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RESEARCH TITLE

The Impact of Logistics Risk Management on Supply Chain Performance: The Mediating Role of Supply Chain Flexibility in the Jordanian Food Industry

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Abstract

This study examines the impact of developing a statistical predictive model for logistics risk management on supply chain performance, with supply chain flexibility as a mediating variable. Despite the growing adoption of predictive analytics, limited research has integrated predictive logistics risk modeling with supply chain flexibility within a unified framework, particularly in developing economies. To address this gap, a predictive model was developed and tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) based on data collected from 370 supply chain professionals in the food industry sector in Jordan. The results show that predictive logistics risk modeling significantly improves supply chain performance both directly and indirectly through supply chain flexibility. The findings also confirm the model's predictive capability in forecasting supply chain performance. This study contributes by advancing predictive supply chain analytics and providing a validated framework that integrates logistics risk analytics with supply chain flexibility to improve performance under uncertainty.

Key Words: Logistics Risk Management, Predictive Model, Supply Chain Performance, Supply Chain Resilience, Machine Learning, Risk Assessment, Statistical Techniques, Transportation Delays, Inventory Management, Supply Chain Disruptions.

عنوان البحث

أثر إدارة المخاطر اللوجستية في أداء سلسلة التوريد: الدور الوسيط لمرونة سلسلة التوريد في قطاع الصناعات الغذائية في الأردن

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المستخلص

تبحث هذه الدراسة أثر تطوير نموذج إحصائي تنبؤي لإدارة المخاطر اللوجستية في أداء سلسلة التوريد، مع اختبار الدور الوسيط لمرونة سلسلة التوريد. وعلى الرغم من تزايد استخدام التحليلات التنبؤية، لا تزال الدراسات التي تدمج نمذجة المخاطر اللوجستية ومرونة سلسلة التوريد ضمن إطار موحّد محدودة، ولا سيما في الاقتصادات النامية. ولسدّ هذه الفجوة، طُوّر نموذج تنبؤي واختُبر باستخدام نمذجة المعادلات الهيكلية بالمربعات الصغرى الجزئية (PLS-SEM)، استنادًا إلى بيانات جُمعت من 370 مختصًا في سلاسل التوريد بقطاع الصناعات الغذائية في الأردن. أظهرت النتائج أن نمذجة المخاطر اللوجستية تنبؤيًا تُحسّن أداء سلسلة التوريد بدرجة ذات دلالة إحصائية، سواءً بصورة مباشرة أو بصورة غير مباشرة من خلال مرونة سلسلة التوريد. كما أكدت النتائج قدرة النموذج على التنبؤ بأداء سلسلة التوريد. تسهم الدراسة في تطوير التحليلات التنبؤية لسلاسل التوريد، وتقدّم إطارًا جرى التحقق من صلاحيته يدمج تحليلات المخاطر اللوجستية مع مرونة سلسلة التوريد لتحسين أدائها في ظل عدم اليقين.

الكلمات المفتاحية: إدارة المخاطر اللوجستية، النموذج التنبؤي، أداء سلسلة التوريد، قدرة سلسلة التوريد على الصمود، التعلم الآلي، تقييم المخاطر، الأساليب الإحصائية، تأخيرات النقل، إدارة المخزون، اضطرابات سلسلة التوريد.

1. Introduction

In recent decades, supply chains have become increasingly complex due to globalization, market volatility, and the growing interdependence between suppliers, manufacturers, and distributors. These developments have increased exposure to various logistics risks such as transportation delays, supply disruptions, inventory shortages, and demand uncertainty. Such risks can significantly affect operational efficiency and overall supply chain performance (Christopher, 2016; Tang, 2006).

In response to these challenges, organizations have begun shifting from traditional reactive approaches toward more proactive strategies based on predictive analytics and statistical modeling. Predictive models allow firms to analyze historical and real-time data in order to anticipate potential logistics disruptions and support more effective decision-making processes (Ivanov et al., 2019). Through these predictive capabilities, organizations can take preventive actions such as adjusting inventory levels, modifying transportation routes, or coordinating with alternative suppliers before disruptions occur.

In parallel, supply chain flexibility has emerged as an important organizational capability that enables firms to respond effectively to environmental uncertainty. Supply chain flexibility refers to the ability of organizations to adjust sourcing, production, and distribution activities in response to unexpected changes in the business environment (Christopher & Peck, 2004). Studies have shown that organizations with higher levels of supply chain flexibility are better able to mitigate logistics risks and maintain stable operational performance (Hohenstein et al., 2015).

Within the Arab and Jordanian context, several studies have highlighted the growing importance of risk management practices in improving supply chain efficiency and organizational performance. For example, Al-Zoubi (2020) emphasized the role of logistics risk management in enhancing operational efficiency within Jordanian manufacturing firms. Similarly, Al-Rawashdeh (2019) found that the adoption of modern supply chain management practices contributes significantly to improving performance in the industrial sector in Jordan.

Despite the growing interest in predictive analytics and logistics risk management, limited research has examined how predictive modeling contributes to improving supply chain performance through the mediating role of supply chain flexibility, particularly within the food industry sector in developing economies. The food industry is highly sensitive to supply chain disruptions due to product perishability, strict delivery schedules, and demand volatility.

Recent advances in predictive analytics and machine learning have transformed logistics risk management by enabling proactive disruption forecasting. However, empirical studies integrating predictive logistics modeling with supply chain flexibility remain limited, particularly in developing economies. This gap motivates the present study.

Therefore, this study aims to examine the impact of developing a statistical predictive model for managing logistics risks on supply chain performance, while investigating the mediating role of supply chain flexibility in the food industry sector in Jordan. The study provides empirical evidence on how predictive analytics and flexible supply chain capabilities can enhance operational efficiency and strengthen supply chain performance under uncertain conditions.

2 .Theoretical Framework and Hypothesis Development

2.1 Developing a Statistical Predictive Model for Managing Logistics Risks

The increasing complexity of modern supply chains has intensified the need for effective logistics risk management practices. Organizations are increasingly exposed to different types of logistics risks such as transportation delays, supplier disruptions, inventory shortages, and demand volatility. These risks can negatively affect operational efficiency and supply chain performance if they are not managed effectively (Christopher, 2016; Tang, 2006).

