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Applications of Artificial Intelligence for Demand Forecasting

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ABSTRACT

Artificial Intelligence (AI) has significantly contributed to the growth of various sectors and industries. One of the most significant contributions of AI applications is in forecasting. Consumer demand fluctuates faster than ever as a result of economic growth, advances in technology, and higher customer expectations, making forecasting future demand more difficult. Demand forecasting is a vital operation of supply chain management that aids in the best matching of supply and demand. Thus, improving demand forecasting accuracy is critical for companies and supply chains. Thanks to AI, businesses can accurately predict customer behavior. The study aims to provide a comprehensive review of how AI has been applied to forecast demand over the last decade. This research collects articles published between 2013 and 2023. According to the findings, AI is increasingly being used for demand forecasting in recent years. Energy and water demand forecasts receive the most attention. Long Short-Term Memory has gained prominence because of its advantages. Besides, this study will highlight the challenges of the adoption of AI. One of these challenges is selecting different reliable and suitable forecasting inputs for each AI method. This review will help supply chain managers and analysts select and implement suitable forecasting methods. Furthermore, this study will suggest some future research directions.

Keywords: *artificial intelligence, demand forecast, forecasting techniques, supply chain management*

1. INTRODUCTION

In this era, the business environment is dynamic and unstable due to several forces, such as technological dependence, increased customer expectations, pandemics, and war (Mediavilla *et al*., 2022). Consequently, businesses must respond quickly to market changes and unexpected events to stay competitive. Applications of information and communication technologies (ICT) assist organizations in making appropriate decisions and developing effective strategies to manage and control unanticipated effects. They assist organizations in dealing with supply chain issues caused by the increased movement of goods and data in the supply chain (Huddiniah & Mahendrawathi, 2019). Thanks to the ICT revolution, many predictions and management tools based on Artificial Intelligence (AI) have been released, allowing enterprises to record large amounts of data and robust information (Rafael González Perea *et al*., 2019).

AI has been widely used in various fields, such as engineering, sciences, banking, finance, economics, tourism, and healthcare. AI is the simulation of human intelligence using software-coded heuristics (Frankenfield, 2023). AI is the primary innovation for creating intelligent machines that mimic human behavior and perform various tasks (Annor *et al*., 2019). AI is better suited for complex input-output relationships (Raza & Khosravi, 2015). Thanks to AI, manufacturers can effectively obtain upstream and downstream product information to make precise product predictions and decisions (Fu & Chien, 2019). AI modelling is being created for intelligent tourism platforms to accurately predict tourism choice behavior patterns (Doborjeh *et al*., 2022). Thus, AI-based techniques have significantly contributed to the evolution of various sectors, industries, and supply chains.

One of the most significant contributions of AI applications is demand forecasting, an essential supply chain management operation (Benkachcha *et al*., 2014). It forecasts future demand to plan supply chain activities and operations to decrease shipping times, inventories, and operational expenses (Kantasa-ard *et al*., 2021). AI can analyze data and forecast demand, optimize logistics and transportation routes, and identify bottlenecks in the supply chain (Mohsen, 2023). Furthermore, AI helps to improve supply chain transparency, which is one of the critical requirements for a successful supply chain (Fu & Chien, 2019).

Future demand information is critical for different actors: customers, businesses, traders, policymakers, and others. For example, supply chain participants make numerous correct operational, tactical, and strategic decisions in various areas, such as production planning, sales budgeting, new product launches, and promotion planning (Abolghasemi *et al*., 2020; Danese & Kalchschmidt, 2011; Mobarakeh *et al*., 2017; Perera *et al*., 2019), purchase quantity (Brahmadeep & Thomassey, 2016), inventory management (Mobarakeh *et al*., 2017). Additionally, governments and policymakers can offer appropriate policies to support decisions about imports, tariff design, maintenance, system expansion, and development of new projects, particularly in national industries, such as energy (Brentan *et al*., 2017; Dwivedi & Gupta, 2022; Panapakidis & Dagoumas, 2017; Raza & Khosravi, 2015), agriculture (Rafael González Perea *et al*., 2019), public transport (Liyanage *et al*., 2022), healthcare (Soltani *et al*., 2022). As a result, accurate forecasting is essential because of its implications and roles.

Accurate forecasting brings many positive effects and benefits. It will mitigate risks and strengthen the supply chain (Bhadouria & Jayant, 2017). Thus, it results in substantial financial savings, increased competitiveness, effective supply chain relationships, and customer satisfaction (Perera *et al*., 2019). On the other hand, inaccurate predictions can lead to excessive spending on logistics, labor, and inventory, which may negatively impact customer satisfaction (Abolghasemi *et al*., 2020). Additionally, they can cause financial loss (Güven & Şimşir, 2020; Mobarakeh *et al*., 2017) and harm the public image (Güven & Şimşir, 2020). Demand forecasting is thus one of the most crucial inputs for businesses to achieve their short-term objectives (Güven & Şimşir, 2020).

For all the reasons mentioned above, precise demand forecasting is vital. Therefore, selecting a reliable forecasting method is indispensable. Different forecast techniques and applications have been proposed and developed based on AI (Aburto & Weber, 2007; Chen *et al*., 2015; Khashei & Bijari, 2011; Kilimci *et al*., 2019; Mediavilla *et al*., 2022). There are some examples of AI-based models, for example, artificial neural networks (ANN), support vector machine (SVM), Long Short-term Memory (LSTM). Those previous studies proved that AI-based techniques increased demand forecast accuracy.

