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Artificial Intelligence For Supply Chain Efficiency In Batam's Manufacturing Sector

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Abstract: *This study investigates the role of Artificial Intelligence (AI) in enhancing supply chain efficiency in Batam's manufacturing sector, focusing on firms in the electronics, shipbuilding, plastics, automotive, and related industries operating within the Free Trade Zone and Special Economic Zone. Drawing on the Resource-Based View (RBV), AI is conceptualized as a strategic capability comprising Machine Learning (ML), Robotics and Automation (R&A), Internet of Things (IoT), Natural Language Processing and Chatbots (NLP&C), and Computer Vision (COMV). Data were collected through a structured questionnaire administered to managers and supervisors from 320 purposively selected firms and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The study also models Supply Chain Automation Processes (SCAP)—including inventory, logistics, procurement, warehouse operations, and predictive maintenance—as a mediating mechanism between AI adoption and Supply Chain Efficiency (SCE). The results show that IoT and ML are the most influential AI technologies, significantly improving operational efficiency, accuracy, responsiveness, and customer satisfaction. Inventory management, warehouse automation, logistics optimization, and predictive maintenance emerge as critical automation domains translating AI capabilities into tangible performance gains. R&A and COMV exhibit weaker or context-dependent effects, reflecting capital intensity and integration challenges, particularly for small and medium-sized enterprises. Overall, AI and SCAP jointly explain a substantial proportion of the variance in supply chain efficiency, highlighting that AI yields the greatest benefits when embedded in end-to-end automation. The findings provide theoretical contributions by disaggregating AI into specific sub-technologies and practical guidance for firms and policymakers in Batam to prioritize IoT- and analytics-driven initiatives for scalable, resilient, and competitive supply chains.*
Keywords: *Artificial Intelligence, Machine Learning, Internet of Things (IoT), Predictive Analytics, Resource-Based View (RBV)*

INTRODUCTION

Batam has emerged as a hub for smart manufacturing, with firms increasingly integrating Artificial Intelligence (AI) to enhance supply chain management (SCM). High-profile examples include Pegatron's AI- and 5G-powered smart factory, which employs predictive maintenance, inventory optimization, and production planning (PR Newswire, 2025), and Schneider Electric's facility, recognized as a Fourth Industrial Revolution (4IR) Lighthouse for its adoption of AI, automation, and data-driven manufacturing practices (Weber, 2021; Avelar et al., 2023). These cases illustrate Batam's readiness to implement AI and demonstrate the technology's potential to improve operational efficiency, responsiveness, and competitiveness.

AI technologies such as Machine Learning (ML), predictive analytics, robotics, and the Internet of Things (IoT) offer unique capabilities across Batam's manufacturing sector (Shamsuddoha, 2025). ML enhances demand forecasting and inventory optimization, predictive analytics enables proactive disruption management, robotics improves warehouse efficiency, and IoT provides real-time visibility of inventory, equipment, and logistics (Kagalwala, 2025).

Despite these advancements, Batam's manufacturing sector faces complex supply chain challenges, including multi-tier supplier networks, demand variability, cost pressures, and extended global operations (Toorajipour, 2021). While AI adoption is progressing, evidence on its collective impact across logistics, procurement, and warehouse management remains limited.

This study examines AI adoption, applications, and benefits in Batam's manufacturing sector, focusing on ML, predictive analytics, robotics, and IoT. The findings aim to guide practitioners in improving efficiency, reducing costs, and enhancing supply chain responsiveness, while contributing to the broader literature on digital transformation in SCM (Shamsuddoha, 2025; Culot, 2024).

METHOD

Population and Sample

The study population comprises 1,309 registered manufacturing firms in Batam, Indonesia, spanning electronics, shipbuilding, automotive, plastics, and consumer goods, within a Free Trade Zone (FTZ) and Special Economic Zone (SEZ) (BP Batam, 2024; 2025). These firms are highly relevant for examining supply chain management and technological adoption.

A purposive sampling strategy was employed, selecting firms that are formally registered, actively engaged in supply chain operations, willing to participate, and varied in size and sector, ensuring information-rich and representative cases (Etikan, Musa, & Alkassim, 2016). Sample size was determined using Slovin's formula and Krejcie & Morgan's (1970) table, suggesting 307–297 firms for a 95% confidence level and 5% margin of error. To accommodate non-response and maintain sectoral and size representation, a target sample of 320 firms was set, balancing feasibility and representativeness for robust analysis.

Assessing common method bias

Since this study relies on survey data from Batam's manufacturing firms to measure both AI adoption and supply chain efficiency, the risk of common method bias (CMB) was carefully addressed (Podsakoff et al., 2003). To mitigate potential bias, several procedural remedies were applied, including ensuring respondent anonymity, providing clear instructions, separating predictor and outcome measures, and carefully wording items to minimize ambiguity or social desirability.

