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Supply and demand prediction by 3PL for assortment planning

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CHRONICLE

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ABSTRACT

To underscore the critical role of predictive capabilities in third-party logistics (3PL) companies for assortment planning, particularly within the rapidly evolving e-commerce sector and business to business (B2B) flows. This study employs a comprehensive literature review on the forecasting capabilities of 3PL firms, enriched by empirical research across nine logistics facilities. It leverages statistical tools and the ARIMA_PLUS algorithm to evaluate the precision and dependability of demand and supply forecasts generated by these companies. The research reveals that 3PLs possess the ability to generate accurate demand and supply forecasts utilizing advanced forecasting tools. The effectiveness of these forecasts is closely linked to the quality of data available, and the expertise of the personnel involved. Challenges arise in forecasting for smaller order volumes, which are more common in e-commerce flows. The study also highlights that technological advancements and investments in data analytics are pivotal in enhancing forecast accuracy. The investigation focuses on a select group of 3PL companies, potentially limiting the generalizability of the findings. Moreover, the study underscores the necessity for further exploration into how technological innovations impact forecasting capabilities. By emphasizing the significance of 3PL firms' predictive abilities, also for e-commerce assortment planning, this paper addresses a notable gap in existing research. Its insights are invaluable for businesses contemplating logistics outsourcing and for 3PL providers aiming to advance their forecasting proficiency. The findings stress the importance of integrating advanced forecasting models and analytics to stay competitive in the dynamic e-commerce landscape.

1. Introduction

In the era of globalization, the business landscape is becoming increasingly competitive, with companies vying for a dominant position in international markets. In this constantly changing environment, supply chain optimization emerges as a key factor in gaining a competitive edge (Worthmann et al., 2016; Jin et al., 2020; Pujiastuti et al., 2023). Striving to streamline operations and expand their market reach, companies are increasingly turning to specialized external firms, such as third-party logistics (3PL) providers, which play a crucial role in managing logistics and supply chain functions across various industry sectors. Effective supply chain management relies on the ability to accurately forecast both demand and supply (Guo et al., 2022; Yang & Manickam, 2023). Such forecasts enable companies to meticulously plan their inventory levels (Zougagh et al., 2020), leading to significant cost reductions (Liu & Wang, 2011) and improved customer service (Zeng, 2020). Accurate forecasting not only allows companies to align with customer expectations but also enables them to maintain control over operational costs. Given these significant benefits, an urgent question arises regarding the ability of 3PL enterprises to generate precise demand and supply forecasts. The importance of this issue is underscored by the growing number of companies considering outsourcing logistics functions and their desire to determine whether partnering with 3PL firms will enhance their forecasting capabilities for demand and supply. Hence, we pose the following research question:

RQ.1: Can a 3PL enterprise effectively create demand and supply forecasts within the distribution network?

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This article aims to delve deeply into the predictive capabilities of 3PL firms through a comprehensive examination of existing literature and the presentation of empirical research findings. An integral aspect of this analysis will be the identification of key factors that may influence the forecasting efficiency of these enterprises. Particular attention will be paid to elements such as the technologies employed by 3PL firms, the availability and quality of data on which forecasts are based, and the overall experience and expertise of these companies within the logistics sector. In addressing these questions, we aim not only to elucidate the capabilities of 3PL enterprises but also to highlight their potential to revolutionize the dynamics of supply chain management, ultimately impacting the competitive landscape in a globalized world, with a special emphasis on the significance of these capabilities in the context of e-commerce flows.

2. Theoretical background

2.1 Research gap

The literature gap analysis was supported by the VOSviewer tool, which was used to search the SCOPUS database. The database was searched for articles, conference papers, and book chapters, and results were narrowed down to only English-language publications. SCOPUS was searched for records containing at least one of the following keywords in author keywords, publisher keywords, or abstract: “supply management”; “demand management”; “supply coordination”; “demand coordination”; “3PL”; “logistics service provider”; “demand forecasting”. The results were further narrowed to fit the disciplines of this study, namely, social sciences, and business, management and accounting. The analysis narrowed down publications to 7,727 documents (with data available up to September 2023). From the obtained results, author keywords and publisher-assigned keywords were extracted, and a connection map between these words was created using VOSviewer software (figure 1). The map was developed using the association strength method with weights total link strength. Clustering was performed with the following settings: resolution equal to 1 and min. cluster size equal to 1.

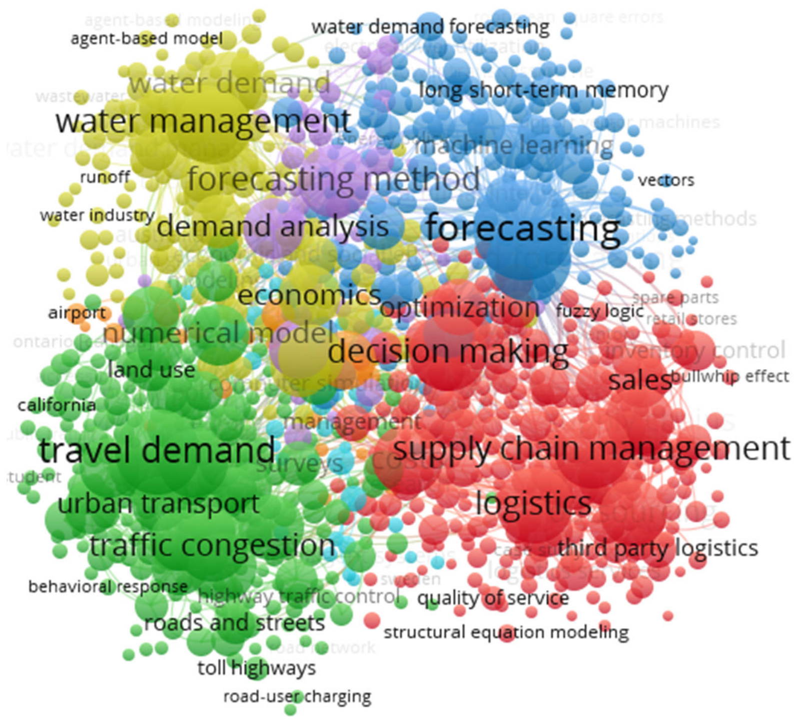

Fig. 1. General overview of keywords connection map

In the map depicting cluster analyses, five predominant thematic areas stand out, drawing particular attention to themselves. They all share a common denominator - each area encompasses at least one of the keywords selected by the author. This approach allows us to track the interrelatedness of topics and how often they appear together in literature or other data sources. The first of these areas focuses on supply chain and logistics analyses. Contemporary markets are becoming increasingly complex, and managing the supply chain has become a critical element of success for many businesses. Research in this domain centers on process optimization, cost minimization, and maximizing efficiency. The next cluster pertains to demand analysis. Understanding the dynamics of demand is essential for businesses that seek to tailor their offerings to consumers' needs and expectations. In this field, researchers and practitioners concentrate on market research, trend identification, and consumer behavior analysis. The third area encompasses forecasting and statistical forecasting methods. In an era of unpredictable market changes and global challenges, the ability to forecast is exceedingly valuable. Statistical techniques, mathematical models, and information technology tools play a pivotal role in accurate and reliable forecasting. The fourth cluster revolves around economics and water resource management. Amidst global climate change and increasing pressure on natural resources, water management has become a priority. Research in this domain is concerned with the efficient use of water, source protection, and crisis management strategies. The final, fifth area addresses urban transport management in the context of city logistics. With the growing urbanization and the need for efficient traffic management in metropolises, these issues have become highly relevant. Research is centered on route optimization, the integration of various modes of transportation, and the impact of transportation on residents' quality of life. Fig. 2 displays the clusters formed in conjunction with the selected analyzed keywords.

