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Advances in Demand Forecasting: A Systematic Review of Methods, The Role of AI, and Data Strategies in Manufacturing

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Advances in Demand Forecasting: A Systematic Review of Methods, The Role of AI, and Data Strategies in Manufacturing

Completed Research Full Paper

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Abstract

This systematic literature review highlights the gap in demand forecasting in the manufacturing sector, which is challenged by complex supply chains and rapid market change. Traditional methods fall short in this dynamic environment, highlighting the need for an approach that combines advanced forecasting techniques, high-quality data, and industry-specific insights. Our research contributes by evaluating advanced forecasting methods, the effectiveness of AI and data strategies to improve accuracy. Our analysis reveals a shift towards machine learning and deep learning to improve accuracy and highlights the untapped potential of external data sources. Key findings provide both researchers and practitioners with guidance on effective forecasting strategies and key data types and offer an integrated framework for improving forecasting accuracy and strategic decision-making in manufacturing. This work fills a critical research gap and provides stakeholders with actionable insights to manage the complexity of modern manufacturing, representing a significant advance in forecasting practice.

Keywords

Demand Forecasting, Sales Forecasting, Forecasting Methods, Manufacturing Industry, Forecasting Data, Systematic Literature Review

Introduction

In a rapidly changing and unpredictable business environment, the limitations of traditional forecasting methods are becoming increasingly apparent. Gronwald (2023) points out these shortcomings particularly in the manufacturing sector, where companies face significant uncertainty due to inaccurate forecasts, supply chain and production delays, and logistical challenges. This situation leads to different inventory management strategies within companies: Some accumulate excess inventory to avoid outages, while others replenish their inventories reactively, affecting strategic decision making. Rapid changes in consumer behavior and increased competition, driven by the introduction of streamlined processes and networked production, require a rethinking of established approaches. Companies must be able to quickly integrate up-to-date information and adapt to disruptions to maintain operational agility. Demand forecasting is essential for companies to proactively manage fluctuations in consumer demand. Inaccurate forecasting can lead to operational and financial problems, such as excessive inventory costs or lost sales due to out-of-stocks. Effective forecasting provides critical insight for risk assessment and supports strategic financial and material planning. It is critical for forecasting models to consider a range of factors, including short-term disruptions and long-term trends.

The manufacturing industry faces unique challenges that make demand forecasting difficult, such as reliance on complex supply networks, the need for multi-stage production processes, and the need to manage global operations (Agostino et al., 2020). The need for reliable forecasting is itensified by the capital-intensive nature of the industry, which requires significant investments in machinery, materials, and technology. The industry's inherent rigidity makes it difficult to adapt quickly to market changes, while the need for long-term planning further complicates accurate demand forecasting. Taken together, these factors highlight the sector's unique challenges, which require a tailored and sophisticated forecasting approach to manage the complexity of manufacturing.

Recent studies have shown the application of demand forecasting in various *domains*. Specifically, studies have focused on energy consumption in the solar and wind industries (Hong et al., 2020; Ağbulut, 2022; Barrera et al., 2020; Räisänen et al., 2019) and the healthcare industry (Alamo et al., 2020; Zubcoff et al., 2023), including public health policymaking (Wu and Kao, 2021). These areas demonstrate the wide range of applications for forecasting and highlight the importance of customized approaches in manufacturing, where such research is still limited.

Demand forecasting *methods* are constantly evolving, with a noticeable trend towards the use of machine learning (ML) and artificial intelligence (AI) techniques. Modern techniques have shown promise in transportation and in the development of robust urban parking demand forecasting models using open data. Despite the complexity and uncertainty in the manufacturing sector, such as the variability of customer demand and supply chain risks, AI and ML offer promising tools to improve forecasting accuracy. Yet, comprehensive reviews scrutinizing these innovative methodologies within the manufacturing context remain limited (Makridakis et al., 2018; Seyedan and Mafakheri, 2020), indicating a significant research opportunity to explore their applicability and effectiveness.