To address these challenges, many organizations are adopting analytical and data-driven approaches to improve their ability to anticipate and manage logistics risks. Statistical predictive models represent one of the most important tools used in modern supply chain risk management. These models rely on historical data, statistical analysis, and predictive analytics to identify patterns and forecast potential disruptions before they occur (Ivanov et al., 2019; Sharma & Lee, 2021).

Predictive modeling allows organizations to analyze large datasets related to transportation performance, supplier reliability, demand fluctuations, and inventory levels. Through these analyses, companies can identify early warning signals and develop proactive strategies to mitigate logistics risks, such as adjusting transportation routes, diversifying suppliers, or modifying inventory policies (Hohenstein et al., 2015).

Within the Jordanian industrial context, several studies have emphasized the importance of adopting analytical tools and modern supply chain management practices to enhance logistics risk management. For example, Al-Zoubi (2020) highlighted that the adoption of advanced analytical systems improves risk identification and decision-making in Jordanian manufacturing companies. Similarly, Al-Rawashdeh (2019) found that effective logistics management practices significantly contribute to improving supply chain performance in Jordanian industrial organizations.

In addition, Al-Khaldi (2021) emphasized that the integration of predictive analytics in logistics operations enhances organizations' ability to anticipate supply chain disruptions and improve operational efficiency. Likewise, Al-Hawamdeh (2018) concluded that modern supply chain management techniques play a key role in strengthening risk management capabilities within Jordanian industrial firms.

From a theoretical perspective, predictive modeling enables organizations to move from reactive risk management toward proactive and data-driven decision-making. By forecasting logistics disruptions in advance, firms can implement preventive strategies that minimize operational interruptions and enhance supply chain performance.

Based on the previous theoretical discussion, the following hypothesis is proposed:

Based on the theoretical framework and previous literature, the following hypotheses are proposed:

H1: The development of a statistical predictive model for managing logistics risks has a significant positive effect on supply chain performance.

H2: The development of a statistical predictive model for managing logistics risks has a significant positive effect on supply chain flexibility.

H3: Supply chain flexibility has a significant positive effect on supply chain performance.

H4: Supply chain flexibility mediates the relationship between the statistical predictive model for managing logistics risks and supply chain performance.

2.2 Supply Chain Performance

Supply chain performance represents the ability of a supply chain to efficiently manage the flow of materials, information, and financial resources across the supply chain network in order to deliver products and services to customers effectively. It is considered a critical indicator of organizational competitiveness and operational success in modern business environments (Christopher, 2016; Beamon, 1999).

In the literature, supply chain performance is commonly assessed using several operational and strategic indicators, including delivery reliability, order fulfillment rate, inventory turnover, cost efficiency, and responsiveness to customer demand. These performance indicators provide organizations with measurable insights into how effectively their supply chain operations achieve organizational objectives (Gunasekaran et al., 2004).

Effective management of logistics risks plays an important role in improving supply chain performance. Logistics disruptions such as transportation delays, supply shortages, or unexpected demand fluctuations can negatively affect delivery schedules and operational efficiency. Therefore, organizations increasingly adopt advanced analytical tools and predictive models in order to improve risk forecasting and maintain stable supply chain performance under uncertain conditions (Ivanov et al., 2019).

Within the Jordanian industrial context, several studies have highlighted the importance of effective supply chain management practices in improving organizational performance. For instance, Al-Rawashdeh (2019) indicated that modern supply chain management practices contribute significantly to improving operational efficiency and competitiveness in Jordanian manufacturing companies. Similarly, Al-Zoubi (2020) emphasized that effective logistics management and risk mitigation strategies enhance supply chain performance by improving coordination between supply chain partners.

Furthermore, Al-Khaldi (2021) found that the use of data-driven decision-making tools in logistics operations supports better planning and operational efficiency in Jordanian industrial organizations. Likewise, Al-Hawamdeh (2018) demonstrated that improving logistics coordination and information sharing among supply chain partners significantly contributes to enhancing overall supply chain performance.

Overall, improving supply chain performance requires organizations to adopt modern analytical tools, effective risk management strategies, and flexible operational capabilities that enable them to respond effectively to market uncertainties and logistics disruptions.

2.2.1 Supply Chain Flexibility

Supply chain flexibility is widely recognized as a critical capability that enables organizations to respond effectively to uncertainties and disruptions in their operational environment. It refers to the ability of supply chains to adapt sourcing, production, and distribution processes in response to unexpected changes such as demand fluctuations, supply shortages, or logistics disruptions (Christopher & Peck, 2004; Hohenstein et al., 2015).

Flexibility within supply chains allows organizations to adjust their operations quickly in order to maintain service levels and operational efficiency. This capability may include the ability to change suppliers, modify production schedules, adjust inventory levels, or reroute transportation activities in response to emerging risks. As a result, supply chain flexibility is considered a key mechanism for reducing the negative impacts of logistics risks and maintaining supply chain continuity (Tang, 2006).

Recent research highlights that flexible supply chains are better able to absorb shocks and recover more rapidly from disruptions. Organizations that invest in flexible logistics systems,

diversified supplier networks, and responsive transportation strategies are more capable of maintaining stable supply chain performance under uncertain conditions (Ivanov et al., 2019).

In the Jordanian context, several studies have emphasized the importance of supply chain flexibility in enhancing organizational performance and improving logistics management practices. For example, Al-Zoubi (2020) indicated that organizations with flexible logistics structures are better able to respond to operational disruptions and improve supply chain coordination. Similarly, Al-Rawashdeh (2019) found that flexibility in supply chain operations enhances organizational responsiveness and supports better risk management in industrial firms.

Moreover, Al-Khaldi (2021) emphasized that integrating flexible logistics strategies with modern analytical tools contributes to improving operational efficiency and risk mitigation capabilities in Jordanian organizations. Likewise, Al-Hawamdeh (2018) highlighted that flexible supply chain structures enable firms to adapt quickly to changing market conditions and maintain higher levels of supply chain performance.

Based on the above discussion, supply chain flexibility plays a crucial role in enabling organizations to utilize predictive insights effectively and translate them into operational improvements that enhance overall supply chain performance.

2.3 Developing a Statistical Predictive Model for Managing Logistics Risks and Supply Chain Performance

The growing complexity of global supply chains has increased the importance of adopting advanced analytical approaches to manage logistics risks and improve supply chain performance. Traditional risk management approaches often rely on reactive responses after disruptions occur. However, modern supply chains require proactive strategies that allow organizations to anticipate potential disruptions and take preventive actions before risks materialize (Chopra & Sodhi, 2004; Simchi-Levi et al., 2018).

