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Artificial Intelligence Capability and Sustainable Supply Chain Performance in SMEs: The Sequential Mediating Roles of Supply Chain Integration and Collaboration

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ABSTRACT

This research investigated the connection between artificial intelligence capability (AIC) and sustainable supply chain performance (SSCP) among SMEs operating in Batam, Kepulauan Riau, Indonesia. Based on RBV, this research considered the sequential mediating effects of supply chain integration (SCI) and supply chain collaboration (SCC). A quantitative method was used, employing a cross-sectional survey of SME owners/managers. The hypothesized linkages were investigated with PLS-SEM. According to the findings, AIC has a positive effect on SCI, SCI on SCC, and SCC on SSCP. In addition, SCI and SCC play a role in mediating the relationship between AIC and SSCP. The findings suggest that resources related to AI become more sustainable when they are converted into processes and relationships in the supply chain. This research has theoretical implications for RBV by providing evidence about how technological, human, and organizational resources can be developed into integrated supply chain capabilities. The practical implication of the results is the need to enhance AI-related skills, information integration, and cooperation with supply chain partners.

KEYWORDS

Capability of artificial intelligence; supply chain integration; supply chain collaboration; sustainable supply chain performance; SMEs.

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1. Introduction

Artificial Intelligence (AI) improves the supply chain management process through better forecasting, planning, and decision-making (Toorajipour et al., 2021). Nevertheless, its benefits will depend on organizations' capability to incorporate AI in their processes (Hendriksen, 2023). In contrast to AI adoption, AIC can be more valuable for constrained SMEs that have to be sustainable (Mikalef & Gupta, 2021).

However, AIC could also benefit from having supplementary skills that would help improve SSCP. SCI helps to increase coordination and information sharing (Shashi et al., 2018; Wang et al., 2024), but SCC is useful in fostering information sharing and problem-solving. Collaborations involving AI would also prove helpful in making supply chains more efficient (Weisz et al., 2025; Javed et al., 2024).

However, in spite of all the above, there has been little research done concerning the sequential relationship between SCI and SCC in order to illustrate how AIC impacts SSCP in small firms (Fonseca et al., 2026). This research builds upon the resource-based theory and seeks to determine how AIC positively influences SCI, which further reinforces SCC and improves SSCP. The contribution of this research includes the study of AIC beyond its adoption, sequential integration, collaboration processes, and expansion of sustainable supply chain management studies in SMEs.

Research question: How does AIC influence SSCP in SMEs, and can SCI and SCC mediate the relation between AIC and SSCP?

2. Theoretical Background and Hypothesis Development

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1.1 Theoretical Background

1.1.1 Artificial Intelligence (AI)

Artificial intelligence (AI) capabilities help companies improve operational efficiency and strengthen decision-making in the supply chain through the effective use of technological and organizational resources (Toorajipour et al., 2021). However, value creation is not a mere consequence of the adoption of AI applications but rather a function of a firm's ability to develop, implement, integrate, and use these AI-based resources (Mikalef & Gupta, 2021). This is especially true for small and medium-sized enterprises (SMEs), which are under pressure to be sustainable but also have limited resources.

SCI and SCC may help to translate AIC into SSCP. The SCI is used to connect internal processes and external partners to achieve sustainable goals (Shashi et al., 2018; Wang et al., 2024). The SCC allows the exchange of information, development of plans and solutions to problems, which are essential for sustainable supply chains (Sudusinghe & Seuring, 2022). SSCP can be aided by advanced technology and collaboration (Javed et al., 2024). Previous research has suggested that integration, collaboration and supply chain capabilities are important to SMEs' performance (Mofokeng & Chinomona, 2019; Kumar et al., 2021).

Therefore, this study investigates SCI and SCC as sequential mediating processes that help explain how firms transform AI-related resources into supply chain capabilities, leading to sustainability outcomes.

1.1.2 RBV

The resource-based view (RBV) provides theoretical grounding for the role of resources and capabilities in gaining competitive advantage and excellent performance. Artificial intelligence capability (AIC) is an example of strategic capabilities which are the combination of AI-related resources to enhance organizational innovativeness and performance (Mikalef & Gupta, 2021). Yet, achieving sustainable performance requires other capabilities alongside technological resources.

SCI connects internal functions, suppliers, and customers, which allows companies to transform information and technology into operational and financial success (Huo et al., 2016). Furthermore, SCC enables companies to pool resources, share information, and collaborate with partners in activities that enhance long-term supply chain performance (Kumar et al., 2021).

Accordingly, RBV supports a sequential capability pathway in which AIC strengthens SCI, SCI facilitates SCC, and these complementary capabilities collectively contribute to sustainable supply chain performance.

