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| RESEARCH ARTICLE

Artificial Intelligence-Driven Supply Chain Capabilities: Enhancing Agility, Resilience, and Competitive Advantage in MSMEs

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| ABSTRACT
Micro, small, and medium enterprises (MSMEs) face increasing disruptions arising from global health crises, geopolitical instability, and climate-related challenges, highlighting the urgent need for agile and resilient supply chain (SC) systems. Due to resource constraints and limited technological readiness, MSMEs are particularly vulnerable to such uncertainties. Drawing on the Resource-Based View (RBV), this study examines how artificial intelligence (AI) capabilities enhance competitive advantage (CA) by strengthening supply chain agility (SCA) and supply chain resilience (SCR), while considering the moderating role of competitive pressure (CP). A conceptual model is developed and empirically tested using data collected from 350 MSME owners and managers, analysed through Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that AI capabilities significantly improve both supply chain agility and supply chain resilience, and directly enhance competitive advantage. Furthermore, both agility and resilience contribute positively to competitive advantage, while competitive pressure strengthens the relationship between AI capability and competitive advantage. This study contributes to the literature by extending AI-enabled supply chain frameworks to the MSME context and highlighting the strategic role of AI as a driver of supply chain capabilities and firm competitiveness. It also offers practical insights for MSMEs to leverage AI technologies in enhancing agility, resilience, and sustainable competitive advantage in dynamic and highly competitive environments.

| KEYWORDS

Artificial intelligence; supply chain agility; supply chain resilience; competitive advantage; competitive pressure; MSMEs.

| ARTICLE INFORMATION

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1. Introduction
Micro, small, and medium enterprises (MSMEs) are increasingly experiencing rapid technological transformation alongside growing market competition and rising customer expectations. Operating in highly dynamic and uncertain environments, MSMEs face significant challenges in maintaining sustainable competitive advantage, particularly due to their limited resources, lower technological readiness, and fragmented supply chain structures (Kraus et al., 2021; Müller et al., 2018). In such conditions, achieving competitiveness requires not only efficiency but also the ability to adapt and innovate. Prior studies have identified differentiation and cost leadership as primary strategies for gaining competitive advantage (Porter, 1985); however, in today's digital era, technological innovation has become a critical driver of long-term competitiveness (Verhoef et al., 2021). More recently, supply chain innovation has emerged as a key mechanism enabling firms to enhance performance in turbulent environments (Ivanov & Dolgui, 2020).

The concept of supply chain management in MSMEs has gained increasing attention in the literature. Existing research largely emphasizes the benefits of effective supply chain management in improving firm performance (Flynn et al., 2010). However, MSME supply chains often face structural weaknesses, including poor integration, limited visibility, and a lack of advanced technological capabilities, which hinder their ability to respond effectively to disruptions (Dubey et al., 2021). Despite the growing importance of digital transformation, the role of artificial intelligence (AI) in enhancing MSME supply chain capabilities remains insufficiently explored. In particular, there is limited empirical evidence on how AI can be leveraged to develop critical capabilities such as supply chain agility and supply chain resilience, which are essential for improving performance and sustaining competitive advantage (Bag et al., 2021).

MSMEs operate within complex and interconnected supply networks involving suppliers, distributors, customers, and supporting institutions. These networks are often characterized by interdependence and fragmentation, making MSMEs more vulnerable to disruptions compared to larger firms (Christopher & Peck, 2004). The increasing frequency of unexpected events—such as global pandemics, geopolitical tensions, economic instability, and climate-related risks—has further intensified uncertainty in business environments (Ivanov, 2021). Consequently, MSMEs must develop the capacity to respond quickly to changes (agility) and recover from disruptions (resilience) in order to sustain their operations and competitiveness.

In the "new normal" business landscape, agility and resilience have become critical capabilities for ensuring supply chain effectiveness and long-term sustainability. The adoption of digital technologies is widely recognized as a key enabler for enhancing these capabilities (Queiroz et al., 2020). From a theoretical perspective, the Dynamic Capability View (DCV) suggests that organizations can achieve superior performance by developing the ability to sense, seize, and reconfigure resources in response to environmental changes (Teece, 2007). In this regard, artificial intelligence represents a strategic capability that can transform MSME supply chains by improving demand forecasting, optimizing inventory management, enhancing coordination with supply chain partners, and enabling real-time decision-making (Wamba et al., 2020).

Accordingly, this study adopts the Dynamic Capability View to address existing research gaps by examining how AI capabilities enhance supply chain agility (SCA) and supply chain resilience (SCR), thereby contributing to competitive advantage (CA) in MSMEs. Furthermore, this study incorporates competitive pressure (CP) as a moderating variable to explore how external environmental forces influence the effectiveness of AI-driven capabilities. By doing so, this research provides a comprehensive understanding of how MSMEs can leverage AI to strengthen supply chain capabilities and achieve sustainable competitive advantage in increasingly uncertain and dynamic environments.

2. Theoretical Background

2.1. Artificial Intelligence (AI) and Competitive Advantage (CA)

Businesses, particularly micro, small, and medium enterprises (MSMEs), increasingly benefit from investments in digital technologies as they enhance competitive performance and enable firms to differentiate themselves in highly competitive markets (Verhoef et al., 2021). In the context of MSMEs, technological adoption is not only a means of improving operational efficiency but also a strategic necessity for sustaining long-term competitiveness in dynamic environments (Müller et al., 2018).

This phenomenon can be explained by the Resource-Based View (RBV), which posits that firm performance is determined by the possession and effective utilization of valuable, rare, inimitable, and non-substitutable (VRIN) resources (Barney, 1991; Wernerfelt, 1984). According to this perspective, organizations that develop unique capabilities can achieve superior performance and sustained competitive advantage. Among such strategic resources, artificial intelligence (AI) capabilities are increasingly recognized as critical intangible assets that enhance decision-making quality, operational efficiency, and innovation (Wamba et al., 2020; Dubey et al., 2021).