Nevertheless, choosing the optimal AI methods can be challenging due to lots of methods. In addition, each method has its drawbacks and strengths. Previous researchers indicated that no forecasting model could work well for all sectors and situations (Song *et al*., 2019; Swaminathan & Venkitasubramony, 2023).

Moreover, forecasting demand is becoming more complicated due to demand volatility in all sectors (Swaminathan & Venkitasubramony, 2023), increasing complexity of demand determination (Song *et al*., 2019), higher customer expectations (Amirkolaii *et al*., 2017; Fu & Chien, 2019), growing global population and innovation technology (Bedi & Toshniwal, 2019; Bot *et al*., 2020) and unexpected events (Mediavilla *et al*., 2022), increasing supply chain collaborations and technological applications (Fu & Chien, 2019). Therefore, it is essential to conduct research that provides a comprehensive review of AI applications for demand forecasting over the past ten years.

However, there is a lack of research that reviews and analyzes the use of AI-based demand forecasting in recent decades. Recently, (Mediavilla *et al*., 2022) reviewed the AI methods for demand forecasting in supply chain management. However, they focused on manufacturing and selected articles from 2017 to 2021. Also, they chose papers from Web of Science, IEEE Explore, and Springer Publishing. Therefore, this study fills the gaps in the current literature review by reviewing articles published between 2013 and 2023 by different publishers. Besides, this research identifies the positive effects of AI-based forecasting techniques and the gaps that must be filled.

The paper's structure is organized as follows. The next section summarizes the evolution of demand forecasting techniques. Section 3 provides the research review methodology. Then, section 3 discussed the findings. Finally, section 4 concludes the paper and future directions.

2. EVOLUTION OF DEMAND FORECASTING TECHNIQUES

Forecasting is the first stage of demand management- a vital supply chain management process, as illustrated in **Figure 1**. Predictions help balance demand and supply at the customer level and utility planning (Bot *et al*., 2020). Demand variability is one of the main variables utilized for calculating the safety stock held by a firm for handling stock-out circumstances caused by fluctuations in supply and demand (Jaipuria & Mahapatra, 2021). Similarly, (Syahrir *et al*., 2022) developed an effective drug order system to estimate optimal order quantities, frequencies, and safety. This system's first stage is to forecast patient numbers and drug demand using a mathematical model (Susceptible-Infectious-Removed and Susceptible-Exposed-Infectious-Recovered). Then, they determine the drug order system using hospital inventory costs in the second stage. Thus, forecasting accuracy is critical in efficient supply chain management and, ultimately, in firm success. Accurate demand forecasting improves supply chain performance (Mobarakeh *et al*., 2017; Moroff *et al*., 2021; Nguyen *et al*., 2021). As a result, many demand forecasting techniques have been developed and proposed.

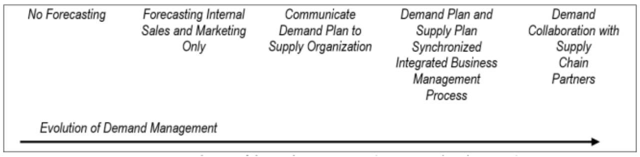

Figure 1 Evolution of demand management (Crum & Palmatier, 2003)

Managers and researchers have employed different techniques to forecast customer demand. They can be categorized into qualitative and quantitative methods (Hofmann & Rutschmann, 2018; İfraz *et al*., 2023; Moroff *et al*., 2021). Qualitative methods are used when the the available data is insufficient for a quantitative analysis or when qualitative information is likely to improve forecast accuracy. Expert opinions or knowledge of special events are examples of qualitative methods. In contrast, quantitative methods analyzed historical data (time series) or specific relationships between system elements (causal models). Some well-known time series methods include autoregressive integrated moving average (ARIMA), ARIMA with exogenous factors (ARIMAX), SVM, ANN, recurrent neural networks (RNN), and LSTM.

Companies can now save significant amounts of data thanks to advances in information technology. The volume of data stored globally has increased significantly (Hofmann & Rutschmann, 2018). As a result, they facilitated the adoption and development of time series methods in the recent decade. Time series methods can be classified into traditional and modern methods (machine learning and deep learning). Besides, modern methods can be regarded as AI methods. AI methods can train large amounts of data, nonlinear trends, and complex data. For example, ARIMA and ARIMAX are traditional methods that work well with linear data but have data limitations. In contrast, LSTM is an AI method that performs well with nonlinear and complex data (Kantasa-ard *et al*., 2021; Narayanan *et al*., 2023; Nguyen *et al*., 2021). As a result, much research has proved that AI methods perform better than traditional ones (Kantasa-ard *et al*., 2021; Nguyen *et al*., 2021; Soltani *et al*., 2022). Therefore, AI demand forecasting techniques play vital roles in dealing with complex and sudden shifts in customer demand, thus boosting forecasting accuracy.

3. METHOD

This study aims to comprehensively review AI applications for demand forecasting in the past decade. **Figure 2** depicts the main research steps, which include research questions, a database, choosing of papers, and analysis.

