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The Impact of Business Intelligence Applications on Supply Chain Risk Management: An Empirical Study

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Abstract

The primary objective of this paper is to explore the impact of business intelligence applications on supply chain risk management through a sample obtained from the Jordanian industrial companies sector. To achieve the research objectives, 185 questionnaires were collected and analyzed using partial least squares-structural equation modeling (PLS-SEM). It was concluded that all proposed hypotheses were acceptable and supported, as there was a strong and positive impact of business intelligence applications on all supply chain risk management practices. Based on this, a set of theoretical and practical recommendations was developed to contribute to enhancing the effectiveness of supply chain risk management.

Keywords: Business Intelligence, Supply Chain Risk Management, Descriptive Analytics, Predictive Analytics, Perspective Analytics

Introduction

In a business environment characterized by uncertainty and ambiguity, focusing on risk management and assessment has become a critical requirement (Emrouznejad et al., 2023). With the increasing dynamism of markets, fluctuations in supply and demand (Al-Khatib and Ramayah, 2025), radical changes in consumer tastes, and increased competitiveness (Jia et al., 2025), these factors have created a set of challenges and disruptions that have led to increased risks (Ke et al., 2025), disrupting the structure of many industries (Lee and Moon, 2025).

Over the past period, numerous challenges and crises, such as the COVID-19 pandemic and geopolitical and military unrest, have played a significant role in devoting additional efforts to understanding crisis management in supply chains (Wang et al., 2025). Frequent supply chain disruptions and associated problems, such as shortages of food and essential supplies, have negatively impacted global trade and the economies of countries around the world (Hsu, 2025).

Previous studies, such as (Guo et al., 2025), have confirmed that supply chain risk management is a key resource in the strategic decision-making process within the supply chain. Supply chain risk management helps identify potential risks that managers may face (Fernandes Lima et al., 2025), then assess the negative impacts of these risks (Okika et al., 2025), develop methods for dealing with and confronting these risks, and finally mitigate the damage caused by these risks (Löffel et al., 2025). There are many sources of risk that can arise in the supply chain. According to a study (Okika et al., 2025), supply chain risks can be divided into operational risks, which relate to the risks of failure and interruptions in supply chain operations; environmental risks, which relate to the risks arising from the use of processes that have negative environmental impacts; logistical risks, which relate to risks in the logistics network and supplier selection; and financial and technological risks.

Companies' use of robust technological systems can help them make appropriate decisions and improve the business value of various activities, thus achieving competitive advantages (Guo et al., 2025). In recent years, the concept of business intelligence has evolved, referring to the use of smart and advanced technologies in decision support systems and business data analysis (El Baz et al., 2023). This concept is described as a set of technologies, infrastructure, skills, and policies that companies possess and use to improve their operations and decisions. There are many technologies associated with this concept, perhaps the most important of which are: big data analytics, artificial intelligence, the Internet of Things, and cloud computing (Al-Khatib, 2025). These technologies also help analyze, process, and collect data and create complex scenarios (Kahya et al., 2025), helping managers and decision-makers make informed and rational decisions that help improve supply chain performance.

The relationship between business intelligence applications and supply chain risk management has been previously discussed in several studies (Žigienė et al., 2022). These technologies help detect and identify potential risks (Aljaafreh et al., 2024), and then propose ways to address and avoid these risks. Therefore, the use of these technologies helps reduce risks in the supply chain and manage them properly and in real time.

Based on previous research gaps, it can be said that the primary objective of this study is to explore the impact of business intelligence applications on supply chain risk management. The Jordanian industrial sector is considered one of the most important economic sectors in Jordan (Al-Khatib, 2025). Over the past years, these companies have been exposed to numerous challenges and risks that have diminished their competitiveness (Al-Shboul, 2023). Therefore, it is important to understand how artificial intelligence applications can enhance supply chain risk management. Business intelligence applications help transition from the traditional supply chain concept to a digital supply chain (Al-Khatib et al., 2024), which is more capable of mitigating supply chain risks. Therefore, Jordanian industrial companies' reliance on such applications can reduce risks.

