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AI-Driven Insights: Enhancing Supply Chain Risk Analysis and Evaluation

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Abstract

The study aims to shed light on artificial intelligence and its role in analyzing and assessing supply chain risks. reducing supply chain risks before, during, and after they occur and explaining the role of artificial intelligence in the sustainability of supply chains. The research explained the concept of artificial intelligence, its dimensions, the concept of the supply chain, and its types. It showed that the use of artificial intelligence technologies includes its role in identifying potential factors that may affect the supply chain and providing accurate predictions of risks that may occur. This in turn helps organizations achieve the required improvement capabilities to improve capacity planning, raise productivity and quality, and reduce costs while increasing outputs, in addition to its role in helping them make sound and accurate decisions to reduce risks and improve supply chain performance. The increasing use of artificial intelligence technologies in many fields enhances efficiency and effectiveness in the sustainability of organizations by controlling the risks that they may be exposed to.

Keywords: *Artificial Intelligence Techniques, Supply Chain Risks.*

1.0 INTRODUCTION

The world is now witnessing modern technological changes that have greatly affected the lives of people and organizations, and are no longer limited to a specific category, but have kept pace with organizations of various types; as the era in which we live now is called the era of technology and the Fourth Industrial Revolution, as a result of the world's great information explosion and inflation (Popelo et al., 2021|), and given the importance of this information and considering it as one of the most important elements that are relied upon when planning and making current and future decisions, and with the development of technology and digital knowledge, the idea of what is known as artificial or artificial intelligence was born (Rajagopal et al., 2022).

This type of intelligence is called, in English, artificial intelligence, which is one of the branches of computer science concerned with how machines simulate human behavior. It is the science of creating computer devices, programmes, and machines that create intelligent behavior similar to human mental capabilities, the pattern of their ability to infer, learn from experiences, and perform various tasks, so that they learn as we learn, decide as we decide, and act as we act (Lucci et al., 2022).

Artificial intelligence and its applications are vital technologies and applications that have been applied in many fields to achieve digital transformation and improve services in many organizations. They are undoubtedly capable of using and applying such applications to facilitate the operations they carry out, which will create a large interactive work environment between the services provided and the beneficiaries in order to facilitate access to the required information and sources that meet their information needs, which is undoubtedly a distinctive qualitative shift that ensures the provision of the service in a distinctive manner (Svetlana et al., 2022).

The impact of artificial intelligence extends to the future of all business sectors, as it is the main driver of emerging technologies such as big data analysis, automated processing, and the Internet of Things. Artificial intelligence and its applications play a crucial and prominent role in improving and developing all aspects of life. This is done through the advancement of computer systems, which operate with high efficiency similar to the efficiency of an expert human, and this also increases the number of individuals interacting with these systems as a result of the continuous progress in the technologies related to them (Kharshi & Al-Zulawi, 2021).

Artificial intelligence also contributes to preserving the accumulated human expertise by transferring it to smart machines and facilitating the monitoring processes of data centres, as it saves huge amounts of time and energy wasted on monitoring data systems by working to monitor them automatically and detect defects, in addition to its role in simplifying the procedures for dealing with its technologies to achieve maximum benefit from them, as these technologies are still new and complex and require expertise in how to create and manage artificial intelligence solutions on a large scale (Jagatheesaperumal et al., 2021).

In addition, artificial intelligence works to relieve human work by using smart machines and reducing risks and psychological pressures by employing machines to perform difficult and dangerous work (Todolí-Signes, 2021). These machines will also play an effective role in fields that include many complex details, which require exhausting mental focus, continuous mental presence, and sensitive and quick decisions that do not tolerate delay or error (Thieme et al., 2020). Artificial intelligence and machine learning are digital technologies with a radical impact that have begun to cause a stir in supply chain risk management and change the way products are manufactured, distributed, and delivered (Calatayud et al., 2019).

Rapid technological development has also affected the supply chain, as supply chains have become more vulnerable to risks and disruptions that can occur at any link along the supply chain, whether from suppliers and customers or during internal operations in the organization. Risk assessment frameworks have also become unable to meet the challenges arising from information technology due to the nature of its infrastructure and the difficulty of physical control over it (Sharma et al., 2022).

The ability to improve the flow of materials and products in supply chains requires stable ecosystems, but they are constantly at risk due to climate change and the instability of economic and security conditions in many countries (Ghadge et al., 2020). Therefore, they must be analyzed from a long-term perspective, and work must begin to reduce their effects when they occur by preparing advanced models that can anticipate these risks well in advance (Nayal et al., 2022).

Supply chain risks represent the potential losses resulting from events that have a negative impact on the supply chain (DuHadway et al., 2019). This impact is manifested in three ways, the most important of which are increased costs, decreased profits, and loss of customers. Supply chain risks represent various threats that occur in the organisation's environment, which have a negative impact on their ability to achieve their strategic and marketing goals, which are reflected in fulfilling their obligations towards customers in terms of quality, quantity, and time required to process and execute orders (Ngo et al., 2024).

Therefore, the current study aims to demonstrate the role of artificial intelligence techniques in analyzing and assessing supply chain risks.

2.0 What is artificial intelligence techniques

Artificial intelligence is defined as the ability of computers, robots, or other machines to characteristics of intelligence and to be able to solve problems and do things associated with humans, such as thinking, communicating, and performing specific tasks and goals, and to improve themselves through the information that has been collected (Ali et al., 2022; Hisham & Boukhari, 2021).

Artificial intelligence is one of the sciences that makes machines imitate the way human intelligence works and acts. It is a group of computers that have been developed and shaped to think like humans and have the ability to learn from their mistakes and perform their tasks quickly and with great skill (Mitchell, 2019).

