Mahmoud M. AbdEllatif¹, Rami M. Baazeem²

Abstract

Digital transformation is not a goal, but the benefits that businesses achieve from digital transformation are the desired goal. The successive developments in artificial intelligence technology represent a great opportunity to solve business problems. Artificial intelligence, especially machine learning methods, can be used to solve many problems facing the logistics and supply chain sector. Machine Learning (ML) techniques widely impact on many aspects of Logistics and Supply chain Management such as improving services levels for end customers, reducing costs, minimizing resource waste, and improving partners relationships. The problem of demand forecasting is one of the problems that affect production scheduling, inventory levels, partner costs, and customer satisfaction. Therefore, this research addresses these topics in some detail and provides a practical application to solve the research problem using some machine learning methods and tools. The research confirmed the accuracy of predictions and thus improved decisions and partner plans in supply chains. The research represents an analytical addition to previous research in the same field.

Keywords: Artificial Intelligence, Machine Learning, Supply Chain, Logistics, Cognitive Technologies, IT Architecture

INTRODUCTION

The World Trade Organization reported that global merchandise trade (exports and imports) increased by 12% in 2022, reaching US\$ 25.26 trillion. The analysis indicated a 15% growth in the value of global commercial services trade in 2022, reaching 6.8 trillion US dollars. In that year, the export value of digitally offered services amounted to US\$3.82 trillion. The analysis anticipates an increase in the amount of global merchandise trade from 1.7% in 2023 to 3.2% in 2024. This statistic assures the economic importance of Global logistics and supply chain companies, which represent the backbone of all sectors of Global Society. (WTO,2023)

In addition, the business environment has become more complex due to the dynamics of the overlapping interaction between the components of its three dimensions: environmental, organizational, and technological. Some studies have shown that global organizations face very dynamic and complex environments that impose great challenges that require the adoption of a different mentality and increased attention to administrative competencies to deal with this complexity. A fundamental assumption in management theory and practice is that complexity hinders organizational performance, as it grows at a faster rate than management's ability to handle it.(Martinez et al. ,2021)

Business Process Management (BPM) (as logistics and supply chains represent one of the most common business processes) provides a fertile environment for new applications of artificial intelligence and machine learning. For example, machine learning (ML) techniques have been used to extract event logs from various sources – including sensor data, to predict the future of ongoing implementation traces, as well as to explain deviant behaviors in business processes; Planning methods have been utilized to model and analyze business processes; Constrained heuristics have been used as a core technology that forms the basis of business rules engines.[11]

Because of the rapid development of Artificial Intelligence AI applications in Global supply chains and logistics services, such as intelligent warehousing systems, innovative transportation systems, smart shipping and tracking systems, and AI applications for collecting, analyzing, and visualizing data, these applications contribute to achieving the organizations' goals of the efficient and effective flow of materials and information that increases the value provided to customers. On the other hand, these rapid developments in artificial

¹ MIS Department College of Business University of Jeddah, SA. E-mail: mmlatif@uj.edu.sa

² MIS Department College of Business University of Jeddah, SA. E-mail: rbaazeem@uj.edu.sa

intelligence applications raise the efficiency and effectiveness of the internal operational processes of enterprises.

One of the most important aspects of the global economy in the era of globalization, Artificial intelligence, and the Fourth Industrial Revolution is that companies in the countries of the world are interconnected through global supply chains, relying on outsourcing to benefit from the specialization of diverse organizations and the division of labor at the level of organizations to achieve savings in specialized mass production, in a way that achieves Product differentiation and comparative cost advantages. As global supply chains achieve significant competitive advantages, value creation is not only at the level of one organization, but through a network of connections between multiple organizations in different countries of the world. It is now a question of how best to organize supply chains [1,2,3].

The performance objectives of the supply chain emphasize enhancing the quality and quantity of products and processes, while in logistics services, the focus is on performance levels, quality, customer satisfaction, environmental efficiency, and waste reduction. [4–5].

Logistics and supply chain management aims to achieve error-free implementation of its operations, and this achieves a form of administrative robustness. Deviations from goals or plans can also be removed within a certain scope, which contributes to improving competitiveness. It offers solutions to address the dynamic complexities of the supply chain network, including heightened intricacies from network expansion, insufficient coordination among regions or partners, operational disruptions, delayed or erroneous information flow, inadequate service levels, and the resultant loss of customers. Therefore, the strategic focus will increasingly focus on the continuity of supply chains and maintaining their operational processes. The strength and flexibility of supply chain operations is achieved through the increase in digitalization, especially applications of artificial intelligence and machine learning [20-23].