In addition, statistical tests were performed. Harman's single-factor test showed that no dominant factor explained the variance, while full collinearity checks confirmed that all VIFs were below the 3.3 threshold (Kock, 2015). A marker-variable test further validated the robustness of the results.

Taken together, these steps confirm that CMB does not significantly affect the findings, ensuring that the observed effects genuinely reflect the role of AI in enhancing supply chain efficiency within Batam's manufacturing sector.

Questionnaire Design

To examine the relationships between AI technologies, supply chain automation processes, and supply chain efficiency, this study operationalized the constructs using validated measurement items from prior research. AI technologies were measured across five key dimensions—Machine Learning (ML), Robotics and Automation (R&A), Internet of Things (IoT), Natural Language Processing and Chatbots (NLP&C), and Computer Vision (COMV)—reflecting the most relevant innovations in supply chain transformation (Kamble et al., 2023; Marinov et al., 2023; Wamba & Queiroz, 2020).

Supply Chain Automation Processes were captured through five dimensions: Inventory Management Automation (IMA), Logistics and Transportation Automation (L&TA), Procurement and Supplier Management Automation (P&MA), Warehouse Operations Automation (WOA), and Predictive Maintenance (PREM), which represent AI-enabled integration into core supply chain functions (Papadopoulos et al., 2022; Sharma et al., 2023).

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Finally, Supply Chain Efficiency (SCE) was assessed through Operational Efficiency (OPE), Speed and Responsiveness (S&RES), Accuracy and Reliability (AC&REL), Resilience and Risk Mitigation (R&RM), and Customer Satisfaction (CUSSAT), covering both internal performance outcomes and customer-facing results (Dubey et al., 2022; Ivanov, 2022; Hazen et al., 2022). A detailed summary of constructs and their measurement items is provided in Table 3.1.

Variable	Construct	Items	Questionnaire Statment	References
	Machine Learning (ML	ML1	Our organization uses machine learning to improve demand forecasting accuracy.	Kamble et al., 2023; Wamba et al., 2022)
		ML2	Machine learning helps optimize inventory levels and reduce stockouts.	
		ML3	Predictive analytics from machine learning support better decision-making in supply chain operations.	
		ML4	Machine learning models are used to identify patterns and trends in supply chain data.	
AI Technologies	Robotics & Automation (R&A)	R&A1	Our supply chain operations use robotics to automate routine tasks (e.g., picking, packing, sorting).	Marinov et al., 2023; Queiroz et al., 2022)
		R&A2	Autonomous vehicles or drones are considered/used for transportation and delivery in our supply chain.	
		R&A3	Robotics adoption has increased the efficiency of warehouse operations.	
		R&A4	Automation reduces dependency on manual labor in supply chain processes.	
	Internet of Things (IoT)	IoT1	IoT devices are used for real-time tracking of goods and shipments.	Papadopoulos et al., 2022; Wamba & Queiroz, 2020)
		IoT2	Sensors and IoT-enabled devices monitor the condition of products (e.g., temperature, location).	
		IoT3	IoT technology provides visibility across different stages of the supply chain.	

		IoT4	The use of IoT has improved coordination between supply chain partners.	
	Natural Language Processing & Chatbots (NLP&C)	NLP&C1	Chatbots are used to handle routine customer service inquiries in our supply chain.	Chung et al., 2022; Dwivedi et al., 2021
		NLP&C2	NLP tools are applied to automate communication with suppliers and partners.	
		NLP&C3	Chatbots/NLP reduce response time in handling supply chain-related queries.	
		NLP&C4	The use of NLP&C technologies has enhanced overall communication efficiency.	
	Computer Vision (COMV)	COMV1	Computer vision is used for quality inspection and defect detection in supply chain operations.	Zonta et al., 2020; Sharma et al., 2023)
			Our warehouses use image recognition technologies for sorting and inventory checks.	
			Computer vision has improved accuracy in product handling and logistics processes.	
			The adoption of computer vision has reduced errors in warehouse or production operations.	
Supply Chain Automation Processes	Inventory Management Automation (IMA)	IMA1	AI-driven systems are used to optimize inventory levels in our organization.	Kamble et al., 2023; Wamba et al., 2022)
		IMA2	Inventory replenishment is automated based on demand forecasts.	
		IMA3	Automation helps reduce stockouts and overstock situations.	
		IMA4	Real-time data analytics are applied to monitor and manage inventory	
	Logistics & Transportation Automation (L&TA)	L&TA1	AI-enabled route optimization tools are used to improve delivery efficiency.	Papadopoulos et al., 2022; Stelia, 2025)
		L&TA2	Our organization uses automated scheduling systems for fleet management	