These technologies consist of ideas and conclusions that computers reach after receiving data inputs. Therefore, the use of human intelligence differs from artificial intelligence in the process of receiving, storing, and analyzing information (Lu, 2019). They are models, algorithms, and technologies for perception, reasoning, interaction, and advanced learning. They also represent a central factor for changes in organizations, as artificial intelligence integrates with and affects most economic activities by providing opportunities for higher productivity and more advanced analysis in various sectors (Dwivedi et al., 2021).

The primary and main goal desired from artificial intelligence technologies lies in the continuous attempts to develop artificial intelligence technologies and applications with the aim of reaching advanced stages of these technologies that are as identical as possible to human intelligence and perception. It constantly seeks to make machines more intelligent and with greater capabilities to learn and understand by employing existing experiences (Palomares et al., 2021).

These smart systems contribute to the areas in which decisions are made. These systems enjoy independence, accuracy and objectivity, and therefore their decisions are free from error, bias, racism or prejudice, especially in organizations that require quick decision-making (Zerilli et al., 2019).

2.1 Dimensions of the artificial intelligence techniques

There are a set of dimensions specific to artificial intelligence, including the following (Al-Ghazawi, 2021):

- **Expert systems**

It is one of the most widely used forms of artificial intelligence that simulates the human ability to make decisions, as it helps solve problems and accomplish tasks in ways that achieve the user's goals. Hence, its fundamental importance in helping humans think of a solution to the problem emerges, not just by providing them with information (Lucci, 2022).

- **Neural networks**

Neural networks work on a simple analogy with the nerves in the human brain, as the nerves are connected to each other in the form of levels. It is considered one of the most important fields of control engineering and artificial intelligence, reflecting developments and changes in the way humans think. The idea revolves around simulating the human mind by using computers (Thakur & Konde, 2021).

- **Genetic algorithms**

Genetic algorithms are considered one of the most important applications of artificial intelligence in the field of activities and businesses, as they are considered one of the means used to improve results and attempt to develop and rise to a level close to idealism. They are computer programs that analyze the problems of evolutionary systems and have been described as genetic due to their reliance on simulating the work of genetic genes to reach the optimal solution (Wirsansky, 2020).

- **Intelligent agents**

It is a system that relies on the information and knowledge stored in it with the aim of completing tasks and making decisions. Some may see it as software applications that manage electronic tasks for companies, as it alerts its users in the event of something happening, and that the smart agent uses the knowledge base stored in it about a specific person or process to make decisions and complete tasks in a way that achieves the user's goals (Sarker, 2022).

3.0 Supply chain risks

Supply chain management has seen an increasing focus on the risks it is exposed to, which has led to the emergence of supply chain risk management (SCRM) as a new area of focus and study for this topic. New tools, methods, and approaches have been developed to manage supply chain risks, and previous approaches have been modified to reflect this increased focus on risks. Supply chain risks are the primary reason why organizations are enhancing their ability to be more flexible and adaptive (Orheim & Utvaer, 2021). Risky events make the supply chain more vulnerable intrinsically. These risks may be attributed to uncertain or unexpected events that hinder the entire supply chain (DuHadway et al., 2019: 6).

Supply chain risks Logistics risks are defined as the distribution of outcomes associated with negative events in the supply activity that affect the organization's ability to meet customer demands in terms of quantity, quality, cost, and time, and which may also pose a risk to the customer and his safety (Shukri & Muhammad, 2021).

The definition of supply chain risks in much of the specialized literature in this field is an event-oriented concept, as risks are closely related to the likelihood of the risk occurring and its potential consequences. This concept is also related to activities that seek to reduce risks (Bugert & Lasch, 2018:4).

There is a classification of supply chain risks that has been prepared based on the degree of their impact on making decisions related to the supply chain, and accordingly they are of two types (Al-Taie & Al-Jabouri, 2023):

- Strategic supply chain risks: are those risks that have a long-term impact, which leads to obligating decision-makers to change their strategies in the supply chain.

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- Operational supply chain risks: These are risks that have a short-term impact on supply chain operations.

3. 1 Types of the supply chain risks

Turkman & Osman, (2022) pointed out a number of types of supply chain risks as follows:

- Environmental risks: These are variables that affect business establishments across different industries and are linked to uncertainty associated with all political, economic, social, and natural aspects (Kobrin, 2022).
- Regulatory risks: These include uncertainty surrounding operating conditions of specialized labor and other inputs, restricting customers from paying their debts to the establishment, and uncertainty about agency relationships within the establishment, such as managers seeking to maximize their benefits at the expense of the benefits of the establishment owners (Settembre-Blundo et al., 2021).
- Industrial risks: These are variables that do not affect all economic sectors but rather specific industrial sectors, such as risks associated with acquiring insufficient quantities of inputs needed for the production process of lower quality, as well as risks associated with the demand for the product and those surrounding the existing competition within the industry (Chen et al., 2021).
- Risks associated with a specific problem: These problems are affected by one or more procedures such as: the overall risk structure and understanding of the main variables, interrelationships, risks associated with the objectives and obstacles that affect the problem, and the complexity of the decision-making task in its various dimensions (Renn et al., 2022).

4.0 **Study Hypotheses**

To answer the study questions, a main hypothesis was formulated:

H01 The first main hypothesis: There is no statistically significant effect at the significance level (a≤0.05) of artificial intelligence techniques and their dimensions (expert systems, neural networks, genetic algorithms, intelligent agents) in analyzing and evaluating supply chain risks.

Several sub-hypotheses emerge from this main hypothesis:

H01.1 There is no statistically significant effect at the significance level (a≤0.05) of expert systems in analyzing and evaluating supply chain risks.

H01.2 There is no statistically significant effect at the significance level (a≤0.05) of neural networks in analyzing and evaluating supply chain risks.