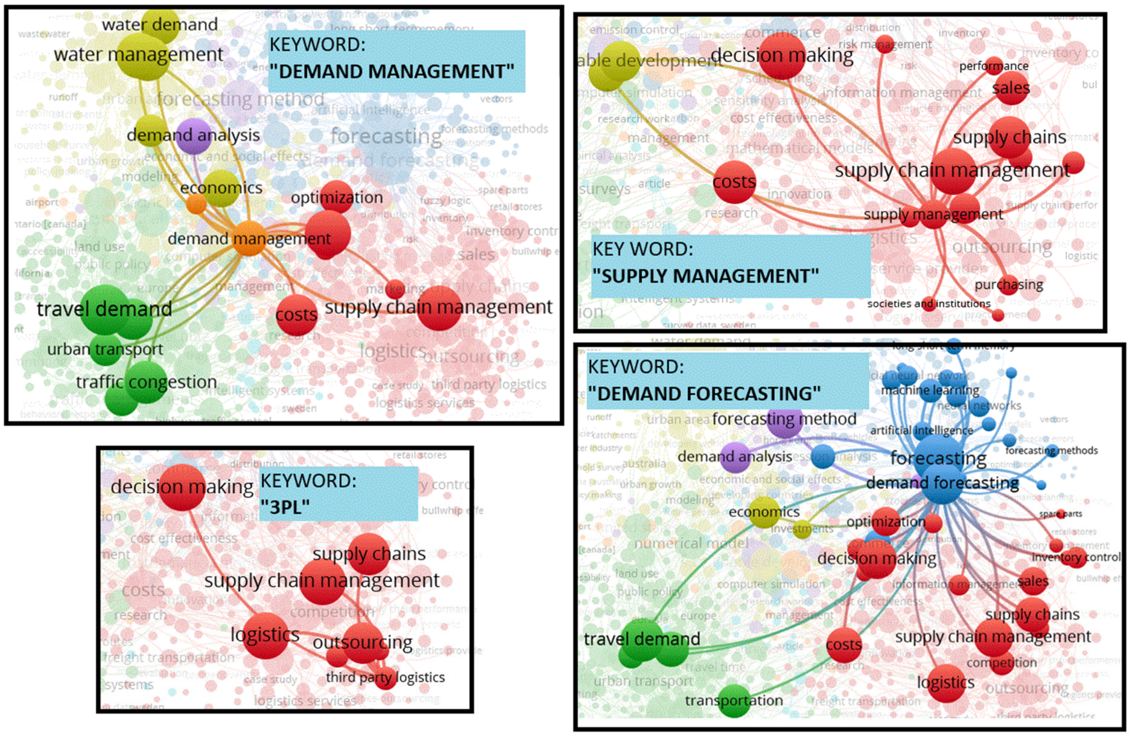

Fig. 2. Clusters and connections – main keywords

In light of the analyses conducted on maps related to demand management, we observe fascinating correlations in the area of logistics. It clearly reveals that the topic of demand management is closely and inherently linked to supply chain management. This significant linkage may result from the increasing need for process optimization and understanding how demand impacts the entire supply chain. A similar pattern can be seen in the area of supply management. In analyses, supply management appears as a topic deeply rooted in supply chain and procurement management. This correlation underscores the importance of understanding the flow of goods and information throughout the chain, from the producer to the end consumer. However, demand forecasting, although also related to supply chain management, shows a slightly different pattern. It is less directly related to supply chain management but demonstrates stronger links with inventory management and decision-making. This aspect emphasizes the importance of demand forecasting in inventory planning and adaptive decision-making in dynamically changing market conditions. It is also interesting that demand forecasting is deeply anchored in the context of data analysis. In the era of digitization and big data, the ability to analyze and interpret complex data sets has become crucial for effective demand forecasting. Finally, when analyzing positions related to 3PL (third-party logistics providers), one can notice their connections with both supply chain management and decision-making. However, they do not show strong correlations with previously mentioned keywords such as demand management, supply management, or demand forecasting. This may indicate the specificity of the 3PL market and its unique challenges and needs, differing from other areas of logistics, and a gap in this area that this article aims to fill.

2.2 Supply and demand management by 3PL

When choosing a logistics service provider, appropriate evaluation criteria are essential. There are many studies on this topic, including those conducted by researchers like Singh et al. (2018). However, an approach based solely on criteria can lead to cooperation problems, especially if logistics companies are treated only as suppliers limited to specific contracts. Huo et al. (2015) highlight such a risk, emphasizing that relationships with logistics providers should be more partnership-oriented. Darko and Vlachos (2022) also point to the importance of valuable relationships with suppliers in the context of their case studies. Academics dealing with supply management, as shown by studies conducted by Metminod et al. (2019), have shown great interest in the relationships between sellers and buyers of logistics services. This interest can be explained by manufacturers and major retailers developing outsourcing strategies, leading to the emergence of powerful logistics service providers. Logistic companies (3PL) play a key role in integration and coordination in supply chains. As Mortensen and Lemoine (2008) noted, 3PLs are essential for effective integration with manufacturers. Other researchers, like Tyan et al. (2003) and Gürler et al. (2014), emphasize their role in coordinating transport and warehousing operations. 3PLs not only positively influence customer experiences (Sheikh & Rana, 2011; Wu et al. 2023) but also play an important role in matters related to ecology and sustainable development (Liu et al. 2020; Hassanzadeh et al. 2022). 3PLs are not just integrators, but also serve as orchestrators of the supply chain, as highlighted in studies by Mir et al. (2021) and Zacharia et al. (2011). They are capable of managing and coordinating, and in some cases, even acting as sub-coordinators (Jiang et al. 2019). They are indispensable in information management and information flow in the supply chain, confirmed by studies by Carrus and Pinna (2011) and Pinna et al. (2010). Although the idea of fully utilizing 3PLs as coordinators is rarely discussed (e.g., in the works of Kmiecik (2022a, 2022b, 2023) or Kramarz and Kmiecik (2022)), it is essential to fully exploit their potential in line with management and business concepts.