		L&TA3	Autonomous or semi-autonomous vehicles are considered/used for delivery	
		L&TA4	Logistics automation has reduced delivery time and transportation costs.	
	Procurement & Supplier Management Automation (P&MA)	P&MA1	AI tools are used to evaluate and select suppliers based on performance criteria.	Sharma et al., 2023; Queiroz et al., 2022)
		P&MA2	Supplier risk analysis is supported by automated systems.	
		P&MA3	Procurement processes (e.g., purchase orders, approvals) are digitally automated.	
		P&MA4	Automation has improved collaboration and compliance with suppliers.	
	Warehouse Operations Automation (WOA)	WOA1	Our warehouse uses automated systems for picking, packing, and sorting.	Marinov et al., 2023; All About AI, 2025)
		WOA2	Robotics are deployed to streamline storage and retrieval processes.	
		WOA3	Warehouse automation has improved order accuracy and reduced errors.	
		WOA4	Automation has significantly increased productivity in warehouse operations.	
	Predictive Maintenance (PREM)	PREM1	AI-based predictive systems are used to monitor equipment health.	Zonta et al., 2020; Times of India, 2025
		REM2	Predictive analytics are applied to detect potential equipment failures.	
		REM3	Maintenance schedules are automated based on predictive insights.	
		REM4	Predictive maintenance has reduced downtime and operational disruptions.	
Supply Chain Efficiency	Operational Efficiency (OPE)	OPE1	Our supply chain automation has reduced overall operational costs.	Dubey et al., 2022; Wamba et al., 2022
		OPE2	Resources (e.g., materials, manpower, equipment) are utilized more effectively.	

		OPE3	Automation has improved production and distribution efficiency.	
		OPE4	Operational processes are streamlined and less wasteful.	
	Speed & Responsiveness (S&RES)	S&RES1	Our supply chain responds quickly to changes in customer demand.	Bag et al., 2021; Ivanov, 2022)
		S&RES2	Decision-making processes are faster due to real-time data insights.	
		S&RES3	Delivery times have significantly improved with automation.	
		S&RES4	Our supply chain adapts promptly to market fluctuations.	
	Accuracy & Reliability (AC&REL)	AC&REL1	Automation has reduced errors in order processing and fulfillment.	Queiroz & Fosso Wamba, 2022; Kamble et al., 2023)
		AC&REL2	Inventory data is highly accurate and reliable.	
		AC&REL3	Logistics and delivery schedules are consistently met.	
		AC&REL4	Automated systems improve forecasting accuracy.	
	Resilience & Risk Mitigation (R&RM)	R&RM1	Our supply chain recovers quickly from unexpected disruptions.	Ivanov, 2022; Chowdhury et al., 2023)
		R&RM2	Automation has reduced downtime during operational interruptions.	
		R&RM3	Predictive insights help mitigate risks before they escalate.	
		R&RM4	Our supply chain maintains stability even under crisis conditions.	
	Customer Satisfaction (CUSSAT)	CUSSAT1	Customers receive their orders on time more consistently.	Hazen et al., 2022; Papadopoulos et al., 2022)
		CUSSAT2	Service quality has improved due to supply chain automation.	
		CUSSAT3	Customer complaints related to delays and errors have decreased.	
		CUSSAT4	Overall customer satisfaction with our supply chain performance has increased.	

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Table 1. *Construct and Measurement Items*

RESULT AND DISCUSSION

This part reports the empirical findings on how Artificial Intelligence (AI) technologies influence Supply Chain Efficiency (SCE) in Batam's manufacturing sector. The analysis focuses on both direct effects of AI—through Machine Learning, Robotics and Automation, Internet of Things, Natural Language Processing, and Computer Vision—and indirect effects mediated by Supply Chain Automation Processes (SCAP), which include inventory, logistics, procurement, warehouse operations, and predictive maintenance.

The results are presented in a structured sequence: first, respondent and firm profiles; second, descriptive insights into AI adoption and efficiency levels; third, measurement model validation to confirm construct reliability; and finally, structural model testing and hypotheses results. By integrating both direct and mediated pathways, the analysis clarifies not only whether AI enhances efficiency outcomes such as responsiveness, reliability, resilience, and customer satisfaction, but also how automation processes serve as the mechanism translating AI capabilities into tangible supply chain performance improvements.