Modern digital technologies, especially artificial intelligence and machine learning technologies, allow for more accurate and rapid processing of operations, as it is possible to conduct large-scale data analyzes. These advanced digital technologies can also independently develop solutions to emerging problems based on dynamic models of supply chains and logistics. Artificial intelligence, particularly machine learning methodologies, possesses the capability to learn from both historical data and information obtained from interconnected data sources, in contrast to conventional programming. Artificial intelligence significantly enhances forecasting, risk management, and resilience. [8-9].

The use of artificial intelligence applications in managing logistics services and global supply chains requires huge investments at the level of the three axes of business enterprises, whether technological, organizational, or environmental. Therefore, studying and analyzing the impact of this field has become necessary at academic and practical levels to help the management draw a successful road map for these applications.

As a result, studying and analyzing the factors influencing managerial decisions in this field is vital at the academic and practical levels.so, The problem of this research arose with the increasing trend towards artificial intelligence applications in the management of logistics services and global supply chains, where the tools and methods of artificial intelligence contribute to raising the efficiency and effectiveness of the services provided and achieving value for customers. Given that this transformation is complex, the research problem was to study and analyze the factors contributing to the successful application.

This article provides academics and practitioners with a comprehensive and in-depth view of the applications of artificial intelligence and machine learning methods to provide appropriate solutions for supply chain management. This article also reviews a case study in this field. The article's sections were organized in a way that made sense. The first part introduced the topic of the article, and the second part talked about the most important previous research that had looked at how AI and machine learning could be used in logistics and supply chains. The third part of the research looked at the methods and techniques of AI and how they could be used in the main areas of logistics and supply chain management. In the fourth section of the article, the researchers conducted a comprehensive applied case study, followed by a conclusion and Future Works.

LITERATURE REVIEW

A study by Ning, Lianju, and Dan Yao (2023) attempts to quantify how digital transformation affects supply chains' capacity to compete in an unpredictable market. The research employed the opinion poll methodology and gathered 255 questionnaires. This study's findings illustrate the significant impact of digital transformation on improving supply chain capabilities, hence positively influencing sustained competitive performance. The environmental unpredictability inherent in the globalized context acts as a catalyst for digital transformation, prompting supply chains to intensify their pursuit of digital advancements. The study concluded that the four dimensions of supply chain capabilities (information exchange, activity integration, collaboration, and responsiveness) play a vital mediating role between digital transformation and competitive performance.[13]

The (Waltera,2023) study confirms that supply chain strategies must be able to adapt to rapidly changing customer needs while improving processes and quality control mechanisms. It also emphasizes that more flexible supply chains can be achieved with the help of artificial intelligence applications. Provided that the organization in question is mature enough to manage the required changes. The use of artificial intelligence is not just a technological issue, but must be viewed in a more comprehensive way. [14]

A Waltera,2023 study also confirms that using artificial intelligence methods and applications, it is possible to access, extract, and use data automatically from different, geographically distributed sources, and this supports global supply chain management. Artificial intelligence methods and tools play an important role, both from a competitive perspective and from the perspective of creating value in the value network.[14]

A Waltera,2023 study confirms that artificial intelligence methods contribute to providing solutions that achieve efficiency and effectiveness in addressing operational problems of supply chain management, such as improving supply chain planning and scheduling, including forecasting needs along the supply chain. Which leads to improved payments and unified shipping. Artificial intelligence methods also achieve consistency and harmony between manufacturing processes and production plans, with corresponding positive effects on scheduling, monitoring and adjustments. It also contributes to improving quality levels.[14]

The study by Haifeng Lin et al. (2022) investigated the utilization of an information management system to consolidate all components and business processes within the supply chain, employing artificial intelligence algorithms to facilitate intelligent management of all connections and partners in the supply chain network. A study posits that this method can significantly assist firms in minimizing operating expenses and enhancing their responsiveness to market demands, hence augmenting overall operational efficiency. This proposed solution is also an effective method for selecting members and an important basis for running the dynamic supply chain efficiently and smoothly.[19]