The issue related to demand and supply management is discussed by researchers much less frequently, and when it is discussed, it is not holistic. Authors usually focus either on demand management or on supply management. For example, a study conducted by Karia et al., (2015) emphasizes the need for 3PL managers to focus on developing and combining their demand management skills and knowledge resources to achieve a cost advantage. Furthermore, incorporating advanced technology into such a resource and capability set is recommended to achieve innovations in customer service. Demand management by 3PL is also discussed as one of the factors in a benchmarking assessment model by Mohanty and Shankar (2020). Krasnov et al. (2019) consider the supply management process, the procurement side, by 3PL when different means of transport are used and an intermediate distribution center. On the other hand, supply management from the perspective of 3PL in the supply chain is extensively discussed in Huemer's (2012) work based on studies conducted in Scandinavian countries. Demand and supply management is the foundation of effective supply chain operation. Demand management allows companies to anticipate and respond to changing market needs (Croxton et al., 2002). Through the analysis of historical data, forecasting trends (Mentzer & Moon, 2004), and collaboration with sales and marketing departments (Currie et al., 2018), companies can better adjust their production and inventories to the actual needs of the market, thereby minimizing the risk of overproduction or product shortages. On the other hand, supply management focuses on ensuring an adequate quantity of raw materials, components, and finished products (Kahkonen, 2014). Through effective negotiations with suppliers, monitoring their performance, and building lasting relationships, companies can reduce costs, improve delivery quality, and shorten order lead times. Modern technologies, such as enterprise resource planning (ERP) or advanced supply chain management (SCM) systems, enable the integration of demand and supply management processes (Nettsträter et al., 2015), leading to a more flexible and resilient supply chain. As a result, effective demand and supply management contributes to increasing a company's competitiveness, better understanding the market, and building stronger relationships with business partners. In some publications, authors point to the great importance of coordinating actions related to supply and demand management (Gligor, 2014; Cox et al., 2005; Mahmood and Kess, 2015) especially from the perspective of sustainable.

2.3 Prediction activity of 3PL

Predicting is the inference of unknown events based on known events. The essence of such reasoning is the assumption that unknown events might depend on the past. Hence, one can anticipate one of the following phenomena: an event will occur because it happened in the past, or its frequency of occurrence suggests it, or it is strongly associated with another event or events that have occurred (Harvey, 1984). A forecast is based on the fullest possible and objective information and is determined using scientific methods (Poll et al., 2018). In distribution networks and other economic practices, it can be inferred that a certain event will occur if: it has occurred in the past, its frequency of occurrence suggests it, or a strong correlation with another event or events that have occurred or are expected to occur suggests it. Phenomena occurring in systems can be characterized by quantitative variables (expressed in quantities) and qualitative variables (described descriptively) (Caniato et al., 2011). The basic forecasting scheme includes transforming past data using a particular model and a forecasting rule into data attempting to map future values, i.e., forecasts. Forecasting is the process of determining the most probable verdict of what the demand level will be in the future based on a set of assumptions based on statistical inference integrated with the analysis of events, phenomena, and facts that happened in the past (Mentzer & Moon, 2004). Methods and types of forecasts are a frequent topic in the literature. It contains many criteria and attempts to group methods. A forecast is considered an essential source of information for preparing logistical plans (Fuqua & Hespeler, 2022), including plans related to distribution and collaboration in distribution networks, and stocks in both distribution networks and supply chains should typically be treated as the ultimate mechanism balancing supply and demand (Ivanov et al., 2016). Forecasting is recognized as one of the key elements of organization management (Morlidge & Player, 2010) and as a category of risk (Christoffersen & Diebold, 2000) in material flows. It affects determining production capacities and methods of production and service delivery, indirectly influencing elements such as the number of employees, cost levels, etc. Risk factors associated with forecasting include: their imprecision, seasonality, product differentiation, short product life cycles, a small customer base, and information distortion. Demand fluctuations can imply inventory management issues (Patil and Divekar, 2014). Forecasts are always burdened with some error. They never describe a phenomenon with 100% accuracy. Uncertainty of demand forecasts arises from the facts that the company will never have full information about buyers, competitors' initiatives can influence actions taken, and the environment is uncontrollable by the company and can change. Many different forecasting methods can be found in the literature, but one of the most frequently used, mainly because of its high verifiability, is the ARIMA (autoregressive integrated moving average) algorithms. The significance and multiplicity of the use of such models are emphasized by Ariyo et al. (2014) and Fattah et al. (2018). ARIMA consists of autoregressive models and moving averages. Autoregressive-type models play a significant role among forecasting models. A characteristic feature of these models is that they show a functional relationship between the values of the forecasted variable in period t and the values of this variable from previous periods (t-1, t-2, … , t-p) with accuracy to the random component. Such models can be used in forecasting demand for durable goods, where there are delay cycles associated with the period of using these goods. Another feature of autoregressive models is that they dispense with the use of many explanatory variables (Wong & Li, 2000). This is particularly important in situations where it is known which explanatory variables should be included in the considerations, but there are problems with collecting the appropriate numerical data. Main ARIMA model elements are described at Table 1.

Table 1
The main elements of ARIMA model

ARIMA element	Equation	Brief description
An autoregression process of order p (AR(p))	$Y_t = \varphi_0 + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \varepsilon_t$	$\varphi_0, \varphi_1, \varphi_2, \dots, \varphi_p$ – parameters of autoregression model; ε_t – random disruptions; p – autoregression row.
The moving average	$\bar{y}_t^{(n)} = \frac{\sum_{i=1}^{n} y_t}{k}$	$\bar{y}_t^{(n)}$- n-period moving average, calculated after period t (t-1, 2, …) y_t – value of vairable in t-period k – number of periods considerated during averaging
The weighted average	$y_{t+1}^{*} = \sum_{i=t-k+1}^{t} y_i w_i$	w_i – number of weights ($w_1 < w_2 < \cdots < w_k \leq 1$, to: $\sum_{i=1}^{k} = 1$)
The MA(q) process in ARIMA models, under the assumption that only the first q weights of the linear process are non-zero	$Y_t = \mu + \varepsilon_t - \vartheta_1 \varepsilon_{t-1} - \vartheta_2 \varepsilon_{t-2} - \cdots - \vartheta_q \varepsilon_{t-q}$	$\varepsilon_t, \varepsilon_{t-1}, \dots, \varepsilon_{t-q}$ – random disruption in the periods t, t-1, …, t-q, $\mu, \vartheta_1, \vartheta_2, \dots, \vartheta_q$ – model parameters , q – delay parameter.
ARIMA – general model	$Y_t = \varphi_0 + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} - \vartheta_1 \varepsilon_{t-1} - \vartheta_2 \varepsilon_{t-2} - \cdots - \vartheta_q \varepsilon_{t-q} + \varepsilon_t$	

Source: elaborated based on: Brandt and Williams (2001); Klinker (2011); Holt (2004); Shumway et al. (2017); Benvenuto et al. (2020).