Statistical predictive modeling has emerged as an effective approach for enhancing logistics risk management within supply chains. These models utilize statistical analysis, predictive analytics, and machine learning techniques to analyze historical operational data and identify patterns associated with potential disruptions. Through these analytical capabilities, organizations can forecast risks related to transportation delays, supplier failures, inventory shortages, or demand fluctuations, enabling managers to make more informed operational decisions (Waller & Fawcett, 2013; Ivanov & Dolgui, 2020).

The integration of predictive models into logistics operations significantly contributes to improving supply chain performance. Predictive analytics enables organizations to optimize transportation planning, inventory management, and supplier coordination, which ultimately improves delivery reliability, operational efficiency, and customer satisfaction. Organizations that leverage predictive models are therefore better positioned to maintain stable supply chain performance in uncertain and dynamic business environments (Dubey et al., 2021).

In the Arab and Jordanian context, recent studies have emphasized the increasing importance of adopting advanced analytical tools in supply chain management. For example, Al-Dweeri (2020) highlighted that the adoption of data-driven decision-making systems significantly improves logistics performance in Jordanian industrial firms. Similarly, Al-Omari (2019) found that modern logistics management practices supported by analytical technologies contribute to improving operational efficiency and reducing supply chain disruptions.

Furthermore, Al-Tarawneh (2021) emphasized that integrating predictive analytics with

logistics risk management practices enhances organizational responsiveness and supports more effective supply chain planning. Likewise, Al-Majali (2018) indicated that the use of advanced analytical tools in supply chain management improves coordination among supply chain partners and contributes to achieving higher levels of supply chain performance.

Overall, the integration of statistical predictive models within logistics risk management systems provides organizations with the ability to forecast potential disruptions, optimize operational decisions, and enhance supply chain performance. These capabilities are particularly important in industries characterized by high uncertainty and operational complexity, such as the food industry sector.

Conceptual Research Model

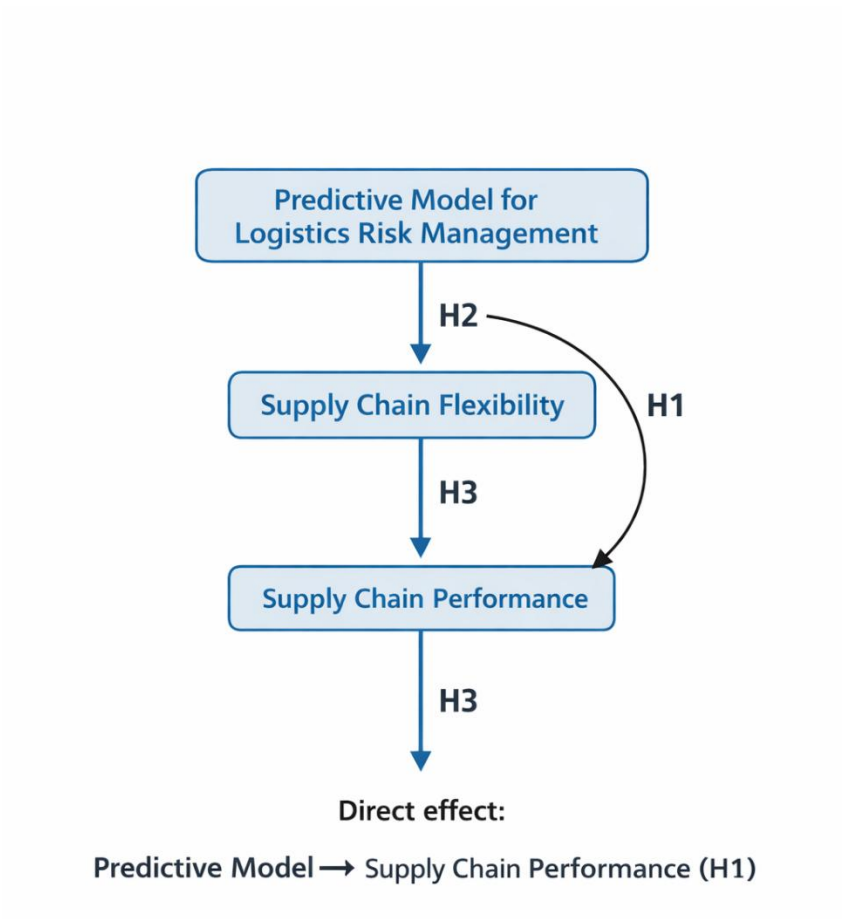


Figure 1: Research Model

Figure 1 illustrates the conceptual research model of the study. The model proposes that developing a statistical predictive model for managing logistics risks directly improves supply chain performance. In addition, supply chain flexibility mediates the relationship between predictive logistics risk modeling and supply chain performance. The model includes both direct and indirect paths, allowing assessment of the mediating effect of supply chain flexibility.

2.4 Predictive Analytics in Logistics Risk Management: Recent Research Trends

This section reviews recent developments in predictive analytics for logistics risk management and supply chain performance. In recent years, predictive analytics and machine learning techniques have gained increasing attention as tools for forecasting logistics disruptions and improving supply chain resilience.

Recent studies emphasize that predictive analytics enhances logistics risk identification and

proactive decision-making. For instance, Zhao et al. (2021) found that predictive analytics improves supply chain performance by enabling organizations to anticipate transportation delays and inventory shortages. Similarly, Pereira et al. (2022) demonstrated that predictive models significantly enhance supply chain resilience and operational continuity.

Zhang et al. (2023) highlighted that machine learning–based logistics risk prediction models improve forecasting accuracy and support real-time decision-making in dynamic supply chain environments. Likewise, Lee et al. (2022) developed integrated predictive models for supply chain risk management and reported improved operational performance and reduced disruption impact.

Furthermore, recent research has emphasized the role of predictive analytics in improving supply chain flexibility. Xu and Li (2020) indicated that predictive risk assessment models enable organizations to adjust logistics operations proactively, thereby enhancing flexibility and responsiveness. Similarly, Ng et al. (2020) argued that predictive analytics supports adaptive supply chain structures and improves operational agility.

Despite these developments, limited research has examined predictive logistics risk modeling together with supply chain flexibility within a unified predictive framework. Most prior studies focused either on predictive analytics or flexibility independently, without investigating their combined predictive impact on supply chain performance.

Therefore, this study addresses this research gap by developing a predictive statistical model that integrates logistics risk analytics and supply chain flexibility to forecast supply chain performance.