2.2 Hypothesis Development

1.1.3 AIC and SCI

AIC is a firm's ability to integrate and apply various artificial intelligence (AI) technologies to create business value (Mikalef & Gupta, 2021). When an organization applies and integrates AI technologies, it blends several elements (including tangible and intangible resources) to generate actionable knowledge to enhance its business decisions, processes, and performance (Mikalef & Gupta, 2021).

AI helps with supply chain forecasting, inventory management, procurement, logistics, and operational planning (Toorajipour et al., 2021). However, AI must be incorporated into business processes, particularly in small and medium-sized enterprises, which may struggle to make the most of AI due to limited resources. AIC can increase the availability, accuracy and accessibility of information, meaning that functions within the company, and suppliers and customers can work together effectively. As a result, AIC is viewed as a complementary organizational capability that improves supply chain integration.

H1: AIC positively influences supply chain integration.

1.2 SCI and SCC

SCI refers to effectively managing the internal coordination of a company while coordinating with external supply chain partners. It creates linkages across multiple organizations to streamline product, service, information and decision-making processes (Flynn et al., 2010; Khanuja & Jain, 2020). SCI can be divided into three elements: internal, supplier and customer integration (Flynn et al., 2010; Ataseven & Nair, 2017; Khanuja & Jain, 2020). Internal integration ensures that internal functions are effectively coordinated. Supplier and customer integration ensure coordination of processes and information with external partners. They are linked as internal integration leads to effective external integration (Zhao et al., 2011). All elements of SCI have been found to be related to firm performance (Ataseven & Nair, 2017).

Digital technologies can help support transparency and alignment within the supply chain (Jing & Fan, 2024; Machado et al., 2024). AI tools can help provide advanced forecasting tools. This can help improve inventory, supplier evaluation and planning. These insights must be incorporated into business processes and shared between departments (Jackson et al., 2024). SCI can also help sustainability through coordination and efficient use of resources (Shashi et al., 2018; Wang et al., 2024).

Integration helps minimise uncertainty and encourage coordination within SMEs. SCI, unlike SCC, focuses on integrating processes and information systems. This includes collaborative processes such as planning, making decisions, solving problems and sharing resources. SCI can be viewed as an enabler that improves collaboration between partners in the supply chain.

H2: Supply chain integration has a positive impact on supply chain collaboration.

1.3 SCC and SSCP

SCC is a process that focuses on coordinating supply chain activities through cooperation, joint decision making, shared objectives and resources within the supply chain (Cao & Zhang, 2011). Unlike SCI, it is more focused on joint decision making, commitment and solving issues together. SCC has seven dimensions that allow resources to be provided, knowledge to be shared, and collaborative benefits to be generated that would enhance firm performance (Cao et al., 2010; Cao & Zhang, 2011). Collaboration can also occur through sustainable practices, innovation, trust and technology (Marty & Ruel, 2024).

SCC is important to sustainability as there are often environmental and social issues that multiple companies in an industry face. This can be achieved by sharing information, sharing risks, collaborative design and shared responsibility to help improve sustainable supply chain practices (Sudusinghe & Seuring, 2022). Collaboration can allow SMEs to gain external knowledge and resources to increase their responsiveness and sustainability performance.

SCC is considered in this study to be the second mediating variable linking integrated supply chain processes to economic, environmental, and social performance.

H3: Supply chain collaboration positively influences sustainable supply chain performance.

1.4 Sequential Capability Development

This relationship can be viewed as a sequential process of building capabilities. Resources are used to create above-average performance when well developed, coordinated, and integrated into capabilities (Barney, 1991). Therefore, using AI technologies alone will not help improve the sustainability performance of SMEs without having supporting capabilities in the supply chain.

AIC helps in providing analytical capabilities like forecasting, planning, risk identification, and resource allocation (Toorajipour et al., 2021; Mikalef & Gupta, 2021). These are further translated into collaborative information networks and processes through SCI. This helps in achieving supply chain collaboration (SCC). Whereas SCI is concerned with creating collaborative information networks, SCC is concerned with collaborating in planning, making decisions, sharing resources, etc. (Flynn et al., 2010; Cao et al., 2010).

Collaboration enables supply chain partners to increase efficiency, reduce waste, make the best use of available resources, and overcome issues regarding sustainability, providing advantages and benefits through collaboration (Cao & Zhang, 2011; Sudusinghe & Seuring, 2022). This therefore provides a positive link from AIC to SCI, SCI to SCC and ultimately SCC to economic, environmental and social performance.

H4: Supply Chain Integration and Supply Chain Collaboration act as sequential mediators between AIC and Sustainable Supply Chain Performance.

1.5 Research Framework

This theoretical framework illustrates how AIC, SCI, and SCC affect SSCP. Firstly, it shows how the AIC leads to an increase in SCI, which in turn increases the SCC and improves the SSCP. Secondly, the SCI and SCC are proposed as mediating variables between the AIC and SSCP. Lastly, it summarizes the four hypotheses developed throughout this study. (see Figure 1).