Literature Review and Hypotheses Development

Business Intelligence

In light of the digital transformation facing companies and business organizations, the shift toward optimal digital practices has become a fundamental requirement for achieving competitive advantage (Pal, 2025). Digital strategies and the shift toward digitization help achieve many organizational benefits (Contuzzi et al., 2025), making companies more capable of innovation (Moh'd Anwer, 2025) and enhancing manufacturing, marketing, and production, enabling them to lead industries and markets toward the highest possible performance standards (Zanardo et al., 2025).

With the significant development witnessed in the business arena, particularly the advanced adoption of digital technologies (Al-Khatib, 2022), these technologies have provided companies with the dynamic ability to sense, seize, exploit, and transform opportunities into unprecedented new business value (Tran et al., 2025). Understanding, adopting, and developing these technologies enables companies to provide new approaches to problem-solving and develop innovative tools used in developing new products or services that reflect the company's progress in adopting digital technology.

Business analytics and business intelligence are among the most popular and widely used applications in light of the digital transformation of companies (Contuzzi et al., 2025). Business intelligence has been one of the most studied and researched fields in recent years (Aljaafreh et al., 2024), given its significant importance in providing a wide range of technologies, such as big data analytics and artificial intelligence (Al-Khatib and Ramayah, 2025), which can be used to improve company activities and enhance operational efficiency. Furthermore, these applications can be used to explore new, unexplored patterns in data, enabling companies to identify the best opportunities and reduce costs (Aljaafreh et al., 2024). Furthermore, these applications help companies develop innovative solutions to problems or develop products and innovations that help companies achieve higher returns (Pal, 2025). Business intelligence can be defined as "technologies used to identify, extract, and analyze data generated in the business environment, with the aim of extracting knowledge from events occurring within organizations. Some of these techniques rely on applying data mining algorithms to the amount of information generated in the business" (Eboigbe et al., 2023).

The use of powerful technological systems by companies can help them make appropriate decisions and improve the business value of various activities, thus achieving competitive advantages (Guo et al., 2025). In recent years, the concept of business intelligence has evolved, referring to the use of smart and advanced technologies in decision support systems and business data analysis (El Baz et al., 2023). This concept is described as a set of technologies, infrastructure, skills, and policies that companies possess and use to improve their operations and decisions.

There are many technologies associated with this concept, perhaps the most important of which are: big data analytics, artificial intelligence, the Internet of Things, and cloud computing (Al-Khatib, 2025). These technologies also help analyze, process, and collect data and create complex scenarios (Kahya et al., 2025), helping managers and decision-makers make informed and rational decisions that help improve supply chain performance.
In this study, business intelligence applications were identified through a set of stages used in data-driven decision-making:

1- Descriptive analytics: This is described as the use of descriptive analyses such as graphs, data summarization, and tables to provide an easy-to-read method (Parrales-Bravo et al., 2025). In other words, descriptive analytics aims to understand a phenomenon through

historical readings (Roy et al., 2022). 2- Predictive analytics: This is described as the use of advanced statistical and mathematical methods to analyze historical data with the aim of predicting or understanding future events (Oyewole et al., 2024). This stage of analysis focuses on understanding future events based on past and existing events.
3- Prescriptive analytics: This refers to the use of optimization and simulation methods to improve decision-making methods (Tariq, 2023). This stage of analysis utilizes advanced and complex statistical and mathematical methods to arrive at optimal solutions (Margaritis et al., 2022). Business intelligence applications are primarily related to how data analysts handle data, particularly big data (Sartzetaki et al., 2025), and exploit it to enhance business activities and operations. In other words, business intelligence is nothing but the methods, philosophies, and technologies that can be relied upon in the process of collecting, processing, and analyzing data to produce useful, high-quality information (Sekhar et al., 2020). This information can be used to reduce uncertainty, enhance efficiency, and reduce waste and costs. Although the current study focuses on three types of business analytics: descriptive, predictive, and prescriptive analytics, the applications and types of technologies that can be placed within the context of business intelligence are diverse (Margaritis et al., 2022). The use of artificial intelligence and the Internet of Things is considered extremely important in enhancing business analytics (Sartzetaki et al., 2025). Furthermore, companies' access to cloud computing technology enhances the effectiveness of business intelligence. Through the use of big data analytics, rich and new information can be obtained that enhances innovation, improves performance, and reduces uncertainty and risk (Stefanovic et al., 2025). Given that the business environment is more complex than ever, business intelligence technology requires the ability to analyze data quickly, on a large scale, with greater intelligence and efficiency. This requires significant investment in infrastructure.