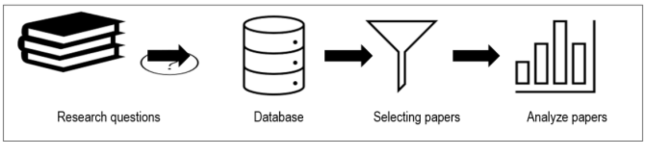

Figure 2 Research framework

All steps will be discussed in detail as follows:

Step 1*: Research questions*

Some questions should be answered:

- Which AI-based techniques have been used to forecast demand?
- What were the main contributions of the previous papers?
- What are the gaps in previous papers?

Step 2*: Database*

The study follows the methodology used in the prior studies (Mohsen, 2023) and (Mediavilla *et al.*, 2022), which collect secondary data from top and famous publishers. ScienceDirect, Emerald, Taylor & Francis, Wiley, and Springer are examples of publishers that will be considered in this study. Furthermore, this review collects recent papers published in Operations and Supply Chain Management: An International Journal (OSCM), our target journal. Thus, this is the first recent study to investigate how AI-based techniques impact demand forecasting to be the best author's knowledge.

Step 3*: Selecting papers*

To achieve the goal of this paper, keywords are straightforward. The keywords utilized during this research are "Artificial Intelligence", "Artificial Intelligence in Demand Forecasting," and "Demand Forecasting".

This study employed an Advanced search engine with various search parameters, such as "Find articles with these terms: "Authors", "Year", and "Title", etc. Then, gathering articles were published between 2013 and 2023. This study was conducted and accessed in August 2023. Only English papers were chosen. Finally, the abstracts and keywords were reviewed to eliminate papers that did not meet the requirements.

Step 4*: Analysis*

This step will be carried out in two stages. The first stage will provide an overview of publications, focusing on papers published in ScienceDirect due to a lack of financial support, access, and time. Thus, there are 37 papers. All selected papers will be evaluated based on the following criteria: document type, source type, number of publications per country, and number of publications per year (Mohsen, 2023). The second stage will investigate how AI applications affect demand forecasting. This paper will analyze research papers published by various publishers, such as ScienceDirect, Emerald, Taylor & Francis, Springer, Wiley, and OSCM, in order to provide a comprehensive evaluation and analysis.

The research findings will be illustrated and discussed in the next section.

4. RESULTS AND DISCUSSION

4.1 Overview of Publications

This part provides a comprehensive summary of selected papers for review. All publications will be assessed regarding article type, source type, number of publications per country, number of publications per year, and area.

Article Type

Figure 3 outlines the distribution of publications by article type. Based on the ScienceDirect research engine and the paper's content, all selected papers can be divided into three categories: review, research, and book chapter. Most publications (29 out of 37) are research articles, accounting for 85%. In comparison, the number of review papers and book chapters is minimal. It highlights a few review articles on AI applications in demand forecasting.

Review papers are essential for researchers and practitioners because they help researchers thoroughly understand the state of the art of a specific field they wish to investigate and study. Review publications provide vital content, such as problems and shortages in the literature review. Future research can use that information to propose new perspectives and approaches.

From 2013 to 2023, this paper found only four review papers. Previous authors conducted a systematic literature review on AI-based demand forecasting techniques. However, they concentrated on specific products, such as electronic load (Raza & Khosravi, 2015), tourism (Song *et al.*, 2019), manufacturing (Mediavilla *et al.*, 2022), and fashion products (Swaminathan & Venkitasubramony, 2023). As a result, this paper fills these gaps because we chose all papers without considering particular products.

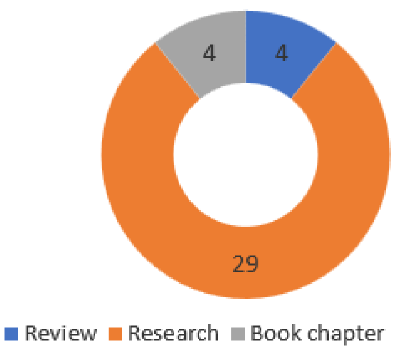

Figure 3 Type of document

Source Type

The source type of documents is depicted in **Figure 4**. There are two kinds of sources: journal articles and book series. As can be seen, most papers (86%) are from journals. There are five papers in the book series.

Computers & Industrial Engineering, IFAC-PapersOnLine, Energy, Sustainable Cities, and Society are the most widely published journals.

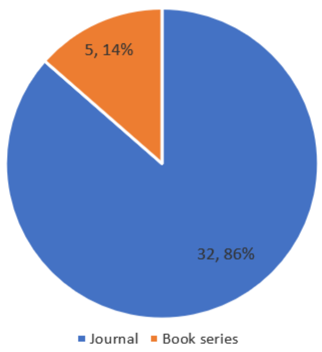

Figure 4 Source type

Country of Origin

The papers studied came from 21 countries, with a mean distribution of 1.76 articles per country. **Figure 5** shows how each country is distributed. Three countries (India, Iran and Spain) produce the most publications, followed by France.