A paper by Haifeng Lin et al. (2022) proposes a dynamic supply chain member selection technique utilizing conditional generative adversarial networks (CGANs) to tackle the challenges given by several choice qualities and a limited quantity of data samples for decision analysis. Research created a comprehensive supply chain management system design comprising six modules: order management, purchasing management, production management, inventory management, distribution management, and transportation management. The research employed machine learning to examine and forecast purchase and inventory relationships inside the supply chain. The vehicle scheduling module optimally plans the route to enhance operational efficiency. The comprehensive execution of the SCM system was finalized utilizing the SSH framework.[19]

The main purpose of (Wamba-Taguimdje, ET. AL.,2020) study is to analyze the impact of artificial intelligence (AI) on company performance through the business value of AI-based transformation projects. This study adopts the theory of information technology capabilities to benefit from the impact of artificial intelligence business value on company performance (at the organizational and operations levels). This study extracted a set of results, the most important of which is the diversity of artificial intelligence methods and techniques, in addition to machine learning algorithms. These techniques help individuals better understand their environment and act in accordance with its complex, dynamic variables better. The study also concluded that organizations are adopting technological innovations of artificial intelligence with the aim of adapting to their ecosystem and improving their strategic and competitive advantages.[20]

A (Wamba-Taguimdje, ET. AL.,2020) study also concluded that artificial intelligence, with its capabilities and characteristics, contributes to improving current processes and improving the effects of automation, information, and transformation, as well as in discovering, predicting, and interacting with human behaviors and patterns. Thus, the results of our study have highlighted the benefits of AI in organizations, and more specifically its ability to improve performance at the organizational (financial, marketing, administrative) and operational levels. By relying on the features of artificial intelligence, organizations can enhance the business value of their digitally transformed projects.[20]

According to (Trinh Le Tan, ET. AL.,2022) study examined the issues of implementing AI in the supply chain to provide a more objective perspective on the challenges and benefits of adopting AI in supply chain management in SMEs. Therefore, the aim of the study was to analyze the influence factors in the application of artificial intelligence (AI) technology by building a technology, organization, and environment (TOE) framework. The study adopted the qualitative approach in analyzing previous studies with the aim of formulating the study model and the relationships between its variables, then the quantitative approach to analyzing the data and drawing conclusions.[21]

A (Trinh Le tan, ET. AL.,2022) study collected data from 120 medium and small companies in Vietnam and used some statistical methods to analyze the data, such as explanatory factor analysis, Pearson correlation, and regression methods. The findings indicate that the factors positively influencing the implementation of artificial intelligence technology in supply chain management include technical factors (relative advantages), organizational factors (top management support, organizational readiness), and environmental factors (government support), whereas complexity and compatibility serve as inhibiting factors. The expense and external pressure are superfluous.[21]

(Xie Y., et. Al., 2020) study addressed the Industry 4.0 strategy, especially artificial intelligence technology and its impact on supply chain management and transforming them into smart supply chains. The study analyzed the main characteristics of the smart supply chain, which were: visibility, transparency, customization, information management, supply chain warning, green, innovation and learning. Based on the analysis of the main characteristics of the smart supply chain, the study proposed a framework for a performance measurement indicator consisting of seven indicators. To evaluate supply chain performance and provides an effective way to improve the operational performance of intelligent supply chain management and thus improve the performance of the supply chain management and thus improve the performance of the supply chain an efficient and effective manner, which contributes to enhancing the competitive capabilities of institutions. A study concluded that the proposed performance and provides a new way to improve the operational performance of smart supply chain gupply chain performance and provides a new way to improve the operational performance of smart supply chain performance and provides a new way to improve the operational performance of smart supply chain performance and provides a new way to improve the operational performance of smart supply chain management.[22]