The quality and type of *data* analyzed are crucial for reliable demand forecasts. However, the literature often overlooks specific data input characteristics, such as collection frequency, input dimensionality, and dataset temporal scope (Walther and Weigold, 2021; Agostino et al., 2020). Recent studies have recognized the importance of data sources (Mediavilla et al., 2022), which contrasts with the lack of detailed specifications for data inputs (Moroff et al., 2021). This highlights the urgent need for a more nuanced understanding of data characteristics in forecasting models. Such an understanding could significantly impact their predictive accuracy and applicability in manufacturing.

To achieve effective demand forecasting, it is important to take a holistic approach that integrates three critical components: Method, Data, and Domain Knowledge. Optimal forecasting depends on using the right mix of detailed internal data and timely external information sources. Additionally, the use of advanced forecasting methods is crucial to producing accurate and actionable forecasts. Incorporating domain-specific knowledge is equally important. This includes understanding business networks, production specifics, and the impact of evolving market conditions.

Despite the recognized importance of these components, the existing literature often examines data, methodological approaches and sector-specific characteristics in isolation. What is striking is the lack of studies that bring these elements together holistically to promote reliable forecasts in the manufacturing sector. This segmented focus leaves a critical gap: There is a lack of comprehensive guidance on how to bring together multiple data sources, state-of-the-art forecasting methodologies, and in-depth expertise to improve the accuracy and utility of forecasts.

This systematic literature review aims to fill this gap by taking an integrative perspective. It aims to clarify how the interplay of data, methods and expertise can be optimized to support effective demand forecasting in manufacturing. In this way, it aims to provide researchers and practitioners with actionable insights tailored to the unique complexities of the manufacturing sector, including its sub-sectors and distribution networks.

As such the paper is guided by the following research question: *What are the key factors for achieving reliable sales and demand forecasting in the manufacturing sector?* This overarching question unfolds into two critical sub-research questions:

RQ1: Which forecasting approaches are most effective in predicting sales and demand within the manufacturing industry?

RQ2: What types of data are crucial for attaining high forecast accuracy in the manufacturing context?

To answer the research questions a systematic literature review is employed to review the current approaches regarding the three components: data, method, and domain knowledge as a basis for reliable forecasting. The following section briefly presents the theoretical background. Afterwards the method employed is presented, followed by the analysis of the current body of knowledge. The results are discussed afterwards, and the conclusion finalizes the paper.

Theoretical Background

Accurate and precise forecasting enables manufacturing companies to adapt to changing trends and plan capacity more efficiently. Forecasting uses statistical, mathematical and algorithmic methods to predict business figures such as sales, demand or market trends. Both internal (e.g. historical sales data) and external sources (e.g. open data) are used two crucial types of demand forecasting: qualitative and quantitative forecasting methods (Farimani et al. 2022). The categorization into these methods, as discussed by Farimani et al. (2022), aligns well with the focus of our work on demand forecasting in the manufacturing industry, illustrated using the automotive sector. Quantative forecasting methods provide data-driven predictions, while qualitative methods are typically based on expert opinions. Although quantitative methods clearly dominate the field of manufacturing forecasting (Agostino et al., 2020), methods can be combined to achieve higher accuracy. Recent technological advances use artificial intelligence (AI) algorithms to uncover patterns and generate forecasts and trends.

This study focuses on quantitative predictive forecasting methods, which uses models and techniques to generate predictions from historical data (Kim, 2023). Farimani et al. (2022) categorize the methods into time series, causal and advanced metaheuristic methods, each offering different predictive capabilities.

Forecasting Methods

Time series forecasting uses historical data to identify patterns and trends for future predictions and is often used in supply chain, production and inventory planning (Kühnapfel 2015). Naive forecasting can be relevant for highly stochastic business models, despite its simplicity and potential inaccuracy due to the lack of causality (Gronwald, 2023). The Simple Moving Average (SMA) predicts the future by averaging past data, while the Weighted Moving Average (WMA) assigns different meanings to data points (Yin et al., 2021). ARIMA models are complex but widely used because they integrate autoregression, differencing and a moving average.