Supply Chain Risk Management

Recently, sudden and urgent changes in business environments have undoubtedly become a major threat to the sustainability of global supply chains (Sun et al., 2025). With increasing dynamic complexities, increased global competitive pressures, and the emergence of a set of unprecedented challenges such as the COVID-19 pandemic (Zhou et al., 2025), supply chain risks have become more complex and more impactful on supply chain operations than ever before. A supply chain risk can be defined as an event or set of events that occur within the supply chain and have a direct or indirect negative impact on its operations (Zhang et al., 2025). In other words, a risk relates to a threat or disruption that may lead to delayed delivery of orders, an increase in the supply-demand gap, failure to deliver raw materials (Mobo et al., 2025), or financial or environmental failure (Lopes, 2022). Based on this, it can be said that supply chain risks reduce the capacity of the supply chain, rendering it unable to meet customer demands or fulfill key business requirements (Kafou et al., 2025). The concept of supply chain risk management has attracted significant attention from researchers in recent years (Rajendran et al., 2025). With the increase in global disruptions and challenges that directly impact global supply chains, supply chain risk management has become one of the key pillars used by companies to ensure the continuity and sustainability of their businesses (Ramadhan et al., 2025).

Supply chain risk management has been defined from several theoretical perspectives. El Baz and Ruel (2021) defined it as a set of strategies implemented by companies to reduce risk in the supply chain and control bottlenecks that occur in logistics network activities. This definition relies on the premise that supply chain risk management relies on strategies capable of overcoming the threats surrounding it. Alternatively, supply chain risk management can be viewed as a multi-step, systems-based approach (Birkel and Müller, 2025) that relies on integrated and sequential stages to overcome risks or threats, or at least minimize significant negative impacts on the supply chain (Long and Feng, 2025). Referring to previous studies on supply chain risk management (Fan and Chen, 2025), effective risk management enables the supply chain to prepare for and respond to risks, then absorb and mitigate their negative impacts. Companies adopting effective supply chain risk strategies gives them high risk resilience capabilities (Xixi et al., 2025), thus mitigating the severity and impact of the risk to a manageable level (Chen et al., 2025). Based on this, companies can reduce their losses or costs associated with these threats (Fan and Chen, 2025). Furthermore, the importance of supply chain risk management is evident not only in mitigating risks, but also in ensuring the supply chain is continuously prepared to confront any threat or emergency change in the supply chain (Xixi et al., 2025). This means that companies with supply chain risk management are able to strengthen their competitive position and better understand the market and its dynamics than other competitors. Supply chain risks arise from multiple sources. As the supply chain environment becomes more complex and the number of suppliers, manufacturers, retailers, and wholesalers increases (Fan and Chen, 2025), problems and differences between supply chain operations become more apparent, increasing the likelihood of threats or disruptions that could eventually develop into potential risks affecting supply chain operations (Chen et al., 2025). Therefore, it is essential for managers to identify sources of risk and explore ways to deal with unreliable suppliers or more volatile markets, which impact supply chain operations and may pose a threat to their continuity if these risks are not addressed in real time (Santos and Marques, 2024).

In this study, supply chain risk management is classified into four phases: identifying supply chain risks, assessing supply chain risks, responding to supply chain risks, and mitigating supply chain risks. 1- Supply Chain Risk Identification
In this stage, a set of analyses are conducted on the company's data to identify the sources of risk (Tessitore et al., 2023). This stage focuses on identifying any potential risk in the supply chain.