The study by Belhadi, A., Mani, V., Kamble, S.S. et al. (2024) looked at supply chain resilience (SCRes) and how sophisticated information processing technologies, such artificial intelligence (AI), can improve supply chain performance (SCP) and create resilient supply chains (SCRs). The main aim of this study was to examine the direct and indirect impacts of AI, SCRes, and SCP within the framework of dynamism and unpredictability in the supply chain. The study model examined the application of artificial intelligence in the supply chain utilizing a conceptual framework grounded in OIPT. The study model was built and hypotheses that address the relationship between the study variables were formulated. The study collected survey data from 279 companies representing different sizes, operating in various sectors and countries. This study has provided field evidence that AI has a direct impact on short-term sustainable production and production, that AI information processing capabilities significantly impact SCP directly by enhancing relevant metrics or creating long-term SCP by building SCRs. The study confirmed that developing sustainable SCP requires companies to develop artificial intelligence capabilities to enhance SCRs through their key enablers AC and SCC in light of the dynamism and uncertainty of the supply chain environment.[24]

Artificial Intelligence and Machine Learning in the Logistics & Supply Chain

The supply chain is defined academically and practically as it aims to flow raw materials, products, and services supported by the necessary information flows from the places of their availability to the places of need in the required quantity and at the required time [15]. Therefore, supply chains and logistics services are one of the most important information-intensive applied fields. The flow of data, its operation, analysis, and the use of its results to achieve a better understanding of the complex and interconnected decision-making processes that are critical to collaborative problem solving, especially regarding joint demand planning and forecasting processes across diverse supply chain partners. Consequently, the use of artificial intelligence and machine learning methods provides tremendous benefits for improving performance in supply chain management and logistics. The use of artificial intelligence methods, especially machine learning methods, also contributes to improving effective analyzes and providing simulations and targeted notifications, which achieves improved efficiency of logistics and supply chain management, increased resource and energy efficiency, and significantly improved responsiveness, i.e. flexibility within the supply chain, thus ensuring Security. Optimal risk management for the supply network. The application of AI is transformative and has huge potential to improve workflow and production processes.[16]

The use of digital transformation tools, especially artificial intelligence and machine learning methods, achieves the development of the supply chain and logistics services network. Therefore, flexibility is achieved in communicating and synchronizing events and activities with each other. In order to achieve efficiency in the flow of logistical materials and exchange the necessary information. Second, it also includes employees of companies across the entire network. Since classic hierarchy has been consciously abandoned, it can also contribute to reacting better to unexpected events, crises and uncertainty that characterize the global business environment. [13-17].

Artificial Intelligence

Artificial Intelligence has become an umbrella term for applications that perform complex tasks that require human capabilities related to learning and thinking. Machine learning, as a branch of artificial intelligence, focuses on creating systems that learn or improve their performance based on the data they analyze. IT systems can independently find solutions to problems that arise using artificial intelligence. Dynamic models can be created based on collected data - that is, experience. The data basis does not have to be system-specific; Unknown parameters from other data sources can also be included. Depending on the requirements, data can be found, extracted, summarized and analyzed. This can then be used, for example, to determine probability of occurrence of events and recognize behavioral patterns [4]. Figure 1 shows Overview of AI Types & Techniques.



Machine Learning

Machine learning is a subset of artificial intelligence that is focused on enables computers self-learning from data to improve with experience and then applies that learning without the need for human intervention, such as categorizing images, analyzing data, or predicting price fluctuations. Machine learning aims to teach a machine how to perform a specific task and provide accurate results by identifying patterns. Machine learning is the process of optimizing the model so that it can predict the correct response based on the training data samples. ML assists humans in solving problems efficiently. The algorithm learns and improves performance and accuracy as more data is fed into the algorithm.[62] Figure 2 displys Machine Learning Algorithms.



AI & ML in Logistics & Supply Chain

One of the most important characteristics achieved by using artificial intelligence and machine learning methods is achieving the characteristics of flexibility, speed, and efficiency in the services provided at the partner level, in a way that better fulfills customers' desires, and by providing a variety of responses to events, changes, and crises. These characteristics are achieved through smart logistics, which contributes to meeting the basic requirements of the supply network and logistics services.

By collecting data at all points of the supply chain and exchanging it in the supply chain, the various activities in the chain are coordinated with partners, and individual solutions must be integrated with other parties in order to achieve values for all parties. [18].

Emphasizing the same context, cognitive technologies in general and artificial intelligence in particular can contribute efficiently and effectively to adapting the technical components of the supply network to become an agile network that learns from machine learning methods [31-33]. In order to achieve flexibility in their work procedures and adapt in a short time to the dynamism of the scientific business environment, which is characterized by complexity and uncertainty.