To better tailor the model for a specific time series, the autoregressive process AR(p) has been combined with the moving average process MA(q). The moving average method focuses on replacing the original time series with forecasted values calculated for each of the k most recent observations (Hunter, 1986). The moving average method is typically used for short-term forecasting, usually one period ahead. The main challenge in this approach is the proper determination of the number of time series periods included in the averaging. It involves a smoothing constant that defines the number of actual values of the forecasted variable that are averaged.

Table 2
Information criterias in ARIMA model

Abbrevation for information criteria (IC)	Full name of IC	Brief characteristic	Equation
AIC	Akaike Information Criterion	Used for comparing statistical models. It doesn't provide information about the fit of the model to the data but is useful in measuring the predictive power of the tested models. The AIC and AICc criteria tend to choose models with too many parameters.	$AIC = 2K - 2\ln L(\Theta)$,where: K – number of models parameters; $L(\Theta)$ – likelihood function for a significant model
AICc	Corrected Akaike Information Criterion		$AICc = AIC + \frac{2K^2 + 2K}{N - K - 1}$,where: N – number of observations,; K – number of parameters; $L(\Theta)$ – likelihood function for a significant model
BIC	Bayesian Information Criterion	It selects a statistical model in which the balance between the simplicity of the model and its fit quality is optimal.	$BIC = K\ln(N) - 2\ln L(\Theta)$,where: N – number of observations,; K – number of parameters; $L(\Theta)$ – likelihood function for a significant model

Source: elaborated based on: Burnham and Anderson (2021); Sarpong (2013)

The larger the k, the smoother the time series becomes, meaning outlier observations will have a diminishing influence on the model, but concurrently, as k increases, more information is lost. Models based on the moving average, similar to exponential smoothing models, are categorized as adaptive models (Carbone, 2009; Peels et al., 2009). The arithmetic moving average model reduces random fluctuations but does not consider the temporal distance of data from the forecast. This can be rectified by introducing weights (Holt, 2004). The number of weights and the smoothing constant are determined arbitrarily by the forecaster, with the weights typically set based on the assumption of the aging of information and the diminished value of older data. As already mentioned, to enhance flexibility in fitting, two processes of autoregression and moving average are combined into the autoregressive and moving average process (ARMA(p,q)) and the integrated autoregressive and moving average process (ARIMA(p,d,q), where p is the order of autoregression, d is the differencing order, and q is the lag size of the moving average). In the ARMA(p,q) model, it is assumed that the forecasted variable's value at time t depends on its future values and on the differences between its past actual values and the values obtained from the model, i.e., past forecast errors. In contemporary forecasting algorithms, there's also a consideration of information criteria (Table 2). These models are often referred to as auto.arima. Currently, ARIMA-based models are additionally supported, apart from the information criterion, by other modern solutions and algorithms. For example, they are often combined with the possibilities offered by artificial neural networks, as emphasized by Tseng et al. (2002), Faruk (2010), and Adamowski et al. (2012). Another very popular market trend is the support of ARIMA models by machine learning tools – such an approach is presented by Wang et al. (2019), Bousqaoui et al. (2021), Kim et al. (2019), and Alegado and Tumibay (2020). The approach related to using the ARIMA model supported by machine learning for predicting supply and demand by 3PL will also be used in this article.

3. Methods

3.1 Case study description

The conducted case study was based on the case of nine logistics plants (LP), which were managed by a 3PL type logistics operator (Table 3). Logistics service recipients (SR) were characterized by a diverse form of activity (e.g., manufacturers or retailers). The number of SRs in individual LPs varied. In the case of serving a larger number of SRs in one LP, we can speak of a multi-client platform in which the 3PL provides services as part of contract logistics for several different entities.

Table 3
Logistics plants description

Logistics plant (LP)	Location	Number of service recipients (SR) in LP	Type of SR		Total number of SKU in LP
			General description	Number of stock keeping units (SKU)	
LP_01	Poland	3	manufacturer of sweets and food products	45 982	48 619
			manufacturer of products for pets.	939	
			manufacturer & retailer of food products.	1 698	
LP_02	Poland	7	manufacturer of medicines and pharmaceutical products	1 838	78 962
			manufacturer of pharmaceutical products	245	
			manufacturer & wholesaler of generic drugs	659	
			manufacturer of bathroom and kitchen fittings	51 849	
			manufacturer of medicines and pharmaceutical products	2 184	
			manufacturer of medicines and pharmaceutical products	592	
			manufacturer of cosmetics and aesthetic procedure products	21 595	
LP_03	Poland	2	wholesaler of food and nonfood products	3 479	4 973
			manufacturer of food, including sweets and snacks	1 494	
LP_04	Poland	2	manufacturer & retailer of kitchen containers and accessories	14 780	17 254
			manufacturer of snacks and chips	2 474	
LP_05	Poland	2	manufacturer & retailer of cosmetics and skincare products	21 278	34 875
			manufacturer of toys	13 597	
LP_06	Poland	1	manufacturer of pet food	7 653	7 653
LP_07	Czech Rep.	2	manufacturer of packaging and labels products	401	64 976
			retailer of baby and child articles	64 575	
LP_08	Czech Rep.	1	retailer of products for gardens and houses	44 715	44 715
LP_09	Czech Rep.	1	retailer of food and nonfood products	13 484	13 484

Within individual LPs, the 3PL type logistics operator provides various services related to the flow of material goods (Table 4). For predictive needs, only those related to in and out operations and which are also the subject of the forecasts made were chosen. This article focuses on the process related to the acceptance of palletized cargo units to individual LPs divided by SR (inbound pallets). For activities related to further goods distribution, activities were divided into three types, as each of these activities generates different management problems and consumes a varied number of resources in warehouse management. Not all SR products are issued in all three ways. Warehouse releases can take place as part of unit picking and full pallet releases (outbound mixed pallets), as part of full pallet releases without unit picking (outbound homogeneus pallets), and as part of carton releases and picking to cartons - mainly for e-commerce distribution within B2C – Business to Customer (outbound boxes). In all LPs, a forecasting tool was implemented, for whose development and implementation the author of this article was responsible. The implementation and use of the predictive tool for the demand side and to improve the work of 3PL in the area of warehouse management were described in Kmiecik (2021; 2022c) and Kmiecik and Wolny (2022). These publications, as well as previous works, did not include the transfer of 3PL forecasting capabilities to the area of the entire LP, but only to the area of individual SRs and did not consider the possibilities related to supply prediction. The forecast results presented later in the article were constructed using a modified ARIMA model.