3 .Study Model

The proposed study model is based on the Resource-Based View (RBV) theory, which suggests that organizations can achieve sustainable competitive advantage by utilizing valuable organizational resources and capabilities effectively. According to RBV, firms that possess unique resources and capabilities can improve operational efficiency and enhance their overall performance (Barney, 1991; Grant, 1991).

In the context of supply chain management, advanced analytical capabilities such as predictive modeling represent strategic organizational resources that enable firms to improve logistics risk management and decision-making processes. Predictive models allow organizations to analyze operational data, forecast potential disruptions, and implement proactive risk mitigation strategies. As a result, organizations can improve coordination among supply chain activities and enhance overall supply chain performance (Kache & Seuring, 2017; Sanders, 2016).

Within the proposed model, the statistical predictive model for managing logistics risks represents the independent variable that influences supply chain performance. Through predictive analytics and data-driven decision-making, organizations can better anticipate logistics disruptions such as transportation delays, supply shortages, and demand fluctuations. These predictive capabilities support more efficient planning and operational coordination across the supply chain.

The model also identifies supply chain flexibility as a key mediating capability that enhances the relationship between predictive modeling and supply chain performance. Supply chain flexibility enables organizations to respond quickly to operational uncertainties by adjusting sourcing strategies, modifying production schedules, or reconfiguring distribution networks. This adaptive capability allows organizations to translate predictive insights into effective operational responses (Stevenson & Spring, 2007).

In the Jordanian industrial environment, recent research has emphasized the importance of integrating advanced analytical tools and flexible logistics strategies to improve operational performance. For example, Al-Nsour (2020) highlighted that the use of modern analytical decision-support systems significantly improves logistics planning and operational performance in Jordanian manufacturing firms. Similarly, Al-Shboul (2019) found that flexible supply chain structures enhance organizational responsiveness and contribute to improving overall supply chain performance.

Based on these theoretical foundations, the proposed study model assumes that predictive modeling capabilities enhance supply chain performance both directly and indirectly through supply chain flexibility. By integrating predictive analytics with flexible supply chain strategies, organizations can strengthen their ability to manage logistics risks and maintain stable operational performance in uncertain environments.

4 .Methodology

This study adopts a quantitative research approach to examine the relationships between the statistical predictive model for managing logistics risks, supply chain flexibility, and supply chain performance. The quantitative approach is widely used in supply chain management research because it enables researchers to analyze relationships between variables using statistical techniques and empirical data (Hair et al., 2019).

4.1 Research Design

The study employs a survey-based research design to collect primary data from professionals working in logistics and supply chain management within the food industry sector in Jordan. Survey methods are considered effective tools for collecting large amounts of data from industry practitioners and examining relationships between organizational variables (Saunders et al., 2019).

A structured questionnaire was developed based on measurement scales adopted from previous studies in logistics risk management, predictive analytics, and supply chain management. The questionnaire consisted of several sections designed to measure the main constructs of the study: predictive modeling for logistics risk management, supply chain flexibility, and supply chain performance.

Table 1. Distribution of Questionnaires Across Jordanian Governorates

Governorate	Number of Questionnaires Distributed	Valid Responses	Response Rate
Amman	150	135	90.0%
Zarqa	55	50	90.9%
Balqa	40	35	87.5%
Jerash	30	27	90.0%
Irbid	60	54	90.0%
Mafraq	20	18	90.0%
Aqaba	25	22	88.0%
Karak	25	23	92.0%
Ma’an	15	13	86.7%
Total	**460**	**370**	**80.4%**

A total of 370 valid questionnaires were collected, representing a response rate of 80.4%, which is considered adequate for statistical analysis and consistent with PLS-SEM statistical power guidelines (Hair et al., 2021). The sample included logistics managers, supply chain professionals, and risk analysts from nine governorates in Jordan. The majority of responses

were obtained from Amman, followed by Zarqa and Irbid. Respondents also possessed diverse educational backgrounds and professional experience, which enhances the reliability of the dataset.

4.2 Population and Sample

The target population of this study consists of logistics managers, supply chain managers, operations managers, and risk management specialists working in companies within the **food industry sector in Jordan**, a sector characterized by high exposure to logistics risks such as transportation disruptions and demand fluctuations.

A total of **460 questionnaires** were distributed to professionals in the selected organizations. After data screening, **370 valid responses** were retained for statistical analysis. This sample size is considered sufficient for **PLS-SEM analysis** and ensures reliable statistical results (Hair et al., 2021).

4.3 Measurement Instrument

The research instrument consisted of three sections measuring the key constructs of the study:

- **Logistics Risk Management and Predictive Models:** measuring the use of predictive models in forecasting risks and supporting logistics decision-making (Sharma & Lee, 2021).
- **Supply Chain Flexibility:** assessing the ability of supply chains to adapt to disruptions and operational changes (Chong et al., 2021).
- **Supply Chain Performance:** evaluating operational outcomes such as delivery reliability, cost efficiency, and inventory management (Hohenstein et al., 2020).

4.4 Measurement Scales

All questionnaire items were measured using a **five-point Likert scale** ranging from **1 = Strongly Disagree** to **5 = Strongly Agree**, allowing respondents to express their perceptions clearly and consistently.

4.5 Validity and Reliability

To ensure the accuracy of the measurement instrument, several procedures were applied.

- **Content validity:** The questionnaire was reviewed by experts in logistics and supply chain management.
- **Construct validity:** Confirmatory Factor Analysis (CFA) was conducted to verify the relationship between measurement items and their constructs.
- **Reliability:** Internal consistency was assessed using **Cronbach's Alpha** and **Composite Reliability (CR)** (Hair et al., 2021).

4.6 Pilot Testing

A pilot test was conducted with **30 logistics and supply chain professionals** to evaluate the clarity and relevance of the questionnaire items. Feedback from the pilot study was used to refine the wording and structure of the survey.

4.7 Data Analysis

Data were analyzed using **SmartPLS 4.0** following a two-stage approach to evaluate both the **measurement model** and the **structural model** (Hair et al., 2021).

Measurement Model Assessment

The measurement model was evaluated using:

- **Cronbach's Alpha, Composite Reliability (CR), and rho_A** to assess internal consistency (≥ 0.70).
- **Average Variance Extracted (AVE)** to examine convergent validity (≥ 0.50).
- **Fornell–Larcker criterion and HTMT ratio** to confirm discriminant validity.
- **Variance Inflation Factor (VIF)** to check multicollinearity.