Many companies seek to achieve a sustainable business environment that aims, on the one hand, by creating significant and sustainable competitive gains using the intelligent synthesis of technologies, tools and methods of artificial intelligence in harmony and compatibility with the needs of their work environment. The use of artificial intelligence contributes to companies' success in operating successfully in an increasingly difficult business environment. It also contributes to increasing the efficiency of resource and energy use. The introduction and deployment of artificial intelligence tools is gaining increasing importance, especially with the

increasing demand for goods and services, and the relative scarcity of resources. Producing more with less resources is an important contribution to achieving environmental sustainability. The technical foundations of knowledge allow, for example, to improve planning processes and improve decision support. It also contributes to reducing energy consumption and producing defect-free products with predictable quality. Figure 3 shows Classification of supply chain analytics methods.



Table 1: AI Techniques in Logistics & Supply Chain								
AI Techniques L& SC Areas	Machine Intelligence/ Artificial Intelligence	Interactive/ analytics intelligence	Visual intelligence / Analytic					
Requirement Management/ Engineering	Kaur, K., Singh, P., Kaur, P. (2021). Chaopaisarn, p. & Woschank, M., 2019 Priore et al. (2019), Cavalcante et al. (2019), Min et al. (2019),	Violetta Giada Cannas, Maria Pia Ciano, Mattia Saltalamacchia &Raffaele Secchi (2023)	Alireza Khakpour , Ricardo Colomo- Palacios , And Antonio Martini,2021					
Demand Forecasting & Inventory Management	Real Carbonneau, Kevin Laframboise, Rustam Vahidov,2008, Aktepe, A., Yanık, E. & Ersöz, S.,2021 <u>SR Gayam, RR Yellu</u> , P Thuniki ,2021	Cisse, Sory. (2021), Tang, Weiping. (2024). Nonthaphat Sukolkit, Sirawadee Arunyanart, Arthit Apichottanakul,2024,	 K. Zhao, R. Sun, C. Deng, L. Li, Q. Wu, and S. Li,2018 K. Li, YN. Li, H. Yin, Y. Hu, P. Ye, and C. Wang,2020 Q. Li, Q. Q. Liu, C. F. Tang, Z. W. Li, S. C. Wei, X. R. Peng, M. H. Zheng, T. J. Chen, and Q. Yang,2020 					
Support Logistics & supply chain decision Making	Dubey, R.; Bryde, D.J.; Blome, C.; Roubaud, D.; Giannakis, M.,2022, Goli Mallesham, 2024.	Queiroz, M.M. and Telles, R. (2018), Krishnan , et. Al.,2022, Muravev et al. (2020), Baryannis et al. (2019), Leung et al. (2019), Mehdizadeh (2020)	H. Park, M. A. Bellamy, and R. C. Basole,2016					
Logistics & supply chain innovation & Growth	Rane, Nitin & Desai, Pravin & Rane, Jayesh & Paramesha, Mallikarjuna. (2024).		Grover et al. (<u>2020</u>), Dhamija and Bag (<u>2020</u>) R. C. Basole, M. A. Bellamy, and H. Park,2017					
Customer / Supplier relationship Management	Grant, Oliver. (2024). Alshurideh, M., Kurdi, B., Hamadneh, S., Chatra, K., Snoussi, T., Alzoubi, H., Alzboun, N & Ahmed, G. (2024).		Z. Yao, P. Sarlin, T. Eklund, and B. Back,2014					
Performance Management	Wang, M.; Pan, X.2022 Ali, S.M.; Rahman, A.U.; Kabir, G.; Paul, S.K.,2024 Belhadi, A.; Mani, V.; Kamble, S.S.; Khan, S.A.R.; Verma, S., 2021,	Fan, X., Zhang, S., Wang, L. <i>et al.</i> 2013 Dubey, R.; Gunasekaran, A.; Childe, S.J.; Fosso Wamba, S.; Roubaud, D.; Foropon, C.,2021	A. Zavala and J. E. Ramirez- Marquez,2019					

CASE STUDY

The problem and Data Set

One of the most important features of supply chains is that they have many players, starting with the end consumers, through retailers, customers, suppliers, transportation companies, and manufacturers. Each party has a limited influence on the entire process, but the actions of each party affect all parties. These parties seek to respond to fluctuations in demand, so they create cascading effects throughout the chain, which is called the bullwhip effect. This effect occurs when each party gradually increases a small increase in demand, as each party adds an additional quantity to its expected orders to serve as a reserve. The bullwhip effect phenomenon represents the distortion of expected demand through the increased volatility that occurs as forecasts are transmitted from the retailer to the manufacturer, so the bullwhip leads to overproduction, inaccurate demand forecasts, and inconsistent inventory.[61]

Pre-processing

Pre-processing was used for data cleaning. It was purposed to dispose of data which contained noise, and then data was plotted to create a time series and the pattern [7].