Table 4
Services provided by 3PL in the particular LP

LP	Percentage of SR with particular activity provided by 3PL			
	Inbound pallets	outbound mixed pallets	outbound homogeneus pallets	outbound boxes
LP_01	100,00%	100,00%	100,00%	66,67%
LP_02	100,00%	100,00%	100,00%	85,71%
LP_03	100,00%	100,00%	100,00%	50,00%
LP_04	100,00%	100,00%	0,00%	100,00%
LP_05	100,00%	100,00%	50,00%	50,00%
LP_06	100,00%	100,00%	100,00%	100,00%
LP_07	100,00%	100,00%	50,00%	50,00%
LP_08	100,00%	100,00%	100,00%	100,00%
LP_09	100,00%	100,00%	100,00%	100,00%

3.2 Modified ARIMA model supported by machine learning for prediction

The used modified ARIMA model is based on the ARIMA_PLUS algorithm created by Google (more about the mentioned model can be found in the publicly available source: www.cloud.google.com). Forecasting is preceded by three stages, namely preprocessing, modeling, and time series decomposing (Fig. 3).

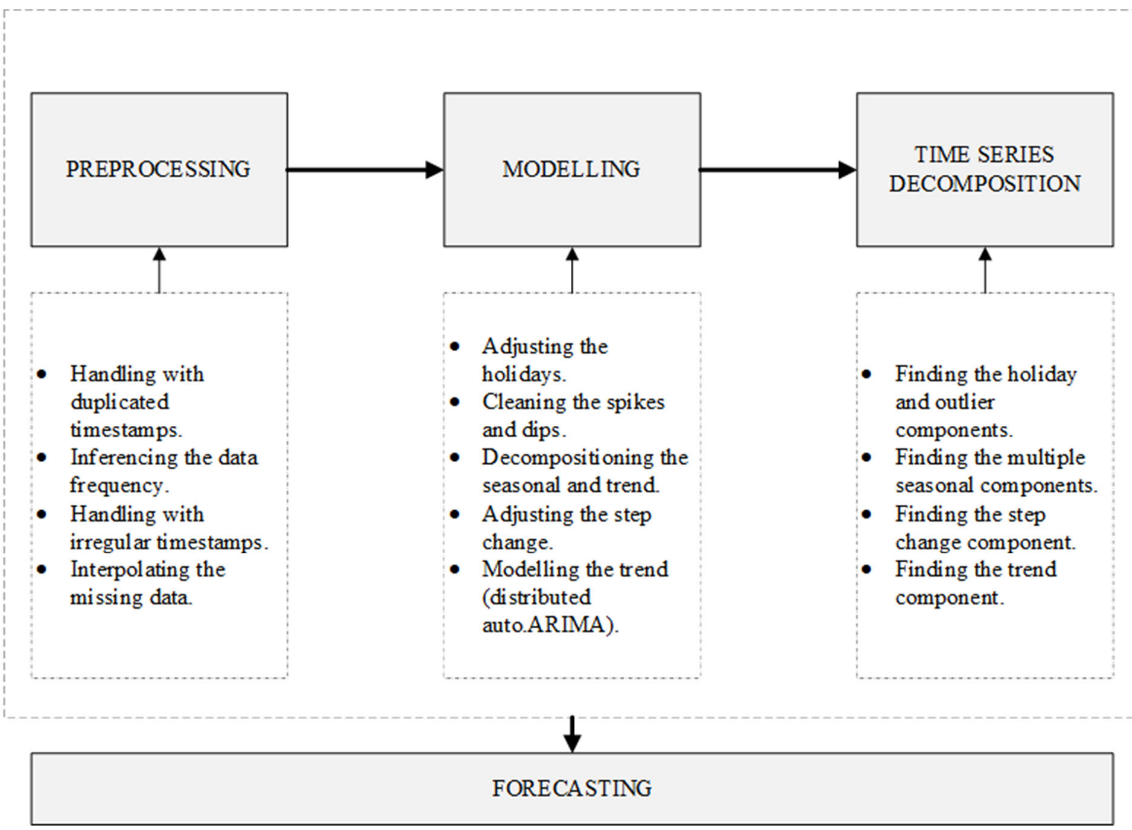

Fig. 3. General logic of prediction algorithm
Source: elaborated based on BigQuery Google Cloud Documentation (www.cloud.google.com)

The preprocessing stage involves addressing irregular and duplicated timestamps, handling data frequency interference, and interpolating missing data. The modeling stage encompasses step change and holiday adjustments, decomposition of trend and seasonality using STL, and trend modeling using auto.arima. This stage also involves cleaning outliers. The final stage decomposes the data into components: holiday, outlier, multiple seasonal patterns, step change, and trend. Forecasts are generated using the ML.FORECAST function, which predicts a time series based on a trained ARIMA_PLUS model. The scripts used for forecasting demand and supply by 3PL were tailored to specific cases after consultation. These scripts incorporated data visualization elements and supported the decision-making processes encountered by the logistics operator, thus representing the company's proprietary knowledge. The use of the ARIMA_PLUS model for forecasting offers several significant improvements over the traditional ARIMA(p,d,q) and auto.arima models. ARIMA_PLUS can automatically detect and account for outliers in the time series data that could impact forecast accuracy. While traditional ARIMA models do account for seasonality to some extent, ARIMA_PLUS can also recognize specific days, such as holidays, which can influence time series patterns. Thanks to cloud integration, ARIMA_PLUS can be trained and used for forecasting on large datasets without the need to transfer them outside of the enterprise environment. Similar to auto.arima in R, ARIMA_PLUS can automatically select the values of the p, d, and q parameters for the model, adapting to the data characteristics.

3.3 Data Description

The analysis presented in this paper is based on data collected by the author, which were used to generate forecasts using the previously discussed algorithm. Table 5 provides an overview of the data characteristics upon which the analysis was based.

Table 5
Specification of data

Data	Short description
Algorithm training time series length	2 years for each service recipient without external regressors
Forecasts updates	Once per week
Forecasts horizon	30 days
Forecasts granulation	Daily forecasts
Accuracy	Based on 2 months MAPE (Mean Absolute Percentage Error)

The study considered logistics plants where the logistics service provider had a contract of at least two years. This criterion ensured the availability of accurate data for the predictive model, enabling it to detect even annual seasonal fluctuations effectively. External regressors were not included in the analysis since logistics operators did not routinely collect them. The data used were sourced from the WMS (Warehouse Management System). Forecasts were made on a daily granularity and updated weekly. The forecast horizon spanned 30 days, and accuracy was evaluated based on the last two months of available data using the MAPE (Mean Absolute Percentage Error) measure. The formula for calculating MAPE was as follows (Tyman & Swanson, 1999):

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

where:

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

MAPE is considered by many researchers as one of the most appropriate metrics for measuring the accuracy of demand forecasts (da Veiga et al., 2016; Yani & Aamer, 2023; Kourentzes et al., 2017). The period analyzed for accuracy did not include seasonal or holiday product sales.