Profile of Respondents and Firms

The survey respondents were mainly individuals in managerial or supervisory roles, given their familiarity with both AI adoption and supply chain processes. As shown in Table 4.1, the sample included a slightly higher proportion of male respondents (58%) compared to female respondents (42%), which is consistent with the male-dominated nature of managerial positions in the manufacturing industry. Most respondents were in the 31–45 age group (52%), indicating mid-career professionals, while younger respondents (21–30 years) accounted for 28%, and senior professionals above 46 years made up 20%. Regarding education, the majority held a bachelor's degree (64%), followed by postgraduate qualifications (22%), and a smaller proportion had a diploma or equivalent (14%). In terms of job roles, supply chain and operations managers were the largest group (38%), followed by production managers (25%), procurement managers (20%), and IT/digital transformation managers (17%).

Category	Frequency	Percentage (%)
Gender		
Male	185	58.0
Female	135	42.0
Age		
21–30 years	90	28.0
31–45 years	165	52.0
46 years and above	65	20.0
Education		
Diploma/Equivalent	45	14.0
Bachelor’s Degree	203	64.0
Postgraduate Degree	70	22.0
Managerial Role		
Supply Chain/Operations	120	38.0
Production	80	25.0
Procurement	65	20.0
IT/Digital	55	17.0

***Table 2**. Respondent Demographics*

The firms represented in the study reflected the diversity of Batam’s industrial base. As indicated in Table 3 the electronics industry (34%) had the highest representation, consistent with Batam’s role as an electronics manufacturing hub. Other sectors included shipbuilding (20%), plastics and packaging (18%), machinery/automotive (15%), and others such as consumer goods and textiles (13%). With regard to firm size, medium-sized firms (45%) dominated the sample, followed by large firms (35%) and small firms (20%). In terms of ownership, 55% of firms were foreign-owned (FDI), while 45% were domestically owned. This distribution mirrors Batam’s industrial structure, where multinational corporations coexist with local firms in the Free Trade Zone (FTZ).

Category	Frequency	Percentage (%)
Industry Type		
Electronics	110	34.0
Shipbuilding/Repair	65	20.0
Plastics/Packaging	58	18.0
Machinery/Automotive	48	15.0
Others (Textiles, Consumer Goods)	42	13.0
Firm Size		
Small (<100 employees)	65	20.0
Medium (100–499 employees)	145	45.0
Large (≥500 employees)	110	35.0
Ownership		

Domestic	145	45.0
Foreign (FDI)	175	55.0

Table 3. *Firm Characteristics*

Descriptive Analysis of Constructs

Table 4 indicates a mixed pattern of adoption for Artificial Intelligence Technologies (AIT) and Supply Chain Automation Processes (SCAP) and their effects on Supply Chain Efficiency (SCE). Among AI technologies, IoT and Machine Learning (ML) show the highest adoption, reflecting their strategic role in enabling real-time connectivity, predictive analytics, and informed decision-making. In contrast, Robotics & Automation (R&A), Natural Language Processing & Chatbots (NLP&C), and Computer Vision (COMV) are moderately adopted due to cost, complexity, and integration challenges.

In terms of efficiency outcomes, organizations report strong improvements in Accuracy & Reliability, Customer Satisfaction, and Operational Efficiency, while Speed & Responsiveness and Resilience & Risk Mitigation remain moderately developed, indicating ongoing challenges in agility and risk management. Within SCAP, adoption is highest in Inventory Management, Logistics & Transportation, and Warehouse Operations, whereas Procurement & Supplier Management and Predictive Maintenance show lower uptake, reflecting emerging capabilities in external integration and proactive asset management.

Overall, firms in Batam are advancing in digital adoption, with IoT, ML, and core automation processes driving efficiency gains, while more advanced technologies and resilience-oriented processes require further investment and maturity to fully enhance supply chain agility and robustness.

Variable	**Dimension**	**Mean**	**SD**	**Interpretation**
AIT	Machine Learning (ML)	3.78	0.82	Moderate to high adoption
	Robotics & Automation (R&A)	3.45	0.90	Moderate adoption
	Internet of Things (IoT)	4.02	0.76	High adoption
	Natural Language Processing & Chatbots (NLP&C)	3.55	0.88	Moderate adoption
	Computer Vision (COMV)	3.40	0.92	Moderate adoption
SCE	Operational Efficiency (OPE)	3.85	0.78	Moderate to high efficiency
	Speed & Responsiveness (S&RES)	3.72	0.81	Moderate efficiency
	Accuracy & Reliability (AC&REL)	3.91	0.74	High efficiency
	Resilience & Risk Mitigation (R&RM)	3.64	0.86	Moderate efficiency

	Customer Satisfaction (CUSSAT)	3.88	0.80	Moderate to high efficiency
SCAP	Inventory Management Automation (IMA)	3.82	0.80	Moderate to high adoption
	Logistics & Transportation Automation (L&TA)	3.76	0.85	Moderate adoption
	Procurement & Supplier Management Automation (P&MA)	3.58	0.88	Moderate adoption
	Warehouse Operations Automation (WOA)	3.69	0.83	Moderate adoption
	Predictive Maintenance (PREM)	3.47	0.90	Moderate adoption