Causal methods are used to determine causal relationships between variables, often requiring sophisticated statistical analysis (Gronwald, 2023). In manufacturing, they are used to optimize inventory, production and sales based on demand signals from the market. Techniques range from simple regression to multiple regression, where dependencies on one or more predictors are evaluated, to non-linear regression, where non-linear relationships are taken into account (Aktepe et al., 2021). These form the basis of advanced models, including neural networks and support vector regression, which are discussed in more detail below.

Machine learning methods such as neural networks (NN) and artificial neural networks (ANN), which are driven by interconnected layers of artificial neurons, are very useful for prediction (Mediavilla et al., 2022). These include variants such as recurrent neural networks (RNNs) and the advanced long short-term memory (LSTM) networks (Wang et al., 2019). Beyond NNs, methods such as Random Forest (RF) use decision trees for ensemble prediction (Panda and Mohanty, 2023; Zhang et al. 2022), while Support Vector Regression (SVR) excels at both linear and non-linear problems (Ingle et al., 2021), illustrating the diversity of tools available for the predictive needs of manufacturing. The forecast methods presented represent are focused on the ones widely used in the manufacturing industry.

Method

To answer our research questions, we conducted a systematic literature review (SLR) in accordance with the procedural framework established by vom Brocke et al. (2009). Our approach is guided by Cooper's (1988) taxonomy, which provides clarity on the scope of our investigation. The categories selected within this taxonomy are indicative of our focus on research findings and our intention to synthesize and integrate the existing literature on demand forecasting methods in manufacturing. Our review adopts a neutral perspective, targeting a broad audience of researchers and ensuring that the viewpoints of the reviewers do not influence the analysis. We conducted a representative review of the literature, examining a selection of databases and publications to ensure breadth of coverage.

In the conceptualization phase (step 2), key terms were to ensure that our sources were comprehensive and authoritative. To capture the relevant literature, we searched the selected academic databases using specific keywords to obtain a detailed overview of the current research landscape and to identify areas of interest (Table 1).

Forecasting		**Focus**		**Context**
Forecasting method **OR** Prediction method **OR** Projection method	**AND**	Demand development **OR** Request development **OR** Sales development	**AND**	Industrial companies **OR** Industry **OR** Manufacturing **OR** Production

Table 1. Keywords for Literature Search

The literature search, the third step of our systematic literature review (SLR), involved selecting relevant databases and defining search terms according to the four-step process suggested by vom Brocke et al. (2009): journal search, database search, keyword search, and backward/forward search.

We chose IEEE Xplore, Web of Science and ScienceDirect due to their comprehensive coverage of scientific articles, especially in the field of manufacturing. Moreover, their multidisciplinary coverage, enables us to incorporate diverse forecasting methodologies effectively. Our search, which was limited to English-language literature from 2018 to 2023, focused on recent advances in prediction methods. Reviews and studies without practical application in real or simulated scenarios were excluded.

Querying search terms with inclusion and exclusion criteria yielded 468 records: 214 from IEEE Xplore, 149 from Web of Science and 105 from ScienceDirect. After reviewing the titles, abstracts and keywords, a significant number of articles were excluded for reasons such as irrelevance to the manufacturing context or lack of application of predictive methods in real or simulated scenarios. Many articles were also excluded due to their focus on energy and electricity demand forecasting, which is outside the scope of this review. After this initial screening, only 56 publications remained. These underwent a full-text review to ensure that they met our criteria, resulting in the exclusion of a further 29 papers. Reasons for this second round of exclusions included lack of real or simulated application and lack of relevance to the manufacturing domain. The remaining 27 articles, supplemented by 8 additional papers identified through forward and backward citation searches, formed the core of our research corpus (Webster and Watson 2002). These steps are illustrated in a PRISMA flowchart (Figure 1).

