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ORIGINAL PAPER

SUPPORTING THE INVENTORY MANAGEMENT IN THE MANUFACTURING COMPANY BY CHATGPT

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ABSTRACT. Background: The decision-making process in the operational context of enterprises is an integral aspect of how they function, and in this area, precise demand forecasting plays a key role. The use of accurate forecasting models not only meets customer expectations but also enables efficient resource allocation and operational cost optimization. In the long term, such actions contribute to increasing the organization's competitiveness in the market. In recent years, there has been a growing trend in the use of advanced analytical technologies, including machine learning, for demand forecasting purposes. This scientific paper focuses on a comparative analysis of demand forecasting effectiveness using the generative language model GPT in relation to the auto ARIMA algorithm.

Methods: A case study analysis for a selected manufacturing organization was conducted based on twelve diversified operational references, for which the supply chain mechanisms are heterogeneous. In the research process, a classification into four reference groups was established, based on the time required to complete the ordering process. Forecast generation was carried out using the auto.arima() algorithm in the R programming environment, as well as through the ChatGPT language model versions 3-5. The forecast results were subjected to comparative analysis, in which weighting was applied for different forecast accuracy indicators, including the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the number of precisely predicted daily forecasts.

Results: The study showed that ChatGPT is more reliable in forecasting compared to ARIMA. However, integrating ChatGPT into the existing systems in the company can be problematic, mainly due to limitations in data operations. Despite this, ChatGPT has the potential to improve the accuracy of inventory management plans both in the short and long term.

Conclusions: The comparative analysis of the effectiveness of forecasting models, including ChatGPT and ARIMA, showed that the ChatGPT algorithm achieves higher levels of forecasting accuracy. This is observed despite increased computational complexity and challenges associated with processing large data sets.

Keywords: ARIMA, ChatGPT, demand forecasting, inventory management

INTRODUCTION

Issues related to assortment management are highly significant, particularly for manufacturing companies whose production activities are often heavily reliant on a well-structured and functioning supply system (Phan et al., 2019). With dynamic changes in customer preferences, increasing competition, and rapid technological advancements, businesses must develop modern assortment management methods that can forecast product demand effectively. Demand forecasting is a crucial element of efficient assortment management in manufacturing companies (Sharma and Singhal, 2019). Accurate forecasts enable process optimization, minimize inventory costs, avoid excess stock, and fulfill customer needs quickly and efficiently. In recent years, numerous modern methods and tools have emerged to support companies in forecasting product demand. One such tool involves utilizing advanced machine learning algorithms, including predictive models based on artificial intelligence (Makridakis et al., 2018; Ahmed et al., 2010). These models can analyze vast amounts of historical data, taking various factors into consideration, such as market trends, seasonality, promotions, and customer

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preferences, thus leading to more precise demand forecasts.

In recent times, we are also witnessing a rapid development of advanced machine learning and artificial intelligence-based language models (Dillon et al., 2023), which are increasingly seen as applicable in various domains of life and industry. One of the most popular language models today is ChatGPT. ChatGPT is a language model that utilizes powerful machine learning algorithms to generate responses to user queries in a natural and interactive manner. According to many authors, ChatGPT has a significant impact on the business sector (George and George, 2023). In this article, the authors focus on examining the performance of ChatGPT in forecasting the demand for references used in production, based on a selected case study.

THEORETICAL BACKGROUND

Meaning of assortment management

Assortment management is a critical aspect of logistics management, which involves managing the inventory of products and services offered by a company to meet the diverse needs and preferences of its customers. According to Waßmuth et al. (2023), assortment management involves selecting the right mix of products and services that can generate maximum revenue and profit for the company, while also meeting the demand and expectations of customers. Inventory management is also a key area of logistics coordination (Kmiecik, 2022b): on the one hand, it aims to reduce unforeseen fluctuations in demand and ensure an appropriate level of customer service in distribution networks; on the other, it is an area that largely depends on the adopted strategies for planning and implementing demand plans (Abdolazimi et al., 2021). The primary goal of assortment management is to optimize the product mix by selecting the right products, at the right time, and in the right quantities to meet customer demand and improve the overall profitability of the company (Dantu and Vasudevan, 2021). This requires a deep understanding of customer preferences, market trends, and supply chain dynamics. Companies need to analyze customer data, such as buying patterns, purchase history, and demographics, to identify the most profitable products and services and tailor their assortment accordingly. Proper handling of inventory management also has a positive impact on supply chain sustainability (Paam et al., 2019) because the coordination in the case of inventory management allows, among other things, for a reduction in the supply level in the whole network and minimizes the waste in stocks. Assortment management can also help companies to manage their inventory efficiently, reduce stock-outs, and improve customer satisfaction. According to Gupta and Ramachandran (2021), effective assortment management can help companies to reduce the cost of inventory holding and improve the availability of products to customers, thereby enhancing customer loyalty and retention. An interesting fact is that while stocks are generally held to meet demand, in some situations, they are held to stimulate demand (Murphy and Wood, 2020) through active influence in the sphere of customers, for example. In the literature, this effect is called the psychic stock effect. To achieve effective assortment management, companies need to adopt advanced technologies such as predictive analytics, artificial intelligence, and machine learning to analyze customer data, market trends, and supply chain dynamics (Bartkowiak and Rutkowski, 2016). These technologies can help companies to identify emerging trends, forecast demand, and optimize their product mix, leading to improved profitability and competitiveness in the market. Some logistics enterprises like logistics operators could both manage inventories for the purpose of their effective deployment in particular places in the supply chain and attempt to eliminate the bullwhip effect (Kmiecik, 2022a). These aspects could be positively influenced by the operator's experience in implementing logistics tasks and their ability to react quickly and adapt activities to the requirements of individual cells. In the supply chains, the manufacturing companies are also responsible for proper material handling in the cases of in-house logistics. The present challenge of inventory management is handling demand fluctuations, stockouts and managing the individual SKUs (Stock Keeping Units), while also handling big data (Patil, 2014). Management from the level of individual SKUs is problematic in terms of the amount of data and information that are associated with it. Inventory management based on big data can lead to advantages, such as (Malik and Jeswani, 2018):