Table 4. *Descriptive Statistics of AIT, ACAP and SCE*

Measurement Model Assessment

Reliability and Validity

Reliability and convergent validity analyses confirm that all constructs and their dimensions are robust measures. For AI Technologies (AIT), factor loadings ranged from 0.70 to 0.88, Cronbach's Alpha values were 0.82–0.85, Composite Reliability (CR) ranged 0.88–0.90, and AVE values were 0.63–0.67, indicating strong internal consistency and convergent validity. Supply Chain Automation Processes (SCAP) also demonstrated satisfactory reliability and validity, with Cronbach's Alpha 0.81–0.84, CR 0.87–0.89, and AVE 0.61–0.66. Supply Chain Efficiency (SCE) showed particularly strong metrics, with Cronbach's Alpha above 0.82, CR between 0.88 and 0.92, and AVE from 0.64 to 0.72.

Overall, all constructs meet the recommended thresholds (Cronbach's Alpha > 0.70, CR > 0.70, AVE > 0.50), confirming that the measurement model is reliable and valid, and suitable for subsequent structural analysis. (See Table 5)

Construct / Dimension	Items	Factor Loadings	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
AI Technologies (AIT)					
Machine Learning (ML)	ML1–ML5	0.72–0.87	0.84	0.89	0.66
Robotics & Automation (R&A)	RA1–RA5	0.70–0.85	0.82	0.88	0.64
Internet of Things (IoT)	IoT1–IoT5	0.74–0.88	0.85	0.90	0.67
NLP & Chatbots (NLP&C)	NLP1–NLP5	0.71–0.86	0.83	0.89	0.65
Computer Vision (COMV)	COMV1–COMV5	0.73–0.85	0.82	0.88	0.63
Supply Chain Automation Processes (SCAP)					

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Inventory Management Automation (IMA)	IMA1–IMA5	0.72–0.87	0.84	0.89	0.66
Logistics & Transportation Automation (L&TA)	LTA1–LTA5	0.70–0.85	0.82	0.88	0.64
Procurement & Supplier Management Automation (P&MA)	PMA1–PMA5	0.71–0.84	0.81	0.87	0.62
Warehouse Operations Automation (WOA)	WOA1–WOA5	0.73–0.86	0.83	0.89	0.65
Predictive Maintenance (PREM)	PREM1–PREM5	0.70–0.84	0.81	0.87	0.61
Supply Chain Efficiency (SCE)					
Operational Efficiency (OPE)	OPE1–OPE5	0.74–0.88	0.85	0.90	0.68
Speed & Responsiveness (S&RES)	SRES1–SRES5	0.72–0.86	0.83	0.89	0.65
Accuracy & Reliability (AC&REL)	ACREL1–ACREL5	0.75–0.89	0.86	0.91	0.70
Resilience & Risk Mitigation (R&RM)	RRM1–RRM5	0.71–0.85	0.82	0.88	0.64
Customer Satisfaction (CUSSAT)	CUS1–CUS5	0.76–0.90	0.87	0.92	0.72

Table 5. *Reliability and Convergent Validity of Constructs*

Discriminant Validity (Fornell–Larcker Criterion)

Discriminant validity assessed using the Fornell–Larcker criterion confirms that all constructs are empirically distinct. The square root of the Average Variance Extracted (AVE) for each construct, shown on the diagonal, exceeds its correlations with other constructs. For example, Machine Learning (√AVE = 0.81) is more strongly associated with its own indicators than with Robotics & Automation (0.62), IoT (0.65), or Customer Satisfaction (0.67). Similarly, IoT (√AVE = 0.82) surpasses correlations with related constructs such as Logistics & Transportation Automation (0.59) and Operational Efficiency (0.66). This pattern holds across all AI Technologies, Supply Chain Automation Processes, and Supply Chain Efficiency dimensions.

Overall, these results demonstrate that each construct shares more variance with its own indicators than with other constructs, confirming strong discriminant validity and supporting the robustness of the measurement model for subsequent structural analysis.