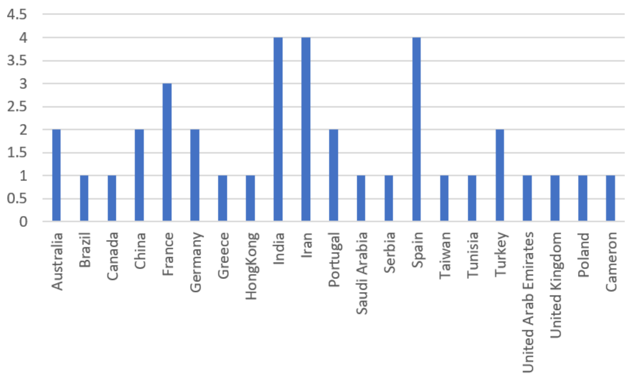

Figure 5 Number of publications per country

Number of Documents Distributed per Year

Figure 6 illustrates the number of papers distributed yearly from 2013 to 2023. In 2013, no articles were discovered. Two distinct periods can be seen, from 2013 to 2019 and 2020 to 2023. The number of publications significantly increased during the first period. They peaked at five papers in 2019. They then fall slightly to 2020. The Covid-19 pandemic and lockdown could influence this decrease. The second period saw a dramatic increase in the number of publications. In 2023, they received the highest number in all of research history. Following the lockdown, the global economy reopened, and customer demand for various types of products began to rise. Demand forecasting is essential in many operations and organizations. Forecasting is critical to supply chain success (Brahmadeep & Thomassey, 2016). Overall, there was an upward trend in the research of AI applications in demand forecasting.

Area

This section describes the area in which AI was used to predict demand. As shown in **Figure 7**, AI has been implemented in 17 sectors. As can be seen, AI-based techniques have been widely used in various industries, such as electricity, water, fashion, tourism, and oil.

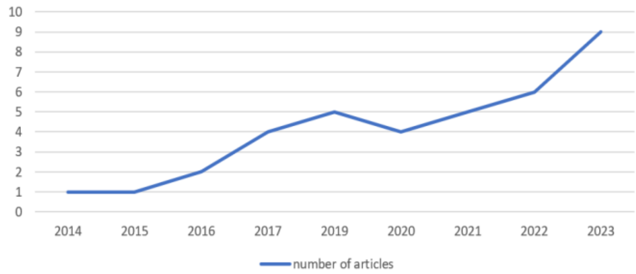

Figure 6 Number of publications per year

Most researchers focused on energy demand forecasting, mainly electricity and water. Electricity demand forecasting is vital because it impacts all aspects of national development (Ofori-Ntow Jnr *et al.*, 2021). Besides, water is essential for human life and the development of agriculture and nations (Panapakidis & Dagoumas, 2017). Moreover, many researchers emphasized the significance of forecasting electricity and water demand because it enables using water more efficiently, spending less money, improving your water distribution system, and exploring supply problems early (Gonzalez Perea *et al.*, 2021). In addition, (Kavya *et al.*, 2023) stated that energy forecasting influences a country's economic patterns and the profits of energy companies and related sectors. Furthermore, predicting future energy demand aids in optimizing and managing energy use, thus reducing greenhouse gas emissions (Kavya *et al.*, 2023; Runge & Saloux, 2023).

Although electricity and water demand are critical, other areas must also be considered. However, research on other industries, such as natural gas, heat, and crude oil, is scarce.

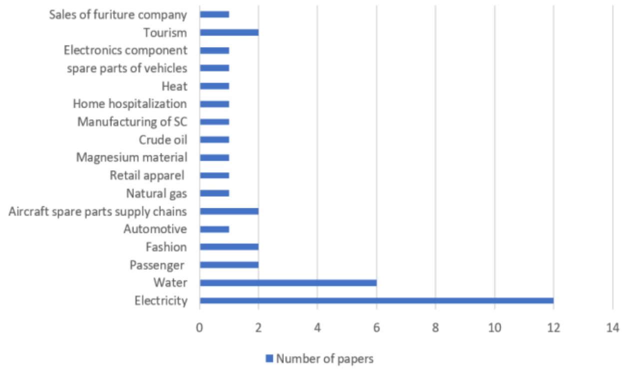

Figure 7 Number of documents distributed by area

4.2 *Impact of AI on Forecast Accuracy*

This section aids academics and practitioners in determining appropriate AI methods based on data dimensions and techniques.

4.2.1 Data

This study will analyze data regarding dimensions, months, and frequency. The data dimension will be classified into univariate and multivariate. Univariate is when only using previous demand information (Mediavilla *et al.*, 2022). As shown in **Table 1**, the majority of papers used multivariate dimensionality. It indicated that using AI-based techniques to train multivariate is dominant because it helps improve forecast accuracy. This finding is consistent with the previous study (Mediavilla *et al*., 2022).

Indeed, demand can be impacted by various factors, which vary depending on the products and industries that researchers wish to forecast. Furthermore, each method has advantages in data handling. Thus, selecting the appropriate technique and input variables will impact predictability. For example, (Bendaoud *et al*., 2021) forecasted daily electricity demand using maximum and minimum temperatures, the day of the week, and the month. While (Moradzadeh *et al*., 2022) forecasted short-term electricity demand, they used inputs including meteorological and environmental data, historical information, and days of the week.

