International Journal of Business, Management & Economics
e-ISSN: 2746-1351
Vol. 7, No. 4, November 2026

The Effect of Enterprise Risk Management on Supply Chain Resilience in the Batam Logistics Industry: The Role of Knowledge Management and Technology Adoption

Nasar Buntu Laulita & Putri Damayanti*

Universitas Internasional Batam
*Corresponding author: 2341443.putri@uib.edu
nasar.buntu@uib.ac.id

Article Information:
Received: October 13, 2026; Accepted: October 23, 2026; Published: November 16, 2026

Abstract

Logistics companies face rising uncertainty from geopolitical conflict, volatile fuel prices, and uneven digitalization, all of which put pressure on their ability to withstand supply chain disruptions. This study analyzes the effect of Enterprise Risk Management (ERM) on Supply Chain Resilience (SCR) in the logistics industry of Batam City, with Knowledge Management (KM) and Technology Adoption (TA) as mediating variables. The study uses a quantitative approach with an explanatory research design and a cross-sectional survey. Primary data were collected through questionnaires from 373 respondents working in logistics companies in Batam between December 2025 and March 2026 and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that ERM has a positive and significant effect on KM, TA, and SCR. KM and TA also have positive and significant effects on SCR, and both partially mediate the relationship between ERM and SCR. The model explains 26.2% of the variance in SCR, a modest level of explanatory power that leaves room for other determinants. These findings suggest that logistics companies build stronger supply chain resilience when risk management works together with knowledge management and technology adoption. The study adds empirical evidence from the Indonesian logistics sector and gives managers practical direction for protecting operational continuity.

Keywords: Enterprise Risk Management, Knowledge Management, Technology Adoption, Supply Chain Resilience, Logistics Industry

JEL Codes: G32, L91, M11

1. Introduction

1.1 Research Background

The logistics industry now operates under a growing level of uncertainty caused by global and domestic disruptions. Geopolitical conflicts, including the war between Russia and Ukraine and tensions in international trade, have disrupted distribution and raised global logistics costs, while fluctuating fuel prices and inflationary pressure have pushed up operating costs. In Indonesia, limited infrastructure, weak integration of logistics systems, and incomplete digitalization in many firms make these conditions worse, leading to delivery delays and poor supply chain visibility. Logistics companies therefore deal with complex operational and

Published by:

strategic risks that call for a comprehensive and integrated risk management system. Enterprise Risk Management (ERM) responds to this need as a strategic approach for identifying, assessing, and controlling risks in a systematic and integrated way (*Quang et al., 2024*), and it can also improve the quality of decision-making (*Tewu et al., 2024*).

Batam adds its own pressures. The city is an industrial and trade hub bordering Singapore and Malaysia. Its economy depends on export-oriented activities and intense market competition, which require local businesses to adopt innovative and adaptive strategies to remain competitive (*Mulyaningrum et al., 2025*). This setting makes Batam a relevant location for examining how logistics companies manage risk.

Knowledge Management (KM) supports the effective implementation of ERM, particularly where organizational knowledge is underused. When companies do not manage the knowledge generated by their risk management processes in a systematic way, organizational learning tends to remain limited. KM allows organizations to manage, store, and distribute knowledge as a basis for decision-making and innovation. Integrating ERM and KM has been shown to strengthen a learning culture and improve the ability to adapt to an uncertain business environment (*Ali et al., 2023*). *Quang et al. (2024)* also showed that effective use of knowledge can strengthen the effect of ERM on organizational performance and resilience.

Digital technology has become another important factor in making risk and knowledge management effective. Technologies such as Enterprise Resource Planning (ERP), big data analytics, Artificial Intelligence (AI), and cloud-based platforms improve visibility and allow information to be exchanged in real time. Where logistics companies adopt these technologies only partially, their response to risk and their decision-making are likely to slow down. Previous studies show that integrating technology into knowledge management can improve the accuracy of risk analysis, operational coordination, and responsiveness to changes in the business environment (*Chen, 2025*; *Hosseini Shekarabi et al., 2025*). Evidence from a Batam-based MSME points to a similar gap, as the firm had not fully used digital technology to raise its visibility and competitiveness, partly because of limited financial resources and digital skills (*Budiman & William, 2024*).

These problems contribute to low Supply Chain Resilience (SCR), which refers to the ability of a supply chain to withstand, adapt to, and recover from disruptions without a decline in performance. In the logistics industry, supply chain resilience is central to business continuity and competitiveness. Earlier research shows that KM strengthens risk culture and speeds up organizational recovery, while collaboration based on knowledge and technology improves supply chain resilience, particularly in complex and dynamic environments (*Ali et al., 2023*; *Zighan et al., 2024*).

1.2 Research Gap and Objectives

Taken together, these strands suggest that ERM, KM, and Technology Adoption (TA) can jointly strengthen SCR through risk mitigation and continuous adaptive learning. Most previous studies, however, have examined these variables separately or have treated firm performance rather than resilience as the outcome. *Quang et al. (2024)*, for example, examined knowledge, technology, and supply chain resilience as parallel mediators between ERM and firm performance in Vietnam, which leaves open the question of whether KM and TA carry the effect of ERM on SCR itself. Empirical evidence from the logistics industry in Indonesia is also limited, even though logistics firms in an export-oriented border city such as Batam face the pressures described above. The study therefore has three objectives. First, it tests the direct

Published by: Training & Research Institute JERAMBA ILMU SUKSES

effects of ERM on KM, TA, and SCR. Second, it tests the effects of KM and TA on SCR. Third, it examines whether KM and TA mediate the effect of ERM on SCR among logistics companies in Batam.

The study contributes in two ways. At the theoretical level, it places SCR at the end of an integrated model in which risk management works through knowledge and technology, extending earlier models that linked ERM mainly to firm performance. At the practical level, it gives logistics managers in Batam evidence on which capabilities to develop alongside their risk management systems. The rest of the article is organized as follows. Section 2 reviews the literature and develops the hypotheses, Section 3 describes the research method, Section 4 presents and discusses the findings, and Section 5 concludes with implications, limitations, and directions for future research.

2. Literature Review

2.1 Previous Studies on ERM, KM, TA, and SCR

This review examines previous studies on ERM, KM, TA, and SCR in order to trace the development of the field, identify the research gap, and establish the empirical basis of the present study.

Studies on ERM show that integrated implementation improves organizational readiness to face operational and strategic risks, especially when it is supported by knowledge and technology (*Quang et al., 2024*). ERM therefore works as a strategic approach that creates long-term value, and its role extends beyond that of a risk mitigation tool.

KM plays an important role in supporting effective risk management and supply chain resilience. Good KM practices allow organizations to learn from past risks and respond to disruptions more quickly and adaptively (*Ali et al., 2023*). Knowledge-based supply chains have also been shown to be more resilient than conventional systems (*Sezer et al., 2023*).