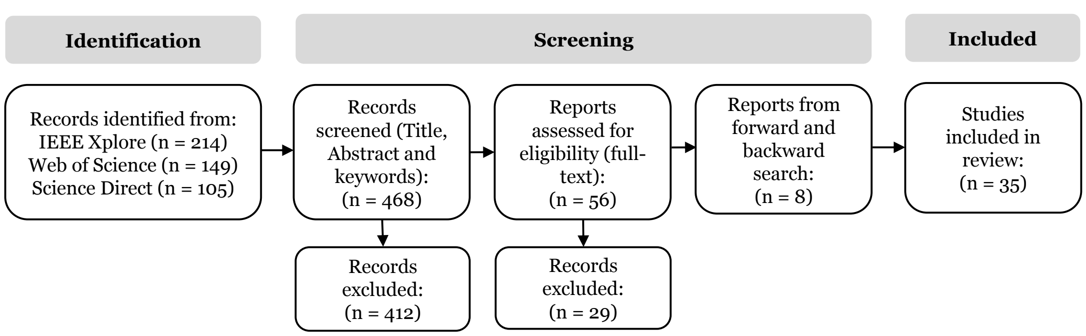

Figure 1. Literature Review PRISMA flow chart

Analysis

The full table of the results is available at this link. The SLR, which covers the period from 2018 to mid-July 2023, shows an upward trend in publications on this topic, as shown in Figure 2. Of the 35 relevant texts, a minority of three focused exclusively on traditional forecasting techniques, including time series and causal models. There is a shift towards intelligent forecasting methods over the years. Most of these publications, 60%, were conference papers, with the remaining 40% published in academic journals, highlighting the strong interest in academic and industry forums.

In Figure 3, the publications are categorized by sector, with the consumer goods category dominating, but the automotive and aftermarket sectors also strongly represented in the literature. This distribution highlights the different application of forecasting methods in different manufacturing sectors.

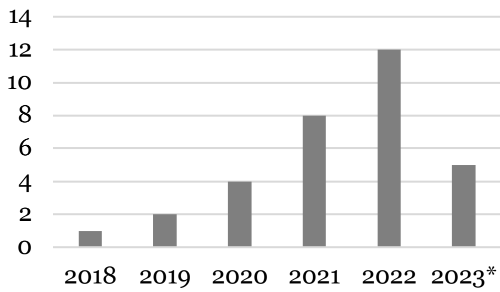

Figure 2. Number of Papers per year

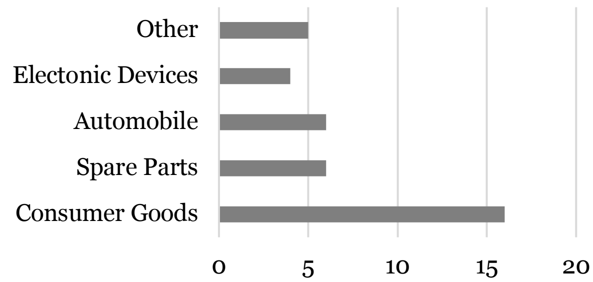

Figure 3. Number of Papers per Sector

Forecasting Methods

In this analysis, we examine the prevalence of forecasting methods across product categories, distribution channels, forecasting horizons, and metrics used. Figure 4 shows the prevalence of different forecasting techniques as described in the literature and illustrates the dominance of neural networks (NNs), including long short-term memory (LSTM) networks, among the methods used.

It is important to clarify that NNs include artificial neural networks (ANNs) as well as specific variants such as Bayesian neural networks (BNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs). Although LSTMs are a subset of RNNs, they are distinguished separately due to their unique structure and function.