4. Results

Through visual assessment, it was evident that the employed algorithm demonstrated a relatively high capability in producing forecasts that aligned with the historical time series data. An example chart displaying both historical data and the forecast for a selected activity of a specific SR is showcased in Fig. 4. The rest of the activities and SRs were not visualized in this paper to avoid overwhelming the readers with excessive data.

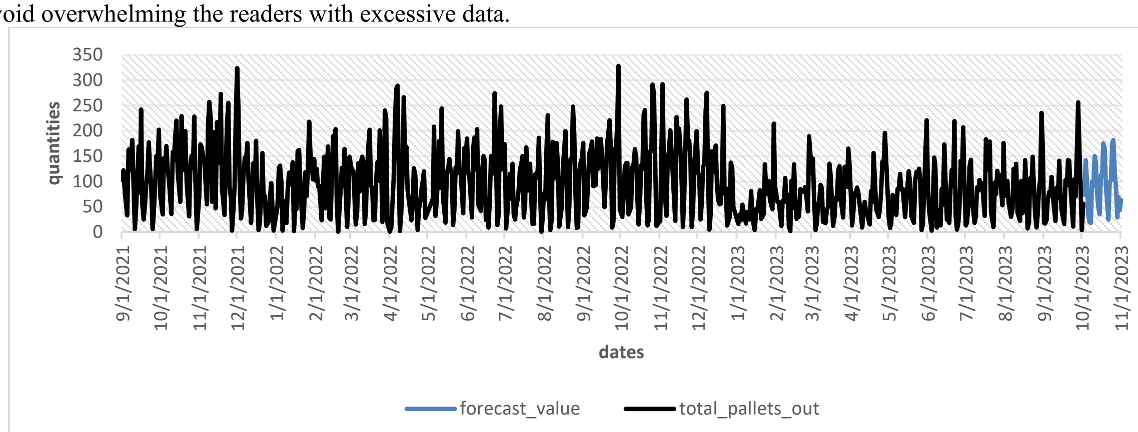

Fig. 4. Outbound total pallets out – history and forecasts for 3rd SR in LP_01

Based on visual analysis, it was determined that, similar to the presented case (outbound total pallets out for 3rd SR in LP_01), the algorithm aimed to identify peaks in demand or supply, and in the forecasted data, there were often observable upward or downward trends. In the examined cases (about 4 types of forecasts made for 21 SRs and 6 LPs, where there was more than one LP), there was no flattening of the forecasts, and no instances where the forecast lacked seasonality or trend. Also, based on visual analysis related to forecast verifiability, it could be concluded that it was a correct assumption made by the algorithm, because the data in the test period characterized by such properties for accuracy. Fig. 5 provides a sample comparison of actual sizes versus forecasted sizes for periods (for the case of outbound homogenous pallets out for 1st SR in LP_01). Similarly, the author used only one visualization to avoid confusion in reading the article's content.

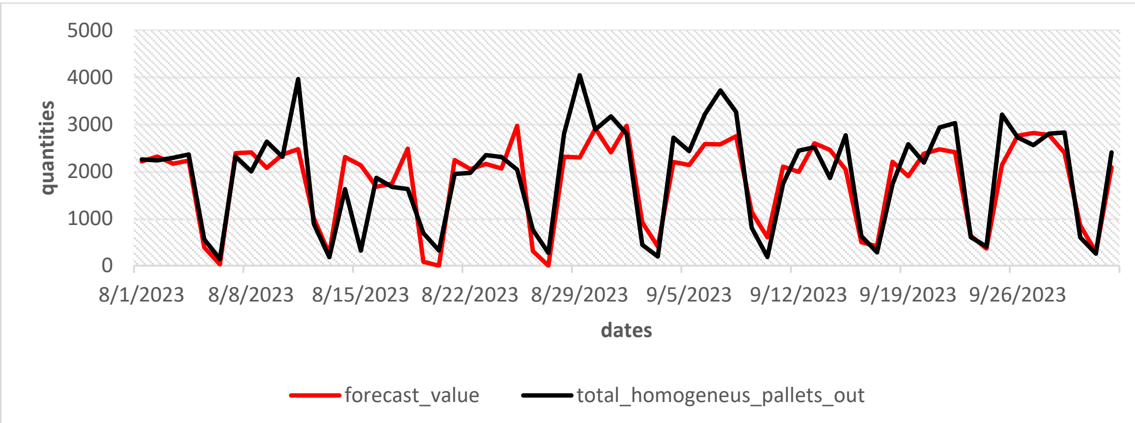

Fig. 5. Forecasted vs real values for outbound homogeneous pallets out for 1st SR in LP_01

The idea of predicting seasonality trends is evident in the cited case, with the algorithm particularly adept at forecasts related to regular decreases in demand and supply, which were detectable based on past patterns in the training data. Based on visual analysis of the charts, the algorithm behaved similarly in the case of other SRs and LPs. Figure 6 shows the accuracy level for all LPs, broken down by forecasts for individual inbound and outbound activities. The results relate to forecasts generated for the entire LP based on aggregated data entering the forecasting system.

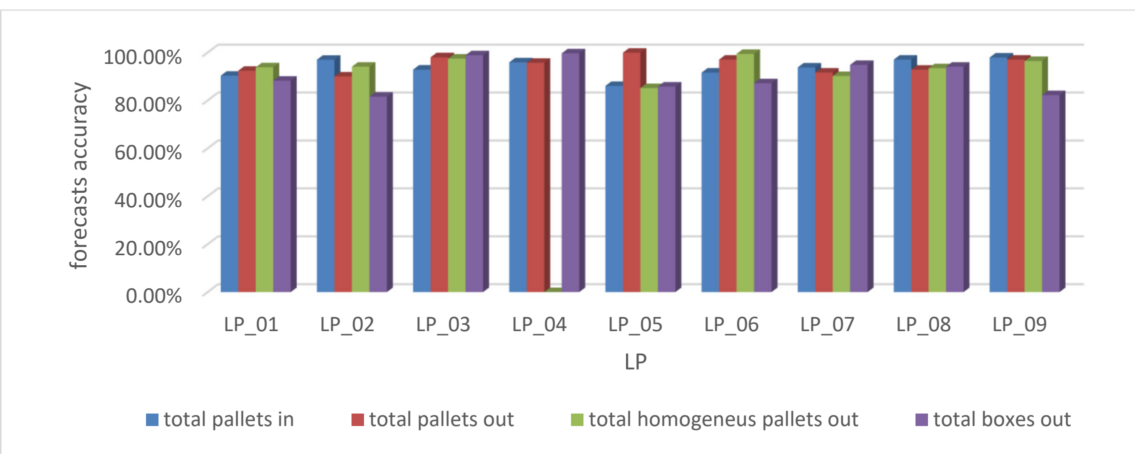

Fig. 6. Forecasts accuracy in the particular LP

Accuracy was calculated as 100% - MAPE. Additionally, basic statistical measures were calculated for the obtained results (Table 6).