Digital technology has become an important element of modern supply chains. The adoption of technology in KM, such as integrated information systems, big data analytics, and cloud-based platforms, improves supply chain visibility and coordination. Digitalization makes real-time risk identification possible and speeds up decision-making (*Hosseini Shekarabi et al., 2025*). In this context, technology acts as an enabler that links ERM and KM.

Research on SCR shows that resilience depends on operational factors as well as on the organization's ability to manage risk and knowledge. Knowledge-based collaboration and technological support have been found to improve the capacity of supply chains to withstand and recover from disruptions (*Zighan et al., 2024*).

Most previous studies, however, have examined ERM, KM, TA, and SCR separately. Studies that test the mediating roles of KM and TA simultaneously remain limited, particularly in the Indonesian logistics industry. The present study addresses this gap by testing an integrated model in the context of the logistics industry in Batam.

2.2 Hypothesis Development

2.2.1 Enterprise risk management and knowledge management

ERM and KM reinforce each other in supporting risk-based organizational decision-making. ERM implementation generates information, experience, and lessons about strategic and operational risks, and the organization needs to manage these systematically before it can reuse

Published by:

them. Without effective KM, the knowledge produced by risk management processes tends to be temporary and does not accumulate as a strategic asset. Quang et al. (2024) stated that integrated ERM implementation increases cross-functional knowledge sharing and organizational learning. This is consistent with the findings of Ali et al. (2023), who reported that a strong risk management culture strengthens KM practices through the documentation and transfer of risk knowledge. Tewu et al. (2024) also found that ERM contributes to stronger KM systems because risk identification and evaluation directly produce explicit and tacit knowledge. Sezer et al. (2023) similarly supported the view that the integration of risk and knowledge forms an important foundation for knowledge-based organizations. Better ERM implementation is therefore expected to make KM more effective.

H1: Enterprise Risk Management has an effect on Knowledge Management.

2.2.2 Enterprise risk management and supply chain resilience

ERM contributes directly to SCR through a proactive approach to identifying, analyzing, and mitigating supply chain risks. It allows organizations to prepare systematic contingency plans and recovery strategies that keep operations running. In a systematic review, Suprayitno and Latunreng (2024) observed that large companies tend to approach supply chain risk in a more structured and proactive way. Similarly, Keswani and Vlachos (2022) linked risk management and mitigation discipline to supply chain resilience and business continuity. Quang et al. (2024) showed that ERM increases organizational readiness for disruption by integrating risk, knowledge, and technology. Bahrami et al. (2022) found that big data analytics capability strengthened supply chain resilience in a survey of 187 Iranian companies, which suggests that data-driven risk management can support resilience. In addition, Wang (2025) stated that digital transformation integrated with ERM significantly strengthens SCR. ERM has also been found to improve competitive advantage and the quality of decision-making, both of which directly affect supply chain resilience (Tewu et al., 2024). ERM is therefore a strategic foundation for building SCR.

H2: Enterprise Risk Management has an effect on Supply Chain Resilience.

2.2.3 Enterprise risk management and technology adoption

ERM encourages TA because identifying, assessing, and mitigating risks requires organizations to use technologies that make risk management more effective. Companies that implement ERM in an integrated way tend to adopt digital technologies such as AI, big data analytics, the Internet of Things (IoT), and ERP to improve the accuracy of risk analysis, operational monitoring, and the quality of decision-making. Quang et al. (2024) showed that effective ERM implementation encourages firms to use technology to improve organizational performance and supply chain resilience. Godson and Salman (2026) found that AI adoption is positively associated with ERM implementation because technology strengthens real-time risk identification, monitoring, and control. Rodríguez-Espíndola et al. (2022) explained that organizations with high risk awareness are more motivated to adopt digital technologies in order to improve their risk management capability and organizational resilience. Better ERM implementation is therefore expected to raise the level of TA in an organization.

H3: Enterprise Risk Management has an effect on Technology Adoption.

2.2.4 Knowledge management and supply chain resilience

KM plays a central role in improving SCR because it allows organizations to treat lessons from

Published by:

earlier supply chain disruptions as a basis for better adaptation and recovery. KM practices such as knowledge storage, information sharing with partners, and collaborative learning have been shown to increase supply chain flexibility and response speed. Ali et al. (2023) showed that effective KM strengthens an organization's capacity to respond to disruptions quickly and in a coordinated way. Sezer et al. (2023) confirmed that knowledge-based supply chains are more resilient than traditional supply chains. Ahmed et al. (2024) found that knowledge transfer among supply chain actors significantly increases the adaptability of logistics systems. In a similar vein, Zighan et al. (2024) stated that KM encourages better collaboration and coordination, which speeds up recovery after disruptions. Atieh Ali et al. (2024) further argued that integrating KM with digital supply chain systems strengthens operational resilience over time. KM is therefore a key capability for building SCR.

H4: Knowledge Management has an effect on Supply Chain Resilience.

2.2.5 Technology adoption and supply chain resilience

TA plays a strategic role in improving SCR by increasing visibility, transparency, and the speed of response to supply chain disruptions. Technologies such as IoT, digital platforms, and data analytics allow real-time risk monitoring and faster decisions. Sezer et al. (2023) found that data-based technology improves risk analysis and supply chain recovery. Wang (2025) described digital transformation as a main catalyst for strengthening SCR. Similarly, Hosseini Shekarabi et al. (2025) confirmed that technological solutions improve supply chain coordination and responsiveness. Fornasiero and Tolio (2025) showed that digital supply chains contribute to the resilience of logistics ecosystems. In addition, Atieh Ali et al. (2024) found that the adoption of digital technology significantly improves supply chain resilience and sustainability. TA is therefore expected to have a positive effect on SCR.

H5: Technology Adoption has an effect on Supply Chain Resilience.

2.2.6 The *Mediating role of knowledge management*

KM serves as a mediating mechanism that explains how ERM can improve SCR. ERM implementation generates information and lessons about risk identification, evaluation, and mitigation. Its effect on supply chain resilience will remain limited, however, unless this knowledge is managed systematically through the creation, storage, and distribution of organizational knowledge. Quang et al. (2024) confirmed that integrating risk management and knowledge management improves organizational performance and readiness for disruption. Ali et al. (2023) found that a risk management culture supported by KM practices strengthens the organization's capacity to respond adaptively to disruption. Sezer et al. (2023) showed that knowledge-based supply chains are more resilient because they integrate risk learning into operational systems. Zighan et al. (2024) confirmed that knowledge-based collaboration accelerates recovery after disruptions. In addition, Tewu et al. (2024) stated that risk-based decisions documented through KM systems improve competitive advantage and firm resilience. KM therefore acts as a bridge that strengthens the effect of ERM on SCR.

H6: Knowledge Management mediates the effect of Enterprise Risk Management on Supply Chain Resilience.