The data show a strong preference for Machine Learning (ML) and Deep Learning (DL) techniques, with the ARIMA model being the most notable non-ML/DL method among the top four. Notably, ARIMA and LSTM are often mentioned together, either in comparative analyses (Oukassi et al. 2023) or as part of integrated approaches (Han 2020). In addition, Random Forest (RF), an ML-based technique, is recognized as one of the top four methods.

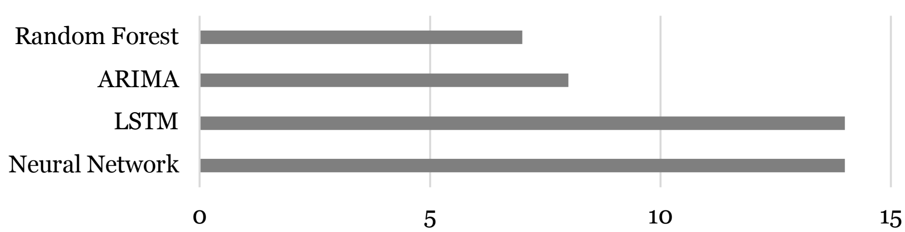

Figure 4. Frequency of Methods

To categorize the areas of application of intelligent forecasting methods, the publications examined were analyzed according to product categories and their respective role in the supply chain. Figure 5 shows the distribution of publications by product type, with the consumer products sector dominating and the aftermarket and automotive sectors lagging behind. The analysis by supply chain role, shown in Figure 6, shows "Producer" as the leading category, followed by "Retailers", "Wholesalers", and "Online Retailers".

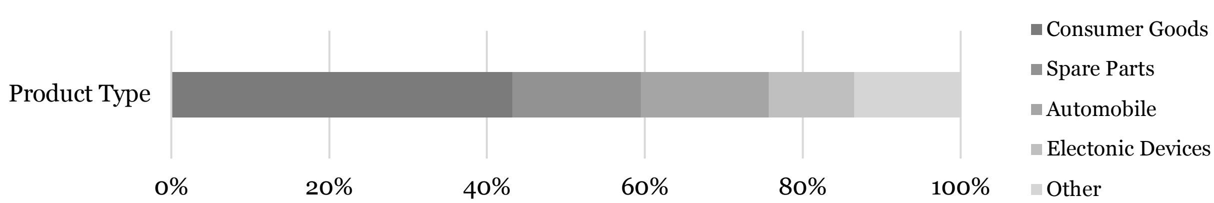

Figure 5. Publications per Product Type

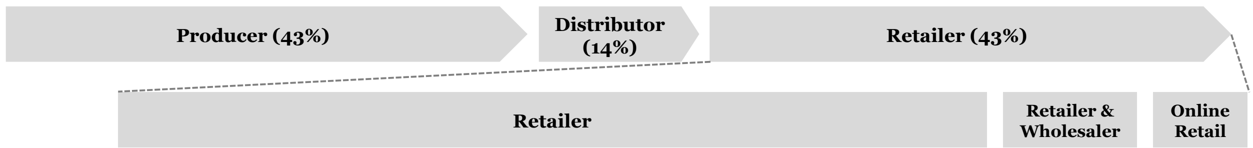

Figure 6. Publications per Supply Chain Role Channel

Data Source, Data Horizon & Accuracy Metrics

Forecasts were divided into short-term (hourly, daily, weekly), medium-term (monthly) and long-term (annual) periods (Mediavilla et al., 2022). A significant proportion of studies focused on medium-term (18 studies) and short-term (13 studies) forecasts, while only 3 studies focused on long-term forecasts. The measures used to evaluate the forecasts varied widely, with mean absolute deviation (MAD), root mean square error (RMSE) and mean absolute percentage error (MAPE) being the most commonly used measures.