Previous researchers have used numerous inputs and exogenous variables in multivariate dimensionality. For example, (Abu Talib *et al*., 2023) anticipated future water demand using five inputs: water consumption in imperial gallons, billed month, account number, account type, and community number. They also consider exogenous factors such as socio-demographic, seasonal, and climatic.

Furthermore, AI-based forecasting techniques can deal with various data and frequencies. Most articles worked with data ranging from one month to 540 months. The average data range is approximately 60 months or almost five years. Most papers tested daily and monthly data. A few papers used short data sets, such as 10 or 15 minutes. It demonstrates that AI applications still work with low data volumes. One of the reasons is the availability and saving of data from the real world.

During the research, only one paper investigated the impact of unexpected events. (Abu Talib *et al*., 2023) studied the effect of COVID-19 on the performance of water demand forecasting models, considering the lockdown measures and various exogenous variables, such as previous consumption and socio-demographic, seasonal, and climatic factors.

As a result, practitioners and managers should pay close attention to selecting different and appropriate forecasting inputs to improve forecast accuracy.

Table 1 Data description

Authors		**Data**		
		Dimension	**Range months**	**Frequency**
(Xiao *et al*., 2014)	(Xiao *et al*., 2014)	Univariate	90	Monthly
(Nikolopoulos *et al*., 2016)	(Nikolopoulos *et al*., 2016)	Univariate	3.25	Weekly
(Brahmadeep & Thomassey, 2016)	(Brahmadeep & Thomassey, 2016)	Multivariate	3	Weekly
(Amirkolaii *et al*., 2017)	(Amirkolaii *et al*., 2017)	Multivariate	48	Monthly
(Mobarakeh *et al*., 2017)	(Mobarakeh *et al*., 2017)	Multivariate	48	Monthly
(Brentan *et al*., 2017)	(Brentan *et al*., 2017)	Univariate	19	Hourly
(Panapakidis & Dagoumas, 2017)	(Panapakidis & Dagoumas, 2017)	Multivariate	30.4	Daily
(Rafael González Perea *et al*., 2019)	(Rafael González Perea *et al*., 2019)	Multivariate	2010, 2012, and 2013 Irrigation Seasons.	Daily
(Fu & Chien, 2019)	(Fu & Chien, 2019)	Multivariate	26	Weekly
(Jahangir *et al*., 2019)	(Jahangir *et al*., 2019)	Multivariate	3	Daily
(Bedi & Toshniwal, 2019)	(Bedi & Toshniwal, 2019)	Multivariate	1	15min
(Güven & Şimşir, 2020)	(Güven & Şimşir, 2020)	Multivariate	12	Monthly
(Hu, 2020)	(Hu, 2020)	Multivariate	156	Yearly
(Bot *et al*., 2020)	(Bot *et al*., 2020)	Multivariate	36	15 Min
(Abbasimehr *et al*., 2020)	(Abbasimehr *et al*., 2020)	Univariate	132	Monthly
(Al-Fattah, 2021)	(Al-Fattah, 2021)	Multivariate	540	Yearly
(Ofori-Ntow Jnr *et al*., 2021)	(Ofori-Ntow Jnr *et al*., 2021)	Univariate	12	Daily
(Gonzalez Perea *et al*., 2021)	(Gonzalez Perea *et al*., 2021)	Multivariate	2015, 2016, 2017 And 2018 Irrigation Seasons	Daily
(Moroff *et al*., 2021)	(Moroff *et al*., 2021)	Univariate	72	Daily
(Bendaoud *et al*., 2021)	(Bendaoud *et al*., 2021)	Multivariate	36	Hourly
(Liyanage *et al*., 2022)	(Liyanage *et al*., 2022)	Multivariate	1	Monthly
(Zdravković *et al*., 2022)	(Zdravković *et al*., 2022)	Multivariate	Three Heating Seasons	Not defined
(Moradzadeh *et al*., 2022)	(Moradzadeh *et al*., 2022)	Multivariate	48	Daily
(Soltani *et al*., 2022)	(Soltani *et al*., 2022)	Multivariate	82	Daily
(Dwivedi & Gupta, 2022)	(Dwivedi & Gupta, 2022)	Multivariate	96	yearly
(Kavya *et al*., 2023)	(Kavya *et al*., 2023)	Multivariate	12	10 Min
(Runge & Saloux, 2023)	(Runge & Saloux, 2023)	Multivariate	72	15min
(İfraz *et al*., 2023)	(İfraz *et al*., 2023)	Univariate	84	Yearly
(R. González Perea *et al*., 2023)	(R. González Perea *et al*., 2023)	Multivariate	36	Daily
(Abu Talib *et al*., 2023)	(Abu Talib *et al*., 2023)	Multivariate	42	Monthly
(Dieudonné *et al*., 2023)	(Dieudonné *et al*., 2023)	Univariate	42	hourly
(Lujano-Rojas *et al*., 2023)	(Lujano-Rojas *et al*., 2023)	Multivariate	96	hourly

4.2.2 AI Methods

Table 2 presents the AI techniques used to predict demand. All papers chosen were classified according to their time horizon and techniques utilized. It is clear that the majority of papers forecast short-term future demand. The reason is that long-term demand patterns are challenging to capture because various expected and unexpected factors can drive demand.