In MSMEs, AI technologies—such as machine learning, natural language processing, and predictive analytics—are increasingly applied to support various business functions. These include customer relationship management, demand forecasting, inventory optimization, pricing strategies, and process automation. AI enables MSMEs to analyze large volumes of data, generate real-time insights, and improve responsiveness to market changes, thereby enhancing overall business performance (Bag et al., 2021). Despite resource constraints, the adoption of AI allows MSMEs to compete more effectively by improving efficiency, reducing operational costs, and delivering more personalized products and services.

Furthermore, the integration of AI into supply chain management (SCM) significantly improves key processes such as procurement, logistics, risk management, and coordination with supply chain partners. AI-driven systems enhance visibility, information flow, and decision-making accuracy, which are essential for achieving both efficiency and flexibility in supply chains (Ivanov & Dolgui, 2020). In addition, complementary technologies such as the Internet of Things (IoT) and blockchain further strengthen supply chain capabilities by improving transparency, traceability, and coordination across supply chain networks (Queiroz et al., 2020).

Given these advantages, AI capabilities can be considered a strategic resource that enables MSMEs to build and sustain competitive advantage by improving operational performance, enhancing customer value, and strengthening supply chain effectiveness. Therefore, the following hypothesis is proposed:

H1. Artificial intelligence (AI) capability has a positive direct effect on competitive advantage (CA) in MSMEs.

2.2. Artificial Intelligence (AI) and Supply Chain Agility (SCA)

Supply chain agility refers to the ability of an organization to sense, respond, and adapt quickly and effectively to unexpected changes in the business environment (Christopher, 2000; Swafford et al., 2008). It encompasses the capacity to adjust operations, reconfigure resources, and respond proactively to market fluctuations, demand variability, and supply disruptions. In highly dynamic environments, agility enables firms to maintain responsiveness and flexibility, which are essential for sustaining performance and competitiveness.

For micro, small, and medium enterprises (MSMEs), supply chain agility is particularly critical due to their limited resources and higher vulnerability to external shocks. MSMEs must be able to rapidly adjust sourcing, production, and distribution processes to cope with uncertainties such as demand fluctuations, supply interruptions, and changing customer preferences. The ability to build adaptive relationships with suppliers and customers, as well as to respond efficiently to market needs, is a key characteristic of agile supply chains (Braunscheidel & Suresh, 2009).

Artificial intelligence (AI) plays a pivotal role in enhancing supply chain agility by enabling real-time data processing, predictive analytics, and intelligent decision-making. AI technologies, such as machine learning and advanced analytics, allow MSMEs to forecast demand more accurately, optimize inventory levels, and improve coordination with supply chain partners. These capabilities enable firms to respond more quickly to environmental changes and reduce delays in decision-making processes (Wamba et al., 2020). Furthermore, AI-driven systems enhance visibility and information sharing across the supply chain, which are essential for improving responsiveness and flexibility (Ivanov & Dolgui, 2020).

In uncertain and rapidly changing business environments, the integration of AI into supply chain processes provides MSMEs with the capability to anticipate disruptions and respond proactively, thereby strengthening supply chain agility. Given these advantages, AI can be considered a critical enabler of agile supply chain practices in MSMEs.

Therefore, the following hypothesis is proposed:

H2. Artificial intelligence (AI) capability has a positive direct effect on supply chain agility (SCA) in MSMEs.

2.3. Supply Chain Agility (SCA) and Competitive Advantage (CA)

Micro, small, and medium enterprises (MSMEs) operate within diverse and interconnected supply networks involving suppliers, distributors, and customers, forming complex and dynamic supply chain structures. Compared to large firms, MSME supply chains are often more fragmented and resource-constrained, which increases their exposure to environmental uncertainty and market volatility (Christopher & Peck, 2004). These characteristics make it more challenging for MSMEs to maintain consistent performance and achieve sustainable competitive advantage.

In such environments, supply chain agility plays a critical role in enabling firms to respond effectively to rapid changes in demand, supply disruptions, and shifting customer preferences. Supply chain agility refers to the ability of firms to quickly adjust operations, reconfigure resources, and respond proactively to market dynamics (Swafford et al., 2008). For MSMEs, agility is particularly important as it allows them to compensate for resource limitations by enhancing responsiveness, flexibility, and speed in decision-making processes.

From a theoretical perspective, supply chain agility can be viewed as a dynamic capability that enables firms to sense and respond to environmental changes, thereby supporting the development of competitive advantage (Teece, 2007). Agile supply chains allow MSMEs to better coordinate with upstream and downstream partners, optimize resource utilization, and deliver products and services more efficiently and effectively. This responsiveness enhances customer satisfaction, reduces operational inefficiencies, and strengthens market positioning.

Moreover, prior studies have shown that effective supply chain management practices, particularly those emphasizing flexibility and responsiveness, contribute significantly to improved firm performance and competitive advantage in dynamic markets (Flynn et al., 2010). By leveraging agile supply chain capabilities, MSMEs can enhance their ability to adapt to uncertainty, respond to customer needs, and sustain superior performance compared to competitors.

Based on the above discussion, the following hypothesis is proposed:

H3. Supply chain agility (SCA) has a positive direct effect on competitive advantage (CA) in MSMEs.

2.4. Artificial Intelligence (AI) and Supply Chain Resilience (SCR)

In the context of supply chains, resilience has emerged as a critical concept, particularly in response to increasing global disruptions such as pandemics, geopolitical tensions, and climate-related events (Ivanov, 2021; Queiroz et al., 2020). Resilience is generally defined as the ability of a system to withstand disruptions and recover to its original or an improved state within an acceptable period (Christopher & Peck, 2004). More specifically, supply chain resilience (SCR) refers to the capacity of organizations to maintain operations, adapt to unexpected changes, and recover quickly from disruptions in order to ensure business continuity (Ponomarov & Holcomb, 2009).