Construct /	ML	R&A	IoT	NLP&C	COMV	IMA	L&TA	P&MA	WOA	PREM	OPE	S&RES	AC&REL	R&RM	CUSSAT

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Dimension															
Machine Learning (ML)	0.81														
Robotics & Automation (R&A)	0.62	0.80													
Internet of Things (IoT)	0.65	0.60	0.82												
NLP & Chatbots (NLP&C)	0.61	0.59	0.64	0.81											
Computer Vision (COMV)	0.63	0.60	0.66	0.62	0.79										
Inventory Mgmt Automation (IMA)	0.58	0.55	0.60	0.59	0.57	0.81									
Logistics & Transp. Automation (L&TA)	0.57	0.56	0.59	0.58	0.56	0.63	0.80								
Procurement & Supplier Mgmt Automation (P&MA)	0.56	0.55	0.58	0.57	0.54	0.60	0.61	0.79							
Warehouse Ops Automation (WOA)	0.59	0.58	0.61	0.59	0.57	0.62	0.60	0.61	0.81						
Predictive Maintenance (PREM)	0.57	0.55	0.59	0.58	0.56	0.61	0.60	0.62	0.63	0.78					
Operational	0.64	0.61	0.66	0.63	0.62	0.65	0.64	0.62	0.63	0.61	0.82				

Efficiency (OPE)															
Speed & Responsiveness (S&RES)	0.62	0.60	0.64	0.62	0.60	0.63	0.62	0.61	0.62	0.60	0.68	0.81			
Accuracy & Reliability (AC&REL)	0.65	0.63	0.67	0.64	0.62	0.66	0.64	0.62	0.63	0.61	0.70	0.69	0.84		
Resilience & Risk Mitigation (R&RM)	0.61	0.59	0.63	0.61	0.60	0.62	0.61	0.60	0.61	0.59	0.65	0.64	0.66	0.80	
Customer Satisfaction (CUSSAT)	0.67	0.64	0.68	0.66	0.63	0.66	0.65	0.63	0.64	0.62	0.72	0.71	0.73	0.68	0.85

Table 6. *Discriminant Validity (Fornell–Larcker Criterion)*

Discriminant validity assessed using the Heterotrait–Monotrait (HTMT) ratio confirms that all constructs in the research model are empirically distinct. For AI Technologies (AIT), HTMT values range from 0.55 to 0.66, indicating that Machine Learning (ML), Robotics & Automation (R&A), Internet of Things (IoT), Natural Language Processing & Chatbots (NLP&C), and Computer Vision (COMV) capture unique dimensions of AI adoption. Similarly, Supply Chain Automation Processes (SCAP) constructs—Inventory Management Automation (IMA), Logistics & Transportation Automation (L&TA), Procurement & Supplier Management Automation (P&MA), Warehouse Operations Automation (WOA), and Predictive Maintenance (PREM)—show HTMT values from 0.59 to 0.72, demonstrating distinct functional areas while contributing collectively to automation.

Across higher-order constructs, HTMT values between AIT, SCAP, and Supply Chain Efficiency (SCE) range from 0.71 to 0.78, confirming that these constructs are moderately correlated but conceptually separate. For example, the HTMT of AIT–SCAP (0.74) and AIT–SCE (0.71) indicates that AI adoption supports automation and efficiency without overlapping entirely, while SCAP–SCE (0.78) shows that automation enhances performance but represents a distinct construct. Overall, these results validate the discriminant validity of all constructs, ensuring confidence in subsequent structural model testing.

Construct Pair	HTMT Value	Interpretation
AI Technologies (AIT)		
ML – R&A	0.64	Acceptable (<0.85)
ML – IoT	0.58	Acceptable
ML – NLP&C	0.61	Acceptable
ML – COMV	0.65	Acceptable
R&A – IoT	0.55	Acceptable
R&A – NLP&C	0.59	Acceptable
R&A – COMV	0.63	Acceptable
IoT – NLP&C	0.57	Acceptable
IoT – COMV	0.66	Acceptable
NLP&C – COMV	0.60	Acceptable
SCAP Constructs		
IMA – L&TA	0.62	Acceptable
IMA – P&MA	0.59	Acceptable
IMA – WOA	0.64	Acceptable
IMA – PREM	0.67	Acceptable
L&TA – P&MA	0.65	Acceptable
L&TA – WOA	0.61	Acceptable
L&TA – PREM	0.70	Acceptable
P&MA – WOA	0.63	Acceptable
P&MA – PREM	0.68	Acceptable
WOA – PREM	0.72	Acceptable
AIT – SCAP – SCE		
AIT – SCAP	0.74	Acceptable
AIT – SCE	0.71	Acceptable
SCAP – SCE	0.78	Acceptable
Others	<0.80	All acceptable

Table 7. *Discriminant Validity (HTMT Ratio)*

Common Method Bias (CMB)

To address potential common method bias (CMB), three statistical techniques were applied: Harman's single factor test, full collinearity VIF, and marker variable analysis. Harman's test showed that the first factor accounted for 38% of variance, below the 50% threshold, indicating no single factor dominates the data. Full collinearity VIF values for AI Technologies (AIT = 2.1), Supply Chain Automation Processes (SCAP = 2.7), and Supply Chain Efficiency (SCE = 1.8) were all below the 3.3 cut-off, suggesting multicollinearity is not a concern. Marker variable analysis

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further confirmed non-significant correlations with the main constructs. Collectively, these results indicate that CMB does not pose a serious threat, supporting the validity of the structural model analysis.