Some papers forecast one demand for a short horizon, like 12 hours or one day. For example, (Panapakidis & Dagoumas, 2017) predicted natural gas consumption for the next day. Besides, (Bot *et al*., 2020) forecasted the power demand for the following 12 hours. Although short-term forecasting is more accurate, modifications to respond to future demands, such as inventory management, demand planning, and logistics, take time to change and implement. As a result, organizations and supply chains have to evolve to respond quickly to changes in demand, which requires strong collaboration between internal and external organizations, increased supply chain speed, and flexible manufacturing.

In terms of techniques, different forecasting techniques were used in the literature review. They are qualitative and quantitative (İfraz *et al*., 2023; Moroff *et al*., 2021). Based on the definitions of each method, AI-based techniques fall into the category of quantitative methods because they primarily use time series data and mathematical models. Moreover, AI-based or computational intelligence methods are considered time series forecasting techniques. Time series forecasting methods generally include statistical and AI-based (computational intelligence) (Abbasimehr *et al*., 2020; Mediavilla *et al*., 2022).

Based on publications selected in this review, AI-based forecasting techniques have many advantages compared to existing methods, for example, handling complex issues (Raza & Khosravi, 2015), performing well with little or no historical data (Brahmadeep & Thomassey, 2016; Hu, 2020), working well with different kinds of data patterns, for example erratic, lumpy, and intermittent demands (Amirkolaii *et al*., 2017), big data dimensions and data volume (Brentan *et al*., 2017). Nonlinear machine learning models outperform ARIMA regarding test error (Tsang & Benoit, 2020). As a result, AI can produce accurate forecasting (Dieudonné *et al*., 2023; Mediavilla *et al*., 2022; Zdravković *et al*., 2022).

Prior research has indicated the potential of deep learn ing in forecasting. Deep learning is currently growing as a prominent method for algorithm learning (Kavya *et al*., 2023). (Mediavilla *et al*., 2022) reviewed AI methods for demand forecasting in SCM published in the last five years, from 2017 to 2021. They obtained 23 papers to analyze. They found higher use of supervised learning methods. Recently, (Narayanan *et al*., 2023) surveyed different forecasting methods, from the traditional statistical-based model to modern deep-learning ones. They discovered that modern forecast models outperform traditional statistical and regression-based models.

Moreover, several comparative studies have examined statistical, machine learning, and deep learning forecasting abilities. For example, (Kavya *et al*., 2023) compared nine machine learning and deep learning models using India's water consumption data from 2020 to 2021. They discovered that the deep learning models performed better than the machine learning ones. LSTM model produced the best prediction performance. Besides, (Runge & Saloux, 2023) compared machine learning and deep learning techniques to predict heating demand over 6 h and 24 h ahead in Canada. The findings demonstrated that the LSTM and XGBoost produced good performance. Besides, training with XGBoost was significantly faster.

As seen in **Table 2**, many AI-based techniques have been used to demand forecasting in the literature, such as ANN, SVM, K-nearest neighbors (KNN), and LSTM (Amirkolaii *et al*., 2017; Bot *et al*., 2020; Brahmadeep & Thomassey, 2016; R. González Perea *et al*., 2023; Rafael González Perea *et al*., 2019; Moradzadeh *et al*., 2022). They are widely used in various goods, environments, and sectors, for example, energy, water, fashion, retail, supply chains, and businesses.

Besides, ANN has been a widely used model (Rafael González Perea *et al*., 2019; Güven & Şimşir, 2020; Jahangir *et al*., 2019). However, it is worth noting that in recent years, authors have preferred to use LSTM (Kavya *et al*., 2023; Runge & Saloux, 2023; Soltani *et al*., 2022). On the other hand, ANN was primarily used for benchmarking. Long Short-term memory is the most applied technique in deep learning. (Moroff *et al*., 2021) compared six forecasting methods grouped as statistical and machine learning methods. It showed that the deep learning methods proved more effective due to the increased computational effort. LSTM is a subset of RNN architectures previously found to provide good prediction accuracy (Mediavilla *et al*., 2022). However, LSTM overcomes the weakness of RNN because LSTM can learn patterns with long dependencies. Thus, LSTM models are generally identified to outperform RNNs in time series data forecasting (Liyanage *et al*., 2022). Besides, LSTM outperformed auto-regression techniques, enabling managers to get a relatively straightforward image of the possibilities in the future (Soltani *et al*., 2022). Moreover, (Yasir *et al*., 2022) proved that employing LSTM decreased demand forecasting errors. Furthermore, BiLSTM has been applied in recent research. BiLSTM models outperformed conventional deep-learning models (Liyanage *et al*., 2022).

As a result, AI is critical in forecasting. An accurate prediction offers helpful data about how we must perform from now to a planned point in the future to achieve the most remarkable outcome (Lujano-Rojas *et al*., 2023). Many AI-based forecasting methods have been developed in the past decade.

4.2.3 Development of Hybrid Method

Previous researchers found the superiority of hybrid methods compared to single ones. Hybrid methods that combine multiple methods are becoming prominent (Dieudonné *et al*., 2023; Mediavilla *et al*., 2022; Moradzadeh *et al*., 2022; Swaminathan & Venkitasubramony, 2023). Demand uncertainty happens in any sector, and no single forecasting model suits all industries (Swaminathan & Venkitasubramony, 2023). Additionally, no method works well in all situations (Narayanan *et al*., 2023; Song *et al*., 2019). Each forecasting method has its advantages and disadvantages.