2.2.7 The Mediating role of technology adoption

TA serves as a mediating mechanism that explains how ERM can improve SCR. ERM creates a need for systems that can identify, monitor, and respond to risks quickly and accurately. To

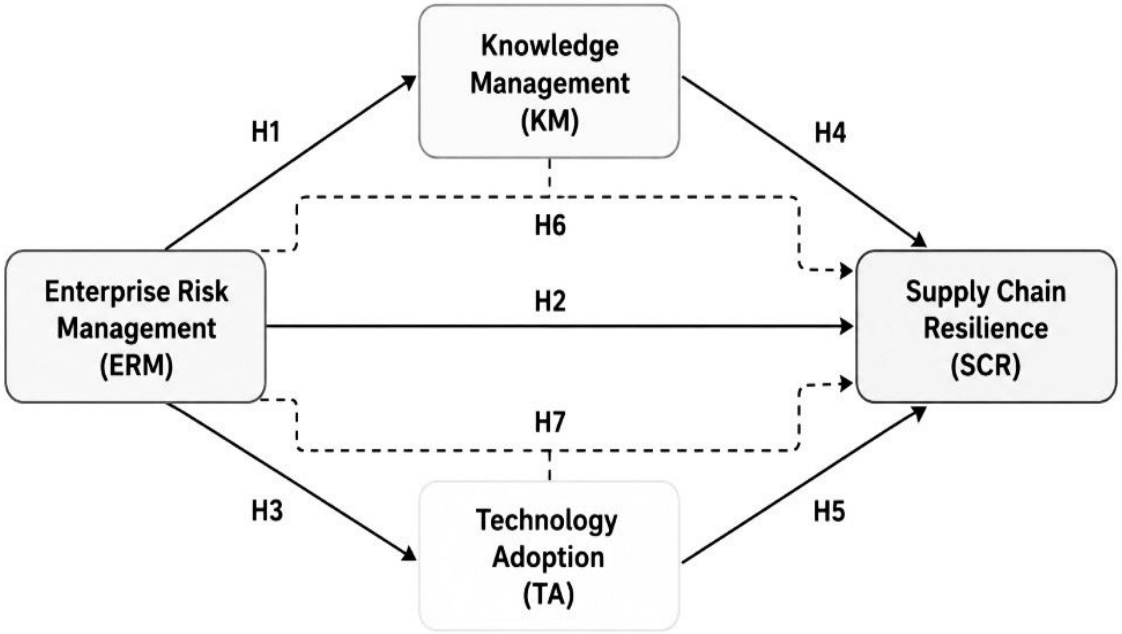
Published by:

meet this need, organizations adopt digital technologies that improve supply chain visibility, coordination, and flexibility. Quang et al. (2024) explained that technology is an important factor that strengthens the effectiveness of ERM in improving organizational performance and operational resilience. W. Li and Liu (2023) found that technology adoption significantly increases SCR by improving a firm's ability to manage risk and deal with supply chain disruptions. Fan et al. (2025) showed that the penetration of digital technology strengthens a firm's ability to adapt to and recover from disruptions, which raises overall supply chain resilience. Achwan et al. (2026) found that information technology adoption contributes positively to supply chain resilience through greater responsiveness and operational flexibility. TA therefore acts as a bridge that strengthens the effect of ERM on SCR.

> H7: Technology Adoption mediates the effect of Enterprise Risk Management on Supply Chain Resilience.

Figure 1 presents the research model and the seven hypotheses tested in this study.

Figure 1. Research Model



Source: Developed by the authors, 2026

3. Research Method

3.1 Research Design

This study uses a quantitative approach with an explanatory research design and a cross-sectional survey. A quantitative approach suits the aim of testing causal relationships between variables objectively through numerical data and statistical analysis. Partial Least Squares Structural Equation Modeling (PLS-SEM) was chosen because it can analyze complex relationships among latent variables simultaneously and is oriented toward prediction (Sarstedt et al., 2021). Recent business research in Batam has also applied PLS-SEM, for example in a survey of 341 respondents from manufacturing MSMEs (Mulyaningrum et al., 2025).

Published by:

3.2 Data and Data Collection

The study uses both primary and secondary data. The population consists of employees of logistics companies operating in Batam City. Primary data were obtained by distributing questionnaires to 373 respondents between December 2025 and March 2026. The target respondents were employees, operational staff, supervisors, and managers directly involved in supply chain activities, because these groups observe how their companies identify risks, share knowledge, use technology, and recover from disruptions. The questionnaire items were adapted from *Quang et al. (2024)* and measured on a five-point Likert scale. Section 3.3 and Table 2 report the items for each construct. Secondary data came from scientific journals, research articles, and other relevant academic publications that support the theoretical foundation of the study (*Schneider et al., 2023*).

Data were collected through the questionnaire and a literature study. The questionnaire produced structured data suitable for statistical analysis, while the literature study strengthened the conceptual framework and supported the formulation of the hypotheses (Daruhadi & Sopiati, 2024).

In addition, short interviews were held with several respondents to help interpret the survey results. Section 4.4 summarizes these interviews.

3.3 Operational Definitions and Measurement

Each construct was measured as a single reflective dimension, and Table 2 in Section 4.2 lists every indicator together with its questionnaire statement. The definitions below follow the source instrument of *Quang et al. (2024)* and the conceptual discussion in Sections 1 and 2.

Enterprise Risk Management (ERM) is defined as an integrated, organization-wide process for identifying, assessing, controlling, and monitoring the risks that affect a company's strategic and operational objectives (*Quang et al., 2024)*. It is measured with four indicators: a policy for addressing major risks (ERM1), standard procedures for identifying major risks and opportunities (ERM2), the assessment of risks and opportunities to decide how to handle them (ERM3), and standard procedures for initiating risk-reduction measures (ERM4).

Knowledge Management (KM) refers to the way an organization acquires, shares, stores, and applies knowledge so that lessons from earlier events can inform current decisions (*Quang et al., 2024)*. Its five indicators capture the acquisition of knowledge from external sources (KM1), learning from suppliers and customers (KM2), knowledge exchange among co-workers (KM3), reliance on experience, skills, and knowledge in daily work (KM4), and the use of written sources such as documentation and procedures (KM5).

Technology Adoption (TA) is defined as the extent to which a company acquires and puts into use technology from external sources, including equipment, software, hardware, and technical knowledge (*Quang et al., 2024*). The four indicators cover the acquisition of advanced equipment, software, or hardware (TA1), the purchase of advanced apparatus or prototypes (TA2), the adoption of technical materials such as patents, drawings, or designs (TA3), and the adoption of technical know-how (TA4). This operationalization measures how actively a company acquires and adopts external technology, including software and hardware, and does not measure the use of specific digital applications such as ERP, big data analytics, or AI, which Sections 1 and 2 discuss as examples of such technology.

Following the definition in Section 1.1, Supply Chain Resilience (SCR) is the ability of a

Published by:

supply chain to withstand, adapt to, and recover from disruptions without a lasting decline in performance. In line with *Quang et al. (2024)*, who adapted these items from Bahrami et al. (2022), the scale focuses on the recovery side of resilience through four indicators: the ease of restoring material flow (SCR1), quick recovery of normal operating performance (SCR2), a quick return of the supply chain to its original state (SCR3), and quick resolution of disruptions (SCR4).