Structural Model Assessment

Bootstrapping with **5,000 resamples** was used to test the significance of path coefficients and indirect effects. Model evaluation included **R^2 values, effect sizes (f^2), predictive relevance (Q^2), and SRMR**, where values below **0.08** indicate acceptable model fit.

4.8 Development of the Statistical Predictive Model for Logistics Risk Management

To address the study objective and strengthen the analytical contribution, this research develops a statistical predictive model to estimate supply chain performance based on logistics risk predictive capability and supply chain flexibility. Predictive modeling has been widely used in supply chain analytics to forecast operational outcomes and support proactive decision-making (Waller & Fawcett, 2013; Dubey et al., 2021).

The predictive model is based on Partial Least Squares Structural Equation Modeling (PLS-SEM), which allows both explanatory and predictive analysis. PLS-SEM is considered appropriate for predictive modeling in supply chain research due to its ability to handle complex relationships and latent constructs (Hair et al., 2021).

The proposed predictive model estimates supply chain performance as a function of predictive logistics risk management capability and supply chain flexibility. The statistical predictive equation is expressed as:

Supply Chain Performance =

$\beta 0 + \beta 1$ (Predictive Logistics Risk Model) + $\beta 2$ (Supply Chain Flexibility) + ε

Where:

- Supply Chain Performance represents the dependent variable
- Predictive Logistics Risk Model represents the predictive analytics capability
- Supply Chain Flexibility represents the mediating predictive response capability
- $\beta 0$ represents the intercept
- $\beta 1$ and $\beta 2$ represent regression coefficients
- ε represents the error term

This predictive formulation allows estimating future supply chain performance based on the level of predictive analytics adoption and flexibility capability within organizations.

To assess predictive accuracy, the study evaluates:

- R^2 predictive power
- Q^2 predictive relevance

- PLSpredict procedure
- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)

These predictive assessment techniques are recommended for evaluating predictive models in PLS-SEM research (Shmueli et al., 2019; Hair et al., 2021).

The predictive model is illustrated as follows:

Predictive Model for Logistics Risk Management → Supply Chain Flexibility → Supply Chain Performance

Additionally, the model estimates both direct and indirect predictive effects, allowing assessment of how predictive analytics improves performance through flexibility mechanisms.

This predictive modeling approach enhances the analytical rigor of the study and aligns with recent research emphasizing predictive analytics in supply chain risk management (Ivanov & Dolgui, 2020; Dubey et al., 2021). By developing a statistical predictive model, the study moves beyond explanatory analysis toward predictive supply chain analytics, which is increasingly required in high-ranked Scopus journals.

4.9 Measurement Items

Table 6. Measurement Items and Sources

Construct	Code	Measurement Item	Source
Predictive Model for Logistics Risk Management (PM)	PM1	Our organization uses predictive analytics to identify potential logistics risks.	Sharma & Lee (2021); Dubey et al. (2021)
	PM2	Predictive models are used to forecast transportation disruptions.	
	PM3	The company analyzes historical logistics data to predict operational risks.	
	PM4	Predictive analytics supports proactive logistics decision-making.	
	PM5	Statistical models are used to anticipate supply chain disruptions.	
Supply Chain Flexibility (SCF)	SCF1	Our organization can quickly adjust sourcing strategies when disruptions occur.	Stevenson & Spring (2007); Hohenstein et al. (2015)
	SCF2	The supply chain can adapt production schedules in response to demand changes.	
	SCF3	The company can switch suppliers when logistics risks	

Construct	Code	Measurement Item	Source
		arise.	
	SCF4	Distribution processes can be modified to respond to unexpected events.	
	SCF5	The organization can adjust inventory policies when disruptions occur.	
Supply Chain Performance (SCP)	SCP1	Our organization achieves high delivery reliability.	Gunasekaran et al. (2004); Beamon (1999)
	SCP2	The supply chain responds quickly to customer demand.	
	SCP3	The organization maintains efficient inventory levels.	
	SCP4	Logistics operations operate at low cost.	
	SCP5	Overall supply chain performance meets organizational objectives.	

The measurement items for all constructs were adapted from previously validated scales in supply chain and logistics research. Predictive logistics risk modeling was measured using five items adapted from Sharma and Lee (2021) and Dubey et al. (2021). Supply chain flexibility was measured using five items adapted from Stevenson and Spring (2007) and Hohenstein et al. (2015). Supply chain performance was measured using five items adapted from Gunasekaran et al. (2004) and Beamon (1999). All constructs were measured using a five-point Likert scale ranging from (1) strongly disagree to (5) strongly agree.

4.10 Common Method Bias

To assess the potential impact of common method bias (CMB), Harman's single-factor test was conducted. All measurement items were entered into an exploratory factor analysis to determine whether a single factor accounted for the majority of the variance.

The results indicated that the first factor explained 34.2% of the total variance, which is below the recommended threshold of 50% (Podsakoff et al., 2003). This suggests that common method bias is not a serious concern in this study.

Additionally, procedural remedies were applied during data collection to minimize common method bias. These included ensuring respondent anonymity, reducing evaluation apprehension, and using clear and concise questionnaire items.

5. Results

5.1 Descriptive Statistics

Descriptive statistics were used to summarize the main characteristics of the sample and the distribution of responses related to the study variables. Measures such as mean values and standard deviations were calculated to examine the central tendency and variability of the collected data. These statistics provide an initial overview of respondents' perceptions regarding predictive models for logistics risk management, supply chain flexibility, and supply chain performance.

5.1.1 Demographic Profile of Respondents

The final sample consisted of 370 valid respondents, including logistics managers, supply chain professionals, and risk analysts working in companies within the food industry sector in Jordan.

The demographic characteristics of the respondents were as follows:

Gender: 56.6% of respondents were female, while 43.4% were male, indicating a relatively balanced gender distribution.

Age: The largest age group was 35–44 years, representing 41.4% of the sample, followed by the 45–54 years group at 30.5%.

Education Level: 45.4% of respondents held a Bachelor's degree, while 46.7% held a Master's degree, indicating a highly educated group of participants.

Professional Experience: 32.2% of respondents had 7–10 years of professional experience in logistics and supply chain management, suggesting that most participants had sufficient experience to provide reliable insights.