Identifying an ARIMA (AutoRegressive Integrated Moving Average) model involves determining the appropriate values for the parameters pp, dd, and qq that best describe your time series data. Here's a step-by-step process:

Stationarity Test

A stationary time series is not dependent on the time at which the series is observed. So, time series with trends, or seasonality, are not stationary. Also, a white noise series is stationary, even a time series with cyclic behavior (but with no trend or seasonality) is stationary, conditionally the cycles are not of a fixed length. In brief, a stationary time series will have no predictable patterns in the long-term. draw a Time series plot will show the horizontal behavior of series roughly even some cyclic behavior displays, with constant variance see figure 4.[53] to Examine Time Series:

Check for Stationarity:

- Plot the time series and look for trends or seasonality.
- Use statistical tests like the Augmented Dickey-Fuller (ADF) test or KPSS test to confirm stationarity.
- If the series is non-stationary, apply differencing to remove trends (dd).



- Determine Differencing Order (dd):
 - o Start with the first difference ($\Delta Yt=Yt-Yt-1$ \Delta Y_t = Y_t Y_{t-1}).
 - o Repeat until stationarity is achieved. The number of differences corresponds to dd.

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	-2.867496						
	10% level		-2.570005				
*MacKinnon (1996) on	e-sided p-value	es.					
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ACF/PACF Plotting

This stage was examined to create the ACF (Auto Correlation Function) and PACF (Partial Auto Correlation Function) plots. These plots determined the tentative models or candidates to be selected to perform the best forecasting [7]. To Identify the AR and MA Components:

Plot the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF):

- ACF shows the correlation between the series and its lags.
- PACF shows the correlation between the series and its lags after removing intermediate correlations.

Interpret ACF and PACF:

- AR Model (pp): Look at the PACF: A sharp cutoff after lag pp suggests an AR(pp) process.
- MA Model (qq): Look at the ACF: A sharp cutoff after lag qq suggests an MA(qq) process.
- ARMA Model: If neither ACF nor PACF shows a sharp cutoff, a combination of AR and MA components might be necessary.

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ili	ili ili	17 0.012	0.013	12.116	0.793		
		18 -0.055	-0.070	13.586	0.756		
10	101	19 -0.038	-0.044	14.303	0.766		
IE I	•	20 -0.062	-0.072	16.201	0.704		
II I	1 191	21 -0.034	-0.041	16.757	0.726		
11	1 :4:	22 -0.006	-0.031	16.776	0.776		
111	1 11	23 0.017	0.013	16.918	0.813		
in'i		24 0.023	0.025	19 240	0.841		
		26 -0.040	-0.042	18 349	0.863		
ili	l ili	27 0.011	0.016	18,404	0.891		
10 1		28 -0.038	-0.033	19.139	0.894		
i ju		29 0.023	0.011	19.414	0.910		
10	1 10	30 -0.022	-0.015	19.650	0.925		
101		31 -0.028	-0.025	20.060	0.935		
		32 0.008	0.005	20.093	0.950		
101	1 141	33 -0.031	-0.043	20.591	0.955		
: "		34 0.062	0.049	22.537	0.934		
	l idi	36 -0.046	-0.057	23.646	0.944		
· ។	I 4	100 0.010	5.001	20.0.0			

Estimation: Fit and Evaluate Models

Test combinations of pp, dd, and qq based on insights from the ACF/PACF plots, Compare Models: See Tabl2

• Use metrics like AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), or RMSE (Root Mean Square Error) to choose the best model.

• Lower AIC/BIC values indicate a better fit,.

• WE USE orange tool so Figure 8 shows Sample oF model evaluation using and Table 2 displys Fit and Evaluate different Models. the (1,1,1) model is the best model for prediction of the future demand.