- Improving operational efficiency;
- Maximizing profits and sales;
- Increasing customer satisfaction rates;
- Reducing IT infrastructure costs by migrating to the cloud.

Assortment management actions are currently focused on providing plenty of services related directly to inventory and stock management. Inventory management from the perspective of the entire network would enable its efficient coordination by means of planning and implementing assumptions related to the allocation of supplies and their effective use. On the other hand, nowadays we are dealing more and more often with a one-day-delivery standard in transport operations (Grzelak et al., 2019). As mentioned by some authors, through appropriate transport planning, enterprises could reduce flow times and reduce inventory levels (Wang et al., 2021) by increasing the speed of reaction and eliminating the need to maintain high-safety stocks. Assortment management is a critical aspect of logistics management that can help companies to optimize their product mix, reduce inventory holding costs, and improve customer satisfaction. Companies need to adopt advanced technologies and data analytics tools to achieve effective assortment management and stay competitive in the ever-changing business environment.

AI usage at assortment management

Traditional methods of inventory management rely heavily on human decision-making and manual processes. It is strictly connected with the knowledge and skills of specialists who work in the company structures. Of course, even in the traditional approach, the human workers are usually supported by IT systems which facilitate their work. The use of IT systems is aimed at achieving similar results as by using AI (artificial intelligence) and ML (machine learning) technologies. Inventory management supported by AI or ML leverages the power of technology and data analysis to make more accurate and efficient decisions. AI and ML can help businesses make better decisions about their inventory levels, improve their operations, and increase their profitability. Traditional methods of inventory management often rely on historical data and basic forecasting techniques, such as moving averages or trend analysis. AI and ML, on the other hand, can analyze large volumes of data from multiple sources to create more accurate forecasts that consider complex factors such as seasonality, promotions, and even weather patterns. Traditional methods also typically involve periodic checks of inventory levels, which can lead to stock-outs or overstocking, if demand patterns change unexpectedly. AI and ML can continuously monitor inventory levels in real-time and adjust replenishment decisions accordingly, reducing the risk of stockouts and improving efficiency. Traditional inventory management often involves balancing trade-offs between stock levels, service levels, and costs. AI and ML can optimize inventory levels based on multiple factors, such as sales patterns, delivery times, and customer demand, to maximize profitability and minimize waste. Traditional ways often require significant manual effort, such as doing the inventory by hand, entering data into spreadsheets, and creating reports. AI and ML can automate many of these processes, freeing up time for employees to focus on higher-value tasks (Mukhopadhyay et al., 2012).

AI-based systems could be used in the area of inventory management, in the field of demand forecasting, and for modeling inventory management actions (Praveen et al., 2019). AI and ML algorithms can analyze historical sales data and use it to predict future demand for different products. This helps businesses optimize their inventory levels and prevent stock-outs or overstocking. The issue of support demand management is one of the most popular areas of AI usage in the context of AI (Albayrak Ünal et al., 2023). AI and ML can also be used to determine the optimal time to restock inventory. This is done by analyzing factors such as lead times, supplier performance, and customer demand patterns. Some researchers are of the opinion that ML could prove to be an excellent technology for supporting the DSS (Decision Support Systems) in companies (Praveen et al., 2020). AI is used in different areas of forecasting, from predicting air pollution (Masood and Ahmad, 2021), and forecasting load demand forecasting techniques for smart grid and buildings (Raza and Khosravi, 2015). Even the tough years of the COVID-19 pandemic were a great period for developing and testing AI tools for forecasting purposes. For example, Elsheikh et al. (2021) proposed an AI tool for forecasting the pandemic spreading around the world, while other scholars proposed AI tools for forecasting this same issue in particular regions, for example, Hu et al. (2020) in China and Al-Qaness et al. (2021) in Russia and Brazil. Another interesting topic is the possibility of using AI to predict new phenomena through analogy (Lee et al., 2007), which was previously challenging to achieve.

By analyzing leading journals in terms of the Impact Factor (IF) that mainly focus on forecasting, namely Technological Forecasting and Social Changes (2023 IF = 12.00) and the International Journal of Forecasting (2023 IF = 7.90), one can also observe a trend in writing about AI in the context of forecasting, especially forecasting related to material planning and demand. AI in research is being considered for use in sales forecasting (Zhang et al., 2022; Lu et al., 2023), export sales (Sohrabpour et al., 2021), demand for problematic products such as fashion products (Swaminathan and Venkitasubramony, 2023), and demand forecasting across supply chains (Boone et al., 2019). The use of AI in inventory planning is highlighted by Petropoulos et al. (2022) and Huynh et al. (2023), where the relevance of using AI in BigData analysis is often emphasized. AI is also indicated as a suitable solution for purchasing and supply management (Delke et al., 2023).