For micro, small, and medium enterprises (MSMEs), supply chain resilience is particularly important due to their limited resources, lower redundancy, and higher exposure to external shocks. MSMEs often lack the buffers and risk management capabilities available to larger firms, making them more vulnerable to supply chain disruptions. Therefore, developing resilience capabilities is essential for ensuring operational stability and long-term sustainability.

Artificial intelligence (AI) plays a significant role in enhancing supply chain resilience by enabling better risk assessment, predictive analytics, and real-time decision-making. AI-driven technologies allow MSMEs to anticipate disruptions, improve demand–supply matching, and optimize resource allocation. For example, AI can enhance forecasting accuracy, improve inventory management, and support more efficient logistics operations, thereby reducing uncertainty and improving responsiveness (Wamba et al., 2020). Additionally, AI enhances visibility across supply chain networks, enabling firms to detect potential risks earlier and respond more effectively to disruptions (Ivanov & Dolgui, 2020).

Furthermore, AI contributes to resilience by strengthening key capabilities such as preparedness, response, and recovery. Through advanced data analytics and automation, MSMEs can improve operational efficiency, maintain service continuity, and adapt more quickly to changing conditions. These capabilities are essential for mitigating supply chain risks and ensuring stable performance in uncertain environments (Dubey et al., 2021).

Based on the above discussion, artificial intelligence can be considered a critical enabler of supply chain resilience in MSMEs. Therefore, the following hypothesis is proposed:

H4. Artificial intelligence (AI) capability has a positive direct effect on supply chain resilience (SCR) in MSMEs.

2.5. Supply Chain Resilience (SCR) and Competitive Advantage (CA)

Supply chain resilience enables organizations to maintain operations, adapt to disruptions, and recover quickly from unexpected events, thereby ensuring business continuity and long-term sustainability (Ponomarov & Holcomb, 2009). For micro, small, and medium enterprises (MSMEs), resilience is particularly critical due to their limited resources and higher vulnerability to external shocks. The ability to effectively prepare for, respond to, and recover from disruptions allows MSMEs to minimize operational risks and maintain stable performance in uncertain environments (Ivanov, 2021).

Resilience strategies—such as preparedness, response, and recovery mechanisms—play a crucial role in reducing supply chain risks and enhancing organizational performance (Christopher & Peck, 2004). In this regard, supply chain resilience has evolved into a key determinant of sustainable competitive advantage, going beyond traditional efficiency-focused approaches. Firms that are capable of maintaining operational continuity during disruptions are better positioned to retain customers, protect market share, and sustain long-term growth.

The theoretical foundation for the strategic importance of supply chain resilience can be explained through the Dynamic Capability Theory (DCT) and the Knowledge-Based View (KBV). From the perspective of dynamic capabilities, resilience reflects an organization's ability to reconfigure resources and adapt to changing environments, thereby enhancing performance (Teece, 2007). Meanwhile, the knowledge-based view emphasizes the role of knowledge integration and learning in enabling firms to respond effectively to disruptions and improve decision-making (Grant, 1996). Together, these perspectives suggest that resilience acts as a critical mechanism through which firms transform knowledge and capabilities into superior performance outcomes.

Furthermore, resilient supply chains not only recover from disruptions but may also emerge stronger by improving processes, enhancing flexibility, and building adaptive capabilities (Ivanov & Dolgui, 2020). This ability to "bounce forward" rather than merely "bounce back" provides MSMEs with a strategic advantage in highly volatile markets.

Based on the above discussion, the following hypothesis is proposed:

H5. Supply chain resilience (SCR) has a positive direct effect on competitive advantage (CA) in MSMEs.

2.6. Supply Chain Agility (SCA) and Supply Chain Resilience (SCR)

Supply chain agility and supply chain resilience are closely interrelated capabilities that enable organizations to effectively manage uncertainty and disruptions. Supply chain agility refers to the ability of firms to sense changes in the environment and respond rapidly, while supply chain resilience emphasizes the capacity to absorb shocks, adapt, and recover from disruptions (Swafford et al., 2008; Ponomarov & Holcomb, 2009). Together, these capabilities play a crucial role in ensuring supply chain continuity and long-term sustainability.

For micro, small, and medium enterprises (MSMEs), the relationship between agility and resilience is particularly significant. Due to their limited resources and higher exposure to external risks, MSMEs must rely on agility to anticipate disruptions and respond proactively. Agile supply chains enable firms to adjust operations quickly, reconfigure resources, and maintain flexibility in response to changing market conditions. These capabilities, in turn, strengthen resilience by enhancing the organization's ability to withstand and recover from disruptions (Christopher & Peck, 2004).

From a theoretical perspective, agility can be viewed as a precursor to resilience within the framework of dynamic capabilities. The ability to sense and respond rapidly to environmental changes allows firms to mitigate risks before they escalate into major disruptions. This proactive responsiveness enhances the organization's preparedness and adaptive capacity, thereby contributing to stronger resilience outcomes (Teece, 2007). In other words, agility supports resilience by enabling firms not only to react quickly but also to anticipate and manage uncertainties more effectively.

In highly dynamic and uncertain business environments, MSMEs must develop both agility and resilience to ensure stable operations and sustained performance. The integration of these capabilities allows firms to respond to immediate challenges while also building long-term robustness against future disruptions.

Based on the above discussion, the following hypothesis is proposed:

H6. Supply chain agility (SCA) has a positive direct effect on supply chain resilience (SCR) in MSMEs.