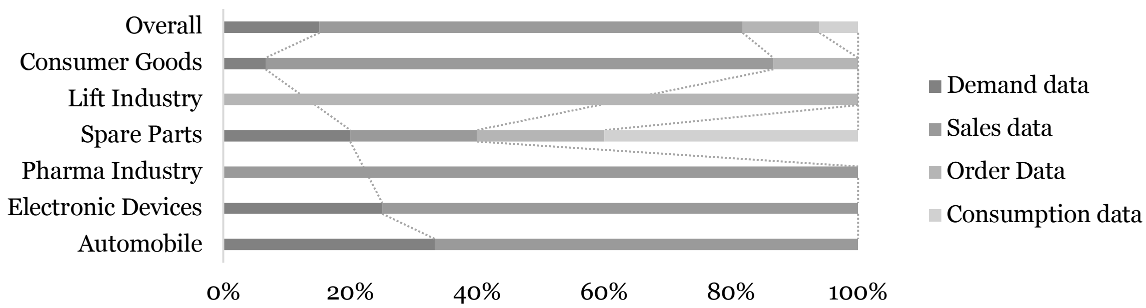

Figure 7 Data Input per Sector

There are two main approaches to forecasting: analyzing historical real data to extract trend information, and simulation, where forecasts are made based on different scenarios by changing demand planning parameters or causal factors. Most of the studies reviewed use real data to generate forecasts, with only two of the 35 studies using simulated data. In particular, Van Steenbergen and Mes (2020) integrate both real and simulated data for a comprehensive analysis. The categorization of data shows a focus on sales, consumption, ordering, and general demand data. This distinction is crucial due to the time lag between ordering and actual sales, with the majority (22 studies) analyzing sales data (Figure 7). An examination of the frequency of data collection shows that monthly data collection is preferred (20 studies), followed by daily (7 studies) and weekly (6 studies). The variability of the data collection periods is remarkable, especially with regard to the duration of the months covered, which is crucial for a comparative analysis (Figure 8). One significant outlier in the data set spans 214 months (Yamamura et al., 2022.

Data Origin and Dimension Analysis

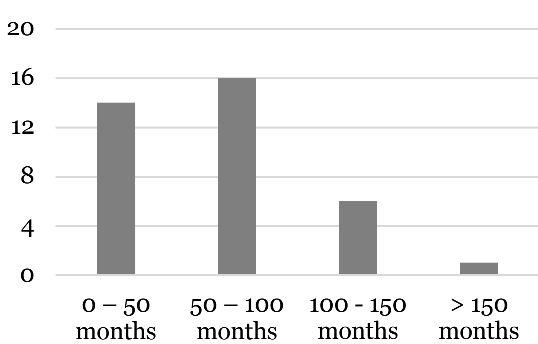

Figure 8. Data collection cycle in months

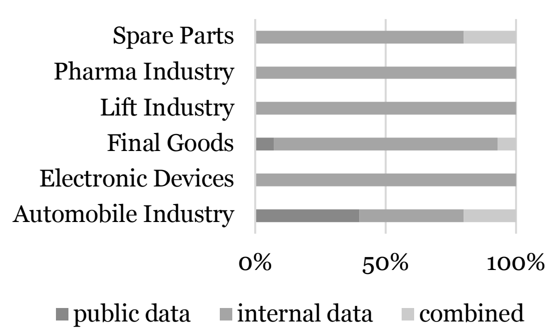

Figure 9. Data Source

This analysis aims to understand the use of external data sources in forecasting. Figure 9 shows that most studies (28) rely on internal data, either exclusively (25) or in combination with external sources (3). Examples include order data from online stores (Deng and Liu 2021) and sales figures from merchandise management systems (Aktepe et al. 2021). External data serve as valuable predictor variables in several studies. For example, Aktepe et al. (2021) use inflation-adjusted USD/TRY exchange rates from the Statistical Institute of Turkey to forecast the demand for spare parts. Similarly, Kim (2023) incorporates exogenous factors such as unemployment rates from the Economic Statistics System of the Central Bank of South Korea, demonstrating the use of various external data sources to improve forecasting accuracy. However, the use of open and public data sources in research is relatively rare. The dimensionality of the data used in these studies shows a predominant preference for univariate analyses (75%), which focus on single variables for forecasting. Multivariate data, where additional external variables are considered alongside internal demand data, are less common but provide a more comprehensive framework for analysis. For example, Lee and Kim (2018) use a multivariate dataset that includes operational metrics and maintenance records to forecast spare parts demand. Panda and Mohanty (2023) examine both univariate and multivariate data to analyze variable dependencies, demonstrating the nuanced approach required for comprehensive forecasting models.