By analyzing sales data, AI and ML can identify which products are selling well and which are not. This allows businesses to adjust their inventory levels and focus on the products that are most profitable. In addition to this, a great deal of research shows that AI or solutions connected with AI like ANN (Artificial Neural Network) could support inventory classification. Even in the early 2000s, some authors tried to use ANN for inventory classification (Partovi and Anandarajan, 2002). Currently, the use of ANN and AI for inventory classification remains a problem. These technologies could be used for multicriteria inventory classification as an element that supports the fuzzy AHP (Analytic Hierarchy Process) (Kabir and Hasin, 2013) or multi-criteria ABC analysis (Yu, 2011). AI and ML can be used to monitor equipment and machinery in warehouses and predict when they will need maintenance or repairs. This helps prevent downtime and ensures that operations run smoothly. Such technologies can also be used to identify patterns of fraud in inventory management. By analyzing sales data and identifying anomalies, these algorithms can help businesses detect and prevent fraud. AI could be used to predict and minimize inventory distortions for improving resiliency (Jauhar et al., 2023). Nowadays it is often claimed that AI could replace traditional inventory management systems (Preil and Krapp, 2022; Praveen et al., 2020) and it should be a basic element of Smart Warehouse Management System (Zunic et al., 2018), which gives the opportunity for achieving the better results.

The increasing adoption of social chatbots is unmistakable, and this is chiefly due to their ability to mimic human communication. Very often chatbots are analyzed in terms of raising the level of customer service or different social issues (Malik et al., 2023l Chang et al., 2023). Such chatbots support clear, text-based conversations, often replacing traditional interactions between humans (Ali et al., 2023). Chatbots are also considered to be tools for improving predictions using behaviour modifications (Shmueli and Tafti, 2023). Various researchers agree that the core components of chatbots include AI, machine learning, deep learning, natural language processing, productive and sentimental analytics (Rawat et al., 2022). It is often the case that chatbots are combined with task automation and data gathering systems, bolstered by innovations like the Internet of Things (IoT) (Wu et al., 2018).

These bots are acknowledged to be able to enhance communication between businesses within supply chain structures (Modgil et al., 2022). Their transformative role in communication is especially worth noting in e-commerce, where they often act as AI-driven aids, particularly when introducing novel customer engagement methods during product distribution (Angelov and Lazarova, 2019; Sharma et al., 2022). The demand for voice-operated chatbot platforms tailored for customer interactions across various supply chain stages, like shopping and order processing, is expected to persist in its upward trend in global logistics

(Suvethashri and Vickram, 2019). Through chatbots, supply chains can offer personalized services and improve procurement, client interactions, and transport operations (Modgil et al., 2022; Sai et al., 2022; Wu et al., 2018). Moreover, academic experts indicate that for cost efficiency, logistics firms often opt for chatbots over designing custom apps (Kolosok and Lazarevska, 2020). Incorporating AI-powered chatbots provides customers with digital helpers for queries on order status and delivery schedules, reducing the need for human involvement (Modgil et al., 2022). It is suggested that around 47% of shoppers might have a positive buying experience when using chatbots, and their inherently emotion-free interaction style might reduce customer complaints (Merdin and Ersoz, 2019).

ChatGPT is a prime example of a chatbot that is currently drawing significant attention from both the academic and business communities.

ChatGPT environment

ChatGPT is an innovative artificial intelligence system that was launched in November 2022. GPT stands for Generative Pre-trained Transformer. It is a language model whose task is to generate responses to user queries based on specialized training. ChatGPT was created by the research laboratory OpenAI, dedicated to artificial intelligence research. The laboratory team is based in San Francisco and aims to develop AI that is friendly to humans and brings societal benefits. The pursuit of creating advanced AI tools like ChatGPT has the potential to revolutionize many aspects of life and work. It relies on advanced machine learning algorithms and, coupled with access to a vast database, enables the tool to generate highly sophisticated responses to almost any query (Božić, 2023). The generation of responses is made possible by utilizing over 175 billion parameters (Firat, 2023). The use of such a database allows the program to stand out due to its ability to understand and interact with users (Chenfei et al., 2023). A significant measure of this tool's success is its achievement of gaining a million users within just five days (Haque et al., 2022). One distinguishing feature of ChatGPT compared to other AI-based tools is its ability to perform specific tasks based on specific user instructions (Shujian et al., 2023). Through literature analysis, this tool finds wide application in radiology (Biwas, 2023), public health (Biwas, 2023), education (Firat, 2023), programming (Nigar et al., 2023), in-context learning (Ori et al., 2023), GPT-based intelligent systems (Zhent et al., 2023), and many other fields. ChatGPT was developed by the OpenAI research laboratory, which conducts research in the field of artificial intelligence. It was established in San Francisco to create friendly artificial intelligence for the benefit of humanity (Mhlanga, 2023).

METHODS

The methods used in the article are related to testing the potential implementation of ChatGPT as a tool to support inventory management in a manufacturing company. The article proposes two research hypotheses:

H1: *It is possible to integrate the ChatGPT tool with the inventory management system of a selected manufacturing company.*

H2: *ChatGPT can increase the accuracy of plans in the area of inventory* management.