2.7. Competitive Pressure (CP) as a Moderator

Competitive pressure refers to the intensity of competition that compels firms within the same industry to maintain or enhance their competitive position (Porter, 1985). It is widely recognized as a key external driver influencing organizational behavior, particularly in terms of technology adoption and strategic decision-making (Zhu & Kraemer, 2005). In highly competitive environments, firms are more likely to adopt innovative technologies to improve efficiency, responsiveness, and overall performance.

For micro, small, and medium enterprises (MSMEs), competitive pressure plays an even more critical role due to their limited resources and vulnerability to market changes. To remain competitive, MSMEs must continuously adapt by leveraging advanced technologies such as artificial intelligence (AI) to enhance their operational capabilities. When firms perceive that adopting AI can provide a competitive edge, they are more likely to invest in such technologies to improve performance outcomes.

Prior research suggests that competitive pressure significantly accelerates the adoption of digital technologies, including AI and big data analytics, by increasing transparency, improving information flow, and reducing inefficiencies within supply chains (Wamba et al., 2020). In addition, competitive pressure strengthens the relationship between technological capability and performance, as firms operating in highly competitive markets are more motivated to fully utilize their technological resources to achieve superior outcomes (Dubey et al., 2021).

In the context of MSMEs, competitive pressure is expected to amplify the impact of AI capabilities on competitive advantage. Firms facing intense competition are more likely to leverage AI-driven insights, enhance decision-making processes, and optimize supply chain operations to maintain their market position. Consequently, competitive pressure acts as a boundary condition that strengthens the effectiveness of AI in generating competitive advantage.

Based on the above discussion, the following hypothesis is proposed:

H7. Competitive pressure (CP) positively moderates the relationship between artificial intelligence (AI) capability and competitive advantage (CA), such that the relationship is stronger under higher levels of competitive pressure in MSMEs.

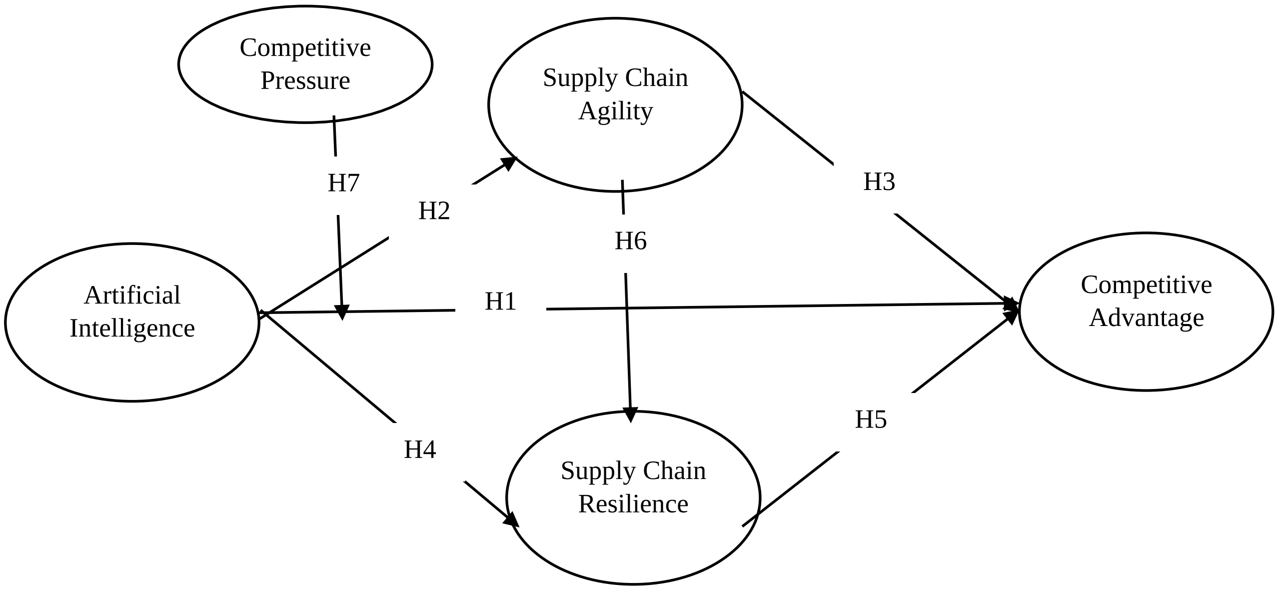

Figure 1: Proposed Model

3. Methods

3.1. Measures

All measurement scales employed in this study were adapted from well-established instruments in prior literature to ensure reliability and validity. Minor wording modifications were made to align the items with the MSME context (Hair et al., 2021).

Artificial intelligence (AI) capability was measured using a five-item scale adapted from previous studies (Ransbotham et al., 2017; Wamba et al., 2020). Sample items include: "Our firm possesses the infrastructure and skilled human resources to implement AI-based information processing systems" and "Our firm uses AI techniques to forecast demand and predict environmental changes."

Competitive advantage (CA) was measured using a seven-item scale adapted from Li et al. (2006). Sample items include: "Compared with our competitors, our firm offers unique products or services to customers" and "Compared with our competitors, our firm provides higher quality products or services."

Supply chain agility (SCA) was assessed using a nine-item scale adapted from Swafford et al. (2008). Example items include: "Our firm can quickly adjust product or service offerings to meet customer needs" and "Our firm responds rapidly to changes in customer demand."

Supply chain resilience (SCR) was measured using a five-item scale adapted from Belhadi et al. (2024), which builds on earlier studies by Ponomarov and Holcomb (2009) and Christopher and Peck (2004). Sample items include: "Our firm's supply chain is well prepared to handle disruptions" and "Our firm's supply chain can quickly recover from unexpected disruptions."

Competitive pressure (CP) was operationalized using a three-item scale adapted from Zhu and Kraemer (2005). Example items include: "Our firm adopts AI-driven solutions because competitors are implementing similar technologies" and "Our industry is increasingly moving toward AI-based business processes."

