Factor)
Dynamic Capabilities	*Sensing* (X1.1)	0,877
	Seizing (X1.2)	0,903
	Reconfiguration (X1.3)	0,911
AI Power	Automation (X2.1)	0,901
	Predictive Analytics (X2.1)	0,907
	Personalization (X2.1)	0,899
	Decision Support (X2.1)	0,905
	Adaptability (X2.1)	0,886
Growth Strategic	Financial perspective	0,889
	Internal business process perspective	0,949
	Customer perspective	0,933
	Learning and growth perspective	0,956

Source: Output SmartPLS

Table 3. Validity (Convergent and Discriminant) and Measurement Items

Code	Measurement Items	Loading Factor
	DIMENSION-1 Financial Perspective	
PK1	Revenue growth has been steadily increasing.	0,857
PK2	The ability to identify opportunities to enter new markets over the past three years.	0,888
PK3	Routinely calculating ROI for every business investment.	0,896
PK4	Routinely calculating ROE to evaluate business performance.	0,898
PK5	Routinely calculating the Debt Ratio to evaluate the financial condition of the	0,900

Code	Measurement Items	Loading Factor
	business.	
PK6	The ability to meet short-term obligations.	0,908
PK7	Understanding the importance of cash flow stability in managing business finances.	0,907
	DIMENSION-2 Internal Business Processes	
PB1	The ability to prepare a budget for new product development.	0,892
PB2	The ability to prepare the number of new products launched.	0,923
PB3	The ability to implement effective measures to reduce product damage.	0,933
PB4	Efficiency in business operational processes to meet customer needs.	0,936
PB5	Speed in responding to customer complaints.	0,924
PB6	Customer satisfaction with the products offered.	0,927
PB7	The ability to comply with regulations on quality standards for products.	0,934
PB8	Investment in employee training.	0,911
PB9	Implementation of new technology to support business processes.	0,938
	DIMENSION-3 Perspektif Pelanggan	
PP1	How satisfied are you with the product you received?	0,931
PP2	How fast is the service provided?	0,932
PP3	Likelihood of repurchasing the product in the future.	0,934
PP4	Likelihood of recommending the product to family or friends.	0,946
PP5	The product consumed functions well according to my needs.	0,950
PP6	This product brand is one of the first brands that comes to mind when purchasing.	0,957
PP7	The product is always available when I need it.	0,961
PP8	The information and features offered by the product are accurate and reliable.	0,935
PP9	I rarely experience issues when using the product.	0,943
	DIMENSION-3 **Growth and Learning Perspective**	
PM1	The frequency of training provided is sufficient to support employee performance improvement.	0,887
PM2	Training is guided by experienced and expert instructors in their field.	0,889
PM3	Skill assessment scores.	0,901
PM4	Employees have the skills necessary to perform their tasks effectively.	0,909
PM5	Technology system downtime during the learning process.	0,918
PM6	Annual investment in technology infrastructure to support learning.	0,890
PM7	The company's information system supports work processes effectively and efficiently.	0,903
PM8	The adoption rate of new technology in the learning process. Technology system downtime during the learning process.	0,921
PM9	Annual investment in technology infrastructure to support learning.	0,936
PM10	The company's information system supports work processes effectively and efficiently.	0,943
PM11	The company encourages innovation and continuous improvement in work processes.	0,953
PM12	Employees are encouraged to share knowledge and learn from colleagues.	0,920
PM13	Employees are satisfied with the growth and development opportunities provided by the company.	0,964
	DIMENSION-1 Sensing	
SS1	Organizations that are able to adopt AI for business processes quickly in line with new technological trends	0,856
SS2	The use of AI to develop new products or services, such as AI-based platforms for personalizing customer experiences or AI-based services offering added value	0,869
	DIMENSION-2 Seizing	
SZ1	The organization's ability to use AI to accelerate adaptation to real-time market changes	0,907
SZ2	The organization's ability to create a continuous learning culture related to AI	0,911
SZ3	The organization's ability to successfully implement AI in business processes	0,891
SZ4	The organization's ability to use AI for product demand forecasting	0,875
ZS5	The organization's ability to optimize the supply chain with the help of AI	0,898
	DIMENSION-3 Reconfiguration	
RF1	The ability to allocate budgets for employee training	0,860
RF2	The ability to integrate AI into operational systems	0,871
RF3	The ability to reorganize managerial structures to align with technological needs	0,889
RF4	The ability to transform organizational culture to be more open to AI-based	0 ,869

Code	Measurement Items	Loading Factor
	innovation and experimentation	
RF5	The ability to integrate AI into customer management systems or operational decision-making	0,866
RF6	The ability to develop new business units to manage and accelerate AI adoption across the organization	0,893
Code	Measurement Items	Loading Factor
	DIMENSION-1 Automation	
AU1	AI-based systems significantly accelerate task completion times compared to manual methods.	0,877
AU2	AI-based systems assist predictive analytics in providing accurate insights into customer needs and preferences.	0,934
AU4	The implementation of AI systems enhances workflow efficiency by streamlining processes and eliminating unnecessary steps.	0,945
	DIMENSION-2 Predictive Analytics	
PA1	Predictive analytics systems proactively identify new trends in the market.	0,936
PA2	With predictive analytics, I can evaluate the impact of specific decisions on organizational performance.	0,921
PA3	Predictive analytics provides accurate insights into customer needs and preferences.	0,941
	DIMENSION-3 Personalization	
PS1	I feel that the services provided by the system are highly relevant to my personal needs.	0,865
PS2	The system can predict my needs based on activities or historical data.	0,896
PS3	The personalized services provided by the system enhance my overall satisfaction.	0,905
	DIMENSION-4 Decision Support	
DS1	The system provides recommendations tailored to my specific needs in the decision-making process.	0,926
DS2	The system helps boost my confidence in making decisions.	0,932
DS3	The system offers highly useful data-driven insights to support strategic decisions.	0,947
DS4	The system accelerates the decision-making process without compromising the quality of outcomes.	0,955
	DIMENSION-5 Adaptability	
AD1	The system can adapt to changes in my needs or preferences.	0,937
AD2	The system quickly responds to changes in my environment or requirements.	0,939
AD3	The system learns from patterns or data I provide to improve its performance.	0,948
AD4	The system's ability to adapt to my preferences enhances my user experience.	0,958

a. Source: Output SmartPLS

Tabel 4 Structural Model Testing (Inner model)