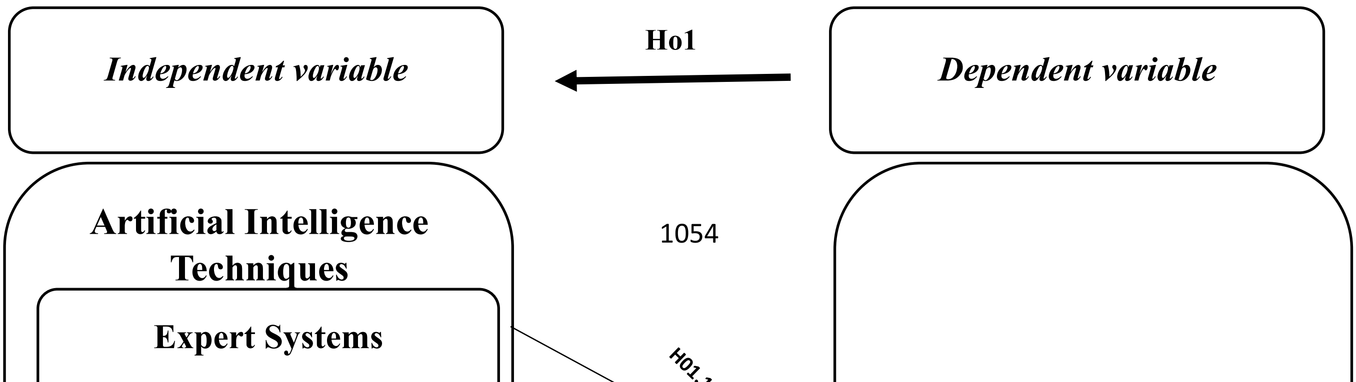
H01.3 There is no statistically significant effect at the significance level (a≤0.05) of genetic algorithms in analyzing and evaluating supply chain risks.

H01.4 There is no statistically significant effect at the significance level (a≤0.05) of intelligent agents in analyzing and evaluating supply chain risks.

5.0**Study model**

The following figure shows the study model and the variables included in the current study.

Figure (1.1): Study



6.0 Research Methodology (Approach and Procedures)

This study is a field-based research that follows a descriptive-analytical approach to investigate the role of artificial intelligence techniques in analyzing and evaluating supply chain risks in the logistics sector in Jordan. The study is applied to a sample of companies operating in the logistics sector, aiming to understand how AI techniques contribute to the assessment of supply chain risks.

6.1 Research Methodology

This study is a field-based research that follows a descriptive-analytical approach to investigate the role of artificial intelligence techniques in analyzing and evaluating supply chain risks in the logistics sector in Jordan. The study is applied to a sample of logistics companies, aiming to understand how AI techniques contribute to the assessment of supply chain risks.

6.2 Data Collection Methods

To achieve the objectives of this study and test its hypotheses, two types of data were collected: primary data and secondary data. The following is a brief explanation of each type:

1- Primary Data: Primary data refers to data collected directly from the field through a survey using a specially designed questionnaire. The questionnaire covers all aspects of the study's theoretical framework and hypotheses. The researcher distributed the questionnaire personally to the sample for direct data collection.

2- Secondary Data: Secondary data consists of existing information used to build the theoretical framework of the study. This includes reviewing various library sources such as books, academic journals, and previous studies. Specifically, the researcher utilized the following resources:

- Scientific books, articles, and references related to artificial intelligence techniques and supply chain risk management.
- Academic journals and specialized publications focused on the topic of this study.
- Theses related to artificial intelligence in supply chain management or risk evaluation.

6.3 Study Population

The study population consists of all companies operating in the logistics sector in Jordan, totaling approximately 200 companies.

6.4 Study Sample

The sample of the study includes all managers of companies operating in the logistics sector in Jordan, totaling 200 managers. Using the Krejcie and Morgan (1970) sample determination formula, the final sample size for the study is 132 managers. However, the number of questionnaires retrieved was **118**. Therefore, the final study sample consisted of 118 individuals. This sample size was selected to ensure the reliability and generalizability of the findings.

6.5 Data Collection Tool

The researcher designed the study tool (the questionnaire) to cover the study questions and hypotheses, including two main sections:

Part 1: Questions related to the independent variable, which pertains to "Artificial Intelligence Techniques." This part consists of dimensions related to AI techniques and is based on a five-point Likert scale:

- Expert Systems: 5 questions
- Neural Networks: 5 questions
- Genetic Algorithms: 5 questions
- Intelligent Agents: 5 questions

Part 2: Questions related to the dependent variable, which is "Supply Chain Risk Evaluation." This section includes 10 questions designed based on a five-point Likert scale.

6.6 Scale Adjustments

The final version of the questionnaire contains 30 paragraphs distributed across the dimensions of the independent variable (Artificial Intelligence Techniques) and the dependent variable (Supply Chain Risk Evaluation). The Likert scale options were coded as follows:

- Strongly Agree: 5
- Agree: 4
- Neutral: 3
- Disagree: 2
- Strongly Disagree: 1

Respondents were asked to mark (√) the box that best reflected their level of agreement with each statement. The results were then analyzed based on the following classification to determine the strength of the mean score:

- Low: 1.00 - 2.33
- Medium: 2.34 - 3.66
- High: 3.67 - 5.00

6.7 Statistical Methods Used

For data analysis, the researcher utilized the Statistical Package for Social Sciences (SPSS) software. The following statistical methods were applied:

- Mean Averages: To describe the respondents' opinions on the variables and assess their level of agreement with the survey statements. This method also helps to determine the importance of the questionnaire paragraphs.
- Standard Deviation: To measure the extent of dispersion of responses around the mean, indicating the consistency or variability of opinions among the sample.
- Multiple Linear Regression: To test the overall effect of the independent variables (AI techniques) on the dependent variable (supply chain risk evaluation).
- Simple Linear Regression: To test the effect of each dimension of the independent variable (AI techniques) on the dependent variable.