2- Supply Chain Risk Assessment
In this stage, the impact of potential risks on the supply chain is assessed (Santos and Marques, 2024). During this stage, the actual weights or levels of impact of each risk are evaluated, thus focusing on the risks with the greatest impact on supply chain operations (Chen et al., 2025).
3- Responding to Supply Chain Risks
In the third stage of supply chain risk management, plans and strategies are developed to address these risks (El Baz and Ruel, 2021). These include allocating resources appropriately, introducing new products, implementing financial hedging strategies, and other strategies that can be used to address risks (Tessitore et al., 2023).
4- Mitigating Supply Chain Risks
In the final stage of supply chain risk management, the focus is on mitigating or reducing the negative impacts of risks (El Baz et al., 2023) by restoring the original state of the supply chain before the risks emerged. This stage thus helps transform risks into normal events that can be easily managed.

The Relationship between Business Intelligence Applications and Supply Chain Risk Management

With the increasing risks in supply chains and the increasing negative impact on all logistics activities, business intelligence applications have emerged as promising tools for enhancing risk management in the context of supply chains (Chen et al., 2025). Business intelligence applications help analyze data and extract new insights (Al-Khatib and Khattab, 2024), enabling managers to identify and assess risks proactively, in real time, and accurately (Al-Khatib, 2025).

Business intelligence applications can also be used to control risks by developing radical and proactive solutions to threats and disruptions facing companies, thereby enhancing operational efficiency (Birkel and Müller, 2025). Business intelligence applications help detect and identify potential risks (Aljaafreh et al., 2024) and then propose ways to address and avoid these risks. Therefore, using these technologies helps reduce and manage supply chain risks properly and in real time.

From the above, it can be said that business intelligence applications have many promising advantages in the future (Al-Khatib and Ramayah, 2025), which can enhance companies' capabilities, make them more responsive to urgent and sudden changes, and enable them to compete and survive in turbulent environments (Al-Khatib, 2025). This makes business intelligence applications a strategic tool capable of bridging and addressing many of the gaps that may arise due to pressures or threats arising from competitive complexities and geopolitical and logistical issues (Santos and Marques, 2024).

From the above, the following hypotheses were proposed:
H1: Business intelligence applications have a positive impact on supply chain risk identification. H2: Business intelligence applications have a positive effect supply chain risk assessment.
H3: Business intelligence applications have a positive effect supply chain risk response.
H4: Business intelligence applications have a positive effect supply chain risk mitigation.

Research Methods

To address the research objectives and test the hypotheses, we relied on a quantitative approach (Sekaran, 2016), which is considered the most appropriate for addressing causal relationships as they are developed in the context of this research (Wilson, 2014). Quantitative inference provides effective and accurate methods for addressing the hypothesized relationships in research models. Therefore, through the use of statistical and mathematical tools that support the quantitative approach, generalizable and reliable results can be reached.

Research Sample

Due to the nature of the study, which primarily focuses on research into supply chain risk management, the industrial sector is the most appropriate sector for this research. Therefore, the Jordanian industrial sector was chosen to represent the study sample. The Jordanian industrial sector is considered one of the most important economic sectors in Jordan (Al-Khatib, 2025). Over the past years, these companies have been exposed to numerous challenges and risks that have reduced their competitiveness (Al-Shboul, 2023). Therefore, it is important to understand how artificial intelligence applications can enhance supply chain risk management.

The Jordanian industrial sector includes a wide range of activities and sub-industries, such as pharmaceuticals, food, plastics, and cosmetics. To achieve the research objectives, 589 industrial companies were contacted, 245 responded, and only 185 questionnaires were returned, representing a 72.8% response rate.
The questionnaire was distributed during the first quarter of 2025. After verifying the responses, 185 questionnaires were used for statistical analysis. Table 1 illustrates the demographic characteristics of the respondents.

Table 1
Descriptive statistics of demographic variables

Characteristics	Category	No.	%
Gender	Males	108	58
	Females	77	42
Education	Bachelor's or less	121	65
	Master	59	32
	PhD	5	3
Years of experience	Less than 5 years	53	29
	5- less than 10	50	27
	10-less than 15	37	20
	Above 15 years	45	24
Total		185	100

Measures
The questionnaire was designed based on similar empirical studies that use such variables. This procedure is considered appropriate and suitable for exploratory and predictive studies (Hair et al., 2019). Items were derived and adapted to suit the context of the research sample. The items used in the questionnaire were translated into Arabic after being modified and reviewed by experts in the field. They were then distributed to respondents. The type of scale used was reflective, using a five-point Likert scale. Therefore, the distribution of responses was as follows: (1 = strongly disagree - 5 = strongly agree).
Table 2 shows the questionnaire used in this study.