To ensure content validity, the measurement instrument was pretested with 21 experts, including academics and MSME practitioners. The panel confirmed that the items were clear, relevant, and appropriate for the study context. Therefore, no substantial revisions were required prior to data collection (Hair et al., 2021).

3.2. Data Collection

This study targeted micro, small, and medium enterprises (MSMEs) operating across various sectors, as these firms are increasingly adopting digital technologies, including artificial intelligence (AI), to enhance their competitiveness and operational efficiency. MSMEs were selected due to their strategic importance in economic development and their growing need to strengthen supply chain capabilities in dynamic and uncertain environments.

Data were collected with the assistance of trained research assistants, including postgraduate students and practitioners who have experience working with MSMEs. The respondents—primarily MSME owners, managers, and supervisors—were directly contacted and provided with an online survey link and QR code to complete the questionnaire. The survey was also disseminated through professional networks and business associations to reach a broader range of participants. The focus on owners and managerial-level respondents is justified, as they are actively involved in decision-making processes and possess sufficient knowledge regarding organizational strategies and supply chain practices (Hair et al., 2021).

An introductory section was included at the beginning of the questionnaire to explain the study's objectives and ensure confidentiality. Respondents were informed that their participation was voluntary and that all responses would be treated anonymously. Completing the questionnaire was considered as providing informed consent. Additionally, respondents were assured that there were no right or wrong answers, thereby reducing response bias.

Data collection was conducted over a three-month period, during which reminder messages were sent to improve response rates. A total of 432 complete and usable responses were obtained. The use of an online survey with a mandatory-response feature helped ensure data completeness and reliability.

Regarding sample adequacy, this study follows established guidelines suggesting that, for large populations (greater than 100,000), a minimum sample size of 384 is sufficient to achieve a 95% confidence level with a 5% margin of error (Krejcie & Morgan, 1970). Therefore, the final sample size of 432 exceeds this threshold, indicating adequate statistical power and supporting the generalizability of the findings.

In terms of respondent characteristics, 61.3% were male and 38.7% were female. The majority of respondents were aged between 25 and 35 years (56.9%), followed by those aged 36 to 50 years (34.3%). Regarding educational background, most participants held a bachelor's degree (66.4%), while 18.3% had completed postgraduate education. These characteristics suggest that the respondents possess sufficient educational and professional backgrounds to provide reliable insights into AI adoption and supply chain practices in MSMEs

3.3. Data Analysis

The proposed research model consists of one independent variable (artificial intelligence capability), two endogenous variables (supply chain agility and supply chain resilience), one dependent variable (competitive advantage), and one moderating variable (competitive pressure). Compared to the original model, the current framework excludes mediating effects and focuses on examining direct relationships and the moderating role of competitive pressure. Given the predictive nature of the study and the model's structural complexity, Partial Least Squares Structural Equation Modeling (PLS-SEM) was considered appropriate and was applied using SmartPLS software (version 3) (Hair et al., 2021).

PLS-SEM is particularly suitable for this study due to its ability to handle complex models, its robustness with relatively small to medium sample sizes, and its emphasis on maximizing explained variance in endogenous constructs (Hair et al., 2021). In addition, PLS-SEM does not impose strict assumptions regarding data normality, making it well-suited for exploratory and prediction-oriented research.

The data analysis was conducted in two main stages. The first stage involved evaluating the measurement (outer) model to ensure the reliability and validity of the constructs. Convergent validity was assessed using factor loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). Acceptable thresholds include factor loadings above 0.70, CR above 0.70, and AVE above 0.50 (Hair et al., 2021). Discriminant validity was evaluated using the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT), where HTMT values below 0.85 indicate adequate discriminant validity (Henseler et al., 2015).

The second stage involved assessing the structural (inner) model to test the proposed hypotheses. This included evaluating the coefficient of determination (R^2) to measure the explanatory power of the model, and the predictive relevance (Q^2) using the blindfolding procedure. Path coefficients (β) and their statistical significance were assessed using the bootstrapping technique with resampling procedures to obtain t-values and p-values (Hair et al., 2021). Furthermore, the moderating effect of competitive pressure was examined by testing the interaction term between artificial intelligence capability and competitive pressure on competitive advantage.

4. Results

4.1. Common Method Bias (CMB)

To assess the potential presence of common method bias (CMB), several statistical procedures were conducted. First, Harman's single-factor test was applied as a preliminary diagnostic approach (Podsakoff et al., 2003). The results indicated that a single factor accounted for 40.23% of the total variance, which is below the recommended threshold of 50%, suggesting that common method bias is not a serious concern in this study.

In addition, multicollinearity diagnostics were performed using variance inflation factor (VIF) values. The results show that all VIF values ranged between 1.518 and 2.958 (see Table 1), which are well below the conservative threshold of 5.0, indicating that multicollinearity among the constructs is not an issue (Hair et al., 2021).

Furthermore, data normality was examined using skewness and kurtosis statistics. The results demonstrate that skewness values ranged from −0.783 to −0.254, while kurtosis values ranged from −0.700 to 0.612 (see Table 1). These values fall within acceptable ranges, indicating that the data distribution does not significantly deviate from normality (Kline, 2015).

Table 1. Descriptive Statistics and Normality Assessment

Construct	Mean	Std. Dev.	Skewness	Kurtosis	VIF
Artificial Intelligence (AI)	3.85	0.742	-0.783	0.612	2.458
Supply Chain Agility (SCA)	3.92	0.701	-0.621	0.485	2.958
Supply Chain Resilience (SCR)	3.88	0.715	-0.534	0.327	2.214
Competitive Advantage (CA)	3.95	0.689	-0.412	0.214	1.874
Competitive Pressure (CP)	3.78	0.756	-0.254	-0.700	1.518

Overall, the results of these diagnostic tests confirm that the dataset is free from significant common method bias and is suitable for further structural analysis.