3.4 Data Analysis

The data were analyzed with PLS-SEM. This method tests the measurement model (outer model) and the structural model (inner model) simultaneously and does not require normally distributed data (*Hair et al., 2019*). The outer model was evaluated through convergent validity and construct reliability, with the criteria of outer loadings > 0.708, Average Variance Extracted (AVE) > 0.50, and Composite Reliability > 0.70 (Hair et al., 2019; *Sarstedt et al., 2021*). Indicators below the loading criterion were retained when their construct still showed acceptable composite reliability, a decision discussed in Section 4.2.1. Discriminant validity was assessed with the Heterotrait-Monotrait Ratio (HTMT), using a threshold of 0.90 (*Sarstedt et al., 2021)*.

Hypotheses were tested with bootstrapping, and a path was considered significant when its p-value was below 0.05, which corresponds to a T-statistic above 1.96 in a two-tailed test (*Sarstedt et al., 2021*). The analysis also covered direct and indirect effects in order to determine the role of the mediating variables in the model. An indirect effect was considered significant when its p-value was below 0.05, and the mediation was classified as partial when the direct effect of ERM on SCR also remained significant. The coefficient of determination (R-Square) measures how well the independent variables explain the dependent variable, and R^2 values of 0.75, 0.50, and 0.25 are described as substantial, moderate, and weak, respectively (Hair et al., 2019). Effect sizes (f^2) of 0.02, 0.15, and 0.35 indicate small, moderate, and large effects (*Sarstedt et al., 2021*).

This analytical approach allows the study to explain the relationships among ERM, KM, TA, and SCR in the context of the logistics industry in Batam City.

4. Findings and Discussions

This section presents the empirical results and discusses the relationships among the research variables. The analysis used PLS-SEM, covering the evaluation of the measurement model and the structural model, to test the hypotheses formulated earlier.

4.1 Descriptive Statistics

Table 1 presents the characteristics of the respondents. Half of the respondents (50.1%) were aged 20 to 25 years, and private employees formed the largest occupational group (74%).

Published by:

Table 1. Respondent Profile

Category	Attribute	Frequency	Percentage
Age	20–25 years	187	50.1%
	26–30 years	95	25.5%
	31–35 years	50	13.4%
	36–40 years	31	8.3%
	>40 years	10	2.7%
	Total	373	100%
Gender	Male	192	51.5%
	Female	181	48.5%
	Total	373	100%
Highest education	Vocational/Senior High School or equivalent (SMK/SMA)	204	54.7%
	Diploma (D1, D2, D3)	36	9.7%
	Bachelor's degree (S1)	120	32.2%
	Master's degree (S2)	12	3.2%
	Doctoral degree (S3)	1	0.3%
	Total	373	100%
Occupation	Civil servant (PNS/ASN)	16	4.3%
	Private employee	276	74%
	Entrepreneur/Business owner	75	20.1%
	Other	6	1.6%
	Total	373	100%

Source: Processed from research data, 2026

4.2 Measurement Model

4.2.1 Convergent validity

Convergent validity measures the extent to which the indicators of a construct share variance. In PLS-SEM, it is assessed through outer loadings, which should exceed 0.708, and AVE values, which should exceed the threshold of 0.50 (Hair et al., 2019; Sarstedt et al., 2021). Table 2 lists each indicator with its questionnaire statement. Thirteen of the 17 indicators have outer loadings above 0.70, while four (ERM3 = 0.654, KM3 = 0.676, KM4 = 0.625, and TA3 = 0.653) fall between 0.62 and 0.68. These indicators were retained in the model because the composite reliability of every construct still exceeds 0.80 (Table 4). The AVE values of ERM, TA, and SCR exceed 0.50. The AVE of KM (0.480) falls slightly below this threshold, but its composite reliability of 0.821 indicates that convergent validity is still adequate (Fornell & Larcker, 1981). The KM results should nevertheless be read with this limitation in mind.

Published by:

Table 2. Convergent Validity

Indicator	Statement	Outer Loadings	(AVE)	Result
ERM1	A policy is implemented to address major risks that affect the company's capacity to attain its strategic goals.	0.748	0.537	Valid
ERM2	Standard procedures are established to identify major risks and opportunities.	0.748		
ERM3	Risks and opportunities are assessed to determine how to handle them.	0.654		
ERM4	Standard procedures exist for initiating measures to reduce risks.	0.739		
KM1	Employees gain valuable knowledge from external sources such as seminars, journals, and expert networks.	0.705	0.480	Adequatea
KM2	Our personnel learn a lot from suppliers and clients.	0.749		
KM3	Knowledge is exchanged among employees and their co-workers.	0.676		
KM4	Experience, skills, and knowledge form the basis on which employees rely in their work.	0.625		
KM5	Employees depend on written sources, such as project documentation and organizational procedures.	0.701		
TA1	The company frequently acquires advanced equipment, components, materials, software, or hardware from external sources.	0.765	0.520	Valid
TA2	Advanced apparatus or prototypes are frequently purchased from external sources.	0.721		
TA3	Technical materials such as patents, drawings, or designs are often purchased and adopted.	0.653		
TA4	Technical knowledge, such as know-how or non-patent inventions, is often purchased and adopted.	0.764		
SCR1	Material flow can be easily restored after a disruption.	0.707	0.529	Valid
SCR2	Normal operating performance recovers quickly.	0.717		
SCR3	The supply chain quickly recovers to its original state.	0.724		
SCR4	Disruptions can be resolved quickly.	0.736		

Note: Statements follow the item wording of the source instrument (Quang et al., 2024), from

Published by:
Training & Research Institute JERAMBA ILMU SUKSES

which the questionnaire was adapted, and were rated on a five-point Likert scale. a The AVE of KM is below 0.50, but its composite reliability (0.821) exceeds 0.70 (*Fornell & Larcker, 1981)*.

Source: Data analysis (2026)

4.2.2 Discriminant validity

Discriminant validity testing ensures that each construct in the model is statistically distinct and does not correlate too highly with other constructs. This study used the Heterotrait-Monotrait Ratio (HTMT), which requires all HTMT values between constructs to be below the threshold of 0.90 (*Sarstedt et al., 2021*). The HTMT values for all construct pairs range from 0.568 to 0.671, with the highest value of 0.671 between Supply Chain Resilience and Enterprise Risk Management. Because all values are below 0.90, the constructs do not overlap. Enterprise Risk Management, Knowledge Management, Technology Adoption, and Supply Chain Resilience therefore meet the required criteria for discriminant validity (*Sarstedt et al., 2022*).