Table (2)
Measure items

Construct	Item code	Item	Source
Descriptive analytics	DA1	The company uses descriptive analytics to summarize data.	(Al-khatib,2025)
	DA2	The company relies on dashboards for real-time decision-making.	
	DA3	The company supports the use of descriptive analytics because of its ability to enhance understanding of performance indicators and measurements.	
	DA4	The company adopts the use of software such as Excel, Power BI, or Tableau to represent and summarize data.	
Predictive analytics	PD1	The company uses advanced forecasting models to identify future trends.	(Al-khatib,2025)
	PD2	The company is dedicated to adopting and utilizing advanced analytical methods, such as machine learning, when forecasting supply and demand.	
	PD3	The company recognizes the importance of predictive analytics in planning and resource allocation.	
	PD4	Senior management supports employee training in software focused on the use of predictive methods in data analysis.	
Perspective analytics	PA1	The company supports the use of simulation and optimization models in data analysis.	(Al-khatib and Ramayah,2025)
	PA2	The company relies on advanced methods such as Solver and Gurobi in its decision-making process.	
	PA3	The company supports the use of heuristic analytics in strategic and tactical decision-making.	
	PA4	The company recognizes the importance of heuristic analytics in the planning and resource allocation process.	
	PA5	Heuristic analytics are integrated with other analyses to achieve high-quality decisions.	
Supply chain risk identification	SCRI1	The company has clear procedures for identifying supply chain risks.	(El Baz and Ruel,2021)
	SCRI2	The risk identification process involves various departments (such as purchasing and logistics).	
	SCRI3	The company proactively monitors external sources that may pose a threat or risk.	
	SCRI4	The company's suppliers are required to report any potential risks.	
Supply chain risk assessment	SCRA1	The company assesses risks based on their likelihood and impact.	(El Baz and Ruel,2021)
	SCRA2	The company implements a formal risk scoring or rating system.	

	SCRA3	The company continuously reviews its supply chain risk assessments.	
	SCRA4	Suppliers are periodically assessed and their activities are assessed for their potential impact on the company.	
Supply chain risk response	SCRR1	The company has contingency plans in place to address major supply chain disruptions.	(El Baz and Ruel,2021)
	SCRR2	Response strategies are well-shared across teams.	
	SCRR3	We categorize risks into avoidable, transferable, and tolerable.	
	SCRR4	The company responds quickly and decisively to disruptions.	
Supply chain risk mitigation	SCRM1	The company has innovative strategies to mitigate supply chain risks.	(El Baz and Ruel,2021)
	SCRM2	The company utilizes its various resources to mitigate supply chain risks.	
	SCRM3	The company works to strengthen its strategic relationships with suppliers and leverage them during times of disruption and risk.	
	SCRM4	The company focuses on measuring the effectiveness of its supply chain risk management strategies.	

Data Analysis

To achieve the objectives of this study, which are based on a set of four hypotheses, the partial least squares-structural equation modeling (PLS-SEM) was used (Ringle et al., 2024). This approach can be considered effective and appropriate for analyzing exploratory and predictive relationships (Magno et al., 2024) and for multivariate analysis (Hair et al., 2019). PLS-SEM provides a measurement model that is used to verify both reliability and validity (Ringle et al., 2024), while hypotheses are tested using the bootstrapping approach using a structural model to estimate causal relationships (Streukens and Leroi-Werelds, 2016). Therefore, based on the above, it can be argued that using statistical methods based on this approach to estimate relationships, particularly the complex causal relationships found in mediation and adjusted models, provides stronger and more robust inferential support (Hair et al., 2021). Literature such as Ringle et al., 2024, confirms that PLS-SEM is a tool with recognized capabilities in dealing with data sets that do not meet the criteria for normality or contain extreme values. This provides the ability to address statistical problems that may arise due to heterogeneity in the data (Hair et al., 2021). Given the nature of the survey data obtained in this study, which suffers from non-normality (Cain et al., 2017), especially when examining multivariate normality (Ringle et al., 2024), moving beyond traditional analytical methods and tools and using flexible analytical methods such as PLS-SEM is a good option and is consistent with the research objectives that focus on understanding phenomena and explaining the variations in dependent variables (Magno et al., 2024).