4.2. Measurement Model

The measurement model was evaluated to assess the reliability and validity of the constructs, following established guidelines for Partial Least Squares Structural Equation Modeling (PLS-SEM) (Hair et al., 2021). The assessment included tests of internal consistency reliability, convergent validity, and discriminant validity.

4.2.1. Reliability and Convergent Validity

Internal consistency reliability was examined using Cronbach's alpha and composite reliability (CR). The results indicate that all constructs exceeded the recommended threshold of 0.70, demonstrating satisfactory reliability.

Convergent validity was assessed using factor loadings and average variance extracted (AVE). All item loadings were above the recommended threshold of 0.70, indicating strong indicator reliability. Additionally, the AVE values for all constructs exceeded the minimum threshold of 0.50, confirming that the constructs explain more than half of the variance of their indicators (Hair et al., 2021).

These results collectively confirm that the measurement model demonstrates adequate reliability and convergent validity (see Table 2).

Table 2. Measurement Model Assessment (Reliability and Convergent Validity)

Construct	Item	Loading	Cronbach's Alpha	CR	AVE
Artificial Intelligence (AI)	AI1	0.812	0.884	0.915	0.682
	AI2	0.845			
	AI3	0.801			
	AI4	0.836			
	AI5	0.828			
Supply Chain Agility (SCA)	SCA1	0.792	0.921	0.934	0.611
	SCA2	0.815			
	SCA3	0.804			
	SCA4	0.788			
	SCA5	0.803			
	SCA6	0.776			
	SCA7	0.781			
	SCA8	0.795			
	SCA9	0.802			
Supply Chain Resilience (SCR)	SCR1	0.823	0.879	0.912	0.674
	SCR2	0.847			
	SCR3	0.801			
	SCR4	0.829			
	SCR5	0.815			
Competitive Advantage (CA)	CA1	0.821	0.903	0.928	0.648
	CA2	0.844			
	CA3	0.798			
	CA4	0.812			
	CA5	0.826			
	CA6	0.803			
	CA7	0.789			
Competitive Pressure (CP)	CP1	0.802	0.812	0.888	0.726
	CP2	0.865			
	CP3	0.879			

4.2.2. Discriminant Validity

Discriminant validity was evaluated using the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT).

First, the Fornell–Larcker criterion was applied, where the square root of the AVE for each construct was greater than its correlations with other constructs, indicating adequate discriminant validity.

Second, the HTMT values were examined, and all values were found to be below the recommended threshold of 0.85, further confirming that the constructs are empirically distinct from one another (Henseler et al., 2015).

Overall, the results demonstrate that the measurement model satisfies the requirements for discriminant validity (see Table 3).

Table 3. Discriminant Validity Assessment
Panel A: Fornell–Larcker Criterion

Panel A: Fornell–Larcker Criterion

Construct	AI	SCA	SCR	CA	CP
AI	**0.826**				
SCA	0.621	**0.782**			
SCR	0.587	0.655	**0.821**		
CA	0.634	0.668	0.701	**0.805**	
CP	0.512	0.533	0.548	0.576	**0.852**

Panel B: HTMT Ratio

Construct	AI	SCA	SCR	CA	CP
AI	—				
SCA	0.734	—			
SCR	0.701	0.768	—		
CA	0.752	0.801	0.829	—	
CP	0.623	0.645	0.667	0.712	—

4.3. Structural Model Assessment

The structural model was assessed to test the proposed hypotheses using path coefficients (β), t-values, and p-values obtained through the bootstrapping procedure. The results indicate that artificial intelligence (AI) capability has a significant positive effect on supply chain agility, supply chain resilience, and competitive advantage. In addition, both supply chain agility and supply chain resilience significantly enhance competitive advantage, while supply chain agility also positively influences supply chain resilience.

Furthermore, the moderating effect of competitive pressure is significant, indicating that the relationship between AI capability and competitive advantage is stronger under higher levels of competitive pressure. Overall, all proposed hypotheses (H1–H7) are supported, confirming the robustness of the research model. (See Table 4)

Table 4. Structural Model Results (Hypothesis Testing)

Hypothesis	Relationship	Path Coefficient (β)	t-value	p-value	Decision
H1	AI → CA	0.284	4.512	0.000	Supported
H2	AI → SCA	0.621	12.347	0.000	Supported
H3	SCA → CA	0.301	5.128	0.000	Supported
H4	AI → SCR	0.587	10.954	0.000	Supported
H5	SCR → CA	0.276	4.763	0.000	Supported
H6	SCA → SCR	0.655	11.276	0.000	Supported
H7	AI × CP → CA	0.143	2.689	0.007	Supported

The structural model findings provide support for the hypothesized relationships (see Table 4 and Figure 2). Artificial intelligence (AI) demonstrates a significant positive effect on competitive advantage (CA), supply chain agility (SCA), and supply chain resilience (SCR), supporting H1, H2, and H4. In addition, both supply chain agility and supply chain resilience significantly enhance competitive advantage, confirming H3 and H5. Furthermore, supply chain agility is found to have a significant positive effect on supply chain resilience, supporting H6.

Regarding the moderating effect, competitive pressure (CP) significantly strengthens the relationship between AI capability and competitive advantage, supporting H7. This finding indicates that the positive impact of AI on competitive advantage becomes more pronounced under higher levels of competitive pressure.

Overall, the results confirm that AI capability plays a critical role in enhancing supply chain capabilities and improving competitive advantage in MSMEs.