Table 3. Heterotrait-Monotrait Ratio (HTMT)

Construct	Enterprise Risk Management	Knowledge Management	Technology Adoption	Supply Chain Resilience
Enterprise Risk Management	-	-	-	-
Knowledge Management	0.580	-	-	-
Technology Adoption	0.581	0.568	-	-
Supply Chain Resilience	0.671	0.605	0.568	-

Source: Data analysis (2026)

4.2.3 Reliability

The reliability test assesses the internal consistency of the research instrument. In PLS-SEM, a construct is considered reliable if its Cronbach's Alpha, Rho-A, and Composite Reliability values exceed 0.70 (*Sarstedt et al., 2021*). In exploratory or developmental research, values between 0.60 and 0.70 are still acceptable as long as Composite Reliability remains high (*Sarstedt et al., 2022*). The results show that Enterprise Risk Management, Knowledge Management, and Supply Chain Resilience have Cronbach's Alpha and Rho-A values above 0.70. Technology Adoption has a Cronbach's Alpha of 0.693 and a Rho-A of 0.695, slightly below the 0.70 threshold. This construct is still considered reliable because its Composite Reliability reaches 0.812, above the minimum of 0.70. Composite Reliability for the four constructs ranges from 0.812 to 0.822, which indicates a high level of internal consistency and confirms that all variables are suitable for further analysis.

Published by:

Table 4. Reliability Test

Construct	Cronbach's Alpha	Rho-A	C. Reliability
Enterprise Risk Management	0.711	0.715	0.822
Knowledge Management	0.729	0.736	0.821
Technology Adoption	0.693	0.695	0.812
Supply Chain Resilience	0.701	0.705	0.817

Source: Data analysis (2026)

4.3 Structural Model and Hypothesis Testing

4.3.1 Direct effects (path coefficients)

The direct effect test assesses the direct impact of an independent variable on a dependent variable without involving a mediating or intervening variable. In PLS-SEM, direct effects are measured through path coefficients, which reflect the strength and direction of the direct relationship between two variables, together with a p-value criterion of < 0.05 (*Rahadi, 2023*).

Table 5. Direct Effect Test

Path	Coefficient	P-Value	Result	Hypothesis
Enterprise Risk Management → Knowledge Management	0.422	0.000	Significant (positive)	H1 Accepted
Enterprise Risk Management → Supply Chain Resilience	0.217	0.001	Significant (positive)	H2 Accepted
Enterprise Risk Management → Technology Adoption	0.478	0.000	Significant (positive)	H3 Accepted
Knowledge Management → Supply Chain Resilience	0.235	0.000	Significant (positive)	H4 Accepted
Technology Adoption → Supply Chain Resilience	0.194	0.002	Significant (positive)	H5 Accepted

Source: Data analysis (2026)

Hypothesis 1 is accepted. ERM has a positive and significant effect on KM, with a coefficient of 0.422 and a p-value of 0.000, which means that better risk management implementation goes together with more effective knowledge management in the organization. Organizations with structured risk mitigation systems tend to be more capable of identifying, storing, and distributing the knowledge they need to face uncertainty, which is consistent with Pradana et al. (2024) and *Dodla and Jones (2023)*. Evidence from outside Indonesia points the same way. In a survey of 312 Indian micro, small, and medium enterprises, *Mukherjee et al. (2024)* found that supply chain risk management was positively related to KM. Similarly, *Ali et al. (2023)* reported that exposure to supply chain risks prompted Australian agri-food firms to deploy specific KM practices. This relationship has a moderate effect size ($f^2 = 0.216$), second only to the effect of ERM on TA ($f^2 = 0.295$), which suggests that risk management shapes how logistics firms in Batam handle knowledge to a meaningful degree.

Hypothesis 2 is also accepted, as ERM has a positive and significant effect on SCR (coefficient = 0.217, p-value = 0.001). The ability to manage risk comprehensively is an important factor in improving supply chain resilience, in line with the findings of Jidda *Jidda et al. (2025)*, whose data from 572 Nigerian firms showed that ERM integration significantly influenced firm resilience. Not every study agrees. *Sakka et al. (2025)* examined 500 Canadian manufacturing

Published by:
Training & Research Institute JERAMBA ILMU SUKSES

SMEs and found no significant effect of formalized risk management on resilience across the full sample, although the effect became positive among firms that already had formal systems in place and only when environmental turbulence was low. Tewu et al. (2024) likewise found that ERM did not directly affect firm performance in Indonesian state-owned enterprises, even though it influenced competitive advantage and decision-making. Two features of the present study help explain the difference. First, the direct effect here is modest ($f^2 = 0.046$). Second, the interview respondents described risk management systems that were already fairly structured, which matches the condition under which Sakka et al. observed a positive effect.

Hypothesis 3 is accepted. ERM has a positive and significant effect on TA ($\beta = 0.478$, $p = 0.000$), and this path has the largest effect size in the model ($f^2 = 0.295$). Risk awareness encourages organizations to adopt technology as a means of mitigation and monitoring, as supported by Kaluku et al. (2025) and by Rodríguez-Espíndola et al. (2022), who linked risk management needs to the adoption of emergent technologies in digital manufacturing. The direction of this relationship deserves some caution, however. Godson and Salman (2026) modeled the reverse path and showed that AI adoption by audit firms in Ghana significantly improved ERM, with IT infrastructure flexibility as a partial mediator. Read together, these results suggest that risk management and technology adoption may reinforce each other over time, a pattern that a cross-sectional design such as the one used here cannot fully separate.

Hypothesis 4 is accepted because KM has a positive and significant effect on SCR, with a coefficient of 0.235 and a p-value of 0.000. Good knowledge management is a key factor in improving organizational resilience, which agrees with Hu et al. (2024), who found among 220 Chinese manufacturing firms that knowledge creation, sharing, and utilization significantly influenced SCR through collaborative innovation capability. However, the effect size in this study is small ($f^2 = 0.056$), and the qualitative literature offers a possible explanation. Zighan et al. (2024) reported that problems with people, processes, and technology held back knowledge management in pharmaceutical supply chains. In addition, Mukherjee et al. (2024) found that supply chain innovation had no significant relationship with KM. Knowledge practices therefore seem to support resilience only when firms remove these organizational barriers.

Hypothesis 5 is accepted. TA has a positive and significant effect on SCR (coefficient = 0.194, p-value = 0.002), showing that the use of technology can increase supply chain transparency and adaptability. This result is consistent with Li et al. (2025), who described technology as a main pillar for building resilient logistics systems in the digital era. It also fits the Batam context, where investment in internal digital capacity has been recommended for a local MSME seeking to strengthen its competitive position (Budiman & William, 2024). Other studies paint a less direct picture. Kaluku et al. (2025) found that supply chain digitalization did not strengthen the link between supply chain risk management and SCR among MSMEs in Gorontalo. Likewise, Mubarik and Maciukaite-Zviniene (2026) showed that the visibility created by intelligent automation did not predict resilience on its own, whereas integration between new technologies and existing systems did. The small effect size found here ($f^2 = 0.036$) is in line with these results: technology contributes to resilience, but the contribution depends on how well firms integrate it into daily operations.