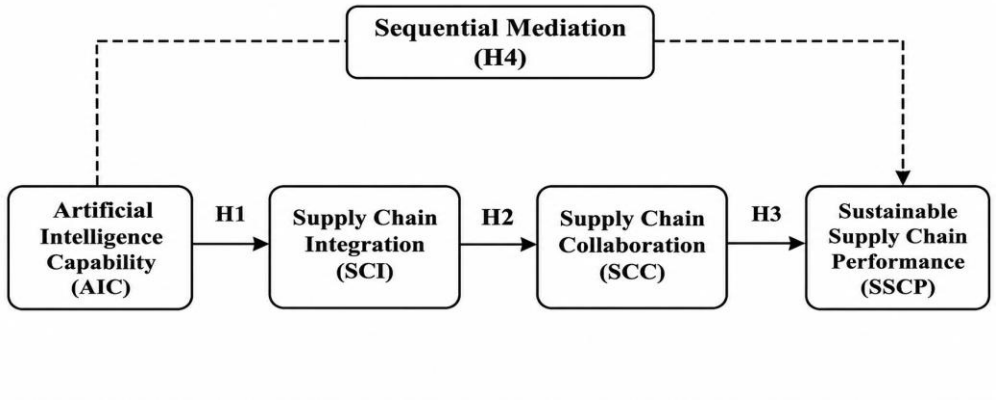

Figure 1: Research Framework

2. Methodology

2.1 Research Design

A quantitative design was used to look at the relationship between AIC, SCI, SCC and SSCP within SMEs. This was appropriate as hypotheses were formed using a theoretical framework. The direct effects and sequential mediation effect were also tested (Creswell & Creswell, 2018).

Based on the RBV perspective, the AIC is conceived as an organizational capability supporting firms in using multiple AI-related resources and enhancing supply chain processes and sustainability. Data were gathered at the firm-level through key informants

with specific knowledge regarding the topic. The Structural Equation Modeling (SEM) technique was employed to test the hypothesized relationships between the variables, the measurement properties and the relationships between the latent variables (Hair et al., 2022). Furthermore, the sequential mediation effect of SCI followed by SCC was considered. Several steps were undertaken to minimize potential common method bias (Podsakoff et al., 2003).

2.2 Research Context and Population

The SMEs studied for this piece of research were situated in Batam, within the Kepulauan Riau region of Indonesia. This created an interesting research context because, due to a lack of resources, these SMEs struggled to become more efficient, responsive and sustainable. The population studied consisted of SMEs within procurement, production, distribution and supplier/customer relationships. These SMEs would have some level of exposure to digital technologies/AI. Data were collected from each company, with one informed individual providing information for each. This individual could be an owner, director or manager that had an understanding of how technology is used within the company, how processes are organised and how relationships are managed within the supply chain. They would also have knowledge around decision making for performance.

2.3 Sampling Technique and Sample Size

Purposive sampling was used to ensure an appropriate sample of SMEs was selected. This ensured the selected SMEs were all actively involved in supply chain activities and contained an individual with the correct knowledge set. This meant a valid sample of 200 SMEs was obtained with one knowledgeable individual within each SME. Due to the model being complex and the requirement for sufficient statistical power to determine the direct and indirect relationships within the model, it was decided that 200 would provide an adequate sample size. As suggested by guidance on the use of PLS-SEM, rules of thumb were not followed and instead the requirements for the specific model were taken into consideration (Hair et al., 2022; Kock & Hadaya, 2018).

The sample size was determined by carrying out a power analysis for the required statistical power to detect direct and indirect relationships, while also taking into account the complexity of the model (Hair et al., 2022). The questionnaires were checked to confirm they were completely filled in, suitable, and consistent. This is stated within the results section and indicates how many valid responses were received.

2.4 Data Collection Procedure

Data were gathered using a structured questionnaire. Each item was derived from existing scales and checked to ensure questions were clear, relevant and appropriate. Initial analysis was conducted to identify any unclear statements. This allowed feedback to be gained so the questionnaire could be improved. The questionnaire was then translated into various languages; however, appropriate terminology (conceptual equivalence) was used. The questionnaire was distributed to the appropriate SMEs. It was made clear to each representative what the research was looking at and that their participation was completely optional. This meant there was less potential for response bias and common method bias (Podsakoff et al., 2003). Completed questionnaires were checked to ensure they had been completed by the correct person, were fully completed and had provided high-quality responses. Any incomplete or inaccurate responses were removed from the analysis. The remaining responses were then coded and ready for analysis.