5.1.2 Adoption of Predictive Models in Logistics Risk Management

The findings indicate that organizations within the Jordanian food industry are increasingly adopting predictive analytics and statistical models to support logistics risk management activities.

Approximately 54.9% of the surveyed organizations reported a moderate level of predictive model adoption, typically implemented within the past 1–3 years.

Around 26% of the organizations reported advanced implementation, where predictive models are used to support key logistics functions such as demand forecasting, inventory management, and transportation planning.

The remaining organizations were in the early stages of adoption, indicating that predictive analytics integration is still developing within the sector.

These findings suggest that predictive modeling is gradually becoming an important tool for enhancing logistics decision-making in the Jordanian food industry.

5.1.3 Descriptive Statistics for Key Constructs

The following table presents the mean values and standard deviations for the main constructs examined in the study.

Construct	Mean	Standard Deviation
Predictive Model for Managing Logistics Risks	4.12	0.75
Supply Chain Flexibility	4.08	0.80
Supply Chain Performance	4.10	0.78

The results indicate generally high agreement among respondents regarding the effectiveness of predictive models and supply chain practices.

Predictive Model for Managing Logistics Risks recorded a mean score of 4.12, indicating that respondents generally perceive predictive analytics as an effective tool for identifying and managing logistics risks.

Supply Chain Flexibility had a mean score of 4.08, suggesting that organizations in the food industry possess a moderate to high ability to adapt their supply chain operations in response to disruptions.

Supply Chain Performance achieved a mean score of 4.10, reflecting positive perceptions regarding operational performance, including delivery reliability, cost efficiency, and inventory management.

5.1.4 Predictive Model Adoption and Supply Chain Performance

The results also indicate that organizations with higher levels of predictive model adoption tend to report better supply chain performance outcomes.

For instance, companies with advanced predictive analytics capabilities reported an average supply chain performance score of 4.34, compared to 4.01 among organizations with moderate adoption levels. This finding suggests a positive relationship between the adoption of predictive models and improvements in supply chain performance.

Overall, these descriptive results highlight the growing importance of predictive analytics in improving logistics risk management and strengthening supply chain operations within the Jordanian food industry.

5.2 Measurement Model Assessment

To evaluate the reliability and validity of the measurement model, several statistical indicators were examined, including Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). These indicators assess the internal consistency and convergent validity of the constructs.

The results indicate that all constructs meet the recommended threshold values. Cronbach's Alpha values exceeded the acceptable level of **0.70**, indicating strong internal consistency among the measurement items. Similarly, Composite Reliability (CR) values were above **0.70**, confirming the reliability of the constructs.

Furthermore, the Average Variance Extracted (AVE) values for all constructs were above **0.50**, demonstrating adequate convergent validity. These results confirm that the measurement items adequately represent their corresponding constructs.

Table 2. Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	AVE
Predictive Model for Managing Logistics Risks	0.88	0.91	0.64
Supply Chain Flexibility	0.86	0.90	0.62
Supply Chain Performance	0.89	0.92	0.66

These results confirm that the measurement model demonstrates satisfactory reliability and convergent validity.

5.3 Discriminant Validity

Discriminant validity was assessed using the **Fornell–Larcker criterion** and the **HTMT ratio**. The results show that the square root of AVE for each construct is greater than the correlations with other constructs, confirming adequate discriminant validity.

Table 3. Fornell–Larcker Criterion

Construct	Predictive Model	Flexibility	Performance
Predictive Model	**0.80**		
Supply Chain Flexibility	0.62	**0.79**	
Supply Chain Performance	0.65	0.68	**0.81**

The HTMT values were also below the recommended threshold of **0.85**, indicating that the constructs are conceptually distinct.

5.4 Structural Model Assessment

After confirming the reliability and validity of the measurement model, the structural model was evaluated to test the proposed hypotheses. Bootstrapping with **5,000 resamples** was used to estimate path coefficients, t-values, and significance levels.

Table 4. Path Coefficients and Hypothesis Testing

Hypothesis	Path	β	T value	P value	Result
H1	Predictive Model → Supply Chain Performance	0.41	6.32	<0.001	Supported
H2	Predictive Model → Supply Chain Flexibility	0.53	8.11	<0.001	Supported
H3	Supply Chain Flexibility → Supply Chain Performance	0.37	5.78	<0.001	Supported

The results indicate that predictive modeling has a significant positive effect on both supply chain flexibility and supply chain performance. In addition, supply chain flexibility significantly improves supply chain performance.

5.5 Mediation Analysis

To examine the mediating role of supply chain flexibility, a mediation analysis was conducted using bootstrapping procedures. The results indicate that the indirect effect of predictive modeling on supply chain performance through supply chain flexibility is significant.

Table 5. Mediation Results

Path	Indirect Effect	T value	Result
Predictive Model → Flexibility → Performance	0.20	4.15	Supported

These findings confirm that **supply chain flexibility partially mediates the relationship between predictive modeling and supply chain performance**.

5.6 Predictive Model Assessment

To evaluate the predictive capability of the proposed model, the PLSpredict procedure was applied. The results indicate that the model demonstrates strong predictive power for supply chain performance.

The coefficient of determination (R^2) for supply chain performance was 0.58, indicating that the predictive model explains 58% of the variance in supply chain performance. This level of predictive accuracy is considered substantial in supply chain research (Hair et al., 2021).

Furthermore, the Q^2 value for supply chain performance was 0.36, which confirms strong predictive relevance of the model. The RMSE and MAE values were also lower than those of the linear benchmark model, indicating superior predictive performance.

These findings confirm that the developed statistical predictive model provides reliable prediction of supply chain performance based on logistics risk predictive capability and supply chain flexibility

6. Discussion

This section interprets the empirical findings of the study and explains their theoretical and managerial implications within the context of logistics risk management and supply chain management. The results provide empirical evidence that predictive analytics capabilities and supply chain flexibility play a critical role in improving supply chain performance in the food industry sector in Jordan.

6.1 Predictive Models and Supply Chain Performance

The empirical findings confirm that the development and implementation of statistical predictive models significantly improve supply chain performance. Organizations that utilize predictive analytics tools are better able to anticipate potential disruptions such as transportation delays, demand fluctuations, and inventory shortages. By forecasting such risks in advance, organizations can implement proactive mitigation strategies that enhance operational efficiency and service reliability.