7.0 Presentation of Study Results

This section provides a detailed analysis of the statistical data related to the study tool "the questionnaire," in order to reach the final study results. The study aims to explore the role of artificial intelligence techniques, represented by their dimensions (Expert Systems, Neural Networks, Genetic Algorithms, and Intelligent Agents), in analyzing and evaluating supply chain risks in companies operating in the logistics sector in Jordan. This will be based on the responses from the study sample, which were distributed by the researcher personally, as indicated in the study management section.

Furthermore, this chapter will present the results of the study by testing its hypotheses, relying on the relevant statistical tests within the Statistical Package for the Social Sciences (SPSS) program. More specifically, this chapter will present and analyze the study results and test its hypotheses in two main sections as follows:

7.1 First: Presentation and Analysis of Results

This section presents a detailed analysis of the study results related to the mean averages and standard deviations for the two study variables, namely the independent variable (Artificial Intelligence Techniques) as a whole, and each of its dimensions (Expert Systems, Neural Networks, Genetic Algorithms, and Intelligent Agents). Additionally, the mean averages and standard deviations for the dependent variable (Supply Chain Risk Evaluation) as a whole, as well as for each of its paragraphs, will be analyzed.

The analysis will be based on the relevant statistical tests to ensure the results are presented scientifically and accurately. Below is a summary of the mean averages and standard deviations for both study variables, their dimensions, and each of their paragraphs.

First: Mean Averages and Standard Deviations for Artificial Intelligence Techniques and Their Dimensions

The table below shows the mean averages and standard deviations for the independent variable "Artificial Intelligence Techniques" and each of its dimensions:

Table (1): Mean Averages and Standard Deviations for the Independent Variable and Each of Its Dimensions

NO.	Dimension	mean	SD	Rank	degree
1	Expert systems	4.17	0.48	2	High
2	Neural networks	4.14	0.45	3	High
3	Genetic algorithms	4.03	0.49	4	High
4	Intelligent agents	4.26	0.46	1	High
Artificial intelligence Techniques as a whole		4.15	0.32	-	High

It is evident from the results of this table that:

The mean scores for the dimensions of the independent variable (Artificial Intelligence Techniques) ranged from (4.26 to 4.03), with the highest score for the dimension of (Intelligent Agents) at a mean of (4.26), indicating a high level. This was followed by (Expert Systems) with a mean of (4.17), also at a high level, then (Neural Networks) with a mean of (4.14) at a high level. Finally, (Genetic Algorithms) ranked last, with a mean of (4.03), still within a high level. The overall mean for the independent variable (Artificial Intelligence Techniques) was (4.15), indicating a high level.

The results show that all dimensions of Artificial Intelligence Techniques have high mean scores, indicating their significant role in evaluating supply chain risks. "Intelligent Agents" had the highest score, suggesting its crucial impact in the context of this study.

Second: Mean Averages and Standard Deviations for the Paragraphs of the (Expert Systems) Dimension, and for Each Paragraph:

The following table shows the mean averages and standard deviations for the paragraphs of the (Expert Systems) dimension, and for each of its paragraphs:

Table (2): Mean Averages and Standard Deviations for the Paragraphs of the (Expert Systems) Dimension and for Each of Its Paragraphs

NO.	Paragraph	mean	SD	Rank	degree
1	Our company relies on expert systems to analyze decisions related to the supply chain.	4.26	0.82	1	High
2	Expert systems in our company contribute effectively to identifying potential risks in the supply chain.	4.03	0.93	5	High
3	Expert systems are used in our company to help make strategic decisions to improve supply chain efficiency.	4.25	0.74	2	High

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4	Expert systems contribute to providing solutions and alternatives for complex issues in the supply chain.	4.09	0.88	4	High
5	The expert systems used in our company save time and resources in making risk-related decisions.	4.22	0.79	3	High
Expert Systems as a whole		4.17	0.48	-	High

It is evident from the results of this table that:

The mean scores for the items of the (Expert Systems) dimension ranged from (4.26 to 4.03), with the highest score for item number (1), which stated: "Our company relies on expert systems to analyze decisions related to the supply chain," with a mean score of (4.26) at a high level. The lowest score was for item number (2), which stated: "Expert systems in our company contribute effectively to identifying potential risks in the supply chain," with a mean score of (4.03), also at a high level. The overall mean score for the (Expert Systems) dimension was (4.17), also indicating a high level.

The results indicate that the use of expert systems in the companies is generally viewed positively, with a particularly strong reliance on these systems for decision-making within the supply chain. However, there is slightly less emphasis on their effectiveness in identifying potential risks, though still rated highly.

Third: Mean Averages and Standard Deviations for the Paragraphs of the (Neural networks) Dimension, and for Each Paragraph:

The following table shows the mean averages and standard deviations for the paragraphs of the (Neural networks) dimension, and for each of its paragraphs:

Table (3): Mean Averages and Standard Deviations for the Paragraphs of the (Neural networks) Dimension and for Each of Its Paragraphs

NO.	Paragraph	mean	SD	Rank	degree
1	Neural networks are used to analyze supply chain data and predict future risks.	4.00	0.72	5	High
2	Neural networks help improve predictions related to supply chain risks.	4.24	0.63	1	High
3	Neural networks in our company are capable of processing and analyzing large amounts of data accurately.	4.11	0.66	3	High
4	Neural networks contribute to improving the company's response to unexpected risks in the supply chain.	4.22	0.59	2	High
5	Neural networks in our company are trained to learn patterns and predict potential risks based on historical data.	4.13	0.81	4	High
Neural networks as a whole		4.14	0.45	-	High

It is evident from the results of this table that:

The mean scores for the items of the (Neural Networks) dimension ranged from (4.27 to 4.00), with the highest score for item number (2), which stated: "Neural networks help improve predictions related to supply chain risks," with a mean score of (4.27) at a high level. The lowest score was for item number (1), which stated: "Neural networks are used to analyze supply chain data and predict future risks," with a mean score of (4.00), also at a high level. The overall mean score for the (Neural Networks) dimension was (4.14), also indicating a high level.