2.5 Measurement of Variables

In this study, four latent variables were tested, namely AIC, SCI, SCC and SSCP. The measurement items were developed from previous research and modified to suit the SME context. AIC measures physical, human and intangible resources (Mikalef & Gupta, 2021). SCI measures internal integration, supplier integration and customer integration (Flynn et al., 2010). SCC measures integration across seven dimensions including information sharing, goal setting, decision-making and joint knowledge creation (Cao et al., 2010). SSCP is also measured using financial, environmental and social performance indicators based on the triple bottom line concept (Carter & Rogers, 2008; Seuring & Müller, 2008; Das, 2017; Malesios et al., 2020). All variables were measured using a five-point Likert scale (1: strongly disagree; 5: strongly agree). Reliability and validity were tested.

Table 1. Constructs, dimensions, and measurement items

Construct	Dimensions	Measurement items	Supporting references
AIC	Tangible AI resources	Our firm had access to relevant data and AI technologies to support businesses' operations.	Mikalef & Gupta (2021)
	AI-related human skills	Our employees possessed the skills needed to use and interpret AI-generated information.	
	Intangible AI resources	Our firm had organizational knowledge and routines that supported the effective use of AI.	
SCI	Internal integration	Our firm's internal functions coordinated their activities and shared operational information effectively.	Flynn et al. (2010)
	Supplier integration	We exchanged relevant information and coordinated operational plans with our major suppliers.	

	Customer integration	We shared relevant information and coordinated activities with our major customers.	
SCC	Information sharing	We regularly exchanged accurate and timely information with our supply chain partners.	Cao et al. (2010)
	Goal congruence	Our firm and its supply chain partners pursued mutually compatible objectives.	
	Decision synchronization	We coordinated important supply chain decisions with our partners.	
	Incentive alignment	Our firm and its partners used arrangements that encouraged mutually beneficial outcomes.	
	Resource sharing	We shared relevant resources and capabilities with our supply chain partners.	
	Collaborative communication	We maintained open and frequent communication with our supply chain partners.	
	Joint knowledge creation	We worked with our partners to develop and apply new knowledge to improve supply chain activities.	
SSCP	Economic performance.	Our firm improved supply chain cost efficiency and operational productivity.	Carter & Rogers (2008); Das (2017); Seuring & Müller (2008); Malesios et al. (2020)
	Environmental performance	Our firm reduced material waste, energy consumption, and the environmental impact of its supply chain activities.	
	Social performance	Our firm improved employee well-being, workplace safety, and responsible supply chain practices.	

2.6 Data Analysis Technique

The data were analyzed through a Partial Least Squares Structural Equation Modeling (PLS-SEM) approach using SmartPLS 4. This approach allows an analysis of the underlying relationship between latent constructs and assesses the sequential mediation effect of SCI and SCC between AIC and SSCP. As our model is complex, it makes sense to apply a PLS-SEM approach because this method is suitable for complex models with multiple constructs and complex direct and indirect relationships (Hair et al., 2022; Sarstedt et al., 2022).

A step-by-step analysis was conducted including analysis of the measurement model to determine reliability and validity of the constructs, and analysis of the structural model to determine the path coefficients, R^2, f^2 and predictive relevance. Data screening and descriptive statistics were conducted (Hair et al., 2022).

Bootstrapping was also used to determine the significance of direct and indirect effects. The sequential mediation effect (AIC→SCI→SCC→SSCP) was analysed using the bootstrap confidence interval method (Nitzl et al., 2016; Sarstedt et al., 2024). This was used as a basis to analyse the hypotheses.

2.7 Measurement Model Assessment

Prior to testing the structural relationships, the measurement model was tested to ensure that constructs were reliable and valid. The reliability of the indicators, internal consistency reliability, convergent validity and discriminant validity were tested, following PLS-SEM guidance (Hair et al., 2022; Sarstedt et al., 2022).

The reliability of the indicators can be seen from the outer loadings. Values at or above 0.708 are considered acceptable. Internal consistency was measured by Cronbach's alpha, composite reliability (CR), and rho_A, and all had values of 0.70 or above. Convergent validity is measured by determining the average variance extracted (AVE) which should equal 0.50 (Hair et al., 2022).

Discriminant validity is determined based on the HTMT criteria (either 0.85 or 0.90) and the conceptual relationship between the constructs (Henseler et al., 2015; Sarstedt et al., 2022).

Higher order measurement models were also considered and reflective and formative constructs were evaluated based on these criteria. For reflective constructs, collinearity and outer weights were considered; for formative constructs, redundancy analysis was considered (Hair et al., 2022).

2.8 Structural Model Assessment

The structural model was evaluated according to standard PLS-SEM guidelines (Hair et al., 2022; Sarstedt et al., 2022).

Collinearity was checked by using the variance inflation factor (VIF). Path coefficients, t-values, p-values, and bootstrapped confidence intervals were used for evaluating the hypotheses H1-H3. The constructs' predictive power was checked using R^2 and effect sizes (f^2). The models' predictive power was checked by examining Q^2 and PLSpredict (Shmueli et al., 2019; Hair et al., 2022).