Variabel laten	AVE	Cronbach Alpha	Rho	R-Square
Dynamic Capabilities	0,936	0,987	0,987	0,870
AI Power	0,927	0,969	0,971	0,887
Growth Strategies	0,940	0,980	0,983	0,895

b. Source: Output SmartPLS

3. Results and Discussion

3.1 Descriptive Statistics and Outer Model Evaluation

Based on the analysis using the Partial Least Squares Structural Equation Modeling (PLS-SEM) method following Hair et al. (2019), the results showed that the Cronbach's Alpha and Composite Reliability values for all constructs indicated good reliability (>0.70). Convergent Validity: The Average Variance Extracted (AVE) > 0.50 indicates adequate convergent validity. Discriminant Validity: The Heterotrait-Monotrait Ratio (HTMT) < 0.85 indicates that discriminant validity is satisfied. The findings highlight the role of dynamic capabilities and AI power in supporting growth strategies for food processing entrepreneurs.The PLS-SEM test results indicate:

Dynamic capabilities (X1) have a positive and significant influence on growth strategies (Y) with a path coefficient value of $\beta = 0.451$, $p < 0.01$.

AI power (X2) has a positive and significant influence on growth strategies (Y) with a path coefficient value of $\beta = 0.325$, $p < 0.01$.

Dynamic capabilities (X1) have a positive and significant influence on AI power (X2) with a path coefficient value of $\beta = 0.506$, $p < 0.01$.

AI power (X2) partially mediates the relationship between dynamic capabilities (X1) and growth strategies (Y) with a path coefficient value of $\beta = 0.366$, $p < 0.05$.

Discussion

The results of this study affirm the importance of dynamic capabilities in supporting the adoption and utilization of AI to drive MSME growth strategies in emerging markets. Dynamic capabilities help MSMEs detect market opportunities, respond to changes in the business environment, and integrate AI technology to enhance efficiency and innovation. These findings are consistent with previous studies, which show that the integration of AI with dynamic capabilities can enhance a company's competitiveness and accelerate business growth (Dwivedi et al., 2021; Garrido-Moreno et al., 2021). Furthermore, the ability of companies to utilize AI acts as a mediator that strengthens the relationship between dynamic capabilities and the success of growth strategies.

Hypothesis H1: Dynamic Capabilities (X1) Have a Positive and Significant Influence on Growth Strategies (Y)

Dynamic capabilities significantly influence MSME growth strategies. This indicates that higher dynamic capabilities enable MSMEs to develop more effective growth strategies. These capabilities allow companies to respond to market changes, seize business opportunities, and enhance competitiveness. These findings align with Teece et al. (1997), who stated that dynamic capabilities are a crucial foundation for achieving sustainable growth.

Hypothesis H2: AI Power (X2) Has a Positive and Significant Influence on Growth Strategies (Y)

AI power significantly supports MSME growth strategies by facilitating data-driven decision-making processes, enhancing operational efficiency, and driving product or service innovation. The ability of MSMEs to utilize AI helps them navigate complex business environments and improve responsiveness to market needs. These findings support Dwivedi et al. (2021), who demonstrated that AI acts as a critical catalyst for creating competitive advantages.

Hypothesis H3: Dynamic Capabilities (X1) Have a Positive and Significant Influence on AI Power (X2)

Dynamic capabilities have a positive and significant influence on AI power, meaning that companies with better dynamic capabilities are more likely to adopt and utilize AI technology effectively. Companies' ability to detect technological opportunities, make strategic decisions regarding technology adoption, and adapt their business processes supports effective AI implementation. These findings are consistent with Kindermann et al. (2020), who emphasized the importance of dynamic capabilities in driving digital technology adoption.

Hypothesis H4: AI Power (X2) Mediates the Relationship Between Dynamic Capabilities (X1) and Growth Strategies (Y)

AI power partially mediates the relationship between dynamic capabilities and MSME growth strategies. This shows that dynamic capabilities not only have a direct influence on growth strategies but also work through AI power to strengthen this relationship. Companies with high dynamic capabilities are more capable of integrating AI into their strategies, which, in turn, enhances the effectiveness of growth strategies. These findings reinforce the theory of Garrido-Moreno et al. (2021), which stated that AI can act as an intermediary that amplifies the value of dynamic capabilities in dynamic business contexts.

4 Conclusion

This study shows that dynamic capabilities and AI power significantly contribute to the development of MSME growth strategies in emerging markets. Dynamic capabilities play a critical role in facilitating AI adoption, which in turn supports the execution of more effective growth strategies. AI power mediates the relationship between dynamic capabilities and growth strategies, underscoring the role of AI technology as a catalyst for innovation and competitiveness. This research provides practical and theoretical contributions by highlighting the importance of developing dynamic capabilities and adopting AI technology to support MSME growth in dynamic business environments. Future research can explore other factors, such as regulatory barriers or the role of organizational culture in supporting AI adoption in MSMEs.

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