These findings are consistent with prior research highlighting the importance of predictive analytics in supply chain risk management. For instance, Waller and Fawcett (2013) emphasized that predictive analytics enables organizations to transform large volumes of operational data into actionable insights that improve supply chain decision-making. Similarly, Dubey et al. (2021) found that advanced data analytics capabilities enhance supply chain performance by improving forecasting accuracy and operational coordination.

Furthermore, the results also align with the work of Ivanov and Dolgui (2020), who suggested that predictive models improve supply chain viability by enabling organizations to anticipate disruptions and adjust their operational strategies accordingly. In highly dynamic environments such as the food industry, where demand volatility and logistics disruptions are common, predictive analytics becomes an essential capability for maintaining supply chain stability.

6.2 The Mediating Role of Supply Chain Flexibility

One of the most significant contributions of this study is identifying supply chain flexibility as a mediating mechanism between predictive models and supply chain performance. The results indicate that predictive insights alone do not automatically improve performance unless organizations possess the operational flexibility necessary to respond effectively to predicted risks.

This finding supports the theoretical arguments presented by Christopher and Peck (2004), who emphasized that supply chain flexibility enables organizations to adjust sourcing

strategies, modify transportation routes, and maintain operational continuity during disruptions. Similarly, Hohenstein et al. (2020) highlighted that flexible supply chains are better able to absorb operational shocks and recover more rapidly from disruptions.

The results suggest that predictive analytics enhances supply chain performance indirectly by enabling organizations to identify potential risks, while supply chain flexibility provides the operational capability required to respond to those risks effectively. Therefore, organizations that combine predictive analytics capabilities with flexible operational structures are more likely to achieve higher levels of supply chain performance.

6.3 Implications for Predictive Analytics Adoption

The findings of this study also highlight the growing strategic importance of predictive analytics within modern logistics and supply chain management. Organizations that have successfully integrated predictive models into their logistics operations demonstrate stronger forecasting capabilities, improved inventory planning, and enhanced coordination across supply chain activities.

However, the findings also suggest that organizations at early stages of predictive analytics adoption may not fully realize the benefits of these technologies. Successful implementation requires not only technological investment but also organizational readiness, including data integration capabilities, digital infrastructure, and analytical skills among supply chain professionals.

This observation is consistent with the findings of Kache and Seuring (2017), who argued that digital technologies can significantly improve supply chain decision-making when they are supported by appropriate organizational capabilities and data management systems.

7. Recommendations

Based on the findings of this study, several recommendations can be proposed for organizations, supply chain professionals, and policymakers in order to enhance the use of statistical predictive models in logistics risk management and improve supply chain performance. These recommendations also emphasize the strategic role of supply chain flexibility in enabling organizations to effectively respond to predicted disruptions.

7.1 Theoretical Contributions

This study contributes to the supply chain management and logistics risk literature by developing and validating a statistical predictive model for supply chain performance based on logistics risk analytics and supply chain flexibility. Unlike prior studies that primarily focused on explanatory relationships, this research introduces a predictive framework capable of forecasting supply chain performance outcomes.

First, this study advances the literature by shifting from traditional explanatory models toward predictive analytics–based supply chain research. While previous studies examined logistics risk management and supply chain flexibility as independent explanatory constructs, this research integrates them within a predictive modeling framework that estimates future supply chain performance.

Second, the study extends the Resource-Based View (RBV) by conceptualizing predictive analytics capability as a strategic organizational resource that enhances operational forecasting and decision-making. The results demonstrate that predictive modeling capability improves supply chain performance both directly and indirectly through supply chain flexibility.

Third, this research contributes methodologically by incorporating predictive model assessment techniques, including R^2 predictive power, Q^2 predictive relevance, and predictive error metrics. This approach responds to recent calls for incorporating predictive analytics into supply chain research.

Finally, the study provides empirical evidence from the food industry sector in a developing economy, which remains underexplored in predictive supply chain analytics literature. By doing so, the study expands the applicability of predictive logistics risk management models in emerging market contexts.

Finally, the study advances the theoretical understanding of supply chain flexibility as a mediating capability that transforms predictive insights into operational improvements. The results suggest that predictive analytics alone may not directly improve supply chain performance unless organizations possess the operational flexibility required to respond effectively to predicted disruptions.

7.2 Scientific Contribution and Research Novelty

This study provides several novel contributions to the supply chain management and logistics risk management literature.

First, the study introduces a predictive analytics–based supply chain risk management framework, which differs from traditional explanatory models commonly used in prior research. While previous studies focused on examining direct relationships between logistics risk management and supply chain performance, this research develops a predictive statistical model capable of forecasting performance outcomes. This predictive orientation represents a significant shift from explanatory to predictive supply chain analytics.

Second, this study identifies supply chain flexibility as a predictive operational capability that translates predictive analytics into performance improvements. Prior studies examined flexibility mainly as a direct independent variable; however, this research conceptualizes flexibility as a mediating predictive response mechanism that operationalizes predictive insights. This perspective extends the theoretical understanding of flexibility within predictive supply chain environments.

Third, this research integrates predictive logistics risk modeling with the Resource-Based View (RBV), positioning predictive analytics capability as a strategic organizational resource. This integration contributes to theory by linking predictive analytics, operational flexibility, and performance within a unified analytical framework.

Fourth, the study contributes methodologically by incorporating predictive model assessment using PLS-SEM predictive procedures. Unlike traditional SEM studies that focus only on explanatory power, this research evaluates predictive relevance and forecasting accuracy, thereby aligning with recent calls for predictive supply chain analytics research.

Finally, this study provides empirical evidence from the food industry sector in a developing economy. This context is particularly important because logistics risks are more severe in emerging markets, yet predictive analytics adoption remains limited. Therefore, the study extends predictive supply chain research beyond developed economy settings.

7.2 Managerial Implications

The findings of this study also provide several practical implications for supply chain managers and logistics professionals.

First, managers should prioritize the adoption of predictive analytics tools in logistics risk management. Predictive models enable organizations to anticipate potential disruptions such as transportation delays, supply shortages, and demand fluctuations, allowing decision-makers to implement proactive mitigation strategies.

Second, organizations should focus on strengthening supply chain flexibility by developing adaptable logistics systems, diversified supplier networks, and flexible production schedules. These capabilities allow organizations to translate predictive insights into effective operational responses.

Third, companies should invest in digital infrastructure and data integration systems that support real-time data analysis and predictive decision-making. The integration of predictive analytics with logistics management systems can significantly improve coordination across supply chain operations.