The second hypothesis is further divided into two parts due to the variety of product ranges and order fulfillment periods:

H2.1: *ChatGPT can increase the accuracy of plans in the area of inventory management for products with a short ordering period.*

H2.2: *ChatGPT can increase the accuracy of plans in the area of inventory management for products with a long ordering period.*

The article also poses two research questions:

RQ1: *What functionalities must ChatGPT possess in order to be integrated into the operations of a manufacturing company?*

RQ2: *What parameters in the area of inventory management must be characterized in order to use ChatGPT?*

In addition to testing ChatGPT, the authors also decided to include results from a predictive algorithm created for the study. This allowed for a comparison of the forecasting results of ChatGPT with both human decisions and results obtained using the algorithm. The authors decided to compare the three solutions connected with assortment management. The first case concerns the current situation in the case study being tested, where supply is based on supply worker decisions. The other two is the authors' proposition of using a simple forecasting algorithm based on *auto.arima()* in the R programming language (2nd case) and with the use of ChatGPT (3rd case).

The assortment examined here consists of parts that are necessary to build a fully functional water dispenser. Out of several thousand elements, three positions were selected that are of the highest importance to the company, with a division based on the delivery lead time from the suppliers. The selection of positions was made after consultation with managers involved in the company's procurement process. The absence of any of these positions is unacceptable as they are integral components of every device manufactured by the company, which would result in a halt in the production process and a suspension of shipments of finished products to customers. The delivery lead time for a particular position is determined by the location of the supplying company, material availability, complexity of production, and the time required to fulfill the order. Due to the company's confidentiality, all positions have been assigned new codes, where the first character represents the number of days needed to fulfill the delivery, and the last character represents the identifier of the position. Positions with a one-week lead time come from local suppliers and have a low level of complexity. Positions with a two-week lead time also come from local suppliers but have a slightly higher level of complexity. Positions with a three-week lead time come from neighboring countries and represent a high level of complexity. Positions with a 12-week lead time are transported from Asia to Poland using trains. These are the elements that, compared to other positions, may sometimes have issues with material availability for production. The two cases considered here were tested based on the logic shown in Figure 1.

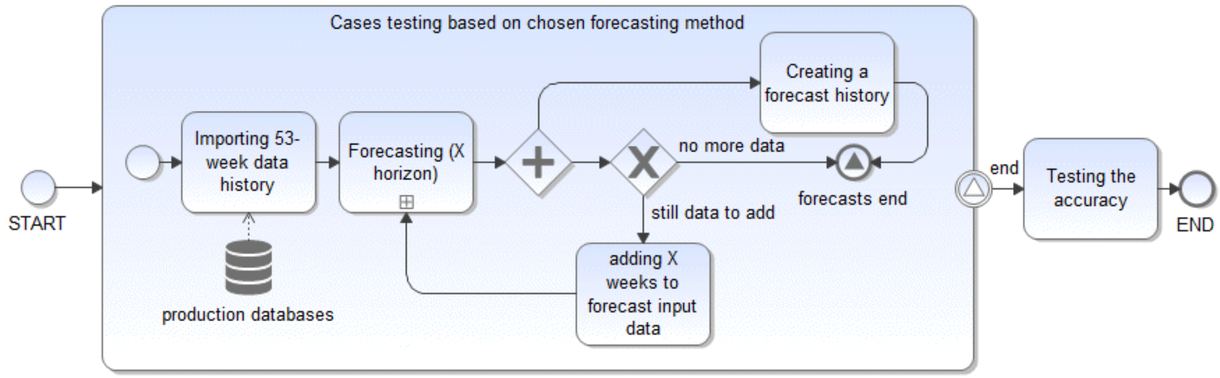

Fig. 1. Workflow of accuracy testing process. Source: Authors' own work.

The initial data for the analysis related to 53 weeks from 2020, and the data on which the results were tested comes from mid-2021. Forecasts were made in weekly granulation. The forecast horizon (X in the figure) was the time needed to complete the order and matched the periods of updating the forecasting tools with new data. There are four groups of products in the company, broken down by waiting for the order, hence X was 1,2,3or 12. For each of the groups, the 3 most important materials ordered by the company were selected. Thus, the cases that were discussed concerned the verifiability of forecasts for 12 products. The particular forecasting method approaches are explained below.

First case - supply based on demand forecasting tool

In this case, a tool based on a modified ARIMA (Autoregressive Integrated Moving Average) algorithm was proposed to control the supply system. ARIMA is a time series forecasting model that is commonly used in statistical analysis to understand the pattern of data over time and forecast future values based on the patterns found. ARIMA models can be used to model and forecast data that has three key characteristics: stationarity, autocorrelation, and seasonality. Stationarity refers to the property of a time series that has a constant mean and variance over time. Autocorrelation refers to the property of a time series, where the values of the series at different time points are correlated with each other. Seasonality refers to the property of a time series that shows regular patterns or cycles over a fixed period of time, such as daily, weekly, or monthly (Hyndman and Athanasopoulos, 2018).The ARIMA model is built by combining the AR (Autoregressive) model, the MA (Moving Average) model, and the differencing method. The AR component models the dependence of the current value on past values of the same series, while the MA component models the dependence of the current value on past errors. The differencing method is used to remove the trend and seasonality of the series, making it stationary and easier to model (Box et al., 2015). ARIMA models are commonly used in demand forecasting because they are able to capture the complex patterns and trends often found in demand data, such as seasonality and autocorrelation. The tool presented in the following paper returns the best ARIMA model, according to either AIC, AICc or BIC values. The function conducts a search for a possible model within the order constraints provided. The algorithm chosen is provided by *library(forecasts)* at R programming language and it is called *auto.arima(),* so the forecasts were calculated in the following parameters:

forecast <- auto.arima(DATA, lambda = "auto", biasadj = TRUE)

The whole script which was used for forecasts calculation is available at the appendix (Appendix 1).