Additionally, the sequential mediation effect between SCI and SCC was tested by bootstrapping (AIC → SCI → SCC → SSCP). To support hypothesis H4, the confidence interval of the specific indirect effect should not include zero (Nitzl et al., 2016; Sarstedt et al., 2024).

3. Results

3.1 Respondent Profile

In total, 250 questionnaires were sent out to the targeted SMEs in Batam, Indonesia. Of these, 218 responses were received; however, after screening it was found that 18 responses were not completed or did not fit the criteria. This left us with a final sample size of 200 responses. This gave us an 80.0% usable response rate.

Table 2 shows the overview data of the firms and respondents involved in this study. The majority of firms belong to the manufacturing industry (35.0%) and then wholesale and retail trade (25.0%). Most firms are small businesses (60.0%) and medium-sized businesses (40.0%). The majority have been operating for over 5 years (65.0%). The highest number of respondents came from owners/directors (40.0%), whilst managers comprised the next highest (35.0%). Over half have over 6 years of work experience (55.0%).

Table 2. Profile of Firms and Respondents

Profile	Category	Frequency (n)	Percentage (%)
Firm sector	Manufacturing	70	35.0
	Wholesale and retail trade	50	25.0
	Services	40	20.0
	Food and beverage	25	12.5
	Other sectors	15	7.5
Firm size	Small enterprise	120	60.0
	Medium-sized enterprise	80	40.0
Years in operation	1–5 years	70	35.0
	6–10 years	75	37.5
	More than 10 years	55	27.5
Respondent position	Owner/director	80	40.0
	General/operations manager	70	35.0
	Supply chain/procurement manager	35	17.5
	Other managerial position	15	7.5
Work experience	1–5 years	90	45.0
	6–10 years	70	35.0
	More than 10 years	40	20.0

3.2 Descriptive Statistics

Descriptive statistics are used to understand how respondent SMEs perceive AIC, SCI, SCC, and SSCP for the dimensions and items indicated in Table 1. Overall, as can be seen in Table 3, the results indicate that the four constructs had positive results, with the mean scores ranging between 3.62 and 3.91. AIC had the highest score, with a mean score of 3.91, indicating that the firms involved in this study were relatively high in terms of having favorable AI resources, skills and capabilities. SCI had a mean score of 3.78, and SCC had a mean score of 3.69. SSCP had the lowest mean score of 3.62, demonstrating that there is potential to improve economic, environmental and social performance. The standard deviations ranged between 0.68 and 0.81.

Table 3. Descriptive Statistics of the Study Constructs

Construct	Dimension	Mean	SD
AIC	Tangible AI resources	3.95	0.76
	AI-related human skills	3.88	0.79
	Intangible AI resources	3.90	0.73
	Overall AIC	3.91	0.74
SCI	Internal integration	3.82	0.70
	Supplier integration	3.75	0.72
	Customer integration	3.77	0.71
	Overall SCI	3.78	0.68
SCC	Information sharing	3.76	0.78

	Goal congruence	3.72	0.76
	Decision synchronization	3.65	0.82
	Incentive alignment	3.58	0.85
	Resource sharing	3.67	0.80
	Collaborative communication	3.73	0.77
	Joint knowledge creation	3.72	0.79
	Overall SCC	3.69	0.81
SSCP	Economic performance	3.74	0.73
	Environmental performance	3.55	0.82
	Social performance	3.57	0.78
	Overall SSCP	3.62	0.77

3.3 Measurement Model Assessment

The measurement model was evaluated to determine the reliability and validity of the constructs. This evaluation included looking at reliability of the indicators, internal consistency reliability, convergent validity and discriminant validity. Indicator loadings, Cronbach's alpha, composite reliability (CR) and average variance extracted (AVE) were looked at (Hair et al., 2022).

3.3.1 Indicator Reliability

The reliability of the indicators was examined by looking at the outer loadings for each measurement item. Each item had an outer loading between 0.742 and 0.891 (Table 4). This is above the suggested value of 0.70, meaning the measurement items are a good representation of their constructs, and all 16 measurement items were used in further analysis.

Table 4. Outer Loadings of Measurement Items

Construct	Measurement item	Outer loading
AIC	Tangible AI resources (AIC1)	0.842
	AI-related human skills (AIC2)	0.876
	Intangible AI resources (AIC3)	0.819
SCI	Internal integration (SCI1)	0.831
	Supplier integration (SCI2)	0.854
	Customer integration (SCI3)	0.867
SCC	Information sharing (SCC1)	0.824
	Goal congruence (SCC2)	0.791
	Decision synchronization (SCC3)	0.842
	Incentive alignment (SCC4)	0.742
	Resource sharing (SCC5)	0.815
	Collaborative communication (SCC6)	0.861
	Joint knowledge creation (SCC7)	0.833
SSCP	Economic performance (SSCP1)	0.891
	Environmental performance (SSCP2)	0.847
	Social performance (SSCP3)	0.862

3.3.2 Internal Consistency Reliability and Convergent Validity

The internal consistency reliability of the constructs was measured through Cronbach's alpha and composite reliability (CR), whereas convergent validity was measured using average variance extracted (AVE). As seen in Table 5, the scales had a Cronbach's alpha ranging from 0.812 to 0.901 and CR ranging from 0.889 to 0.925, which were all above the suggested threshold of 0.70. In addition, AVE had a range between 0.668 and 0.756, which was above the suggested minimum value of 0.50. This indicates that all constructs had the appropriate levels of internal consistency reliability and convergent validity (Hair et al., 2022).