The results show a strong positive view of the role of neural networks in improving risk predictions, though slightly less emphasis was placed on their use for analyzing supply chain data and forecasting future risks. Overall, neural networks are highly valued in the context of supply chain risk management.

Fourth: Mean Averages and Standard Deviations for the Paragraphs of the (Genetic algorithms) Dimension, and for Each Paragraph:

The following table shows the mean averages and standard deviations for the paragraphs of the (Genetic algorithms) dimension, and for each of its paragraphs:

Table (4): Mean Averages and Standard Deviations for the Paragraphs of the (Genetic algorithms) Dimension and for Each of Its Paragraphs

NO.	Paragraph	mean	SD	Rank	degree
1	Genetic algorithms are used in our company to improve solutions related to risks in the supply chain.	4.46	0.64	1	High
2	Genetic algorithms help achieve optimal solutions for managing risks in the supply chain.	3.88	0.65	3	High
3	Genetic algorithms contribute to improving logistics operations and reducing associated risks.	4.30	0.56	2	High
4	Genetic algorithms are used in our company to develop new strategies for managing risks.	3.78	0.62	4	High
5	Genetic algorithms help improve decisions related to balancing risks and benefits in the supply chain.	3.75	0.90	5	High
Genetic algorithms as a whole		4.03	0.49	-	High

It is evident from the results of this table that:
The mean scores for the items of the (Genetic Algorithms) dimension ranged from (4.46 to 3.75), with the highest score for item number (1), which stated: "Genetic algorithms are used in our company to improve solutions related to risks in the supply chain," with a mean score of (4.46) at a high level. The lowest score was for item number (5), which stated: "Genetic algorithms help improve decisions related to balancing risks and benefits in the supply chain," with a mean score of (3.75), at a relatively high level. The overall mean score for the (Genetic Algorithms) dimension was (4.03), also indicating a high level.
The results highlight that genetic algorithms are highly regarded, especially for improving risk-related solutions in the supply chain. However, there is slightly less emphasis on their role in balancing risks and benefits, though still rated positively. Overall, genetic algorithms are perceived as a valuable tool in supply chain risk management.

Fifth: Mean Averages and Standard Deviations for the Paragraphs of the (Intelligent agents) Dimension, and for Each Paragraph:

The following table shows the mean averages and standard deviations for the paragraphs of the (Intelligent agents) dimension, and for each of its paragraphs:

Table (5): Mean Averages and Standard Deviations for the Paragraphs of the (Intelligent agents) Dimension and for Each of Its Paragraphs

NO.	Paragraph	mean	SD	Rank	degree
1	Our company uses intelligent agents to continuously monitor and analyze risks in the supply chain.	4.15	0.57	5	High
2	Intelligent agents in our company assist in making quick and effective decisions to manage risks.	4.16	0.62	4	High
3	Intelligent agents in our company can interact with users and improve operations automatically.	4.45	0.60	1	High
4	Intelligent agents contribute to improving information flow and making smart decisions to mitigate risks.	4.17	0.67	3	High
5	Our company relies on intelligent agents to analyze patterns and predict potential risks in the supply chain.	4.38	0.72	2	High
Intelligent agents as a whole		4.26	0.46	-	High

It is evident from the results of this table that:
The mean scores for the items of the (Intelligent Agents) dimension ranged from (4.45 to 4.15), with the highest score for item number (3), which stated: "Intelligent agents in our company can interact with users and improve operations automatically," with a mean score of (4.45) at a high level. The lowest score was for item number (1), which stated: "Our company uses intelligent agents to continuously monitor and analyze risks in the supply chain," with a mean score of (4.15), also at a

high level. The overall mean score for the (Intelligent Agents) dimension was (4.26), also indicating a high level.

The results demonstrate a strong positive perception of intelligent agents, especially their ability to interact with users and improve operations automatically. While their role in continuous monitoring of risks is still highly valued, it received a slightly lower rating. Overall, intelligent agents are seen as a valuable tool for managing supply chain risks.

Sixth: Mean Averages and Standard Deviations for the Paragraphs of the Dependent Variable (Supply Chain Risk Evaluation), and for Each of Its Paragraphs:

The following table shows the mean averages and standard deviations for the paragraphs of the dependent variable (Supply Chain Risk Evaluation), and for each of its paragraphs:

Table (6): Mean Averages and Standard Deviations for the Paragraphs of the (Supply Chain Risk Evaluation) Dimension, and for Each of Its Paragraphs

NO.	Paragraph	mean	SD	Rank	degree
1	Our company evaluates risks in the supply chain periodically.	4.24	0.95	6	High
2	The risk evaluation process in our company involves analyzing the probabilities and potential impacts of unexpected events.	3.81	1.16	10	High
3	Our company relies on a set of tools to assess potential risks in the supply chain.	4.11	0.99	8	High
4	Risk evaluation in our company includes analyzing risks associated with suppliers and customers.	4.12	1.18	7	High
5	We use historical data to evaluate future risks in the supply chain.	4.34	0.57	4	High
6	Technological risks are considered an essential part of our company's risk evaluation process.	4.09	1.16	9	High
7	We evaluate risks that could affect the continuity of logistics operations in our company.	4.44	0.59	2	High
8	Senior management is involved in the risk evaluation process and determining necessary actions.	4.31	0.64	5	High
9	Risk evaluation in our company includes prioritizing the risks that need to be addressed first.	4.52	0.50	1	High
10	Our company relies on advanced technologies to evaluate risks in the supply chain and determine effective solutions to address them.	4.38	0.69	3	High
Supply Chain Risk Evaluation as a whole		4.24	0.34	-	High

It is evident from the results of this table that:

The mean scores for the items of the dependent variable (Supply Chain Risk Evaluation) ranged from (4.52 to 3.81), with the highest score for item number (9), which stated: "Risk evaluation in our company includes prioritizing the risks that need to be addressed first," with a mean score of (4.52) at a high level. The lowest score was for item number (2), which stated: "The risk evaluation process in our company involves analyzing the probabilities and potential impacts of unexpected events," with a mean score of (3.81), at a high level. The overall mean score for the dependent variable (Supply Chain Risk Evaluation) was (4.24), also indicating a high level.