The use of the auto.arima() function was motivated by the fact that currently in demand forecasting, ARIMA-based algorithms are among the most commonly used for predicting demand. It is often the case that ML-(machine learning) supported algorithms are also algorithms related to the one presented. In the later part of the article, the terms ARIMA, auto.arima, and Aarima are used interchangeably to describe the presented algorithm.

Second case - demand forecasting based on ChatGPT

The forecast was generated using Chat GPT. The forecasting process was carried out in two stages. The first stage involved ChatGPT generating a template, which enabled further forecasting. This was made possible by making the query "Generate a template that will allow you to make a forecast of material consumption." In response, Chat GPT generated the following template that needs to be filled in.

- Forecast period (weeks, months, quarters, etc.):
- Type of production downturns (quantitative, qualitative):
- Time range for which historical data is available:
- Observation frequency (daily, weekly, monthly, quarterly):
- Historical data (please attach data in the appropriate format, e.g., spreadsheet):
- Factors that may affect the variability of production downturns (e.g., weather, seasonality, holidays, etc.):
- Forecast objective (production planning, human resource management, etc.):
- Any other information that may impact on the forecast (e.g., changes in the production process, changes in the company's strategy, etc.)
- The second step was to send ChatGPT the completed form for each item.
- Forecast period (weeks, months, quarters, etc): **Weeks;**
- Type of production downturns (quantitative, qualitative): **Quantitative;**
- Time range for which historical data is available: **53 weeks (for the initial inquiry.**

For each subsequent inquiry, this value was increased by the delivery time);

- Observation frequency (daily, weekly, monthly, quarterly): **Weekly;**
- Historical data (please provide data in the appropriate format, e.g., spreadsheet):

Historical demand for individual items has been implemented as the data;

- Factors that may affect the variability of production downturns (e.g., weather, seasonality, holidays, etc.): **Seasonality and weather;**
- Forecast objective (production planning, human resource management, etc.):

Production planning;

- Other information that may impact on the forecast (e.g., changes in the production process, changes in the company's strategy, etc.): **None.**

As an additional element, a request was added to provide a forecast in the form of a table for the next 26 weeks.

To evaluate the forecast accuracy, indicators such as MAPE, RMSE and MAE were used.

The authors are aware that these are not the only methods for measuring the accuracy of forecasts. Among other measurement methods, one can mention the Janus coefficient (Anderson, 2012) or the regression coefficient (Maciejowska et al., 2016). The authors chose to use the aforementioned indicators considering that these are measures frequently used both in practice and by researchers in publications describing the issues of verifiability and accuracy of forecasts (this is discussed, for instance, in the works of Chicco et al. (2021); Zhou et al. (2018); and Ostertagova and Ostertag (2012)). The authors are also aware of the issue associated with the correct selection of an indicator for forecast assessment and the problems and risks of choosing only one indicator for verifiability assessment. Therefore, in the subsequent analysis, they decided to test various indicators and, based on a weighted assessment, select the best forecast. The use of weighted assessment for the final verifiability evaluation is mentioned, among others, in the works of Kramarz and Kmiecik (2022), Sohrabpour et al. (2021), and Qi et al. (2014). The authors calculated the MAPE, RMSE, and MAE indicators using standard formulas.

Mean absolute percentage error (MAPE) is defined by the formula (Jeżyk and Tomczewski, 2014):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_i - y_p}{y_i}\right|$$

where:
y_p – represents the predicted value;
y_i – represents the actual value;
n – represents the number of periods.

The root mean squared error (RMSE) is defined by the formula (Hodson, 2022):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_p\right)^2}$$

where:
n – represents the number of periods;
y_p – represents the predicted value;
y_i – represents the actual value.

The mean absolute error (MAE) is defined by the formula (Chai, 2014):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_p\right|$$

where:
n – represents the number of periods;
y_p – represents the predicted value;
y_i – represents the actual value.

RESULTS

In this study, two forecasting models generated by ChatGPT and an ARIMA-based algorithm were compared. Performance evaluation of the forecasts was done using indicators such as MAPE, RMSE, and MAE. Figure 2 presents a comparison of forecast results by ChatGPT and ARIMA based on the MAPE indicator.