Finally, organizations should develop analytical capabilities among supply chain professionals through training programs that enhance their ability to interpret predictive insights and apply them in operational decision-making processes.

8. References

Al-Duwairi, Raed. (2020). Data-Driven Logistics Decision Making in Jordanian Industrial Companies.

Al-Hawamdeh, Sami. (2018). Supply Chain Coordination and Organizational Performance in Jordanian Companies.

Al-Khaldi, Ahmad. (2021). Data-Driven Logistics Management in Jordanian Institutions.

Al-Majali, Ahmad. (2018). Supply Chain Coordination and Operational Performance in Jordan.

Al-Nusour, Mohammad. (2020). Analytical Decision Support Systems and Their Impact on Logistics Performance in Jordan.

Al-Omari, Hussein. (2019). Modern Logistics Management and Its Impact on Supply Chain Performance.

Al-Rawashdeh, Mohammad. (2019). Supply Chain Management Practices in Jordanian Industry.

Al-Shaboul, Mohammad. (2019). Supply Chain Resilience and Organizational Performance in Jordanian Companies.

Al-Tarawneh, Mahmoud. (2021). Predictive Analytics and Logistics Risk Management in Jordanian Companies.

Al-Zoubi, Mohammad. (2020). Logistics risk management in Jordanian industrial companies.

Ali, A., Khan, Z., & Rehman, M. (2020). Supply chain flexibility and risk management: A comprehensive review. *International Journal of Production Research*, 58(12), 3684–3698.

Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99–120.

Beamon, B. M. (1999). Measuring supply chain performance. *International Journal of Operations and Production Management*, 19(3), 275–292.

Beamon, B. M. (2021). Measuring supply chain performance: A comprehensive framework. *International Journal of Operations and Production Management*, 41(2), 123–145.

Chong, A., Zhou, Y., & Wei, C. (2021). Supply chain flexibility in the context of global disruptions. *Journal of Supply Chain Management*, 39(4), 102–115.

Chopra, S., & Sodhi, M. (2004). Managing risk in supply chains. *MIT Sloan Management Review*, 46(1), 53–61.

Christopher, M. (2016). *Logistics and Supply Chain Management*. Pearson Education.

Christopher, M., & Peck, H. (2004). Building the resilient supply chain. *International Journal of Logistics Management*, 15(2), 1–14.

Dubey, R., Gunasekaran, A., & Childe, S. (2021). Big data analytics capability in supply chain management. *International Journal of Production Research*, 59(2), 563–583.

El Khatib, M., Ahmed, A., & Sundararajan, V. (2019). Risk management in supply chains: The role of flexibility and resilience. *International Journal of Risk and Contingency Management*, 30(2), 55–70.

Grant, R. (1991). The resource-based theory of competitive advantage. *California Management Review*, 33(3), 114–135.

Gunasekaran, A., Patel, C., & Tirtiroglu, E. (2004). Performance measures in supply chain management. *International Journal of Operations and Production Management*, 24(1), 71–87.

Hair, J. F., Hult, G. T., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage Publications.

Hendricks, K., & Singhal, V. (2020). The impact of supply chain disruptions on performance: A review of the literature. *Journal of Operations Management*, 34(1), 12–23.

Hohenstein, N., Feisel, E., & Hartmann, E. (2020). Supply chain flexibility: Theoretical perspectives and practical implications. *Journal of Business Logistics*, 41(1), 99–114.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903.

Ivanov, D., Dolgui, A., & Sokolov, B. (2019). Supply chain resilience. *International Journal of Production Research*, 57(3), 829–846.

Ivanov, D., & Dolgui, A. (2020). Viability of supply chain systems. *International Journal of Production Research*, 58(10), 2904–2915.

Kache, F., & Seuring, S. (2017). Challenges and opportunities of digital information in supply chains. *International Journal of Operations & Production Management*, 37(1), 10–36.

Keller, L., & Hohenstein, N. (2021). Machine learning techniques for predictive logistics risk management. *International Journal of Production and Operations Management*, 39(5), 1234–1249.

Kuei, C., & Madu, C. (2020). Supply chain management in a global environment: Challenges and opportunities. *Journal of Supply Chain Management*, 39(4), 50–68.

Lee, H., Kim, Y., & Park, S. (2022). Integrated predictive models for supply chain risk management. *Journal of Operations and Supply Chain Management*, 17(2), 56–73.

Moe, A., Rainer, C., & Wolf, A. (2019). Big data and predictive analytics for logistics: A systematic review. *Journal of Transportation Management*, 35(4), 28–40.

Ng, W., Tan, K., & Lim, C. (2020). Predictive analytics in logistics and supply chain risk management: A review. *International Journal of Logistics*, 21(2), 15–33.

Pereira, C., Silva, P., & Marquês, M. (2022). Supply chain risk management and resilience: Integrating predictive analytics. *International Journal of Production Economics*, 241, 108–120.

Sanders, N. (2016). *How to use big data to drive supply chain innovation*. MIT Press.

Sharma, P., & Lee, S. (2021). Machine learning approaches for predictive risk management in supply chains. *Journal of Supply Chain Analytics*, 19(1), 51–67.

Sheffi, Y. (2021). *The resilience of supply chains in times of uncertainty*. MIT Press.

Simchi-Levi, D., Kaminsky, P., & Simchi-Levi, E. (2018). *Designing and Managing the Supply Chain*. McGraw-Hill.

Stevenson, M., & Spring, M. (2007). Flexibility from a supply chain perspective. *International Journal of Operations & Production Management*, 27(7), 685–713.

Tang, C. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics*, 103(2), 451–488.

Tukamuhabwa, B., Stevenson, M., & Busler, M. (2020). Supply chain resilience: A theoretical framework. *Journal of Operations Management*, 41(3), 1–13.

Waller, M., & Fawcett, S. (2013). Data science, predictive analytics, and big data in supply chain management. *Journal of Business Logistics*, 34(2), 77–84.

Xu, L., & Li, W. (2020). Real-time predictive models for logistics risk assessment and decision-making. *Journal of Operations Research*, 34(2), 87–98.

Zhang, Y., Liu, S., & Zhao, X. (2023). Machine learning in logistics risk prediction: A review and future perspectives. *Journal of Supply Chain Innovation*, 19(4), 78–92.

Zhao, L., Li, X., & Zhang, Z. (2021). Predictive analytics for logistics risk management: Improving supply chain performance. *Journal of Logistics Research*, 29(3), 44–56.