Table 6
Statistical measures of LPs accuracy measures

Measure	total pallets in	total pallets out	total homogeneus pallets out	total boxes out
average accuracy	93,62%	94,97%	93,77%	90,29%
median accuracy	93,80%	95,74%	93,97%	88,28%
standard deviation	0,0364	0,0316	0,0418	0,0642
coefficient of variation	3,89%	3,32%	4,46%	7,12%
minimal value of accuracy	86,08%	90,04%	85,20%	81,57%
Maximum value of accuracy	97,94%	99,94%	99,46%	99,67%

The average forecast accuracy for all four activities is relatively high, exceeding 90%. The highest accuracy is in the "total pallets out" category with a score of 94.97%, while the lowest is in "total boxes out" with 90.29%. This may indicate that 3PL has greater forecasting capabilities for predicting supply rather than forecasting large volumes of small shipments. This can pose challenges in precise resource planning, as this type of operation is the most labor-intensive, which means the provider must emphasize improving forecasts in this area. For all categories, the median and mean are very close, suggesting that the data is relatively symmetrical and there are no significant outliers that would distort results. Low values of standard deviation, especially in the "total pallets in" and "total pallets out" categories, indicate that forecasts are fairly stable and consistent. This indicator measures relative data variability. The higher the value, the greater the relative variability. The greatest variability is in the "total boxes out" category (7.12%), which may indicate greater uncertainty in forecasts for this category compared to others. The widest range of accuracy (difference between minimum and maximum values) is observed in the "total boxes out" category (81.57% - 99.67%). This might indicate greater fluctuations in forecasts for this category. The results suggest that forecasts are generally accurate and stable for all categories, although the "total boxes out" category seems to be slightly less predictable than the rest. Therefore, if further forecast optimizations are necessary, it would be worth focusing primarily on this category. The results confirm that in forecasting for the entire LP, the logistics operator can achieve satisfactory results in terms of forecast accuracy. The most problematic aspect is forecasting demand for activities related to the issuance of small logistical units in large quantities. Fig. 7 shows forecast accuracy, calculated in the same way as in the previous example, this time for individual SRs.

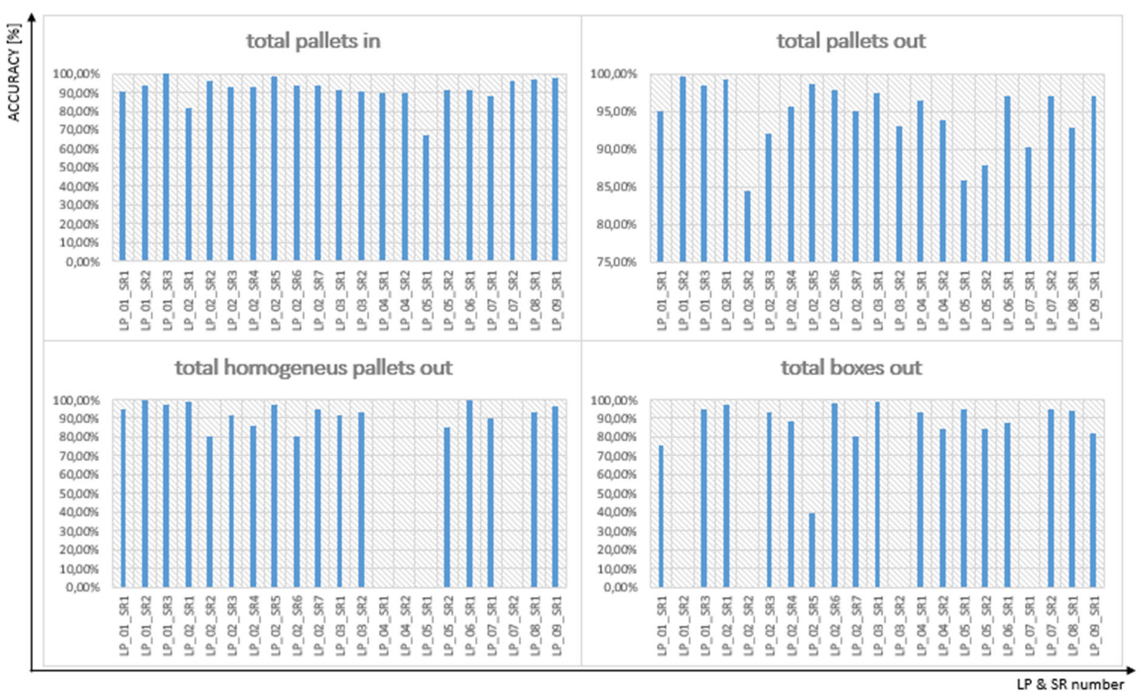

Fig. 7. Accuracy per activities and SR

Additionally, Table 7 provides information on basic statistical measures for forecast accuracy made for individual SRs.

Table 7
Statistical measures of SRs accuracy measures

Measure	total pallets in	total pallets out	total homogeneus pallets out	total boxes out
average accuracy	91,61%	94,50%	92,38%	87,14%
median accuracy	93,08%	95,66%	93,45%	93,11%
standard deviation	0,0676	0,0424	0,0595	0,1373
coefficient of variation	7,38%	4,48%	6,44%	15,75%
minimal value of accuracy	67,23%	84,35%	80,37%	39,12%
Maximum value of accuracy	99,83%	99,63%	99,63%	98,88%

An analysis of forecast accuracy for various warehouse activities of the 3PL company for 21 service recipients (SR) revealed that the average accuracy of the forecast for the total number of incoming pallets is 91.61%, suggesting a high level of precision in forecasting these values. However, forecasting accuracy for outgoing pallets, both in general (94.50%) and for homogeneous pallets (92.38%), was slightly higher. In the context of outgoing boxes, the average accuracy was 87.14%, which is somewhat lower compared to pallets. The median accuracy for all four categories (93.08% for incoming pallets, 95.66% for outgoing pallets, 93.45% for homogeneous outgoing pallets, and 93.11% for outgoing boxes) suggests that most forecasts were quite accurate, with over half of the forecasts approximating actual values in the range of 93% to 96%. However, the standard deviation, which measures the spread of values around the mean, was quite different depending on the category. The smallest spread was observed for outgoing pallets with a value of 0.0424, indicating relatively consistent forecasts. In contrast, the largest spread occurred in the category of outgoing boxes with a value of 0.1373, suggesting greater variability in forecast accuracy for this category. The coefficient of variation, a measure of relative data dispersion, also confirms these observations. The largest coefficient of variation was observed for outgoing boxes (15.75%), while the smallest was for outgoing pallets (4.48%). The lowest forecast accuracy was 67.23% for incoming pallets, indicating some forecasts that were significantly less accurate than others. Nonetheless, the highest accuracy for all categories approached 100%, indicating the perfection of some forecasts. The obtained results, in interpretation, are similar to those obtained for LP.