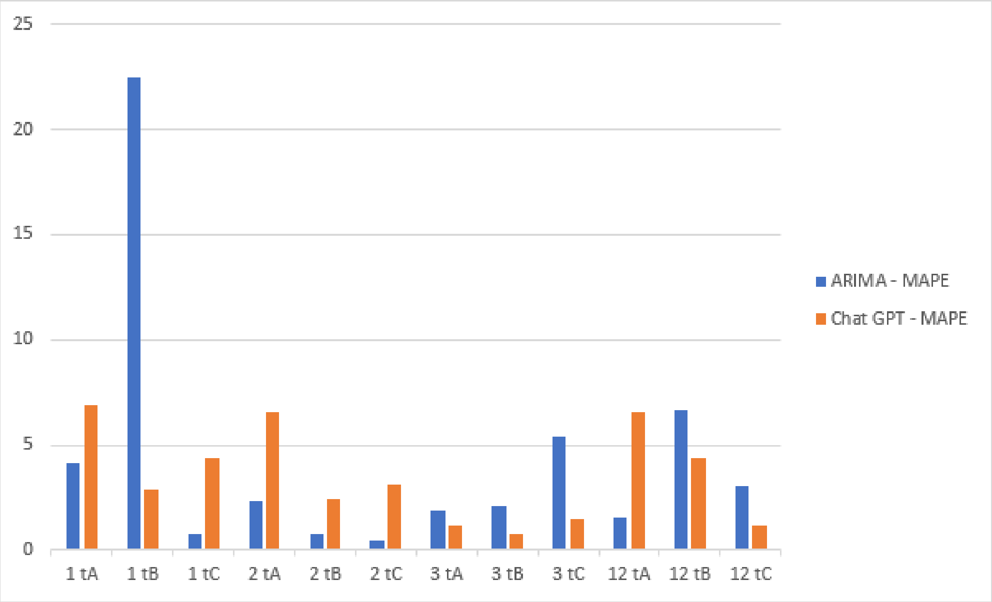

Fig. 2. Comparison of forecast results generated by ChatGPT and ARIMA based on the MAPE indicator. Source: Authors' own analysis based on data from the company.

By evaluating the forecast performance using the MAPE indicator, which measures the deviations of forecasts from actual values, it was assumed that lower MAPE values indicate smaller forecasting errors and greater accuracy of the model's predictions (Tofallis, 2013). The analysis of the results revealed that the forecasts generated by ARIMA were more accurate compared to ChatGPT for 6 references: 1 tA, 1 tC, 2 tA, 2 tB, 2 tC, and 12 tA. On the other hand, the forecasts generated by ChatGPT were more accurate for 6 references: 1 tB, 3 tA, 3 tB, 3 tC, 12 tB, and 12 tC. Analyzing Figure 2, a significant disparity can be observed between the two forecast models for each reference. Through analysis, it can be inferred that ARIMA made more accurate forecasts for references with a short LT (1-2 weeks). Meanwhile, ChatGPT proved to be more precise for references with a longer LT exceeding 3 weeks. Figure 3 presents a comparison of forecast results generated by ChatGPT and ARIMA based on the MAPE indicator.

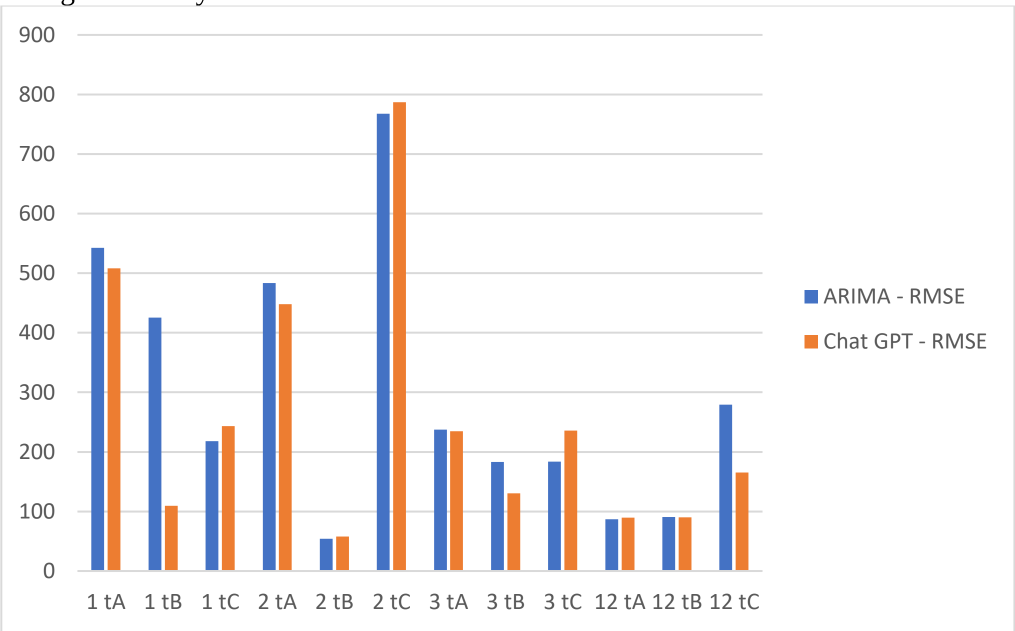

Fig. 3. Comparison of forecast results generated by ChatGPT and ARIMA based on the RMSE indicator. Source: Authors' own analysis based on data from the company.

The effectiveness of the forecast models was analyzed using the RMSE indicator, which measures the average squared error between the forecasted values and the actual data. Utilizing the RMSE indicator, smaller values indicate smaller deviations of forecasts from reality and greater accuracy of the predictive model (Botchkarev, 2018). The forecasts generated by ARIMA were more precise for the references: 1 tC, 2 tB, 2 tC, 3 tC. On the other hand, the forecasts generated by ChatGPT were more precise for the references: 1 tA, 1 tB, 2 tA, 3 tB, and 12 tC. References that obtained very close RMSE values for both forecasts are: 3 tA, 12 tA, 12 tB. Based on this analysis, it can be inferred that the forecast model generated by ARIMA is more accurate for positions with an LT of 2 weeks, while ChatGPT produced a forecast that achieved better results in terms of the RMSE indicator for positions with an LT of 1 week. Figure 4 presents a comparison of forecast results generated by ChatGPT and ARIMA based on the MAE indicator.