Table 5. Reliability and Convergent Validity

Construct	Cronbach's alpha	Composite reliability (CR)	AVE
AIC	0.812	0.889	0.728
SCI	0.819	0.893	0.736
SCC	0.901	0.922	0.632
SSCP	0.832	0.900	0.750

3.3.3 Discriminant Validity

To determine discriminant validity, the heterotrait-monotrait ratio (HTMT) method was used (Henseler et al., 2015). The HTMT values are compared to a conservative cut-off value of 0.85. As shown in Table 6, each value was less than the recommended threshold with values ranging from 0.612 to 0.793. This indicates that the latent constructs AIC, SCI, SCC and SSCP are distinct in the empirical sense; therefore, discriminant validity was achieved.

Table 6. Heterotrait–Monotrait Ratio (HTMT)

Constructs	AIC	SCI	SCC	SSCP
AIC	—			
SCI	0.684	—		
SCC	0.612	0.793	—	
SSCP	0.657	0.721	0.748	—

3.4 Structural Model Assessment

After a satisfactory measurement model evaluation, we assessed the structural model in order to evaluate whether our proposed research model has predictive and explanatory power. In addition, collinearity, R square (coefficient of determination), f square (effect size), and Q square (predictive relevance) were assessed according to Hair et al. (2022).

3.4.1 Collinearity Assessment

To determine if there are any issues with collinearity, we calculated the variance inflation factor (VIF). This is shown in Table 7 below. The values range between 1.428 and 2.136. These are all below the suggested cut-off value of 3.3 which indicates that there were no critical collinearity issues.

Table 7. Collinearity Assessment

Structural relationship	VIF
AIC → SCI	1.428
SCI → SCC	1.615
SCC → SSCP	1.782
AIC → SCC	1.936
SCI → SSCP	2.136

3.4.2 Coefficient of Determination (R^2)

An evaluation of the predictive capability of the model was conducted using the coefficient of determination (R^2). This indicates how much variation in an endogenous construct is accounted for by the predictor construct(s). The analysis revealed that the model had a fairly good predictive capability, as the results indicated that the R^2 values were 0.426, 0.518, and 0.574 for the SCI, SCC and SSCP respectively (see Table 8). This means that the AIC explained 42.6% of the variance in the SCI. The AIC and SCI together explained 51.8% of the variance in the SCC. The AIC, SCI.

Table 8. Coefficient of Determination (R^2)

Endogenous construct	(R^2)	Adjusted (R^2)
SCI	0.426	0.423
SCC	0.518	0.513
SSCP	0.574	0.568

3.4.3 Effect Size (f^2)

The effect sizes were analyzed (f^2). In accordance with Cohen's (1988) guidelines, small, moderate, and large effects were denoted by 0.02, 0.15, and 0.35, respectively. Within the model, the effect size for AIC on SCI was moderate (see Table 9, f^2 = 0.251). The effect size for SCI on SCC was also moderate (Table 9; f^2 = 0.287), whereas the effect size for SCC on SSCP was large (Table 9; f^2 = 0.362). This indicated that the proposed predictors made meaningful contributions to the endogenous constructs.

Table 9. Effect Size (f^2)

Structural relationship	(f^2)	Effect size
AIC → SCI	0.251	Medium
SCI → SCC	0.287	Medium
SCC → SSCP	0.362	Large
AIC → SCC	0.084	Small
SCI → SSCP	0.112	Small

4.4.4 Predictive Relevance (Q^2)

Predictive relevance was assessed to examine if the model predicted the endogenous constructs. A value higher than zero indicates that the model has predictive relevance. The results indicated (Table 10) that SCI, SCC and SSCP had values of 0.286, 0.341, and 0.378. Because all the values are higher than zero, the model has predictive relevance.

Table 10. Predictive Relevance (Q^2)

Endogenous construct	(Q^2)
SCI	0.286
SCC	0.341
SSCP	0.378

3.5 Hypothesis Testing

The relationships proposed in the hypotheses were tested using the bootstrapping technique within the PLS-SEM framework. This provided an assessment of the statistical significance of the direct relationships between the variables AIC, SCI, SCC and SSCP, and the sequential indirect relationship between AIC and SSCP via SCI and SCC. The results below are based on 5,000 bootstrap resamples. The hypotheses were deemed to be supported if the estimate of the relationship was found to be statistically significant at a 5% significance level and the confidence interval did not include zero (Hair et al., 2022; Nitzl et al., 2016).