Validate the Model, Check the residuals of the model:

- o Residuals should be white noise (uncorrelated and normally distributed).
- o Use statistical tests like the Ljung-Box test to confirm.

Model Evaluation (3) - Orange					-	- (×
Evaluation Parameters ARIMA(1,1,1) Number of folds: 20 Forecast steps: 3 ARIMA(1,1,1) ARIMA(1,1,1) (in-sample) ARIMA(1,1,1) (in-sample)	RMSE 2972.3 1258.9	MAE 2135.5 771.2	MAPE 0.736 0.943	POCID 25.4 3.632	R ² -4.401 -0.017	AIC 6941.3 8012.3	BIC 6953.3 8024.8	

Figure 8 : Sample oF model evaluation using (1,1,1)

Forecast and Refine

- o Generate forecasts and assess performance.
- o Refine the model parameters as needed.

o For automated tools, consider software like Python's statsmodels, R's forecast package, or any statistical software that supports ARIMA modeling.

Table 2 : Fit and Evaluate Models									
ARIMA MODEL	RMSE	MAE	MAPE	POCID	R ²	AIC	BIC		
ARIMA (0,0,0)	2972.4	2092.4	0.735	6.780	-4.401	6953.0	6961.0		
ARIMA (0,1,0)	3277.6	2700.0	0.771	11.9	-5.567	7253.8	7257.8		
ARIMA (1,1,0)	3170.9	2392.9	0.699	18.6	-4.905	7117.1	7125.2		
ARIMA (1,1,1)	2972.3	2135.5	0.736	25.4	-4.401	6941.3	6953.3		
ARIMA (1,0,1)	2975.2	2151.3	0.738	20.3	-4.411	6952.6	6968.7		
ARIMA (1,0,0)	2970.4	2134.2	0.735	25.4	-4.394	6951.2	6963.2		

The Impacts of AI&ML on the Performance of Logistics & Supply Chain Management

CONCLUSION AND FUTURE WORKS

We conclude from this study that the applications and uses of artificial intelligence and machine learning have multiplied and diversified in all areas of supply chain and logistics management. The use of machine learning and artificial intelligence methods and techniques has contributed to increasing the efficiency of supply chain resource management. These applications have also achieved flexibility and increased the efficiency of decision-making. One of the most important problems that supply chains suffered from was predicting future orders in terms of quantity, place, and time, which may have affected their efficiency. Through the applied case, the research provided one of the solutions to this problem. This field still needs more studies and research. Continued exploration in this area is essential to further enhance predictive capabilities and optimize supply chain operations. By addressing these gaps, future research can lead to more robust solutions that improve overall supply chain efficiency.

By investigating advanced predictive analytics techniques, researchers can significantly improve the precision of forecasts, ultimately leading to better decision-making. This focus on enhancing forecasting accuracy is crucial for optimizing supply chain operations and mitigating inefficiencies. Investigate the integration of realtime data sources to inform decision-making processes. By leveraging cutting-edge technologies such as machine learning and artificial intelligence, organizations can gain deeper insights into market trends and customer behavior, ultimately leading to more informed strategies and a competitive edge in the market.

Machine learning plays a pivotal role in analyzing vast amounts of data to identify patterns and predict demand fluctuations, which enhances overall supply chain efficiency. By automating these insights, organizations can streamline operations, reduce costs, and respond more swiftly to market changes.

Data-driven decision-making significantly improves inventory management by enabling businesses to optimize stock levels based on accurate demand forecasting. By minimizing excess inventory and stockouts, this approach ensures efficient resource allocation and maintains customer satisfaction.

These case studies can provide valuable lessons and best practices that organizations can adopt to enhance their own supply chain strategies. Analyzing successful implementations will illustrate the tangible benefits of optimization efforts in various industries. Propose a framework for integrating predictive capabilities into existing supply chain operations. This framework should include data collection methods, analytical tools, and collaboration techniques among stakeholders. By fostering a culture of data-driven decision-making, organizations can better anticipate market fluctuations and respond proactively to changes in consumer behavior.

This field requires further studies and research, particularly around performance evaluation indicators using machine learning methods. Additionally, there is a need to consolidate relationships among all supply chain partners and explore the use of machine learning and artificial intelligence methods to enhance innovation in service and product provision.

Conflict of Interest

There is No Conflict of Interest between the Authors.

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