The results indicate a strong focus on prioritizing risks in the supply chain, which is likely due to the company's need to address the most critical issues first to minimize potential disruptions. The slightly lower score for analyzing probabilities and impacts could suggest that while risk analysis is valued, it may not be as deeply integrated into the decision-making process. Overall, the high ratings across the board indicate that the company generally feels confident in its risk evaluation practices.

7.2 Testing the Study Hypotheses

Based on the previous section and the presentation of the study results, which showed high mean scores across various paragraphs, dimensions, and variables, these results were utilized in the statistical calculations and analysis in the current section through the use of the SPSS software. This was done for the purpose of testing the study hypotheses and determining their validity in examining the impact of artificial intelligence techniques, represented by its dimensions (Expert Systems, Neural Networks, Genetic Algorithms, and Intelligent Agents), on Supply Chain Risk Evaluation in companies operating in the logistics sector in Jordan. The following statistical tests will be conducted to evaluate the main hypothesis and the related sub-hypotheses of the study:

1- Main hypothesis: H01 The first main hypothesis: There is no statistically significant effect at the significance level (a≤0.05) of artificial intelligence techniques and their dimensions (expert systems, neural networks, genetic algorithms, intelligent agents) in analyzing and evaluating supply chain risks.

To test the validity of the first main hypothesis, the Multiple Regression analysis was employed to examine the impact of artificial intelligence techniques, represented by their dimensions (Accuracy of Information, Adaptability, and Accessibility), on Supply Chain Risk Evaluation in companies operating in the logistics sector in Jordan. The following table presents this analysis:

Table (7): Multiple Regression Analysis to Determine the Impact of Artificial Intelligence Techniques and Their Dimensions on Supply Chain Risk Evaluation (N=118)

Dimensions of the independent variable	t-value	t.sig	R	R^2	f-value	Sig.
Expert systems	1.895	0.61	0.357	0.128	4,13	0.004
Neural networks	0.573	0.568				
Genetic algorithms	0.830	0.408				
Intelligent agents	2.001	0.048				

Dependent variable: analyzing and evaluating supply chain risks

It is evident from the results of the table above that there is an effect of Artificial Intelligence Techniques with its dimensions (Intelligent agents, Expert systems, Genetic algorithms, Neural networks) on analyzing and evaluating supply chain risks. The effect of all four dimensions is evident, but it varies. The dimension with the greatest effect on analyzing and evaluating supply chain risks is Intelligent agents, with a t-value of (2.001), which is a high value. The significance value for this effect (t.sig.) is (0.048), indicating a significant effect.

Following this dimension, Expert systems showed a t-value of (1.895), which is also a relatively high value, and its significance value was (0.61). Then came Genetic algorithms, which showed a t-value of (0.839), indicating a positive and relatively high effect, with its significance value being (0.408). Finally, Neural networks showed the least effect, with a t-value of (0.573) and a significance value of (0.568), indicating a relatively positive effect.

The correlation value for the model (R) was (0.357), which is considered a high value as it exceeds zero. The R^2 value was (0.128), meaning that the effect of the independent variable dimensions contributes to about 12.8% of the change in the analyzing and evaluating supply chain risks, through the correlation between the items of both variables.

On the other hand, the coefficient of variation (f) was (4.13), which indicates a diverse and significant relationship between all the dimensions and items of the study tool in relation to both the independent and dependent variables. This is a positive value as it exceeds zero.

Finally, the statistical significance value for the effect of the independent variable Artificial Intelligence Techniques and its dimensions (Intelligent agents, Expert systems, Genetic algorithms, Neural networks) on analyzing and evaluating supply chain risks was (0.004). This value indicates a significant effect. The statistical significance value is considered to have a very strong effect the closer it is to zero. Therefore, based on this result, it can be concluded that there is an effect of Artificial Intelligence Techniques on analyzing and evaluating supply chain risks.

Based on the above, the null hypothesis is rejected, which states: "There is no statistically significant effect at the significance level ($\alpha \le 0.05$) of artificial intelligence techniques and their dimensions (expert systems, neural networks, genetic algorithms, intelligent agents) in analyzing and evaluating supply chain risks."

It is replaced with the alternative hypothesis, which states: There is a statistically significant effect at the significance level (α ≤ 0.05) of artificial intelligence techniques and their dimensions (expert systems, neural networks, genetic algorithms, intelligent agents) on analyzing and evaluating supply chain risks.

2- Sub-hypothesis 1: H01.1 There is no statistically significant effect at the significance level (a≤0.05) of expert systems in analyzing and evaluating supply chain risks.

To test the validity of the first sub-hypothesis, a simple linear regression analysis (Simple Regression) was used to examine the effect of expert systems on analyzing and evaluating supply chain risks in companies operating in the logistics sector in Jordan. The following table presents the results of the analysis:

Table (14): Results of Simple Regression Analysis to Examine the Effect of Expert Systems on Analyzing and Evaluating Supply Chain Risks (N=118)

Dimension	t-value	t.sig	R	R^2	f-value	Sig.
Expert systems	**2.420**	**0.000**	**0.219**	**0.48**	**5.857**	**0.017**

Dependent variable: analyzing and evaluating supply chain risks

The data from the table indicate that the expert systems dimension has an impact on analyzing and evaluating supply chain risks, with a t-value of (2.420), which is a high probability value indicating a strong effect, and a statistical significance of (0.000). The correlation value for the overall model (R) was (0.219), and the explanatory value for this correlation (R^2) was (0.48).