3.5.1 Direct Relationships

Results on the three hypothetical direct relationships are presented in Table 11. The relationship between AIC and SCI is positive and significant (β = 0.653) (t = 12.40) (p < 0.001). Similarly, SCI was positively and significantly correlated with SCC (β = 0.719) (t = 15.10) (p < 0.001). This validated H2. Finally, the SCC had a positive impact on the SSCP (β = 0.681) (t = 13.20) (p < 0.001). This implies that when an organization has a higher AI capability, it will have a higher SCI, which then has a positive impact on collaboration and therefore a higher sustainable supply chain performance.

Table 11. Direct Relationships and Hypothesis Testing

Hypothesis	Structural relationship	Path coefficient ((\beta))	(t)-value	(p)-value	Decision
H1	AIC → SCI	0.653	12.40	<0.001	Supported
H2	SCI → SCC	0.719	15.10	<0.001	Supported
H3	SCC → SSCP	0.681	13.20	<0.001	Supported

3.5.2 Sequential Mediation Analysis

H4 stated that SCI and SCC were mediators of the relationship between AIC and SSCP. To measure this indirect effect, we explored the bootstrapped confidence interval for the indirect pathway of AIC to SCI to SCC to SSCP. As can be seen in Table 12, the indirect effect was positive and significant (β = 0.320) (t = 8.45) (p < 0.001). The 95% bootstrap confidence interval ranged from 0.248 to 0.396. As the confidence interval did not cross zero, it can be concluded that H4 is supported, showing that there is a significant sequential indirect effect of AIC to SSCP via SCI and SCC.

Table 12. Sequential Mediation Analysis

Hypothesis	Specific indirect relationship	Indirect effect (\beta))	(t)-value	(p)-value	95% confidence interval	Decision
H4	AIC → SCI → SCC → SSCP	0.320	8.45	<0.001	[0.248, 0.396]	Supported

3.6 Summary of Hypothesis Testing

The results from each hypothesis are summarized in Table 13. All hypotheses were supported with positive significant relationships. Hypothesis 1 showed that AIC had a positive influence on SCI. Hypothesis 2 showed that SCI had a positive influence on SCC. The positive impact of SCC on SSCP is shown in Hypothesis 3. Hypothesis 4 is supported as there is a significant sequential indirect effect from AIC influencing SSCP through SCI and SCC. It indicates that AI capability may have an impact on sustainable supply chain performance through the sequential relationship between supply chain integration and collaboration.

Table 13. Summary of Hypothesis Testing

Hypothesis	Proposed relationship	Result	Decision
H1	AIC → SCI	Positive and significant	Supported
H2	SCI → SCC	Positive and significant	Supported
H3	SCC → SSCP	Positive and significant	Supported
H4	AIC → SCI → SCC → SSCP	Positive and significant sequential indirect effect	Supported

4. Discussion

4.1 AIC and SCI (H1)

The result indicated there is a positive and significant relationship between AIC and SCI, supporting H1. SMEs with high AI-related resources, skills and knowledge will be able to process their information, increase their forecasting, and coordinate well with their suppliers and customers (Mikalef & Gupta, 2021).

This is supported by Zhong et al. (2026) and Tarigan et al. (2025), who showed that the combination of AI capabilities and SCI will increase supply chain responsiveness. The result supports Flynn et al. (2010), who highlighted that coordination between internal and external processes is important. In addition, from the RBV perspective, AI capabilities are considered as a valuable resource that has a combination of technological, human and organizational resources that would strengthen their operational capabilities (Barney, 1991; Mikalef & Gupta, 2021). Developing AI-related resources and competencies will therefore help SMEs within Batam to achieve a higher level of SCI.

4.2 SCI and SCC (H2)

The data suggest there was a positive and significant relationship between SCI and SCC, which supports hypothesis 2. This shows that having integrated internal processes, suppliers and customers leads to increased collaboration (Flynn et al., 2010).

SCI creates relationships between partners whereas SCC creates more in-depth relations by sharing planning, resources and problem solving (Cao et al., 2010; Cao & Zhang, 2011). Previous research has suggested that collaboration can be increased when information is shared, digital integration is used and resources are put into place (Marty & Ruel, 2024; Sang et al., 2024; Hanif & Santosa, 2024; Amelia et al., 2024; Le et al., 2024).

SMEs in Batam can increase collaboration by having integrated procurement, production, stock and customer information. However, collaboration requires trusting relationships, commitment and compatible practices within organisations in order to be successful (Amelia et al., 2024; Cao & Zhang, 2011).