The Measurement Model

Reliability, convergent, and discriminant validity can be measured through the measurement model (Hair et al., 2021). In this step, the psychometric properties of the items used to form the constructs are explored. According to statistical recommendations (Ringle et al., 2024), the structural model cannot be tested until all assumptions related to the measurement model have been met (Magno et al., 2024). Looking at Table (3), it is clear that the average variance extracted AVE test was used to measure convergent validity, and since the values exceeded 0.5, this confirms that convergent validity is of acceptable quality across the constructs (Hair et al., 2019). In addition to what was previously reported, the factor loading values were generally higher than 0.7, which supports their ability to explain the variance occurring in the constructs (Sarstedt et al., 2022). On the other hand, the constructs were reliable, as they reached Cronbach's alpha and composite reliability values reached the acceptable limits of 0.70.

Table (3)
Reliability and Convergent Validity

First-order construct	Item	Factor loading	AVE	CR	α	VIF
Descriptive analytics	DA1	0.764	0.506	0.863	0.785	1.639
	DA2	0.793				
	DA3	0.887				
	DA4	0.895				
Predictive analytics	PD1	0.709	0.736	0.843	0.763	1.848
	PD2	0.744				
	PD3	0.861				
	PD4	0.798				
Perspective analytics	PA1	0.941	0.709	0.963	0.855	1.320
	PA2	0.837				
	PA3	0.726				
	PA4	0.869				
	PA5	0.939				
Supply chain risk identification	SCRI1	0.695	0.571	0.738	0.737	2.201
	SCRI2	0.632				
	SCRI3	0.985				
	SCRI4	0.711				
Supply chain risk assessment	SCRA1	0.708	0.569	0.836	0.798	1.895
	SCRA2	0.781				
	SCRA3	0.770				
	SCRA4	0.734				
Supply chain risk response	SCRR1	0.900	0.744	0.932	0.824	1.258
	SCRR2	0.814				
	SCRR3	0.883				
	SCRR4	0.849				
Supply chain risk mitigation	SCRM1	0.790	0.669	0.847	0.710	2.639
	SCRM2	0.825				
	SCRM3	-				
	SCRM4	0.768				

The HTMT criterion was used to determine the extent to which discriminant validity was achieved (Roemer et al., 2021), as discriminant validity expresses the extent of empirical difference between constructs, assuming there is a theoretical difference between them. Since the HTMT values did not exceed 0.90, it can be said that the discriminant validity assumptions were achieved (Hair et al., 2019), as shown in Table (4).

Table (4)
Discriminant validity: HTMT criterion

	DA	**PD**	**PA**	**SCRI**	**SCRA**	**SCRR**	**SCRM**
DA							
PD	0.526						
PA	0.105	0.051					
SCRI	0.852	0.236	0.777				
SCRA	0.111	0.415	0.769	0.556			
SCRR	0.325	0.365	0.325	0.730	0.366		
SCRM	0.415	0.236	0.345	0.569	0.125	0.514	

The Structural Model (Hypotheses Testing)
This research focused on testing a set of positive vector hypotheses to examine the impact of business intelligence applications on supply chain risk management by analyzing a sample of respondents from Jordanian industrial companies. The bootstrapping approach was implemented to test relationships and generate 5,000 samples (Streukens and Leroi-Werelds, 2016) to enhance accurate impact estimation. Before testing the research hypotheses in the empirical model, the model's predictive suitability was verified through R^2 values. The value for the endogenous construct was 0.571, indicating that the model's predictive ability was satisfactory and reliable (Hair et al., 2019). Table (5) shows the beta and p-values that are used in evaluating the hypotheses, where all four hypotheses were accepted, as there was a positive impact of business intelligence applications on all supply chain risk management practices, as follows: (H1: $\beta = 0.369$, $t = 6.254$, $p = 0.000$; H2: $\beta = 0.208$, $t = 2.337$, $p = 0.000$; H3: $\beta = 0.147$, $t = 5.655$, $p = 0.000$; H4: $\beta = 0.289$, $t = 5.160$, $p = 0.000$).