Discussion

Forecasting Approaches and Accuracy

The results of the systematic literature review (SLR) underscore the effectiveness of modern demand forecasting methods in various manufacturing scenarios. Intelligent methods generally provide more accurate forecasts than traditional statistical methods. Studies by Spiliotis et al. (2022), Moroff et al. (2021), and Wang et al. (2019) show the superiority of machine learning (ML) methods over classical statistical approaches, considering not only the forecasting accuracy but also the relative implementation effort. ML methods such as Random Forest (RF) are characterized by their efficiency and low implementation effort, while statistical methods require intensive data preparation and parameterization, and deep learning (DL) techniques involve significant computational effort (Moroff et al. 2021).

Mejri et al. (2021) and Oukassi et al. (2023) highlight the advantages of Long Short-Term Memory (LSTM) over the ARIMA model, although Moroff et al. (2021) recognize scenarios where traditional statistical methods are still applicable. Farimani et al. (2022) and Falatouri et al. (2022) present cases where traditional methods outperform ML, suggesting that ML does not uniformly guarantee higher accuracy, especially when comparing methods such as Box-Jenkins and ANN, or in the context of stable versus seasonal demand forecasting.

Combining forecasts from different methods proves to be highly effective and improves accuracy, as shown in the studies by Steenbergen and Mes (2020) combining K-means, RF, and Quantile Regression Forest (QRF), and Han (2020) combining LSTM and ARIMA. Honjo et al. (2022) and Henzel et al. (2022) also confirm the success of hybrid forecasting approaches, such as the combination of Pooling Attention-Gated Recurrent Unit (PA-GRU) with CNN and the integration of Linear Mixed Model (LMM) with K-Nearest Neighbor (KNN), which significantly improve forecasting accuracy. Neural networks (NNs), including LSTM, dominate in terms of prevalence and performance, often outperforming traditional benchmarks (Babai et al. 2020). İfraz et al. (2023) also demonstrate the high accuracy of artificial neural networks (ANNs) in forecasting, highlighting the differentiated landscape of demand forecasting methods, where no single approach has absolute dominance, but intelligent methods often offer significant advantages.

Sector Analysis and Forecasting Variability

Comparing the effectiveness of forecasting methods across studies is difficult since differences in the metrics used for evaluation, the timing of data collection, and the specific sector in which the forecasting method is applied exist. For example, Yamamura et al. (2022) use a mixture of artificial neural networks (ANN) and expert knowledge to forecast demand for new car models. This method differs from the combination of LSTM and ARIMA used by Oukassi et al. (2023) to forecast a car manufacturer’s demand based on historical data. Although both studies focus on the automotive sector, the differences in data availability and forecasting approaches make a direct comparison difficult.

The LSTM's architecture, with Its emor’ cell consisting of Input, output and forgetting gates, is particularly well suited to sales and demand forecasting, especially given its ability to adapt to changing consumer buying patterns. This is critical in industries such as consumer products, where demand forecasting must consider rapidly changing consumer preferences to ensure timely and accurate production and inventory decisions.

Seasonality plays a central role in supply chain demand forecasting, especially for products with predictable cyclical variations. The ARIMAX and SARIMA models offer improved forecasting accuracy for seasonal demand patterns by incorporating parallel time series and seasonal factors, respectively. By integrating these models into SARIMAX, the forecasting accuracy for consumer goods is further improved by taking into account both external variables and seasonal trends.