Test	Result (per framework construct)	Threshold / Interpretation
Harman's Single Factor Test	First factor explained 38% of total variance	<50% → No severe CMB detected
Full Collinearity VIF	AIT (2.1), SCAP (2.7), SCE (1.8)	<3.3 → Acceptable, no multicollinearity
Marker Variable Correlation	Non-significant correlations across AIT, SCAP, and SCE	Confirms absence of major CMB

Table 8. Common Method Bias (CMB) Tests

Structural Model Assessment

Path Coefficients and Significance Testing

The structural model results indicate that most AI technologies positively influence supply chain efficiency (SCE). Machine Learning (ML, $\beta = 0.28$, $p < 0.001$) and the Internet of Things (IoT, $\beta = 0.33$, $p < 0.001$) have the strongest effects, enhancing forecasting, operational optimization, and real-time visibility. Robotics & Automation (R&A, $\beta = 0.15$, $p < 0.05$) and Natural Language Processing & Chatbots (NLP&C, $\beta = 0.21$, $p < 0.01$) also significantly improve efficiency, whereas Computer Vision (COMV, $\beta = 0.08$, $p > 0.05$) shows a non-significant effect, suggesting limited practical impact in the sampled firms.

Regarding automation processes, Inventory Management Automation (IMA, $\beta = 0.26$, $p < 0.001$), Warehouse Operations Automation (WOA, $\beta = 0.24$, $p < 0.001$), Predictive Maintenance (PREM, $\beta = 0.20$, $p < 0.01$), and Logistics & Transportation Automation (L&TA, $\beta = 0.18$, $p < 0.05$) significantly enhance efficiency, while Procurement & Supplier Management Automation (P&MA, $\beta = 0.11$, $p > 0.05$) is not statistically significant.

Mediation analysis confirms that AI technologies also indirectly improve SCE through automation ($\beta = 0.29$, $p < 0.001$), highlighting the dual role of AI: directly influencing performance and indirectly enhancing efficiency via automation processes. Overall, 9 out of 11 hypotheses are supported, demonstrating that AI adoption and automation are key drivers of supply chain efficiency, with effectiveness contingent on technology maturity and organizational context. (See Table 9)

Hypothesis	**Relationship**	**Path Coefficient (β)**	**t-value**	**p-value**	**Supported?**
H1	ML → SCE	0.28	4.12	0.000	Yes
H2	R&A → SCE	0.15	2.05	0.041	Yes
H3	IoT → SCE	0.33	5.25	0.000	Yes
H4	NLP&C → SCE	0.21	2.94	0.003	Yes
H5	COMV → SCE	0.08	1.20	0.230	No
H6	IMA → SCE	0.26	4.01	0.000	Yes
H7	L&TA → SCE	0.18	2.35	0.019	Yes
H8	P&MA → SCE	0.11	1.75	0.081	No
H9	WOA → SCE	0.24	3.65	0.000	Yes
H10	PREM → SCE	0.20	2.88	0.004	Yes
H11	AIT → SCAP → SCE (indirect effect)	0.29	4.45	0.000	Yes

Table 9. *Path Coefficients and Hypothesis Testing Results*

Coefficient of Determination (R^2)

The coefficient of determination (R^2) measures the proportion of variance in endogenous constructs explained by their predictors, with values of 0.25, 0.50, and 0.75 interpreted as weak, moderate, and substantial, respectively (Hair et al., 2019).

In this study, AI Technologies (AIT) explain 47% of the variance in Supply Chain Automation Processes (SCAP) ($R^2 = 0.47$), reflecting moderate explanatory power. This indicates that AI significantly drives automation practices such as inventory management, logistics, and predictive maintenance, though other factors also play a role. For Supply Chain Efficiency (SCE), the combined effect of AIT and SCAP explains 61% of the variance ($R^2 = 0.61$), a substantial level, showing that efficiency outcomes are strongly influenced by AI both directly and indirectly through automation. Overall, the R^2 results confirm the model's strong predictive accuracy, validating the hypothesized relationships and emphasizing the critical role of AI-enabled automation in enhancing supply chain performance, including operational efficiency, reliability, responsiveness, resilience, and customer satisfaction (See Table 10).

Endogenous Construct	R^2	Interpretation

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Supply Chain Automation Processes (SCAP)	0.47	Moderate
Supply Chain Efficiency (SCE)	0.61	Substantial

Table 10. *Coefficient of Determination (R^2)*

Effect Sizes (f^2)

Effect size (f^2) analysis assesses the unique contribution of each predictor to the variance of its corresponding endogenous construct, complementing R^2 by showing whether a specific predictor meaningfully enhances model explanatory power (Cohen, 1988). Values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively.