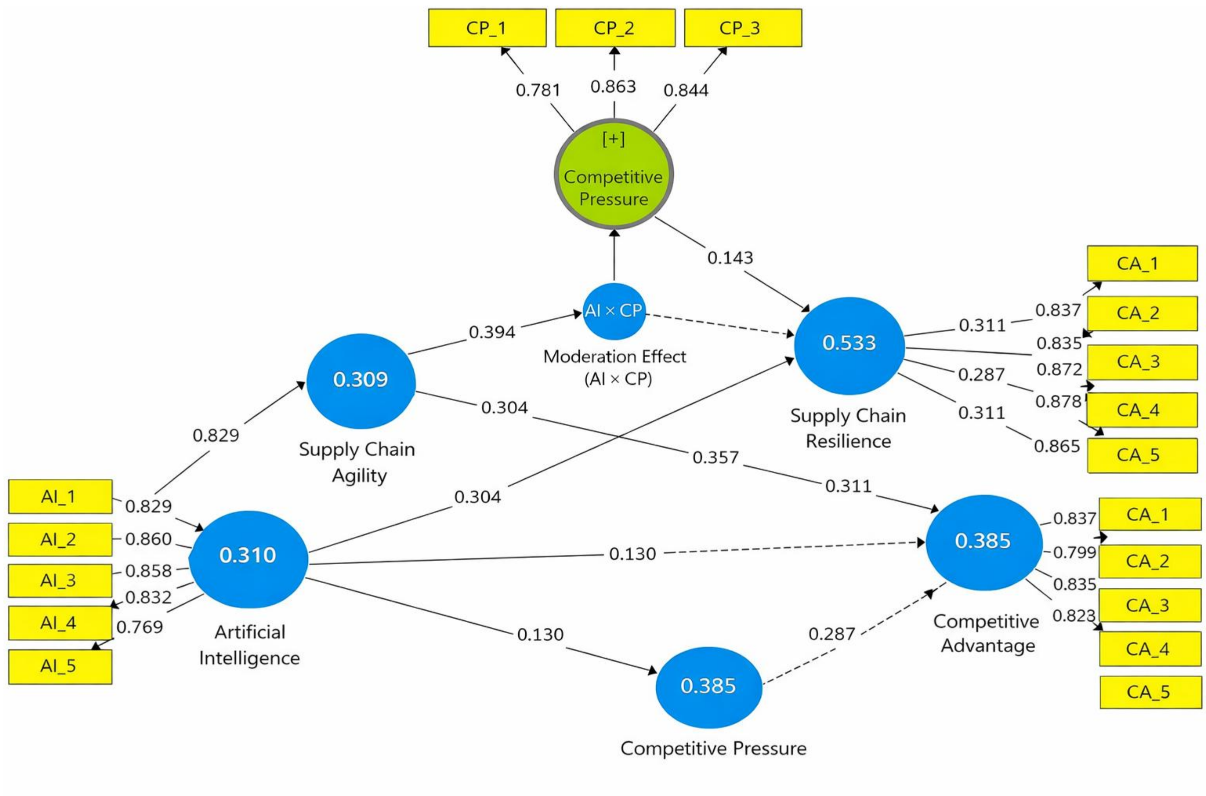

Figure 2: Tested Model

5. Discussion and Implications

Artificial intelligence (AI) is increasingly transforming business operations across industries, particularly within supply chain management. In the context of micro, small, and medium enterprises (MSMEs), AI adoption has become a critical driver for improving operational efficiency, responsiveness, and long-term competitiveness. While prior studies have explored AI and digital technologies in supply chains, limited research has empirically examined how AI capabilities influence supply chain agility, resilience, and competitive advantage simultaneously, particularly in MSMEs. This study addresses this gap by investigating the direct effects of AI on supply chain agility (SCA), supply chain resilience (SCR), and competitive advantage (CA), as well as the moderating role of competitive pressure (CP).

The findings reveal that artificial intelligence has a significant positive effect on competitive advantage, supporting H1. This result is consistent with prior research suggesting that AI enhances organizational performance by improving decision-making, reducing operational inefficiencies, and enabling data-driven strategies. In MSMEs, AI plays a crucial role in automating routine processes, improving forecasting accuracy, and enhancing customer responsiveness, thereby strengthening competitive positioning.

Regarding H2, the results indicate that AI significantly enhances supply chain agility. This finding suggests that AI enables MSMEs to respond more rapidly to market changes by improving information visibility, demand forecasting, and operational flexibility. Through real-time data analytics and predictive capabilities, AI allows firms to adapt quickly to fluctuations in demand and supply conditions.

The findings also confirm that supply chain agility positively influences competitive advantage (H3). Agile supply chains allow MSMEs to respond effectively to uncertainty, customize offerings, and maintain service quality, all of which contribute to superior market performance. This highlights agility as a critical operational capability in dynamic business environments.

In addition, AI is found to have a significant positive effect on supply chain resilience (H4). AI enhances resilience by improving risk identification, disruption forecasting, and recovery planning. MSMEs that leverage AI are better equipped to anticipate supply chain disruptions and maintain continuity under uncertain conditions.

Furthermore, supply chain resilience significantly improves competitive advantage (H5). Resilient supply chains enable firms to sustain operations during disruptions, minimize losses, and recover more quickly, thereby ensuring long-term competitiveness. This finding reinforces the strategic importance of resilience beyond traditional efficiency considerations.

The results also demonstrate that supply chain agility positively affects supply chain resilience (H6). Agile firms are better able to anticipate disruptions and respond proactively, which strengthens their resilience capabilities. This highlights the complementary relationship between agility and resilience as key dynamic capabilities in supply chain management.

Importantly, the study confirms that competitive pressure significantly moderates the relationship between AI and competitive advantage (H7). Under higher levels of competitive pressure, the positive impact of AI on competitive advantage becomes stronger. This suggests that MSMEs operating in highly competitive environments are more likely to leverage AI strategically to enhance performance and maintain their market position.

5.1. Theoretical Implications

This study contributes to the literature by extending the Resource-Based View (RBV) and Dynamic Capability Theory. It demonstrates that AI should not be viewed merely as a technological tool, but as a strategic capability that enables firms to build critical supply chain competencies such as agility and resilience.