4.3.2 Indirect effects

The indirect effect test measures the impact of an independent variable on a dependent variable through one or more mediating variables. In this case the effect does not occur directly but

Published by: Training & Research Institute JERAMBA ILMU SUKSES

passes through another variable first. An indirect effect is significant when its p-value is < 0.05 and not significant when its p-value is ≥ 0.05 (Balu & Rathnasabapathy, 2025).

Table 6. Indirect Effect Test

Path	Indirect Effect (a × b)	P-Value	Result
ERM → KM → SCR	0.099	0.004	Significant (positive)
ERM → TA → SCR	0.093	0.008	Significant (positive)

Note: Indirect effects are the products of the corresponding path coefficients in Table 5 (0.422 × 0.235 and 0.478 × 0.194). P-values are from the bootstrapping procedure.

Source: Data analysis (2026)

Hypothesis 6 is accepted because KM significantly mediates the effect of ERM on SCR, with an indirect coefficient of 0.099 and a p-value of 0.004. Risk management therefore affects resilience directly and also works through stronger knowledge governance in the organization. Because the direct path from ERM to SCR also remains significant, the mediation is partial. Organizations that mitigate risk well create an environment rich in strategic information, and this environment gives them the intellectual capability to survive disruption. This result is consistent with *Imanuddin et al. (2024)* and *Unik et al. (2024)*, who described KM as an important bridge that turns risk strategy into real operational resilience. It also agrees with *Quang et al. (2024)*, who found that KM fully mediated the effect of ERM on non-financial performance among Vietnamese firms, and with *Ali et al. (2023)*, whose serial mediation model showed KM practices building a risk management culture that in turn produced supply chain resilience. One difference stands out. *Quang et al. (2024)* found no significant direct effect of ERM on non-financial performance, whereas the present study found both a direct and an indirect route to SCR, which suggests that in Batam's logistics firms, risk management does part of its work without passing through knowledge management.

Hypothesis 7 is accepted because TA significantly mediates the effect of ERM on SCR, with an indirect coefficient of 0.093 and a p-value of 0.008. As with KM, the direct path from ERM to SCR remains significant, so this mediation is also partial. Risk awareness leads organizations to adopt digital technology as a protective solution, which then increases supply chain flexibility and responsiveness. When technology integration follows from risk evaluation, companies gain real-time visibility, and this visibility is essential for business continuity. The finding is in line with *Ayo and Ruth (2023)* and *Raja and Venkatachalam (2022)*, who showed that technology adoption acts as a mediating mechanism that strengthens the link between strategic risk management and competitive advantage in logistics, and with Quang et al. (2024), who found that technology adoption mediated the effect of ERM on firm performance. The mediating role of technology is not automatic, however. *Mubarik and Maciukaite-Zviniene (2026)* concluded that technology alone is not enough to build resilience without organizational integration. Similarly, *Kaluku et al. (2025)* found no beneficial moderating role of digitalization in the risk management and resilience relationship. TA is also the weaker of the two predictors of SCR in this model ($f^2 = 0.036$ compared with 0.056 for KM), which fits this more cautious view.

4.3.3 Coefficient of determination (R-Square)

The R-Square value shows how well the model explains the variation in the dependent variables. KM has an R^2 of 0.178, which means that ERM explains 17.8% of the variation in

Published by:

knowledge management, while the remainder is influenced by other factors outside the model. SCR has an R^2 of 0.262, indicating that ERM, KM, and TA together explain 26.2% of the variation in supply chain resilience, and TA has an R^2 of 0.228 (Table 7). Against the benchmarks of 0.25, 0.50, and 0.75 for weak, moderate, and substantial explanatory power (*Hair et al., 2019*), the R^2 for SCR lies just above the weak level, while the values for KM and TA fall below it. Risk management, knowledge management, and technology adoption therefore explain a meaningful but limited part of organizational resilience to logistics disruptions, which is consistent with the recent study of *Kaluku et al. (2025)* that pointed to the importance of these variables for operational efficiency.

Table 7. R-Square Test

Construct	R-Square	R-Square Adjusted
KM	0.178	0.176
SCR	0.262	0.256
TA	0.228	0.226

Source: Data analysis (2026)

4.3.4 Effect Size (f-Square)

The f-Square (f^2) test evaluates the relative contribution of each predictor to the dependent variable. Based on the criteria described by Sarstedt et al. (2021), f^2 values of 0.02, 0.15, and 0.35 indicate small, moderate, and large effects, respectively. ERM has moderate effects on TA ($f^2 = 0.295$) and KM ($f^2 = 0.216$). Its direct effect on SCR (0.046) is small, and KM (0.056) and TA (0.036) also make small contributions to SCR. All relationships are significant, but risk management does most of its work by shaping technology adoption and knowledge governance. Each predictor, by contrast, adds only a small share to resilience, which is consistent with the observation of *Sarstedt et al. (2022)* on the variation in predictor strength across structural models.

Table 8. f-Square Test

Construct	Enterprise Risk Management	Knowledge Management	Technology Adoption	Supply Chain Resilience
Enterprise Risk Management	-	0.216	0.295	0.046
Knowledge Management	-	-	-	0.056
Technology Adoption	-	-	-	0.036
Supply Chain Resilience	-	-	-	-

Source: Data analysis (2026)

4.4 Interview Findings

Interviews with several respondents working in logistics companies in Batam City indicate that ERM plays an important role in supporting company operations. Most respondents stated that their companies already had a fairly structured risk management system, covering the stages from risk identification to mitigation. Employees found this system helpful for understanding potential disruptions and for improving their readiness for uncertainty.

Published by:

Respondents also reported that ERM implementation encouraged better KM in their organizations. Risk-related information and experience are usually documented and shared among employees, turning them into shared learning. This supports the quantitative finding that ERM has a positive and significant effect on KM.

Regarding supply chain resilience, most respondents considered KM very helpful for improving SCR. By sharing knowledge and experience, companies can respond to disruptions faster and coordinate better. Respondents also stressed the importance of cross-divisional communication and collaboration to strengthen operational resilience.

Respondents further noted that TA, such as the use of information systems, logistics software, and digital platforms, helps them manage knowledge and monitor risks in real time. They viewed technology as a way to speed up access to information and improve the quality of decisions, which in turn strengthens supply chain resilience.

Taken together, the interview results suggest that the integration of ERM, KM, and TA makes a real contribution to SCR. They also support the quantitative results, which show significant direct and indirect effects, especially the mediating role of KM in strengthening the relationship between ERM and SCR.

5. Conclusion

This study analyzed the effect of ERM on SCR, with KM and TA as mediating variables, in the logistics industry of Batam City. The PLS-SEM analysis supports all seven hypotheses.

ERM has a positive and significant direct effect on KM, TA, and SCR. Good risk management helps organizations deal with uncertainty, and it also encourages stronger knowledge management and wider technology adoption. ERM thus forms a main foundation for improving supply chain resilience.

KM and TA also have positive and significant effects on SCR. Organizations that manage knowledge effectively and use digital technology are better able to respond to, adapt to, and recover from supply chain disruptions.