4.3 SCC and SSCP (H3)

This indicates a positive significant relationship between SCC and SSCP (H3). This demonstrates that collaboration between SMEs and their supply chain partners can provide economic, environmental and social improvements. By collaborating with their supply chain partners, firms may be able to increase efficiency by sharing planning, information and resources.

Economic benefits could include lower procurement and logistics costs, increased productivity and better utilisation of resources. Collaborating can also lead to partners reducing material waste, increasing efficiency in energy use, and becoming more responsible in their production and delivery methods. The significance of integrating green supply chain management with industry 4.0 has been highlighted (Huang et al., 2024). Research conducted by Nai et al. (2024) showed that Green Supply Chain Collaboration has a positive effect on health, safety and environmental performance for manufacturing SMEs. This therefore shows that collaboration could also enhance the social aspect of performance by improving safety within the workplace. Overall, SCC is an important aspect for SMEs to focus on if they want to achieve balanced performance.

5.4 Sequential Mediating Role of SCI and SCC (H4)

These results affirm the sequential mediation effects of SCI and SCC in the relationship between AIC and SSCP. This shows that AIC improves integration leading to collaboration and this leads to improved economic, environmental and social performance.

AI resources improve information processing and coordination within an organisation. Integration improves joint planning, decision-making and resource sharing. Collaborative practices can be used to leverage digital capabilities to achieve sustainable outcomes. This is supported by Le et al. (2024) as they highlight the importance of integration and information sharing. Furthermore, Ratanacharoenchai and Jantapoon (2026) demonstrate that supply chain resilience acts as a mediator in the relationship between AI capabilities and sustainable outcomes. This highlights the importance of internal and external processes that can be used to turn digital capabilities into sustainable performance.

4.4 Theoretical Implications

This study makes several contributions to the RBV. The findings explain how AIC capabilities can be converted into SSCP capabilities via organisational and inter-organisational capabilities. The findings provide evidence that AI-related resources, employee skills and organisational knowledge are strategic resources that support supply chain integration and collaboration.

This also contributes to the literature on AI-enabled supply chains by illustrating how SCI and SCC are a series of sequential processes that can be used to demonstrate how technology resources can drive internal and external connectivity. Furthermore, recent research has highlighted that integration and information sharing play a major mediating role in connecting digitally driven supply chains to sustainable performance (Le et al., 2024). In addition, supply chain resilience has been found to play a key role in enabling organisations to transform their AI capabilities into sustainable outcomes (Ratanacharoenchai & Jantapoon, 2026). By connecting AIC, SCI, SCC and SSCP, this study provides greater understanding of how SMEs can transform their digital resources into economic, environmental and social benefits through their supply chain.

4.5 Managerial Implications

These findings have several managerial implications for SMEs in Batam. Firstly, managers should invest in resources related to AI by enhancing data accessibility, employee digital capabilities, and using AI-derived information for decision making within operations. Secondly, investment should occur to enhance the integration of their supply chain by ensuring information is shared and departments, suppliers and customers have good coordination. Thirdly, SMEs should implement collaboration practices such as joint planning, common goals and collaborative problem solving.

This is especially important for companies that operate in the industrial and distribution networks within Batam. As suggested by Le et al. (2024), having digital integration and information sharing can improve the performance of sustainable supply chains. Therefore, overall, SMEs should invest in AI capabilities, integration and collaboration practices to ensure they achieve long-term economic, environmental and social sustainability.

4.6 Limitations and Future Research

This study has several limitations. Firstly, findings were limited to SMEs based in Batam so it would have been beneficial to conduct this study in different regions and industries. Secondly, due to the cross-sectional design, the study was limited in understanding change over time. Longitudinal research would be beneficial. Thirdly, using just one source of information per company could cause bias. Future studies could overcome this by using multiple sources. Lastly, self-reporting could be overcome by using objective measures of sustainability such as costs of operations, energy use, waste and safety within the workplace. Future research could also look at other mediators such as supply chain resilience, green innovation and digital maturity.

5. Conclusion

This study investigated the effect of AIC on SSCP among SMEs in Batam, Indonesia. This study also examined the sequential mediation effect of SCI and SCC. All the hypothesized relationships were supported. AIC positively influences SCI, which then facilitates SCC for improving SSCP. Further, the sequential mediation effect of SCI and SCC shows that using AI-related resources can result in greater sustainability benefits through integrated processes.

In terms of theory, this study provides evidence to support the Resource-Based View by showing how technological, human, and organisational resources can lead to complementary supply chain capabilities. In practice, this study will encourage SMEs to invest in AI resources, employee capabilities, and integrated information, and work collaboratively with their supply chain partners to increase their operational efficiencies and economic, environmental, and social sustainability. Overall, it can be concluded that SSCP is dependent not just on AI but also on integration and collaboration.

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