Several hybrid models have been proposed to take full advantage of the strengths of single ones. For instance, (Roach *et al*., 2021) found that mixed models may increase forecasting accuracy and measure variations in energy usage in numerous designing configuration cases. (Dwivedi & Gupta, 2022) highlighted that the hybrid modeling approach, which leverages long-term autoregression or moving average trend along with economic growth, has provided credible macro-level and long-term forecasting results. Recently, (Dieudonné *et al*., 2023) proposed a hybrid model based on ANN models, multiple linear regression, and Holt exponential smoothing for short-term electricity. They demonstrated that the proposed hybrid model produced the best prediction results among selected models. Moreover, (Vanting *et al*., 2021) stated that employing a hybrid deep learning multivariate model comprising a convolutional and recurrent neural network could improve performance. Recently, (Sahoo *et al*., 2023) developed a hybrid forecasting model that used a convolutional neural network (CNN) and LSTM for daily water demand.

Table 2 AI applications for demand forecasting

Authors		AI methods	
		Time horizon	Techniques
(Xiao *et al*., 2014)	(Xiao *et al*., 2014)	Short-Term	Adaptive-Network-Based Fuzzy Inference System (ANFIS)
(Nikolopoulos *et al*., 2016)	(Nikolopoulos *et al*., 2016)	Short Term	Nearest Neighbors
(Brahmadeep & Thomassey, 2016)	(Brahmadeep & Thomassey, 2016)	Short-Term And Long-Term	Extreme Learning Machine (ELM)
(Amirkolaii *et al*., 2017)	(Amirkolaii *et al*., 2017)	Short Term	Neural Network
(Mobarakeh *et al*., 2017)	(Mobarakeh *et al*., 2017)	Short Term	Bootstrapping BS
(Brentan *et al*., 2017)	(Brentan *et al*., 2017)	Short-Term	Support Vector Regression
(Panapakidis & Dagoumas, 2017)	(Panapakidis & Dagoumas, 2017)	Short Term	Feed-Forward Neural Network (FFNN)
(Rafael González Perea *et al*., 2019)	(Rafael González Perea *et al*., 2019)	Short Term	Dynamic Artificial Neural Networks (ANN)
(Fu & Chien, 2019)	(Fu & Chien, 2019)	Short Term	Machine Learning Technologies and Temporal Aggregation Mechanism
(Jahangir *et al*., 2019)	(Jahangir *et al*., 2019)	Short Term	Artificial Intelligence-Based Method -Feed-Forward and Recurrent Artificial ANN
(Bedi & Toshniwal, 2019)	(Bedi & Toshniwal, 2019)	Short Term	LSTM
(Güven & Şimşir, 2020)	(Güven & Şimşir, 2020)	Short Term	ANN and SVM
(Hu, 2020)	(Hu, 2020)	Short Term	Grey Prediction, NN
(Bot *et al*., 2020)	(Bot *et al*., 2020)	Short Term	ANN
(Abbasimehr et al., 2020)	(Abbasimehr et al., 2020)	Short Term	Multi-Layer LSTM Networks.
(Feizabadi, 2020)		Short Term	ANN and ARIMAX
(Al-Fattah, 2021)	(Al-Fattah, 2021)	Long Term	Genetic-Algorithm, Neural-Network, And Data-Mining Approach for Time-Series Models (GANNATS).
(Ofori-Ntow Jnr et al., 2021)	(Ofori-Ntow Jnr et al., 2021)	Short Term	Discrete Wavelet Transform (DWT), Particle Swarm optimization (PSO), And Radial Basis Function Neural Network (RBFNN)
(Gonzalez Perea et al., 2021)	(Gonzalez Perea et al., 2021)	Short Term	Artificial Intelligence Techniques
(Moroff et al., 2021)	(Moroff et al., 2021)	Short Term	Holt Winters - Triple Exponential Smoothing (ETS), Seasonal Auto-Regressive Integrated Moving Average Extended (SARIMAX) Extreme Gradient Boosting (Xgboost), Random Forest (RF), LSTM, Multi-layer Perceptron (MLP)
(Bendaoud et al., 2021)	(Bendaoud et al., 2021)	Short Term	Generative Adversarial Networks (GAN).
(Nguyen et al., 2021)		Short- Term	ARIMAX, LSTM