Effectiveness of Forecasting Approaches (RQ 1)

The results show a clear shift towards ML and DL techniques for forecasting demand in the manufacturing sector. This trend reflects the superior ability of these methods, such as neural networks and LSTM, to handle complex and volatile demand patterns more effectively than traditional statistical methods (Spiliotis et al., 2022; Moroff et al., 2021). Despite the significant benefits of AI in improving forecast accuracy, the use of AI in demand forecasting presents several challenges. First and foremost, AI-enabled forecasting is a data-intensive endeavor; it requires large amounts of high-quality data to achieve better performance than traditional methods. In addition, AI methods are often not as transparent and explainable as traditional forecasting models, which are based on solid mathematical foundations. Understanding the reasoning behind the predictions is as important to strategic decision making as the accuracy of the predictions themselves.

The Integration of ML/DL methods with traditional statistical modelling in the form of hybrid approaches is proving to be a highly effective strategy. This combination makes use of the strengths of both methodologies and offers improved prediction accuracy. For example, the combination of ARIMA and LSTM has been shown to offer significant advantages, highlighting the potential of hybrid models to capture both linear and non-linear patterns in the data (Moroff et al., 2021).

The effectiveness of forecasting approaches varies widely across manufacturing sectors and is influenced by sector-specific factors such as product life cycle, data availability and market dynamics. This variability underscores the necessity for tailored forecasting models that account for the unique characteristics and challenges of each sector.

Data Basis for reliable Forecasting (RQ 2)

The analysis highlights the over-reliance on internal data sources for forecasting, while pointing to the underestimated potential of external data sources. The inclusion of external data, such as economic indicators and social media trends, can significantly enrich forecasting models and provide a more comprehensive understanding of the factors influencing demand. The current underutilization of public and open data sources in forecasting research represents a research gap. These data sources have the potential to improve forecasting models by providing more comprehensive insights into market trends and consumer behavior, which is a valuable direction for future research.

It is noted that univariate data is prevalent forecasting practice and a case is made for the inclusion of multivariate data to better capture complex demand dependencies. In addition, the frequency of data collection (monthly, weekly, daily) has an impact on forecast accuracy, suggesting that more frequent data updates are needed to improve the responsiveness of forecasting models.

Conclusion

The use of advanced forecasting techniques in the manufacturing industry is becoming increasingly important due to competitive pressure, economic uncertainty and supply chain disruptions. This research contributes by characterizing methods for demand forecasting in manufacturing, evaluating the demand forecasting capability of AI, and outlining a data strategy for optimal forecasting accuracy. These contributions serve to benchmark advanced techniques, evaluate the practicality of AI, and guide effective data use in the evolving manufacturing landscape.

The findings reveal a significant gap in the use of external data for demand forecasting in manufacturing, with a preference for internal sources despite the potential benefits of integrating public and open data. While advanced forecasting methods are highlighted, the diversity of data sources remains unexplored. In particular, studies that incorporate external data, such as those by Kim (2023) and Aktepe et al. (2021), illustrate the benefits of combining open or public data with internal data to improve accuracy. This suggests that the value of external data is still emerging, and that future research should focus on expanding the use of different data sources, integrating external and internal data for better forecasting outcomes, understanding the barriers to open data adoption, and evaluating different forecasting methods in the manufacturing context. Advancing demand forecasting in manufacturing will require the adoption of both new data sources and forecasting techniques to ensure that models are adaptable to the evolving needs of the industry. In conclusion, domain knowledge such as industry and supply chain structure are crucial in combination with data and methods for reliable forecasts.

The systematic literature search is limited to English-language publications and is not exhaustive, so relevant studies may have been missed. In addition, only recent publications were considered, which may not adequately reflect the longer-term development of predictive approaches. Finally, the review does not consider qualitative approaches and their possible combination with quantitative approaches.

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