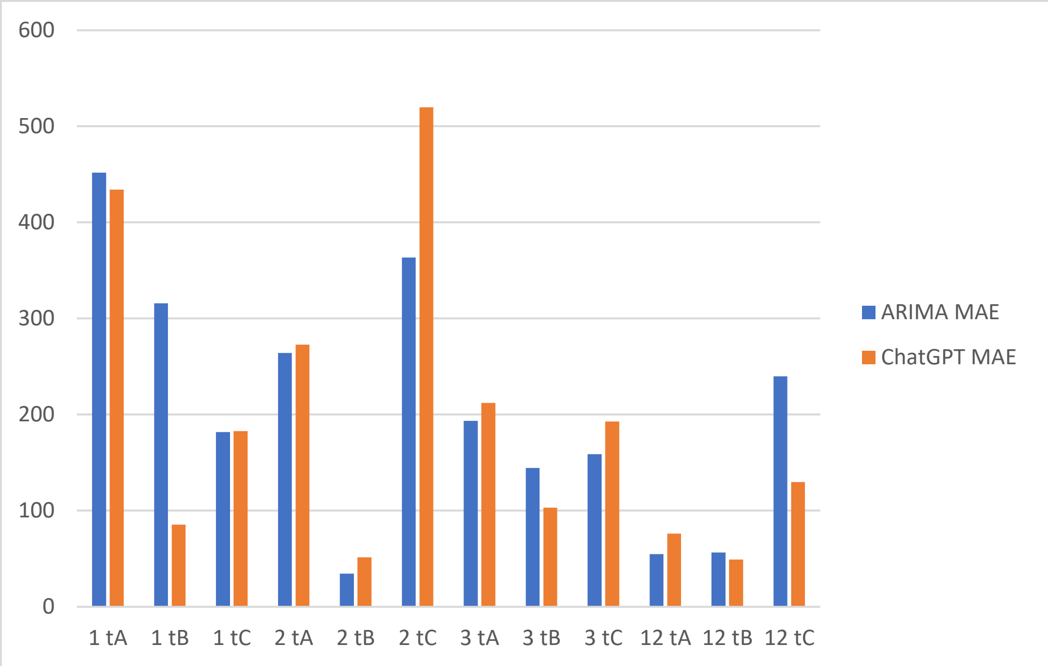

Fig. 4. Comparison of forecast results generated by ChatGPT and ARIMA based on the MAE indicator. Source: Authors' own analysis based on data from the company.

Another analysis of the forecast models' effectiveness was based on the MAE indicator, which measures the average absolute error between the forecasted values and the actual data. The smaller the value, the smaller the forecasting errors and the greater the accuracy of the predictive model (Robeson, Willmott, 2023). This analysis revealed that the forecast model generated by ARIMA achieved better results compared to ChatGPT for references such as 2 tA, 2 tB, 2 tC, 3 tA, 3 tC, 12 tA. On the other hand, ChatGPT proved to be more effective for references 1 tA, 1 tB, 3 tB, 12 tB, and 12 tC. The reference that obtained very close RMSE values for both forecasts was 1 tC. Based on this data, it can be inferred that the forecast generated by ARIMA was more accurate primarily for positions with an LT higher than 2 weeks, while ChatGPT proved to be more precise for positions with an LT of approximately one week. The final evaluation of ChatGPT's performance and the ARIMA-based algorithm is presented in Table 1. The weights and comparison intervals were consulted with managers responsible for assortment management and procurement operations.

Table 1. Final assessment for the analyzed cases.

		Total result (A)	Weight (B)	Final result (A * B)	Solution final score (C)
ChatGPT	MAPE	7.5	0.4	3	7.3
	RMSE	8	0.2	1.6	
	MAE	7.5	0.2	1.5	
	Number of better results	6	0.2	1.2	
Aarima	MAPE	6	0.4	2.4	5.8
	RMSE	4	0.2	0.8	
	MAE	7	0.2	1.4	
	Number of better results	6	0.2	1.2	

Source: Authors' own analysis based on data from the company.

The evaluation of references was based on intervals developed by the company that agreed to provide data for research purposes. For each reference, MAPE, RMSE, and MAE indicators were calculated using a specific forecasting model. The comparison of forecasts based on the analysis of these indicators allowed values to be identified that represent the absolute difference between the specific indicator results for a given reference, presented as a percentage of the highest absolute difference value. For each reference, unified intervals were adopted based on different indicators, as utilized by the company according to the following logic:

- 0.5 if the percentage of the absolute difference for a specific indicator falls within the range of 0-5% for a given reference;
- 1 if the percentage of the absolute difference for a specific indicator falls within the range of 5%-40% for a given reference;
- 2 if the percentage of the absolute difference for a specific indicator falls within the range of 40%-80% for a given reference;
- 3 if the percentage of the absolute difference for a specific indicator falls within the range of 80%-100% for a given reference.

The results were summed for each forecast accuracy indicator (column A), and then the results were multiplied by specified weights. The determination of weights for different indicators has been previously presented by Kramarz and Kmiecik (2022), among other researchers. In this article, the authors arbitrarily assigned the following weights: MAPE - 0.4; RMSE - 0.2; MAE - 0.2, and the number of better results - 0.2. This provided the basis for calculating the weighted assessment and determining the final evaluation of the two proposed tools (column C). Based on the above steps, it was concluded that in the case examined here, ChatGPT is a better solution for forecasting than Aarima (ChatGPT score - 7.3; Aarima score - 5.8).

DISCUSSION

Forecasting is an incredibly important element of decision-making processes. Errors in forecasting can lead to significant losses. Underestimation results in potential profit loss, while overestimation increases the costs for the company (Duda, 2017). One of the key areas that can be utilized in forecasting is product sales (Duda, 2016). The present study focuses on evaluating the accuracy of forecasts generated by ChatGPT and ARIMA. In this article, ChatGPT achieved better reliability in terms of the generated forecasts compared to the algorithm it was compared with. This provides a basis to explore the potential use of ChatGPT as a tool for forecasting demand in a manufacturing company. Due to its forecasting capabilities, this tool can support the assortment management system conducted within the company.