Unlike prior studies that emphasize mediation mechanisms, this research highlights the direct and interconnected roles of supply chain capabilities in translating AI investments into competitive advantage. The findings suggest that agility and resilience function as complementary operational capabilities that enhance firm performance rather than acting solely as mediators.

Furthermore, the study emphasizes the role of competitive pressure as a contextual factor that strengthens the value of AI adoption. This provides a more nuanced understanding of how external environmental conditions influence the effectiveness of digital transformation strategies.

5.2 Managerial Implications

From a practical perspective, this study provides several important insights for MSME managers and decision-makers.

First, organizations should invest in AI technologies to enhance decision-making, forecasting, and operational efficiency. AI-driven tools such as predictive analytics, automated inventory systems, and smart procurement platforms can significantly improve supply chain performance.

Second, firms should focus on developing supply chain agility by leveraging AI for real-time data analysis and flexible operations. This enables quicker responses to market changes and improves customer satisfaction.

Third, enhancing supply chain resilience should be a strategic priority. MSMEs can use AI to identify potential risks, monitor disruptions, and implement proactive recovery strategies, ensuring business continuity.

Fourth, managers should recognize the interdependence between agility and resilience. Building agile processes will naturally strengthen resilience, allowing firms to better navigate uncertainty.

Finally, competitive pressure should be viewed as a catalyst for innovation. Firms operating in highly competitive environments should accelerate AI adoption to maintain their competitive edge. This includes investing in employee training, digital skills development, and data-driven organizational cultures.

6. Limitations and Avenues for Future Research

Despite providing valuable insights into the role of artificial intelligence (AI) in enhancing supply chain agility (SCA), supply chain resilience (SCR), and competitive advantage (CA) in MSMEs, this study has several limitations that should be acknowledged.

First, this study relies on cross-sectional survey data, which limits the ability to capture dynamic changes over time. Future research should adopt longitudinal designs to better understand how AI capabilities evolve and how firms sustain competitive advantage through continuous development of supply chain capabilities.

Second, the use of self-reported data may introduce potential response bias, despite efforts to ensure reliability and validity. Future studies are encouraged to incorporate objective performance indicators or secondary (archival) data to strengthen the robustness of findings.

Third, the data were collected from MSMEs within a specific context, which may limit the generalizability of the results. Future research should extend the analysis to different industries, regions, or larger organizations to validate the applicability of the findings across diverse settings.

Fourth, although this study focuses on supply chain agility, supply chain resilience, and competitive pressure, other important organizational and environmental factors may also influence these relationships. Variables such as leadership style, organizational culture, digital readiness, and employee AI competencies could be incorporated in future models to provide a more comprehensive understanding.

Finally, the rapid evolution of AI technologies presents new research opportunities and challenges. Emerging technologies, such as generative AI, large language models (LLMs), and AI-integrated platforms, may further transform supply chain processes and decision-making. Future research should explore how these advanced technologies reshape supply chain strategies and whether they contribute to sustainable competitive advantage in the long term.

Appendix A. Measurement of Study Variables

Construct	Code	Measurement Items	Scale
Artificial Intelligence (AI)	AI1	We possess the infrastructure and skilled resources to implement AI-based information processing systems.	1–5 Likert
	AI2	We use AI techniques to forecast demand and predict environmental changes.	1–5 Likert
	AI3	We develop data-driven insights using AI techniques such as machine learning and predictive analytics.	1–5 Likert
	AI4	We apply AI techniques across different levels of our supply chain operations.	1–5 Likert
	AI5	We use AI-generated insights to support and inform supply chain decision-making.	1–5 Likert
Competitive Advantage (CA)	CA1	Compared with our competitors, we offer unique benefits and innovative features to our customers.	1–5 Likert
	CA2	Compared with our competitors, we offer high-quality products/services.	1–5 Likert
	CA3	Compared with our competitors, we provide reliable delivery performance.	1–5 Likert
	CA4	Compared with our competitors, we provide customized products/services.	1–5 Likert
	CA5	Compared with our competitors, we deliver products/services to the market quickly.	1–5 Likert
	CA6	Compared with our competitors, we offer competitive pricing.	1–5 Likert
	CA7	Compared with our competitors, we are able to compete effectively based on quality.	1–5 Likert
Supply Chain Agility (SCA)	SCA1	Speed in reducing service lead time.	1–5 Likert
	SCA2	Speed in reducing product development cycle time.	1–5 Likert
	SCA3	Speed in increasing the frequency of new product introductions.	1–5 Likert
	SCA4	Speed in increasing levels of product/service customization.	1–5 Likert
	SCA5	Speed in adjusting delivery capabilities.	1–5 Likert

	SCA6	Speed in improving customer service responsiveness.	1–5 Likert
	SCA7	Speed in improving delivery reliability.	1–5 Likert
	SCA8	Speed in responding to changing market demands.	1–5 Likert
Supply Chain Resilience (SCR)	SCR1	Our firm's supply chain is well prepared to handle supply chain disruptions.	1–5 Likert
	SCR2	Our firm's supply chain can rapidly plan and implement contingency actions during disruptions.	1–5 Likert
	SCR3	Our firm's supply chain can effectively respond to unexpected disruptions by restoring operations quickly.	1–5 Likert
	SCR4	Our firm's supply chain can swiftly recover to its normal operational state after disruptions.	1–5 Likert
	SCR5	Our firm's supply chain can achieve improved performance after recovering from disruptions.	1–5 Likert
Competitive Pressure (CP)	CP1	Our firm adopts AI-driven solutions because competitors are implementing similar technologies.	1–5 Likert
	CP2	Our industry is increasingly shifting toward AI-based processes and business models.	1–5 Likert
	CP3	Our firm experiences external pressure (e.g., competitors, institutions) to adopt AI-based solutions.	1–5 Likert

Notes: All items were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

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