(Kantasa-ard et al., 2021)		Short- Term	LSTM
(Liyanage et al., 2022)	(Liyanage et al., 2022)	Short Term	LSTM And Bilstm Deep Learning Models
(Zdravković et al., 2022)	(Zdravković et al., 2022)	Short Term	LSTM
(Moradzadeh et al., 2022)	(Moradzadeh et al., 2022)	Short Term	Variational Autoencoders and Bidirectional Long Short-Term Memory (BiLSTM)
(Soltani et al., 2022)	(Soltani et al., 2022)	Short Term	LSTM
(Dwivedi & Gupta, 2022)	(Dwivedi & Gupta, 2022)	Long-term	exponential smoothing, ARIMA
(Kavya et al., 2023)	(Kavya et al., 2023)	Short Term	Long-Short Term Memory,
(Runge & Saloux, 2023)	(Runge & Saloux, 2023)	Short Term	LSTM, Extreme Gradient Boosting Model
(İfraz et al., 2023)	(İfraz et al., 2023)	Short Term	Multivariate Nonlinear Regression, Gaussian Process Regression, Additive Regression, Regression By Discretion, Support Vector Regression), Rule-Based Methods (Decision Table, M5Rule), Tree-Based Methods (Random Forest, M5P, Random Tree, Reptree) And ANNs.
(R. González Perea et al., 2023)	(R. González Perea et al., 2023)	Short-Term	ANN, Bayesian Training Framework
(Abu Talib et al., 2023)	(Abu Talib et al., 2023)	Short Term	MLR, Decision Trees DT, ANN, Random Forest RF, Gradient Boosting Machines Extreme Gradient Boosting XGB, Light Gradient Boosting LGB, and Stack Regressor STK.
(Dieudonné et al., 2023)	(Dieudonné et al., 2023)	Short-term	ANN, LRM and HES
(Lujano-Rojas et al., 2023)	(Lujano-Rojas et al., 2023)	Short term	NN
(Narayanan et al., 2023)	(Narayanan et al., 2023)	Short term	Machine learning (ML) and traditional method

4.3 Impact of AI Methods on Supply Chain Performance

Supply chain performance helps organizations to discover areas for improvement and optimization. Improving supply chain performance is critical to business success. (Mohsen, 2023) stated that AI applications may aid in reducing inventory costs, improving warehouse efficiency, reducing lead times, and lowering costs. Previous research has demonstrated the practical importance of AI-based techniques for demand forecasting. However, there has been little evidence of AI applications' impact on supply chain performance.

Prior research has primarily concentrated on how AI methods improve forecast accuracy, one of the supply chain performance indicators (Feizabadi, 2020; Kantasa-ard *et al.*, 2021; Nguyen *et al.*, 2021). However, the performance of the supply chain should be thoroughly evaluated using a variety of key performance indicators. Thus, investigating how AI methods affect all aspects of supply chain performance is one of the most critical tasks for academics and practitioners.

Recent studies have provided empirical evidence regarding the impact of AI forecasting methods on supply chain performance measured by various key performance indicators, including the bullwhip effect, inventory turns, and transportation costs. For example, (Weisz *et al.*, 2020) found that AI could help mitigate the supply chain's bullwhip effect. Besides, (Feizabadi, 2020) demonstrated that ML-based forecasting methods improve supply chain performance better than the traditional forecasting method regarding forecast accuracy, inventory turns, and cash-conversion cycle. Also, (Nguyen *et al.*, 2021) discovered that LSTM outperformed ARIMAX regarding operating and financial metrics such as bullwhip effect, net stock amplification, transportation cost, and inventory turn. Similarly, (Jaipuria & Mahapatra, 2021) developed a hybrid ARIMA and GARCH (ARIMA-GARCH) approach to evaluate the safety stock level and order quantity. Its performance was better than ARIMA in terms of BWE and net-stock amplification. Therefore, adopting AI applications may improve various aspects of supply chain performance.

5. CONCLUSION

AI has contributed significantly to the development of various fields and industries. AI significantly improves forecasting accuracy. Many different AI-based forecasting techniques have been developed and proposed. They offer helpful information to various stakeholders, including customers, managers, decision-makers, and investors. This study reviews research papers that used AI applications for demand forecasting over ten years. According to the review findings, AI-based techniques have been widely employed for demand forecasting due to their advantages over traditional methods. The findings stated that AI is adopted in various industries, particularly electricity and water. In addition, LSTM has been adopted more in recent years. As a result, the findings assist managers and practitioners in selecting appropriate demand forecasting methods.

This comprehensive review of forecasting method developments over the last decade provides numerous valuable findings. Despite numerous publications on AI-based techniques for demand forecasting, there is a scarcity of research that investigates and proposes forecast models for dealing with unanticipated events like the COVID-19 pandemic. Future research may help organizations react to demand uncertainty and changes more quickly by investigating AI methods in the context of unexpected events such as pandemics, which would prevent revenue loss and supply chain disruptions. Besides, various factors, such as datasets and circumstances, affect the performance of forecasting methods. As a result, future research may focus on other products and industries, such as gas and oil.

Furthermore, forecasting methods are still evolving because forecasting performance can be affected by the characteristics of datasets and circumstances. Thus, several future directions should be considered. First, proposing and developing new AI-based methods remains critical for future research. One prominent trend is the development of hybrid methods that exploit and leverage the advantages of existing single ones. Second, supply chain performance should be fully measured using a variety of metrics. Then, researching and investigating a list of performance metrics that can be employed in different industries and situations is a fascinating subject. Furthermore, investigating the relationship between AI-based techniques and performance indicators is critical to demonstrating and confirming the importance of AI applications in various aspects of supply chain management. Third, future research could compare existing forecasting models in each sector and then propose a framework that assists practitioners in selecting the most appropriate method.

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CONFLICTS OF INTEREST

The authors have no conflicts of interest to declare.

DATA AVAILABILITY STATEMENTS

The data supporting this study's findings are openly available at locations cited in the reference section.

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