The use of the auto.arima() algorithm has many advantages. The ARIMA-based model is a model that is one of the most commonly used models for forecasting demand in business operations (Fattah et al., 2018). Using this algorithm and modifications to it provides a wide range of possibilities in assortment management supported by forecasting. On the other hand, ChatGPT is a relatively new tool that also enables forecasting, as observed in stock price movement forecasting (Lopez-Lira and Tang, 2023), forecasting the effects of global warming (Biswas, 2023), and forecasting activity in the textile industry (Rathore, 2023). However, forecasting demand or other variables is an ongoing development. Based on the research conducted and the case study mentioned previously, it can be stated that ChatGPT can be used in a company to forecast the demand for products ordered by a manufacturing company. The ChatGPT forecasting algorithm operates correctly and provides relatively good results when compared to those obtained using auto.arima. However, integrating the ChatGPT tool with the systems currently used in the company can be problematic. H1 was verified negatively, as the tested ChatGPT tool in its basic form is difficult to implement in business operations. This is due to the fact that data operations (such as import and export) are limited in terms of the number of characters manually entered by the user or generated by the tool. One potential solution could be to implement the GPT language itself as a plugin for the ERP software currently used in the company (Chen et al., 2023). H2 was verified positively, as ChatGPT can improve the accuracy of plans in assortment management both in short- and long-term order fulfillment. ChatGPT demonstrated better reliability in forecasting compared to the standard ARIMA-based forecasting tool. In order to integrate ChatGPT into business operations, it would need to demonstrate the ability to integrate and utilize the GPT language model as a plugin for the currently employed solution. Full integration between the ERP system used in the company and the GPT language is necessary to ensure smoothness and efficiency in the forecasting process. In ChatGPT, appropriate prompts can also be specified to automate the process of requesting a forecast. However, a significant issue for long-term use of ChatGPT is the fact that most machine learning models degrade over time (Vela et al., 2022), thus there is a risk of decreased reliability of forecasts in the longer term. Additionally, the use of such solutions often raises questions regarding copyright, data processing security, and confidentiality when utilizing such solutions for sharing a company's know-how (Oviedo-Trespalacios et al., 2023). This risk, along with the lack of standardization in the utilization of large language models based on machine learning and artificial intelligence, can lead to opportunism in the implementation and use of such solutions by businesses.

CONCLUSIONS

From the research on generating forecasts using ChatGPT, several important conclusions regarding this tool can be observed. Firstly, it is not possible to attach any data files to the conversation with ChatGPT, which means that all data must be manually copied and pasted. This method can be time-consuming, especially when generating forecasts for a large number of references. Another issue is the possibility of interruption during the generation of a forecast at random moments. In such cases, it is necessary to resend the completed form, resulting in an extended time dedicated to the forecast generation process.

Another important aspect is the format of the forecasts generated by ChatGPT, which is presented in textual form. Transferring data from the OpenAI platform to a program for further analysis may require additional operations. This entails additional effort and potential risks of errors when transferring the data.

In summary, despite certain limitations and inconveniences associated with using ChatGPT for generating forecasts, the tool has demonstrated higher accuracy compared to auto.arima in estimating production outputs. However, further investigation and refinement of the forecast generation process using ChatGPT are necessary to optimize the time and efficiency of this tool.

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APPENDIX

Appendix 1: Forecasting script for auto.arima() for the items with 12 weeks of forecasts horizon and 12 weeks of data updating.

```
library(readxl)
data <- read_excel("data_file_path") #import of data from .xlsx
data$quantity <- abs(data$quantity) # change the quantities to absolute value
X <- 12 #setting the forecasts horizion and update period for forecasts X = OR(1;2;3;12)
library(forecast)
forecast <- auto.arima(data[1:53, "quantity"], lambda = "auto", biasadj = TRUE) #forecasts by using
an auto.arima() function
forecast_sheet <- data.frame(Forecast = forecast(forecast, h = X)$mean * -1) #first forecasts
write.xlsx(forecast_sheet, "output_path")
# Creation and update condition based on X parameter
if(X == 12) {
  update <- 3
} else if(X == 3) {
  update <- 9
} else if(X == 2) {
  update <- 13
} else if(X == 1) {
  update <- 26
}
# Data update and creation of next Excel sheets with forecasts
for(i in 1:update) {
  data <- rbind(data, data[nrow(data), ])
  forecast <- auto.arima(data[(nrow(data)-52):nrow(data), "quantity"], lambda = "auto", biasadj =
TRUE)
  forecast_sheet <- data.frame(Forecast = forecast(forecast, h = X)$mean * -1)
  write.xlsx(forecast_sheet, paste0("output_path", i+1, ".xlsx"))
}
forecast_sheet$Forecast <- forecast_sheet$Forecast* -1
library(openxlsx)
output_sheet <- createWorkbook()
for(i in 1:(update+1)) {
  sheet <- read.xlsx(paste0("output_path", i, ".xlsx"), sheet = 1)
  addWorksheet(output_sheet, sheetName = paste0("Arkusz ", i))
  writeData(output_sheet, sheet = i, x = arkusz)
}
saveWorkbook(output_sheet, "output_path")
```

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