The results further show significant indirect effects. KM and TA both partially mediate the relationship between ERM and SCR. The effect of ERM on supply chain resilience therefore works directly and is also reinforced through knowledge management and the use of technology.

The model explains 26.2% of the variance in SCR ($R^2 = 0.262$), which represents modest explanatory power. ERM, KM, and TA therefore make a relevant contribution to supply chain resilience, although other factors outside the model also play a substantial role.

The findings carry theoretical implications. They support treating ERM as a capability that works partly through organizational knowledge and technology rather than as a stand-alone control system, and they show that the mediating roles of knowledge and technology reported for firm performance by Quang et al. (2024) also appear when supply chain resilience is the outcome.

The integration of ERM, KM, and TA is a key factor in improving SCR in the logistics industry. For managers, the results suggest that risk management systems pay off more when they are linked to knowledge practices and technology investment. Logistics companies in Batam can document and share the lessons produced by risk assessments and tie technology adoption to the risks they have identified, so that both feed into faster recovery from disruptions. These

Published by:

steps can improve their competitiveness and business sustainability in an increasingly complex environment.

This study has several limitations. The cross-sectional design cannot establish causal direction, and the relationship between ERM and TA may run both ways, as the work of Godson and Salman (2026) suggests. The data come from self-reports by individual employees in a single city, which limits generalization and may introduce common method variance. The sample also includes respondents who described themselves as civil servants (4.3%) or entrepreneurs and business owners (20.1%), which makes the respondent group more heterogeneous than the target of logistics company employees. The AVE of KM is slightly below 0.50, and the model leaves most of the variance in SCR unexplained. Future studies could use longitudinal or multi-informant designs, extend the sample to other Indonesian logistics hubs, and add variables such as supply chain collaboration or visibility to explain more of the variation in resilience.

References

Achwan, K. T., Tarigan, Z. J. H., & Nasir, Z. A. bin. (2026). The influence of information technology adoption on supply chain resilience through purchasing strategy, production flexibility, and supply chain responsiveness. Jurnal Teknik Industri: Jurnal Keilmuan dan Aplikasi Teknik Industri, 28(1), 76–91. https://doi.org/10.9744/jti.28.1.76-91

Ahmed, H. F., Hosseinian-Far, A., Sarwar, D., & Khandan, R. (2024). Supply chain complexity and its impact on knowledge transfer: Incorporating sustainable supply chain practices in food supply chain networks. Logistics, 8(1), Article 5. https://doi.org/10.3390/logistics8010005

Ali, I., Golgeci, I., & Arslan, A. (2023). Achieving resilience through knowledge management practices and risk management culture in agri-food supply chains. Supply Chain Management: An International Journal, 28(2), 284–299. https://doi.org/10.1108/SCM-02-2021-0059

Atieh Ali, A. A., Sharabati, A. A. A., Allahham, M., & Nasereddin, A. Y. (2024). The relationship between supply chain resilience and digital supply chain and the impact on sustainability: Supply chain dynamism as a moderator. Sustainability, 16(7), Article 3082. https://doi.org/10.3390/su16073082

Ayo, A. S., & Ruth, I. (2023). Technological adoption in logistics management: Review of literature and agenda setting. Lagos Journal of Geographic Issue, 3(1), 119–134. https://ljgi.unilag.edu.ng/article/view/1798

Bahrami, M., Shokouhyar, S., & Seifian, A. (2022). Big data analytics capability and supply chain performance: The mediating roles of supply chain resilience and innovation. Modern Supply Chain Research and Applications, 4(1), 62–84. https://doi.org/10.1108/MSCRA-11-2021-0021

Balu, N., & Rathnasabapathy, M. (2025). Indirect effect of psychological capital by using partial least square (PLS) path analysis. MethodsX, 14, Article 103162. https://doi.org/10.1016/j.mex.2025.103162

Published by:
Training & Research Institute JERAMBA ILMU SUKSES

Budiman, J., & William, W. (2024). Optimalisasi dan pengembangan company profile digital pada UMKM Sukses Sejahtera untuk menarik peminat funiture [Optimization and development of a digital company profile for UMKM Sukses Sejahtera to attract furniture buyers]. Journal of Human and Education, 4(6), 1305–1309. https://doi.org/10.31004/jh.v4i6.2047

Chen, Y. (2025). Research on enterprise supply chain risk management under digital transformation: From the perspective of resilience enhancement. In Proceedings of the 2025 5th International Conference on Enterprise Management and Economic Development (ICEMED 2025) (pp. 155–162). Atlantis Press. https://doi.org/10.2991/978-94-6463-811-0_16

Daruhadi, G., & Sopiati, P. (2024). Research data collection. International Journal of Social Service and Research, 4(7). https://doi.org/10.46799/ijssr.v4i7.863

Dodla, T. R., & Jones, L. A. (2023). Mitigating knowledge management internal and external risk factors: A literature review of best practices. Scientific Bulletin, 28(1), 44–54. https://doi.org/10.2478/bsaft-2023-0005

Fan, L., He, J., Su, B., & Wang, C. (2025). Digital technology penetration and supply chain resilience improvement: Enterprise innovation strategies in the digital age. International Review of Financial Analysis, 108, Article 104722. https://doi.org/10.1016/j.irfa.2025.104722

Fornasiero, R., & Tolio, T. A. M. (2025). Digital supply chains for ecosystem resilience: A framework for the Italian case. Operations Management Research, 18(1), 210–225. https://doi.org/10.1007/s12063-024-00511-2

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.1177/002224378101800104

Godson, K. T. K., & Salman, S. A. (2026). Artificial intelligence (AI) adoption and enterprise risk management (ERM): The roles of information technology (IT) infrastructure flexibility, technology competence, and organizational culture in Ghana. Journal of Risk and Financial Management, 19(3), Article 229. https://doi.org/10.3390/jrfm19030229

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hosseini Shekarabi, S. A., Kiani Mavi, R., & Romero Macau, F. (2025). Supply chain resilience: A critical review of risk mitigation, robust optimisation, and technological solutions and future research directions. Global Journal of Flexible Systems Management, 26(3), 681–735. https://doi.org/10.1007/s40171-025-00458-8

Hu, L., Hua, X., Zhang, L., Zhou, J., & Tu, Y. (2024). How does knowledge management matter for supply chain resilience? Mediator of collaborative innovation capability and moderator of social media use. Journal of Organizational and End User Computing, 36(1), 1–23. https://doi.org/10.4018/JOEUC.340721

Published by:
Training & Research Institute JERAMBA ILMU SUKSES

Imanuddin, K. A., Astrianty, R. A., & Sensuse, D. I. (2024). Knowledge management factors and its impact on green innovation: A systematic literature review. The Indonesian Journal of Computer Science, 13(4), 5147–5163. https://doi.org/10.33022/ijcs.v13i4.4146