Table (5)
Structural model results

Hypothesis	Relationship	Std. Beta	Std. Dev.	t-value	p-value	Remark
H1	BI→ SCRI	0.369	0.059	6.254	*0.000*	*Accepted*
H2	BI→ SCRA	0.208	0.089	2.337	*0.000*	*Accepted*
H3	BI → SCRR	0.147	0.026	5.655	*0.000*	*Accepted*
H4	BI→ SCRM	0.289	0.056	5.160	*0.000*	*Accepted*

Discussion
This research focused on examining the impact of business intelligence applications (descriptive analytics, predictive analytics, and prescriptive analytics) on supply chain risk management in a sample of Jordanian industrial companies.

The results of this research concluded that business intelligence applications have a significant and fundamental impact on supply chain risk management. The results confirmed that business intelligence applications (descriptive analytics, predictive analytics, and prescriptive analytics) had a positive impact on supply chain risk identification. Business intelligence applications help identify risks in the supply chain through data analysis (Aljaafreh et al., 2024), which helps identify sources of threats in the supply chain and enhances its ability to effectively predict, which enhances risk identification (Zhou et al., 2025). The study results also showed that business intelligence applications enhanced the supply chain's ability to effectively assess risks. Business intelligence applications had a positive impact on supply chain risk assessment. These applications can be used to design and develop data-driven assessment methods (Sun et al., 2025), which facilitate intelligent and appropriate risk assessment, enabling companies to prioritize potential risks.

In addition, business intelligence applications had a positive impact on responding to supply chain risks. This means that companies' use of business intelligence applications will help them develop appropriate and appropriate strategies to address risks (Aljaafreh et al., 2024) through innovation, rapid response, entering new markets, and reducing costs.
Finally, business intelligence applications had a positive impact on mitigating supply chain risks. Therefore, using these applications will help companies reduce the costs associated with risks, thus reducing and mitigating their negative impacts (Sun et al., 2025).

Implications and Limitations

Theoretical and Practical Implications

This study stands out from previous studies through its theoretical contributions, which have expanded the discussion about the impact of business intelligence on the global supply chain landscape in general and supply chain risk management in particular.

First, this study presented an innovative conceptual model unexplored in previous studies, as previous relationships are limited in the literature. Therefore, this study was able to address many of the research gaps related to the use of business intelligence applications and their impact on supply chain risk management.

Second, this study presented a set of hypotheses based on dynamic capabilities theory. Consequently, the current research was able to understand how supply chain risks can be reduced through companies' dynamic capabilities. Third: This study is one of the few studies that explored a new empirical context, particularly in emerging countries, where data was obtained from industrial companies in Jordan. Although concepts such as business intelligence and supply chain risk management are well-recognized and well-researched in developed countries, this is not true in emerging countries, where these concepts have been limitedly researched. This makes this study significant in the literature.

In terms of practical contributions, this study recommends that managers invest in business intelligence applications due to their importance in reducing supply chain risks. They also recommend diversifying supply sources and continuously analyzing data to reduce sources of risk in the supply chain. They also recommend developing proactive plans to address and mitigate potential risks in the supply chain due to operational, logistical, and environmental risks.

Limitations and Future Directions

Although the current study has made substantial contributions at the theoretical and practical levels, it is not without limitations and limitations. First, this study was methodologically developed based on cross-sectional data. Therefore, some limitations may arise due to the data being obtained over a single period. Therefore, it is important to conduct longitudinal studies that take time into account. Second, the type of measures used was closed and self-reported. Therefore, biases may appear when using this type of data collection method. Therefore, it is recommended to use interviews and multiple data collection methods in the future. Third, the study relied on a single data collection context, namely the industrial sector. Therefore, it is important to consider diverse and multiple contexts, such as the health and financial sectors.

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