In this study, Table 4.10 showed the AI Technologies (AIT) had a medium-to-large effect ($f^2 = 0.28$) on Supply Chain Automation Processes (SCAP), indicating that AI adoption—through ML, IoT, robotics, and predictive analytics—substantially supports automation in inventory management, logistics, and production planning. The direct effect of AIT on Supply Chain Efficiency (SCE) was smaller ($f^2 = 0.12$), suggesting that AI's impact on efficiency is more pronounced when mediated through automation. SCAP itself showed a large effect on SCE ($f^2 = 0.34$), highlighting that automation processes are the key driver of efficiency outcomes, including operational performance, responsiveness, reliability, resilience, and customer satisfaction.

Relationship	**f^2 Value**	**Interpretation**
AIT → SCAP	0.28	Medium to large effect
AIT → SCE	0.12	Small to medium effect
SCAP → SCE	0.34	Large effect

Table 11. *Effect Sizes (f^2)*

This study empirically examined the role of Artificial Intelligence (AI) in enhancing supply chain efficiency in Batam's manufacturing sector. Analysis ranged from descriptive statistics and measurement validation to hypothesis testing. Findings show that AI adoption is strongest in Internet of Things (IoT) applications and predictive analytics. IoT strengthens supply chain reliability and customer satisfaction through real-time monitoring, while predictive analytics enhances resilience by enabling firms to anticipate and mitigate disruptions. Machine Learning (ML) was identified as a key driver of operational efficiency, improving demand forecasting and inventory optimization. In contrast, Robotics & Automation showed weaker effects, reflecting high costs, integration challenges, and limited adoption among SMEs. Overall, AI significantly enhances responsiveness and operational efficiency, providing firms with agility to respond to market fluctuations. Impacts on resilience and customer satisfaction were positive but moderate, highlighting the importance of complementary factors such as human expertise, process integration, and customer engagement.

From a Resource-Based View (RBV), AI capabilities are valuable, heterogeneous resources that generate competitive advantage when combined with complementary assets like data infrastructure and managerial skills (Culot et al., 2024). ML improves operational efficiency via better forecasting, IoT drives reliability and customer satisfaction through sensorization and visibility (Rejeb et al., 2020; Taj et al., 2023), and predictive analytics supports resilience through proactive risk mitigation (Belhadi et al., 2022; Zamani et al., 2023). Robotics' limited effect is consistent with SME-focused studies, where adoption requires human capital and process redesign to realize efficiency gains (Ballestar et al., 2020).

Contextually, Batam's industrial mix—dominated by electronics—favors IoT and ML adoption, which build on existing digital data and require relatively low capital. SMEs face financial and skill constraints that limit robotics implementation to pilots or sub-processes, reducing aggregate benefits. These patterns align with regional studies emphasizing organizational readiness and digital infrastructure as key enablers of AI adoption in Indonesia (Albert & Alijoyo, 2024; Wardhani et al., 2025). In summary, AI is reshaping supply chain management in Batam, with the greatest benefits from technologies that enhance visibility and analytics, while robotics adoption remains a phased, strategic endeavor. The findings offer clear guidance for firms and policymakers seeking to harness AI for sustained competitiveness.

CONCLUSION

This study advances the AI–SCM literature by demonstrating that AI sub-technologies have heterogeneous effects, emphasizing the importance of treating AI as a multi-dimensional capability (IoT, ML, PA, RA) rather than a single construct. Complementary resources such as data quality and human capital are critical for realizing AI's full potential, aligning with RBV and dynamic capability perspectives. For practitioners, a phased adoption strategy is recommended: prioritize connectivity and analytics (IoT + ML/PA) for quick gains in reliability and forecasting, invest in data governance and analytics skills, implement robotics strategically with process redesign and workforce upskilling, and leverage ecosystem solutions (shared testbeds, vendor partnerships) to reduce adoption barriers. Policymakers and industrial authorities like BP Batam can facilitate adoption through pilot funding, shared labs, training programs, and collaboration platforms, supporting the diffusion of AI and Industry 4.0 capabilities in emerging. The non-significant effect of robotics on operational efficiency may be due to timing (benefits materialize post-reengineering), sectoral heterogeneity, or integration gaps, consistent with SME robotics studies. Limitations include the cross-sectional design and perceptual measures. Future research should use longitudinal designs, multi-respondent surveys, or objective metrics, and explore mediators (data quality, process integration) and moderators (firm size, ownership) to better understand heterogeneity in AI outcomes.

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