The variance ratio (f) was (5.857), and the statistical significance was (0.017), indicating a significant impact of the expert systems dimension in analyzing and evaluating supply chain risks.

Based on the above results, the null hypothesis is rejected: H01.1 There is no statistically significant effect at the significance level (α ≤ 0.05) of expert systems in analyzing and evaluating supply chain risks. And this hypothesis is replaced with the following alternative hypothesis: There is a significant effect at the significance level (α ≤ 0.05) of expert systems in analyzing and evaluating supply chain risks

- Sub-hypothesis 2: H01.2 There is no statistically significant effect at the significance level (a≤0.05) of neural networks in analyzing and evaluating supply chain risks.

To test the validity of the first sub-hypothesis, a simple linear regression analysis (Simple Regression) was used to examine the effect of Neural networks on analyzing and evaluating supply chain risks in companies operating in the logistics sector in Jordan. The following table presents the results of the analysis:

Table (14): Results of Simple Regression Analysis to Examine the Effect of Neural networks on Analyzing and Evaluating Supply Chain Risks (N=118)

Dimension	t-value	t.sig	R	R^2	f-value	Sig.
Neural networks	**2.189**	**0.000**	**0.199**	**0.040**	**4.793**	**0.031**

Dependent variable: analyzing and evaluating supply chain risks

It is evident from the table above that the Neural networks dimension has a significant impact on analyzing and evaluating supply chain risks, with a t-value of (2.189), which is a very high probability value, indicating a statistically significant effect for this dimension. The explanatory value (t.sig) was (0.000), and the correlation value for the overall model (R) was (0.199), with the explanatory value for this correlation (R^2) being (0.040). The variance value (f-value) was (4.793), and the overall statistical significance was (0.031), which is a highly statistically significant value indicating the effect of Neural networks in analyzing and evaluating supply chain risks.

Based on the above results, the null hypothesis is rejected: There is no statistically significant effect at the significance level (α ≤ 0.05) of neural networks in analyzing and evaluating supply chain risks. This hypothesis is replaced with the alternative hypothesis: There is a significant effect at the significance level (α ≤ 0.05) of neural networks in analyzing and evaluating supply chain risks.

- Sub-hypothesis 3: H01.3 There is no statistically significant effect at the significance level (a≤0.05) of genetic algorithms in analyzing and evaluating supply chain risks.

To test the validity of the first sub-hypothesis, a simple linear regression analysis (Simple Regression) was used to examine the effect of genetic algorithms on analyzing and evaluating supply chain risks in companies operating in the logistics sector in Jordan. The following table presents the results of the analysis:

Table (14): Results of Simple Regression Analysis to Examine the Effect of Genetic algorithms on Analyzing and Evaluating Supply Chain Risks (N=118)

Dimension	t-value	t.sig	R	R^2	f-value	Sig.
Genetic algorithms	2.833	0.000	0.254	0.065	8.028	0.005

Dependent variable: analyzing and evaluating supply chain risks

It is evident from the table above that there is an effect of genetic algorithms in analyzing and evaluating supply chain risks, with a t-value of (2.833), which is considered very high, indicating an effect of this dimension on the dependent variable as a whole. The explanatory value for the t-value is (0.000), and the correlation value for the overall model (R) is (0.254), with the explanatory value for this correlation (R^2) being (0.065). The variance value (f-value) is (8.028), and the overall statistical significance is (0.005), which is a highly statistically significant value indicating the effect of genetic algorithms in analyzing and evaluating supply chain risks.

Based on the above results, the null hypothesis is rejected: There is no statistically significant effect at the significance level ($\alpha \leq 0.05$) of genetic algorithms in analyzing and evaluating supply chain risks. This hypothesis is replaced with the alternative hypothesis: There is a significant effect at the significance level ($\alpha \leq 0.05$) of genetic algorithms in analyzing and evaluating supply chain risks.

- **Sub-hypothesis 4: H01.4 There is no statistically significant effect at the significance level (a≤0.05) of intelligent agents in analyzing and evaluating supply chain risks.**

To test the validity of the first sub-hypothesis, a simple linear regression analysis (Simple Regression) was used to examine the effect of Intelligent agents on analyzing and evaluating supply chain risks in companies operating in the logistics sector in Jordan. The following table presents the results of the analysis:

Table (14): Results of Simple Regression Analysis to Examine the Effect of Intelligent agents on Analyzing and Evaluating Supply Chain Risks (N=118)

Dimension	t-value	t.sig	R	R^2	f-value	Sig.
Intelligent agents	3.410	0.000	0.302	0.091	11.630	0.001

Dependent variable: analyzing and evaluating supply chain risks

It is evident from the table above that there is an effect of intelligent agents in analyzing and evaluating supply chain risks, with a t-value of (3.410), which is considered very high, indicating an effect of this dimension on the dependent variable as a whole. The explanatory value for the t-value is (0.000), and the correlation value for the overall model (R) is (0.302), with the explanatory value for this correlation (R^2) being (0.091). The variance value (f-value) is (11.630), and the overall statistical significance is (0.001), which is a highly statistically significant value indicating the effect of intelligent agents in analyzing and evaluating supply chain risks.

Based on the above results, the null hypothesis is rejected: There is no statistically significant effect at the significance level ($\alpha \leq 0.05$) of intelligent agents in analyzing and evaluating supply chain risks. This hypothesis is replaced with the alternative hypothesis: There is a significant effect at the significance level ($\alpha \leq 0.05$) of intelligent agents in analyzing and evaluating supply chain risks.

8.0 CONCLUSIONS

Artificial intelligence technologies play a significant role in analyzing and assessing supply chain risks. By using technologies such as machine learning and big data analytics, organizations can identify potential factors that may negatively impact the supply chain and predict potential risks. Moreover, AI technologies help develop accurate predictive models to assess and analyze potential risks, which contributes to making sound strategic decisions to reduce these risks and improve overall supply chain performance. It is important to note that the increasing use of AI technologies in this field contributes to enhancing efficiency and effectiveness and improving risk management in the supply chain, which enhances competitiveness and ensures sustainability in business markets.

8.0 Results

1. The study found a statistically significant effect at the significance level (0.004) of artificial intelligence techniques and their dimensions (expert systems, neural networks, genetic algorithms, intelligent agents) in analyzing and evaluating supply chain risks.

This result emphasizes the overall impact of artificial intelligence techniques as a collective force in improving the analysis and evaluation of supply chain risks. The significance level of 0.004 highlights that AI techniques, when integrated and applied together, are essential tools in predicting and mitigating potential disruptions in the supply chain. The result suggests that these techniques collectively enhance the ability of organizations to foresee and react to risk factors in a more efficient manner.

2. The study revealed a statistically significant effect at the significance level (0.017) of expert systems in analyzing and evaluating supply chain risks.

Expert systems are designed to simulate human decision-making, and their significant effect (with a p-value of 0.017) in supply chain risk analysis reflects their capability to process complex decision-making scenarios. These systems are capable of analyzing vast amounts of historical data to provide insights into potential risks, making them a valuable asset in forecasting and managing supply chain uncertainties. Their ability to store and process knowledge enhances decision-making processes and provides a more systematic approach to identifying risks.

3. The study demonstrated a statistically significant effect at the significance level (0.031) of neural networks in analyzing and evaluating supply chain risks.

The impact of neural networks in analyzing supply chain risks, as revealed by the p-value of 0.031, reflects their strength in recognizing patterns and relationships within large datasets. These systems can process and learn from historical data to predict future events and potential disruptions, which makes them invaluable in risk management. Neural networks are particularly effective when dealing with complex, nonlinear problems, providing insights that traditional methods may miss. This capability enables organizations to develop more robust strategies to manage risks proactively.

4. The study found a statistically significant effect at the significance level (0.005) of genetic algorithms in analyzing and evaluating supply chain risks.

Genetic algorithms play a significant role in optimizing solutions for complex problems in supply chain risk management. The result (with a p-value of 0.005) shows that genetic algorithms can efficiently search for the optimal solution in situations with many variables and potential outcomes. These algorithms mimic the process of natural selection to find the best possible configurations, making them highly suitable for identifying risk factors and optimizing supply chain operations. Their ability to refine solutions iteratively ensures that risks are mitigated in a more precise and systematic manner.

5. Finally, the study revealed a statistically significant effect at the significance level (0.001) of intelligent agents in analyzing and evaluating supply chain risks.

Intelligent agents, with a p-value of 0.001, show a remarkable effect in automating decision-making processes within the supply chain. These agents use stored knowledge and adapt to changes in real-time, which allows for quick responses to dynamic supply chain conditions. Their ability to make informed decisions and monitor operations automatically leads to more efficient risk management, as they can anticipate potential issues before they escalate. The low p-value of 0.001 strongly reinforces their vital role in managing supply chain risks by reducing human error and increasing operational efficiency.

8.0 Recommendations

Based on the results of the current study, a number of recommendations can be made to enhance the use of artificial intelligence techniques in analyzing and evaluating supply chain risks and to ensure their optimal utilization in improving management and operational strategies within organizations. These recommendations are as follows:

- **Encouraging the Use of Artificial Intelligence Techniques:**

Based on the results showing a statistically significant effect of artificial intelligence techniques and their various dimensions (expert systems, neural networks, genetic algorithms, and intelligent agents) in analyzing and evaluating supply chain risks, it is recommended that companies and organizations promote the application of these technologies within their operations to reduce risks and improve decision-making accuracy in supply chain management.

- **Investing in Employee Training on AI Techniques:**

Given the importance of artificial intelligence in risk management, it is recommended that organizations invest in training their employees on how to effectively use these techniques. This could include training programs and workshops focusing on developing skills in data analysis and the application of expert systems and neural networks to improve risk management.

- **Integrating Expert Systems with Modern Analytical Tools:**

Given the significant role of expert systems in supporting decision-making, it is recommended to integrate these systems with other modern analytical tools, such as artificial intelligence and big data analytics, to provide comprehensive solutions that enhance operational efficiency across various organizational departments.

- **Leveraging Neural Networks for Identifying Complex Risks:**

It is advised to use neural networks to analyze large data sets and detect hidden patterns that may represent potential risks. This technology can be applied to predict supply chain issues early on, enabling preventive solutions to be implemented effectively.

- **Developing and Utilizing Genetic Algorithms for Optimal Solutions:**

Based on the study results, it is recommended to expand the use of genetic algorithms in complex work environments that require continuous improvements in supply chain processes. By simulating natural evolutionary processes, genetic algorithms can provide innovative solutions to complex management problems, enhancing supply chain sustainability and mitigating risks.

- **Activating the Role of Intelligent Agents in Real-Time Risk Monitoring and Analysis:**

According to the findings of the study, the significant impact of intelligent agents should be utilized within organizational systems for real-time monitoring of operations and continuous risk analysis. This will facilitate quick and accurate decision-making, enhancing the organization's ability to respond effectively to emerging issues.

- **Conducting Future Studies to Analyze the Evolution of AI Impact:**

It is recommended to continue research on the evolving impact of artificial intelligence techniques on supply chain risk management, particularly in light of the continuous development of these technologies. Future studies could focus on the impact of modern tools such as machine learning and big data technologies on improving risk prediction and management accuracy.

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