Jidda Jidda, D., Zhen, L., Ashraf, S. F., Nasir, A., & Amoako, T. (2025). Value of enterprise risk management integration and supply chain performance: Mediating role of firm's resilience capability. Sage Open, 15(1). https://doi.org/10.1177/21582440241305618

Kaluku, M. R. A., Sumiati, S., Rofiq, A., & Hadiwidjojod, D. (2025). Enhancing firm performance with supply chain risk management and supply chain resilience: The enabling role of supply chain digitalization adoption. Brazilian Journal of Operations & Production Management, 22(3), Article 2655. https://doi.org/10.14488/BJOPM.2655.2025

Keswani, H., & Vlachos, I. (2022). Achieving supply chain resilience through risk management and mitigation discipline. In Proceedings of the International Conference on Industrial Engineering and Operations Management, Istanbul, Turkey (pp. 1519–1528). IEOM Society International. https://ieomsociety.org/proceedings/2022istanbul/291.pdf

Li, P., Chen, Y., & Guo, X. (2025). Digital transformation and supply chain resilience. International Review of Economics & Finance, 99, Article 104033. https://doi.org/10.1016/j.iref.2025.104033

Li, W., & Liu, Z. (2023). Social, environmental, and governance factors on supply-chain performance with mediating technology adoption. Sustainability, 15(14), Article 10865. https://doi.org/10.3390/su151410865

Mubarik, M., & Maciukaite-Zviniene, S. (2026). Technology or innovation alone is not enough: A SEM-fsQCA based study on intelligent automation driven supply chain resilience. Journal of Innovation & Knowledge, 13, Article 100930. https://doi.org/10.1016/j.jik.2025.100930

Mukherjee, S., Nagariya, R., Mathiyazhagan, K., & Scuotto, V. (2024). Linking supply chain resilience with knowledge management for achieving supply chain performance. Journal of Knowledge Management, 28(4), 971–993. https://doi.org/10.1108/JKM-12-2022-0985

Mulyaningrum, M., Yuwono, W., Esfandiany, S., & Budiman, J. (2025). How to increase product innovation and competitive advantage of MSMEs in Batam City. Trikonomika: Jurnal Ekonomi, 24(2), 139–147. https://doi.org/10.23969/trikonomika.v24i2.33002

Pradana, B. D., Akbar, B., Lukman, S., & Kusworo, K. (2024). The impact of risk management implementation on the effectiveness of SAI's internal audit function. Jurnal Tata Kelola dan Akuntabilitas Keuangan Negara, 10(2), 143–160. https://doi.org/10.28986/jtaken.v10i2.1614

Quang, L. V., Ngoc-Long, N., & Giang, P. X. (2024). Enterprise risk management and firm performance: Exploring the roles of knowledge, technology, and supply chain. Problems and Perspectives in Management, 22(2), 150–164. https://doi.org/10.21511/ppm.22(2).2024.13

Published by:

Rahadi, D. R. (2023). Pengantar partial least squares structural equation modeling (PLS-SEM) [Introduction to partial least squares structural equation modeling (PLS-SEM)]. Lentera Ilmu Madani.

Raja, R., & Venkatachalam, S. (2022). Adoption of digital technology in global third-party logistics services providers: A review of literature. FOCUS: Journal of International Business, 9(1), 105–129. https://doi.org/10.17492/jpi.focus.v9i1.912206

Rodríguez-Espíndola, O., Chowdhury, S., Dey, P. K., Albores, P., & Emrouznejad, A. (2022). Analysis of the adoption of emergent technologies for risk management in the era of digital manufacturing. Technological Forecasting and Social Change, 178, Article 121562. https://doi.org/10.1016/j.techfore.2022.121562

Sakka, O., St-Pierre, J., Bahri, M., & Fadil, N. (2025). SMEs' resilience in the manufacturing sector: The role of formalized risk management and risk culture. Journal of Risk Research, 28(7), 815–837. https://doi.org/10.1080/13669877.2025.2553857

Sarstedt, M., Hair, J. F., Pick, M., Liengaard, B. D., Radomir, L., & Ringle, C. M. (2022). Progress in partial least squares structural equation modeling use in marketing research in the last decade. Psychology & Marketing, 39(5), 1035–1064. https://doi.org/10.1002/mar.21640

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In C. Homburg, M. Klarmann, & A. Vomberg (Eds.), Handbook of market research (pp. 1–47). Springer. https://doi.org/10.1007/978-3-319-05542-8_15-2

Schneider, A., Wagenknecht, A., Sydow, H., Riedlinger, D., Holzinger, F., Figura, A., Deutschbein, J., Reinhold, T., Pigorsch, M., Stasun, U., Schenk, L., & Möckel, M. (2023). Primary and secondary data in emergency medicine health services research: A comparative analysis in a regional research network on multimorbid patients. BMC Medical Research Methodology, 23(1), Article 34. https://doi.org/10.1186/s12874-023-01855-2

Sezer, M. D., Ozbiltekin-Pala, M., Kazancoglu, Y., Garza-Reyes, J. A., Kumar, A., & Kumar, V. (2023). Investigating the role of knowledge-based supply chains for supply chain resilience by graph theory matrix approach. Operations Management Research, 16(3), 1220–1230. https://doi.org/10.1007/s12063-023-00391-y

Suprayitno, D., & Latunreng, W. (2024). Supply chain resilience: Strategies for mitigating disruptions and enhancing business continuity. Management Studies and Business Journal (PRODUCTIVITY), 1(5), 711–719. https://journal.ppipbr.com/index.php/productivity/article/download/284/267

Tewu, M. L. D., Suwarno, Lisdiono, P., Friska, R., & Pramono, A. J. (2024). Enterprise risk management and supply chain management: The mediating role of competitive advantage and decision making in improving firms performance. Uncertain Supply Chain Management, 12(2), 1131–1140. https://doi.org/10.5267/j.uscm.2023.11.021

Unik, M., Rizki, Y., Sitanggang, I. S., & Syaufina, L. (2024). Knowledge management system for forest and land fire mitigation in Indonesia: A web-based application development. Jurnal Manajemen Hutan Tropika, 30(1), 12–20. https://doi.org/10.7226/jtfm.30.1.12

Published by:
Training & Research Institute JERAMBA ILMU SUKSES

Wang, Y. (2025). The impact of digital transformation on enterprise supply chain resilience. Advances in Economics, Management and Political Sciences, 196(1), 112–118. https://doi.org/10.54254/2754-1169/2025.bj24934

Zighan, S., Dwaikat, N. Y., Alkalha, Z., & Abualqumboz, M. (2024). Knowledge management for supply chain resilience in pharmaceutical industry: Evidence from the Middle East region. The International Journal of Logistics Management, 35(4), 1142–1167. https://doi.org/10.1108/IJLM-05-2022-0215

Copyrights

Copyright for this article is retained by the author(s), with first publication rights granted to the journal.

This is an open-access article distributed under the terms and conditions of the Creative Commons Attribution license (http://creativecommons.org/licenses/by/4.0/)

Published by: