THE IMPACT OF ARTIFICIAL INTELLIGENCE (AI) ON SUPPLY CHAIN DECISION-MAKING IN SAUDI ARABIA

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Abstract:
This study investigates the adoption and impact of AI-driven demand forecasting in supply chain management, emphasizing the transformative potential of artificial intelligence (AI) in improving operational efficiency, forecast accuracy, and inventory management. With the increasing complexity of modern supply chains and the need for more accurate predictions, organizations are turning to AI technologies to address challenges such as market volatility, fluctuating consumer demands, and supply chain inefficiencies. For the study, a quantitative method is used to find out what stakeholders think and have experienced about how Artificial Intelligence (AI) effects on Supply Chain Decision-Making in Saudi Arabia. A full review of the literature will be done to find the most important theories, ideas, and real-world studies on how to use Artificial Intelligence (AI) to improve Supply Chain Decision-Making in Saudi Arabia. It will be used to make a structured questionnaire with the information from the literature study. On a 5-point Likert scale, where 1 means "strongly disagree" and 5 means "strongly agree," people will be asked to rate how much they agree or disagree with each statement. The results of the research provided strong proof in favor of the presumptions that Artificial Intelligence (AI) had a significant and positive impact on Supply Chain Decision-Making. More precisely, it was found that Internet of Things, Data Analytics, Sensors and Drones impact significantly on Supply Chain Decision-Making. This study emphasizes the important part effective Artificial Intelligence (AI) Technologies have in improving Supply Chain Decision-Making in Saudi Arabia.

Keywords: Artificial Intelligence (AI), Supply Chain Decision-Making, Internet of Things, Data Analytics, Sensors and Drones, Saudi Arabia.

1. Introduction:

In recent years, Artificial Intelligence (AI) has gained significant traction in supply chain management, particularly in demand forecasting. Traditional demand forecasting methods, which relied heavily on historical data and manual processes, often led to inefficiencies, inaccuracies, and operational bottlenecks (Khan et al., 2024). As the global business environment grows more complex and data-driven, organizations are increasingly turning to AI-driven solutions to enhance decision- making, reduce uncertainty, and improve supply chain performance (Akanbi et al., 2024). AI's ability to process vast amounts of real-time data, analyze patterns, and generate predictions with greater accuracy makes it a valuable asset in demand forecasting. The integration of AI into supply chain processes has created new opportunities for organizations to optimize inventory levels, improve customer satisfaction, and minimize operational costs (Khan et al., 2025). Demand forecasting is one of the most critical aspects of supply chain management, as it drives decisions related to procurement, production planning, and inventory management. The accuracy of demand forecasts directly impacts a company's ability to meet customer demand while minimizing overstocking or stockouts. Traditional forecasting methods, including statistical approaches like moving averages and exponential smoothing, have been widely used in the past. However, these methods are limited in their ability to handle the complexity and variability of modern supply chains (Barcia et al., 2018). AI-driven forecasting models, on the other hand, utilize advanced algorithms, machine learning techniques, and deep learning models to better understand the underlying patterns and relationships in demand data, making them more accurate and adaptive to changing conditions (Emon & Khan, 2024). As a result, AI has the potential to significantly improve the efficiency of supply chains by providing more precise and dynamic forecasts that can be adjusted in real time to account for disruptions, demand shifts, and other factors (Khan

& Emon, 2024). The adoption of AI in demand forecasting is not just about technological advancements; it is also about reshaping organizational processes and strategies. Firms that successfully adopt AI-driven demand forecasting are able to enhance operational efficiency, reduce costs, and improve their overall competitiveness in the market (Didwania et al., 2024).

1.1. Problem Statement:

This research problem seeks to address the critical question of how artificial intelligence (AI) can be applied to optimize supply chain processes, from demand forecasting to inventory management and logistics. It aims to explore the potential benefits, challenges, and best practices associated with artificial intelligence (AI) driven supply chain solutions.

This research problem seeks to address the challenges faced by organizations in managing their supply chains, such as:

- **Improve forecasting accuracy**: enhance demand forecasting models to reduce forecast errors and optimize inventory levels.
- **Optimize logistics and transportation**: optimize routing, scheduling, and load planning to minimize costs and improve delivery times.
- **Enhance supply chain visibility**: gain real-time insights into supply chain operations to identify potential disruptions and take proactive measures.
- **Improve decision-making**: empower decision-makers with data-driven insights to make informed choices.
- **Mitigate risks and disruptions**: develop robust strategies to respond to unforeseen events such as natural disasters or supply chain disruptions.
- **Demand forecasting accuracy**: how can artificial intelligence (AI) improve the accuracy of demand forecasting to optimize inventory levels and reduce stockouts?
- **Supply chain visibility**: how can artificial intelligence (AI) enhance visibility into the supply chain to identify potential disruptions and bottlenecks?
- **Decision-making speed and quality**: how can artificial intelligence (AI) accelerate decision-making processes and improve the quality of decisions made by supply chain managers?
- **Risk mitigation**: how can AI help organizations identify and mitigate risks, such as supply chain disruptions and cyberattacks?

1.2. Research Objectives:

This study investigates how Artificial intelligence (AI) Technologies effect on Supply Chain Decision-Making in Saudi Arabia.

- To examine Internet of Things impact on Supply Chain Decision-Making in Saudi Arabia.
- To examine Data Analytics impact on Supply Chain Decision-Making in Saudi Arabia.
- To examine Sensors and Drones impact on Supply Chain Decision-Making in Saudi Arabia.

1.3. Research Questions:

The main question: What is the impact of Artificial intelligence (AI) Technologies on Supply Chain Decision-Making in Saudi Arabia?

- What is the impact of internet of Things impact on Supply Chain Decision-Making in Saudi Arabia?
- What is the impact of Data Analytics impact on Supply Chain Decision-Making in Saudi Arabia?
- What is the impact of Sensors and Drones impact on Supply Chain Decision-Making in Saudi Arabia?

1.4. Research Hypothesis:

Research hypotheses are testable predictions about the relationship between variables. In my research on artificial intelligence (AI) in Supply Chain Decision-Making (SCDM) in Saudi Arabia, hypotheses will guide my data collection and analysis.

H1: *There is no significant relationship between Artificial intelligence (AI) Technologies and Supply Chain Decision-Making taken as a whole for in the sample from Saudi Arabia.*

H2: *Artificial intelligence (AI) Technologies has a significantly positive effect on Supply Chain Decision-Making in Saudi Arabia.*

H2.1: *Internet of Things has a significantly positive effect on Supply Chain Decision-Making in Saudi Arabia.*

H2.2: *Data Analytics has a significantly positive effect on Supply Chain Decision-Making in Saudi Arabia.*

H2.3: *Sensors and Drones has a significantly positive effect on Supply Chain Decision-Making in Saudi Arabia.*

1.5. Research Importance:

Academic Contribution: the research will contribute to the existing body of knowledge by exploring the theoretical and practical implications of artificial intelligence (AI) in supply chain management.

Practical Implications: the findings of this study will provide valuable insights for practitioners and policymakers to understand the potential benefits and challenges of artificial intelligence (AI) adoption.

Industry Relevance: the study will help businesses identify opportunities to leverage artificial intelligence (AI) to improve their supply chain performance, reduce costs, and enhance customer experience.

Policy Implications: the research may inform the development of policies and regulations that support the adoption of artificial intelligence (AI) in supply chain management.

1.6. Methodology:

For the study, a quantitative method is used to find out what stakeholders think and have experienced about how Artificial Intelligence (AI) effects on Supply Chain Decision-Making in Saudi Arabia. A full review of the literature will be done to find the most important theories, ideas, and real-world studies on how to use Artificial Intelligence (AI) to improve Supply Chain Decision-Making in Saudi Arabia. It will be used to make a structured questionnaire with the information from the literature study. On a 5-point Likert scale, where 1 means "strongly disagree" and 5 means "strongly agree," people will be asked to rate how much they agree or disagree with each statement. Some people who know a lot about Artificial Intelligence (AI) and Supply Chain Decision-Making will look over the survey questions and make sure they are true and accurate. Based on what they say, we will make any changes that are needed.

2. Literature Review:

2.1. The potential benefits and challenges of artificial intelligence (AI) driven solutions in optimizing various aspects of supply chain operations:

The integration of artificial intelligence (AI) into supply chain management has gained significant traction in recent years. Numerous studies have explored the potential benefits and challenges of artificial intelligence (AI) driven solutions in optimizing various aspects of supply chain operations.

The integration of Artificial Intelligence (AI) into demand forecasting has rapidly emerged as a transformative development in supply chain management, with several researchers highlighting the potential of AI-driven models to significantly enhance forecasting accuracy and operational efficiency (Akanbi et al., 2024).

The need for more accurate and dynamic demand forecasting has grown in response to the increasing complexity of global supply chains, where traditional statistical models often struggle to account for rapidly changing market conditions, consumer behaviors, and external disruptions (Khan et al., 2024).

AI offers an advanced approach, allowing supply chain practitioners to leverage machine learning algorithms, deep learning models, and predictive analytics to make better-informed decisions that are based on large volumes of real-time data (Barcia et al., 2018). In particular, machine learning models like neural networks, decision trees, and ensemble methods have been found to offer significant improvements over conventional methods in forecasting accuracy by uncovering hidden patterns in data (Kiranmai et al., 2023).

AI's application to demand forecasting has proven effective in numerous sectors, including retail, manufacturing, and logistics, where timely and accurate demand predictions are crucial for inventory management and optimizing production schedules (Kolasani, 2024).

For instance, in retail, accurate demand forecasts ensure that products are available on shelves without overstocking, thus preventing excess inventory and reducing associated storage costs (Lal et al., 2024).

The benefits of AI-driven forecasting are also evident in manufacturing, where companies can better align their production schedules with customer demand, reducing downtime and improving supply chain synchronization (Li, 2023).

AI models can process a wider range of variables than traditional models, including seasonality, economic indicators, and even social media trends, allowing for more nuanced and adaptive forecasts (Olasiuk et al., 2023).

The ability of AI to handle large datasets and adapt to changing circumstances is one of its key strengths. Historical data alone cannot always account for all the factors that influence demand, such as market dynamics, consumer preferences, and environmental conditions (Emon et al., 2024).

By integrating external data sources such as weather patterns, consumer sentiment analysis, and social media trends, AI can help businesses anticipate demand fluctuations that might otherwise be missed by traditional forecasting methods (Tiwari et al., 2024). This capacity to incorporate diverse data types makes AI-driven demand forecasting more accurate and responsive, offering organizations a more complete picture of future demand (Khan & Emon, 2024).

Despite the promising advantages of AI in demand forecasting, several challenges accompany its adoption. One major obstacle is the requirement for high-quality, clean data. AI algorithms rely on large amounts of accurate and up-to-date data to generate reliable forecasts. Poor-quality or incomplete data can severely limit the performance of AI models, leading to forecasting errors that may disrupt supply chain operations (Didwania et al., 2024).

Ensuring that organizations have the necessary data infrastructure to support AI models is thus crucial for the successful implementation of AI-based demand forecasting systems (Sánchez-Partida et al., 2018). In this regard, companies must invest not only in AI tools but also in improving their data collection and management practices to ensure that they can provide the quality of data required for AI to perform optimally (Sharifmousavi et al., 2024). Another challenge related to AI adoption is the skill gap in the workforce.

AI and machine learning technologies require specialized knowledge in data science, analytics, and software engineering, and many supply chain professionals may not possess the technical expertise necessary to operate AI-driven forecasting systems (Ladva et al., 2024). Addressing this gap requires significant investment in employee training, reskilling, and the recruitment of qualified personnel (Singh et al., 2024). Companies must therefore foster a culture of continuous learning and collaboration between supply chain professionals and data scientists to fully harness the potential of AI in demand forecasting (Ramu et al., 2024).

Additionally, organizations may face resistance to change from employees who are accustomed to traditional forecasting methods. Overcoming this resistance requires strong leadership and clear communication about the benefits of AI adoption and the necessary steps for its integration into existing systems (Dwivedi, 2023). Transparency and interpretability are also key concerns when implementing AI-driven demand forecasting. Machine learning models, especially deep learning algorithms, are often regarded as "black boxes," meaning their decision-making processes are not always transparent or easy to understand (Emon & Khan, 2024).

In supply chains, where decisions based on AI forecasts can have far-reaching consequences, it is essential that AI models are interpretable, enabling decision- makers to understand the reasoning behind the forecasts and make informed choices (Elyashevich et al., 2024). Several researchers emphasize the importance of developing explainable AI models that provide clear insights into the factors influencing demand predictions (Wang, 2021).

Moreover, companies need to ensure that their AI models are regularly monitored and updated to account for any changes in underlying data patterns (Khan et al., 2024). AI-driven demand forecasting also involves significant capital investment, which can be a barrier for smaller companies or those in developing markets. The costs of developing, integrating, and maintaining AI-based systems may be prohibitive for many organizations, especially when they are uncertain about the return on investment (Tadayonrad & Ndiaye, 2023). Nevertheless, as the technology matures and AI tools become more accessible, the costs associated with implementing AI solutions are expected to decrease, making them more feasible for a wider range of companies (Thejasree et al., 2024).

Moreover, the long-term benefits, such as improved accuracy, cost reduction, and better customer satisfaction, often outweigh the initial investment (Poo & Qi, 2023). Over time, as AI becomes an industry standard in supply chain management, the economic barrier to entry will likely continue to decrease, allowing even small and medium-sized enterprises (SMEs) to capitalize on AI-driven demand forecasting (Ye, 2024). The impact of AI on demand forecasting also extends beyond efficiency gains and cost reduction.

AI can contribute to more sustainable supply chains by enabling better management of resources and reducing waste. Accurate demand forecasts allow organizations to better plan their procurement and production processes, minimizing overproduction and excess inventory, which can lead to wastage (Mahat et al., 2023). AI’s ability to optimize inventory levels also helps businesses reduce the environmental impact of excess storage, transportation, and disposal of unsold goods (Vinoth et al., 2024).

Additionally, AI can play a role in ensuring that supply chains are more resilient to external disruptions, such as natural disasters, political instability, or supply shortages. By continuously learning from real-time data and adjusting forecasts accordingly, AI- driven systems allow companies to adapt more quickly to changes in demand and avoid potential disruptions (Sboui et al., 2002).

The research surrounding AI-driven demand forecasting in supply chains has continued to expand in recent years, with numerous studies exploring various models, algorithms, and case studies across different industries. Studies have shown that AI can help businesses achieve a higher level of integration between demand forecasting and other key supply chain functions, such as procurement, production, and logistics, thus improving overall supply chain performance (Pasupuleti et al., 2024). This integration is essential for ensuring that supply chain operations are aligned with demand forecasts, reducing inefficiencies and improving responsiveness (Tiwari et al., 2024).

As the literature on AI in supply chains grows, researchers continue to focus on addressing the challenges of data quality, transparency, and workforce readiness while seeking ways to enhance the capabilities of AI models. Future developments in AI-driven demand forecasting are expected to focus on improving the adaptability of models, especially in highly volatile environments. As the use of AI continues to spread, there is likely to be a greater emphasis on integrating AI with other emerging technologies, such as the Internet of Things (IoT), blockchain, and 5G networks, which could further enhance forecasting accuracy and supply chain visibility (Lal et al., 2024).

For example, the combination of IoT sensors and AI could provide real-time data on stock levels, customer preferences, and supply chain conditions, which would allow businesses to make more precise forecasts and rapidly respond to changes in demand (Kiranmai et al., 2023). Blockchain could also be used to enhance the transparency and security of data shared across supply chain partners, improving the reliability of AI forecasts (Zhu & Vuppalapati, 2024). These advancements in technology will continue to drive the adoption and effectiveness of AI-driven demand forecasting systems, further reshaping the landscape of supply chain management.

In conclusion, AI-driven demand forecasting is rapidly becoming an essential tool for modern supply chains. Through advanced algorithms, machine learning, and real-time data analysis, AI provides a more accurate and dynamic method for predicting demand, enabling companies to optimize inventory, reduce costs, and improve operational efficiency.

While the adoption of AI comes with challenges related to data quality, workforce skills, and model interpretability, the long-term benefits of AI-driven demand forecasting outweigh these hurdles. As the technology evolves and becomes more accessible, its potential to revolutionize supply chains will continue to expand, offering significant opportunities for businesses to gain a competitive edge in the global marketplace (Eldred et al., 2023).

2.2. Varieties of AI Applications in Supply Chain Operations:

Supply chain management (SCM) has entered a new era of efficiency, agility, and creativity with the introduction of artificial intelligence (AI). Applications of AI in supply chain management are numerous and cover everything from planning and forecasting to execution and monitoring. Demand forecasting and inventory management are two of SCM's most important uses of AI. Torres-Franco (2021) demonstrates how AI technology can accurately forecast future demand by analysing large datasets. With the help of these forecasts, companies may maximise customer pleasure and minimise expenses by optimising inventory levels and minimising overstock and stock outs. Compared to conventional techniques, machine learning algorithms can more precisely predict demand by analysing past sales data, market trends, and even sentiment on social media.

AI is also essential for relationship management and supplier selection. Pournader et al. (2021) talk about how AI may assess providers according to a number of factors, including price, quality, delivery time, and dependability. AI systems are able to track supplier performance continually, giving real-time feedback and facilitating proactive supplier relationship management. This promotes strategic alliances that can result in innovation and expansion in addition to guaranteeing a more robust supply chain.

Another area where AI technologies have gained traction is in the optimisation of transportation and logistics. Helo and Hao (2022) investigate how AI may improve scheduling and routing by accounting for variables like delivery windows, vehicle capacity, and traffic conditions. Better delivery times, lesser carbon emissions, and lower transportation costs are the results of this optimisation. Drones and AI-powered autonomous cars are also starting to be used for last-mile deliveries, with the potential to completely transform the logistics industry. AI applications also include quality control and compliance monitoring, where machine learning models use picture recognition technologies to find product flaws or irregularities. (Ajala, 2024). This guarantees adherence to legal requirements while also improving the quality of the final product. AI is becoming a vital tool for businesses dedicated to corporate social responsibility since it can also track and evaluate data from the whole supply chain to guarantee compliance with sustainability and ethical sourcing standards.

The predictive power of AI greatly aids in risk management and reduction. AI can detect possible supply chain risks and vulnerabilities, such as supply disruptions or geopolitical threats, by assessing data from a variety of sources. This enables businesses to proactively reduce these risks by creating backup plans and strategies. Lastly, increased customisation and better customer service are made possible by AI. Chatbots and virtual assistants driven by AI can respond to enquiries, manage returns and exchanges, and give clients real-time tracking information. Higher customer satisfaction and loyalty result from this quality of customer care, which also improves the overall customer experience.

As a result, there are many different types of AI applications in supply chain operations that cover almost every facet of SCM. AI is making the supply chain a more intelligent, responsive, and efficient system in a variety of areas, including demand forecasting, inventory control, logistics optimisation, and customer support. It is anticipated that these technologies' influence on SCM will increase as they develop further, providing even more chances for creativity and advancement.

2.3. Evaluating the Impact of AI on Supply Chain Efficiency:

Artificial Intelligence (AI) has revolutionised supply chain management (SCM), greatly increasing sustainability and operational efficiency. Xue (2023) explores the revolutionary impact of artificial intelligence (AI) in big company supply chains, emphasising the ways in which computer vision, machine learning, and natural language processing technologies have increased dependability and efficiency. AI makes it easier to analyse vast volumes of supply chain data, which helps businesses anticipate possible problems, optimise scheduling and planning, and enhance automation through robotics. This all-encompassing use of AI technologies improves security and transparency while streamlining operations, strengthening the supply chain ecosystem.

A comprehensive analysis of AI applications in supply chain management is given by Atwani et al. (2022), who highlight AI's potential to solve problems like demand uncertainty, stochasticity, and the bullwhip effect. By enhancing performance, resilience, and efficiency, artificial intelligence (AI) technologies transform the planning, prediction, procurement, transportation, and distribution processes. The study emphasises how crucial AI is to enabling Industry 4.0, an industrial revolution in supply chain management where gaining a competitive edge is largely dependent on digital transformation.

The potential of AI to match supply chain procedures with environmental concerns and sustainability imperatives is examined by Gupta et al. (2023). In addition to improving operational effectiveness, AI integration with SCM helps supply chains move towards a more environmentally friendly future. Accurate demand forecasting, resource optimisation, and energy-efficient transportation routing are made possible by AI-driven solutions. These developments demonstrate AI's vital role in fostering sustainable supply chain transitions by lowering waste, energy consumption, and carbon emissions. Although there are many advantages, there are drawbacks to integrating AI into SCM, such as issues with data privacy, the requirement for qualified staff, and integrating AI technology with current systems. Technology companies, supply chain experts, and legislators must work together to create standards, promote education and training, and stimulate investment in AI infrastructure in order to address these issues.

As a result, artificial intelligence (AI) significantly affects supply chain efficiency by providing solutions that improve operational performance, encourage innovation, and advance sustainability. As AI technologies advance, integrating them into supply chain management will need resolving issues with workforce development, ethics, and data privacy. Adopting AI-driven innovations can help businesses better manage the intricacies of global supply chains, fostering creativity and giving them a competitive edge in the digital era.

3. Data Analysis & Testing Hypotheses

3.1. Research Sample

Due to the large size of the population and considerations of time and cost, the researcher will draw a representative sample of the study population. The sample size was determined according to the following formula: -

$$n = \frac{Z^2\ p(1-p)}{e^2}$$

$$n = \frac{1.69^2 * 0.5 * 0.5}{0.05^2} = 384.16$$

Where:-
n = the sample size
Z = Z value (1.96 for 95% confidence level)
P= percentage picking a choice, expressed as decimal (.5 used for sample size needed)
e = Sampling error expressed as decimal (5%)
In this study the sample size required to achieve statistical significance has been determined to 385 respondents after rounding up the result of formula.

3.2. The reliability and validity assessment of the research scales:

The Artificial intelligence (AI) Technologies scale comprises 13 items that represent its four dimensions: Internet of Things, Data Analytics, Sensors and Drones. The Alpha correlation coefficient (ACC) was used to measure the correlation between Consumption numbers on a comprehensive scale and on each individual dimension of the four associated variables.

Table (1): Coefficient of Reliability of Artificial intelligence (AI) Technologies Scale

Variables	Item	Cronbach's Alpha	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Internet of Things	1. Supply chain process automation level is high	**0.887**	**0.722**	**0.865**
	2. Supply chain operations automation has reduced supply chain operational costs		**0.829**	**0.838**
	3. Process automation has improved our supply chain responsiveness		**0.769**	**0.854**
	4. IOT has improved our communications		**0.750**	**0.857**
	5. Improvement in our communications has endured us to our clients		**0.572**	**0.895**

	6. IOT has improved on our research and development		**0.701**	**0.862**
	7. Improved on our research and development has led to more customer centric products		**0.784**	**0.847**
	8. Most of our supply chain tasks are digitalized		**0.732**	**0.873**
	9. Most of our supply chain operations are cloud based		**0.765**	**0.859**

Data Analytics	10. Data analytics influences our key decisions in our supply chain operations	**0.862**	**0.695**	**0.830**
	11. Data analytics plays a significant influence in reducing costs		**0.754**	**0.808**
	12. Data based decision making plays a significant influence in reducing costs		**0.741**	**0.812**
	13. Big data analytics is a key consideration for our customer relations		**0.669**	**0.848**
	14. Big data analytics influences the type of customer relations to adopt		**.0610**	**0.826**
	15. We have adopted predictive maintenance		**.0635**	**0.841**
	16. Adoption of predictive maintenance has significantly helped reduce our supply chain operational costs		**0.689**	**0.819**
	17. Big data is critical in undertaking repair and maintenance		**.0748**	**0.854**
	18. Big data is critical timely repair and maintenance which in turn improves our supply chain performance		**.0628**	**0.837**
Top-of mind	19. We use sensors and drones to achieve high order fulfillment levels	**0.827**	**0.539**	**0.843**
	20. We use sensors and drones has led to high responsiveness of our supply chain		**0.747**	**0.739**
	21. We use sensors and drones to achieve high supply chain flexibility		**0.686**	**0.771**

	22. Use of sensors and drones has led to low operational costs		**0.670**	**0.775**
	23. Drones are applied in our security management to a great extent		**0.679**	**0.925**
	24. Application of drones in our security management has boosted our supply chain responsiveness to a great extent		**0.653**	**0.919**
	25. Use of sensors has boosted our supply chain operational efficiency to a great extent		**0.555**	**0.919**
	26. We have adopted smart factory/remote systems to a great extent		**0.568**	**0.918**
	27. Adoption of smart factory/remote systems has boosted our operational efficiency		**0.532**	**0.832**
Artificial intelligence (AI) Technologies		**0.918**		

Source: Statistical analysis results

Table (1) shows the value of Cronbach's alpha coefficient for Artificial intelligence (AI) Technologies (α) = 0.889, and Internet of Things (α) = 0.647, also Data Analytics (α) = 0.863, also Sensors and Drones (α) = 0.885, finally (α) = 0.792. Accordingly, it is clear that the value of Cronbach's Alpha coefficient for each dimension of Artificial intelligence (AI) Technologies and also for the entire Artificial intelligence (AI) Technologies scale is greater than 0.7, and all items have item-total correlation coefficient greater than 0.30, which indicates the stability of Artificial intelligence (AI) Technologies scale used in the current study.

Supply Chain Decision-Making scale consists of 4 items that reflect the variable. Alpha correlation coefficient (ACC) was applied on Supply Chain Decision-Making scale in a total manner for the entire scale and for each dimension of its related four dimensions separately. This can be presented through table (2).

Table (2): Coefficient of Reliability of Supply Chain Decision-Making Scale

Variables	Item	Cronbach's Alpha	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Supply Chain Decision-Making	1. We easily combine and integrate information from many data sources for use in our decision making	**0.934**	**0.674**	**0.933**
	2. We often deploy dashboard applications / information to our managers' communication devices (e.g., smart phones, computers)		**0.588**	**0.938**

	3. Our systems automatically make operational changes, based on performance criteria/business rules, in response to signals from sensors		**0.761**	**0.926**
	4. Our systems give us the ability to decompose information to help root cause analysis and continuous improvement		**0.783**	**0.925**

Source: Statistical analysis results

Table (2) displays the Cronbach's Alpha coefficient value for Consumer purchasing intention (α) as 0.934. It is evident that the Cronbach's Alpha coefficient for each dimension of Supply Chain Decision-Making, as well as for the entire scale, exceeds 0.7. Additionally, all items demonstrate an item-total correlation coefficient greater than 0.30, indicating the stability of the Supply Chain Decision-Making scale utilized in this study.

3.3. Descriptive Analysis of Research Sample:

The researcher has analyzed the data contained in the questionnaires which related to the demographic characteristics through calculating frequencies and percentages. This is in order to describe the participants under investigation in terms of their personal and demographic characteristics (gender, educational level, Age and Years of Experience). This is shown in table (3).

Table (3): Descriptive Analysis of Research Sample

Demographic Variables	Sub Variable	Frequency	Percent
Gender	Male	**159**	**41.3**
	Female	**226**	**58.7**
	Total	**385**	**100.0**
Age	From 25 to less than 35 years	**141**	**36.6**
	From 35 to less than 45 years	**137**	**35.6**
	From 45 to less than 55 years	**87**	**22.6**
	56 years old and more	**20**	**5.2**
	Total	**385**	**100.0**
Educational level	Diploma Certificate	**122**	**31.2**
	Bachelor Degree	**201**	**51.4**
	Postgraduate Degree	**68**	**17.4**
	Total	**385**	**100.0**
Years of Experience	**Less than 5**	**91**	**23.64**
	From 5 to 10 years	**205**	**53.25**
	From 11 to 15 years	**70**	**18.18**
	More than 15 years	**19**	**4.94**
	Total	**385**	**100.0**

Source: Statistical analysis results

The demographic features of the study sample that was involved in the application of Artificial Intelligence (AI) technologies in Saudi Arabia are presented in Table (3), with a particular emphasis on four critical variables: "Gender," "Age," "Educational level," and "Years of Experience." Regarding the "Gender" category, the data reveals that "Female" participants constituted 58.7% of the sample, while "Male" participants accounted for 41.3% of the sample. The largest proportions were discovered in the "25 to less than 35 years" category (36.6%) and the "35 to less than 45 years" group (35.6%). The percentage of the sample that was aged "45 to less than 55 years" was lower than the percentage of those aged "56 years and more," which was just 5.2%.

As far as "Educational level" is concerned, the bulk of the individuals held a "Bachelor Degree" (51.4%), followed by a "Diploma Certificate" (31.2%), and then a smaller fraction that had a "Postgraduate Degree" (17.4%). The majority of participants had "From 5 to 10 years" of experience, which accounted for 53.25 percent of the total. Meanwhile, 23.64 percent of the participants had "Less than 5" years of experience, and 18.18 percent had "From 11 to 15 years of experience." Only 4.94 percent of the staff had "More than 15 years" of experience.

3.4. Testing Hypothesis:

In this section, the researcher presents the most important results of testing the study's hypotheses, along with an analysis and discussion of these results. These results have been divided into two main hypotheses;

3.4.1. Testing the first Hypothesis

In this section the researcher tested the first hypothesis of the current study, which states that there is no significant relationship between Artificial intelligence (AI) Technologies and Supply Chain Decision-Making for in the sample from Saudi Arabia. To test this hypothesis, the researcher used Pearson correlation coefficient at the level of 5% significance because of its ability to demonstrate the effect of an independent variable on a dependent variable. This can be shown through table (4).

Table (4) Correlation Coefficients Matrix

Variables	Internet of Things	Data Analytics	Sensors and Drones	Artificial intelligence (AI) Technologies	Supply Chain Decision-Making
1. Internet of Things	1	.662**	.661**	.875**	.709**
2. Data Analytics	.662**	1	.778**	.907**	.781**
3. Sensors and Drones	.661**	.778**	1	.901**	.743**
4. Artificial intelligence (AI) Technologies	.875**	.907**	.901**	1	.832**
5. Supply Chain Decision-Making	.709**	.781**	.743**	.832**	1

**** It indicates significant at the level of statistical significance 0.0001.**

According to table (4), there is a positive statistical relationship between Artificial intelligence (AI) Technologies and Supply Chain Decision-Making in Saudi Arabia, where the value of the

correlation coefficient is (0.832*), in addition to positive statistical relationship between Artificial intelligence (AI) Technologies dimensions (Internet of Things, Data Analytics, and Sensors and Drones) and Supply Chain Decision-Making in Saudi Arabia with correlation coefficients (0.709**), (0.781**), and (0.587**) respectively.
Accordingly, it is evident from the above results that there is a positive relationship between the three variables and thus it is possible to test the hypothesis of the effect for each of the first hypotheses. So, the first hypothesis is rejected that there is no significant relationship between Artificial intelligence (AI) Technologies and Supply Chain Decision-Making for in the sample from Saudi Arabia.

3.4.2. Testing the second Hypothesis

In this section the researcher tested the second hypothesis of the current study, which states that there is significant impact of Artificial intelligence (AI) Technologies on Supply Chain Decision-Making for in the sample from Saudi Arabia. To test this hypothesis, the researcher used simple regression analysis at the level of 5% significance because of its ability to demonstrate the effect of an independent variable on a dependent variable.
The researcher explains through table (5) the results of simple regression analysis to indicate the effect of the independent variable (Artificial intelligence (AI) Technologies) on Supply Chain Decision-Making as a dependent variable.

Table (5): Results of Simple Regression Analysis for Artificial intelligence (AI) Technologies on Supply Chain Decision-Making

Dependent Variable	Independent Variable	Beta	T-Value	Sig.
Supply Chain Decision-Making	**(Constant)**	**0.987**	**7.283**	**0.000**
	Artificial intelligence (AI) Technologies	**0.678**	**19.683**	**0.000**
R= 0.709 **R^2 = 0.502**		**F- Value = 387.405** **Sig = 0.000**		

Source: Statistical analysis results

Table (5) shows that there is a positive significant effect of Artificial intelligence (AI) Technologies on Supply Chain Decision-Making in Saudi Arabia, as the regression coefficient reached (0.678) at the level of significance 0.000. While F- value reached (387.405) with a significant level of (0.000), which is less than (1%), that means the model is valid to predict the values of the dependent variable (Supply Chain Decision-Making in Saudi Arabia).
As for the explanatory ability of this model, which shows the percentage of change in the dependent variable (Supply Chain Decision-Making in Saudi Arabia) due to the change of the independent variable (Artificial intelligence (AI) Technologies), it was found that the determination coefficient reached (0. 678) and this means that the independent variable (Artificial intelligence (AI) Technologies) model explains an amount of (Only 50.2%) of the change in the dependent variable (Supply Chain Decision-Making in Saudi Arabia).
From the previous explanation, the null hypothesis is rejected that there is no significant impact of Artificial intelligence (AI) Technologies (overall) on Supply Chain Decision-Making for in the sample from Saudi Arabia.
In details, the researcher explains through table (6) the results of simple regression analysis to indicate the effect of the independent variable (Internet of Things) on Supply Chain Decision-Making as a dependent variable.

Table (6): Results of Simple Regression Analysis for Internet of Things on Supply Chain Decision-Making

Dependent Variable	Independent Variable	Beta	T-Value	Sig.
Supply Chain Decision-Making	**(Constant)**	**0.586**	**4.666**	**0.000**
	Internet of Things	**0.732**	**24.481**	**0.000**
R= 0. 781 **R^2 = 0. 61**		**F- Value = 599.310** **Sig = 0.000**		

Source: Statistical analysis results

Table (6) shows that there is a positive significant effect of Internet of Things on Supply Chain Decision-Making, as the regression coefficient reached (0.732) at the level of significance 0.000. While F- value reached (599.310) with a significant level of (0.000), which is higher than (5%), that means the model is valid to predict the values of the dependent variable (Supply Chain Decision-Making).
As for the explanatory ability of this model, which shows the percentage of change in the dependent variable (Supply Chain Decision-Making) due to the change of the independent variable (Internet of Things), it was found that the determination coefficient reached (0.803) and this means that the independent variable (Internet of Things) model explains an amount of (Only 61.0%) of the change in the dependent variable (Supply Chain Decision-Making).
From the previous explanation, the null hypothesis is rejected that there is no significant impact of Internet of Things on Supply Chain Decision-Making for in the sample from Saudi Arabia.
The researcher explains through table (7) the results of simple regression analysis to indicate the effect of the independent variable (Data Analytics) on Supply Chain Decision-Making as a dependent variable.

Table (7) Results of Simple Regression Analysis for Data Analytics on Supply Chain Decision-Making

Dependent Variable	Independent Variable	Beta	T-Value	Sig.
Supply Chain Decision-Making	**(Constant)**	**0.460**	**3.136**	**0.002**
	Data Analytics	**0.752**	**21.728**	**0.000**
R= 0.743 **R^2 = 0.552**		**F- Value = 472.089** **Sig = 0.000**		

Source: Statistical analysis results

Table (7) shows that there is a positive significant effect of Data Analytics on Supply Chain Decision-Making, as the regression coefficient reached (0.752) at the level of significance 0.000. While F- value reached (472.089) with a significant level of (0.000), which is less than (1%), that means the model is valid to predict the values of the dependent variable (Supply Chain Decision-Making).
As for the explanatory ability of this model, which shows the percentage of change in the dependent variable (Supply Chain Decision-Making) due to the change of the independent

variable (Data Analytics), it was found that the determination coefficient reached (0.813) and this means that the independent variable (Data Analytics) model explains an amount of (Only 55.2%) of the change in the dependent variable (Supply Chain Decision-Making).
From the previous explanation, the null hypothesis is rejected that there is no significant impact of Data Analytics on Supply Chain Decision-Making for in the sample from Saudi Arabia.
The researcher explains through table (8) the results of simple regression analysis to indicate the effect of the independent variable (Sensors and Drones) on Supply Chain Decision-Making as a dependent variable.

Table (8): Results of Simple Regression Analysis for Sensors and Drones on Supply Chain Decision Making

Dependent Variable	Independent Variable	Beta	T-Value	Sig.
Supply Chain Decision-Making	**(Constant)**	**-0.041**	**-0.324**	**0.746**
	Sensors and Drones	**0.952**	**29.343**	**0.000**
R= 0.832 **R^2 = 0.692**		**F- Value = 860.99** **Sig = 0.000**		

Source: Statistical analysis results

Table (8) shows that there is a positive significant effect of Sensors and Drones on Supply Chain Decision-Making, as the regression coefficient reached (0.952) at the level of significance 0.000. While F- value reached (860.99) with a significant level of (0.000), which is less than (1%), that means the model is valid to predict the values of the dependent variable (Supply Chain Decision-Making).
As for the explanatory ability of this model, which shows the percentage of change in the dependent variable (Supply Chain Decision-Making) due to the change of the independent variable (Sensors and Drones), it was found that the determination coefficient reached (0. 952) and this means that the independent variable (Sensors and Drones) model explains an amount of (Only 69.2%) of the change in the dependent variable (Supply Chain Decision-Making).
From the previous explanation, the null hypothesis is rejected that there is no significant impact of Sensors and Drones on Supply Chain Decision-Making for in the sample from Saudi Arabia.

4. Conclusion:

This paper investigated the relationships among Artificial Intelligence (AI) on Supply Chain Decision-Making in Saudi Arabia. The results of the research provided strong proof in favor of the presumptions that Artificial Intelligence (AI) had a significant and positive impact on Supply Chain Decision-Making. More precisely, it was found that Internet of Things, Data Analytics, Sensors and Drones impact significantly on Supply Chain Decision-Making. This study emphasizes the important part effective Artificial Intelligence (AI) Technologies have in improving Supply Chain Decision-Making in Saudi Arabia.
The degree of Artificial Intelligence (AI) Technologies as well as the influence that Supply Chain Decision-Making in Saudi Arabia were found to be rather influenced by demographic traits. The ANOVA tests produced statistically significant variations in terms of age, gender, educational level and years of experiences between the groups. Particularly remarkable were the differences in Educational level and age groups, which This indicates that younger populations have a greater level of involvement with artificial intelligence and individuals in Saudi Arabia who make use of artificial intelligence technology are often well educated professionals who are in the beginning to middle stages of their professions.

Ultimately, these results support more evidence that companies in Saudi Arabia should stress Artificial Intelligence (AI) Technologies as a main component of their attempts to increase Supply Chain Decision-Making efficiency. Companies may maximize the efficiency of their Supply Chain Decision-Making, and create a lasting competitive edge in a market that is getting more and more digital by knowing and purposefully addressing demographic variations.

5. Recommendations:

- Organizations must enhance understanding among supply chain managers on the actual applications of AI technologies, enabling them to utilize these resources effectively to enhance accuracy and responsiveness in operations.
- It is recommended to use sensors and drones more extensively into supply chain operations to provide real-time tracking and enhenced inventory management systems.
- Staff training programs should be augmented to incorporate practical experiences with contemporary AI technologies to facilitate improved assistance for supply chain transformation.
- Policymakers have to provide incentives and supportive structures that motivate small and medium enterprises to embrace AI technnology without apprehension about exorbitant expenses or intricate integration.
- The study emphasizes the necessity for improved colaboration between IT teams and supply chain divisions to facilitate the seamless integration of AI-driven solutions.
- Companies should conduct pilot projects prior to the comprehensive use of AI technology to accurately assess risks and adventages within their particular industrial setting.
- Companies should consistently assess the success of their AI systems by utilizing important indicators associated with supply chain efficiency, speed, and customer satisfaction.

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