5. Discussion

The case study presented here on demand and supply coordination by a 3PL logistics operator unveils several critical insights and conclusions. Foremost among these findings is the remarkable forecasting capability exhibited by the 3PL logistics operator, particularly in the domain of supply forecasting. This discovery challenges conventional assumptions, as predictive capabilities in supply management are often overlooked by researchers, as noted by Huemer (2012). The article highlights that the 3PL's forecasting prowess is exemplified by an exceptional average forecast accuracy of over 90% across most studied categories. This achievement is particularly noteworthy, given the intricate structure of multiple supply regions operating under a single logistics provider's umbrella and the associated coordination challenges. However, while this high precision is commendable, there may still be room for optimization. This is particularly evident in the "total boxes out" category, where forecast accuracy is slightly reduced. This could signify the unique challenges in predicting demand for small logistic units in bulk, a central challenge for logistics operators, especially in the context of the burgeoning e-commerce sector. This observation aligns with the broader difficulties in forecasting within the e-commerce sector, as demonstrated by the studies of Saksi (2021), Ren et al. (2020), and Noh et al. (2020).

It is crucial to underscore the effectiveness of the ARIMA_PLUS model developed by Google in identifying seasonality and trends within the data. This model, tested and validated in various domains by researchers such as Choi et al. (2021), Chalise (2021), and Silva et al. (2020), had not been previously explored for predicting demand and supply within a 3PL operator's context. This adaptation is particularly pivotal for a 3PL operator, as it must navigate the challenges of managing demand and supply fluctuations related to different times of the year or sales seasons. However, a noteworthy limitation of this study is its reliance solely on Warehouse Management System (WMS) data without considering external regressors. Future research should consider integrating additional variables that influence warehouse demand and supply, such as promotional activities, holidays, or significant industry events.

While this study offers indispensable insights into forecasting within the realm of 3PL, it is equally vital to understand how these forecasts are practically harnessed by the logistics operator for resource management, coordination, and operational decision-making. Subsequent studies might delve into the correlation between forecast accuracy and the operational and financial performance of a 3PL operator. Coordinating demand and supply within a 3PL logistics operator is undeniably challenging, but as this study demonstrates, advanced forecasting tools can significantly enhance the efficiency of this process. Nonetheless, the pursuit of continuous improvement and the adaptability of predictive models to the dynamically changing business environment will be instrumental in ensuring long-term success in this field. In an era of ever-evolving logistics and supply chain dynamics, the ability to forecast with precision and adapt to emerging challenges will be the linchpin for maintaining a competitive edge in the 3PL sector. This study makes a significant contribution to the literature on the forecasting capabilities of 3PL companies. Until now, most research has focused on general aspects of supply chain management, overlooking the specificity and challenges associated with precise forecasting in 3PL companies, especially the often-neglected aspect of supply forecasting. This study addresses this gap by focusing on a detailed analysis of the ability to predict demand and supply, and the impact of advanced statistical tools, such as the ARIMA_PLUS model, on the accuracy of these forecasts. An important element of the research is the potential support of the ARIMA model through machine learning techniques. For example, machine learning algorithms can be used to identify non-standard patterns and anomalies that may be difficult to detect using traditional statistical methods. Supporting ARIMA with machine learning methods is discussed in many research papers (such as: Junior et al. (2019); Gupta and Kumar (2020); Nguyen (2020) and (Musarat et al., 2021). Such a hybrid approach could better handle the dynamic and complex data characteristic of the 3PL logistics sector, especially in the face of the growing influence of e-commerce and continuous changes in consumer behavior. The model presented in the studies, based on a modified approach to ARIMA, seems to be a good proposition to explore the area of combining predictive models with machine learning. Thanks to the ability to quickly process and analyze large data sets, machine learning can provide 3PL companies with greater flexibility and the ability to respond quickly to changes in demand and supply. This study not only fills an important gap in the literature on forecasting in 3PL companies but also opens the door to further research on the application of hybrid forecasting models, combining traditional statistical methods with advanced machine learning techniques. Such an approach has the potential not only to increase forecast accuracy but also to provide 3PL companies with the tools necessary to effectively manage the complexity of modern supply chains.

Building on the case study's findings on demand and supply coordination by a 3PL logistics operator, it becomes imperative to further accentuate the significance of predictive capabilities within 3PL enterprises, particularly for assortment planning in the context of e-commerce flows. The remarkable forecasting ability of the 3PL logistics operator, especially in supply forecasting, sets a precedent for the vital role these capabilities play in navigating the complexities of e-commerce logistics. The digital marketplace's volatile nature, characterized by sudden shifts in consumer preferences and rapid changes in product trends, demands an agile and predictive approach to supply chain management. In this regard, the superior forecast accuracy demonstrated by the 3PL logistics operator becomes a cornerstone for ensuring the availability of the right products, in the right quantities, at the right time. The ability to anticipate market changes and adjust inventory levels accordingly minimizes stockouts, reduces excess inventory, and optimizes the overall supply chain efficiency. Such precision in forecasting is particularly critical in the e-commerce sector, where customer satisfaction hinges on fast and reliable delivery of a wide array of products. The utilization of the ARIMA_PLUS model, as demonstrated in the case study, highlights the potential of incorporating advanced statistical and machine learning tools in enhancing the predictive accuracy of 3PL companies. This innovative approach to forecasting not only aids in identifying seasonality and trends but also in adapting to the unpredictable dynamics of the e-commerce marketplace. The integration of machine learning algorithms, as suggested by various researchers, could further refine these predictive models by identifying complex patterns and anomalies that traditional methods might miss. This hybrid approach, combining the strengths of ARIMA with machine learning, represents a significant advancement in the field of logistics forecasting, providing 3PL companies with a more nuanced and dynamic tool for managing the uncertainties of e-commerce supply and demand. Moreover, the emphasis on the need for continuous improvement and adaptability of predictive models underscores the evolving nature of the logistics and e-commerce sectors. As consumer behaviors shift and new market trends emerge, 3PL companies must remain at the forefront of technological innovation to maintain their competitive advantage. This involves not only the adoption of advanced forecasting models but also a commitment to ongoing research and development in predictive analytics. The enhanced focus on the predictive capabilities of 3PL enterprises, particularly in the context of e-commerce flows, is not merely a strategic advantage but a necessity in today's fast-paced market environment. The ability to accurately forecast demand and supply, supported by advanced statistical and machine learning techniques, equips 3PL companies with the necessary tools to effectively manage their inventory, optimize their operations, and ultimately satisfy customer demands. This study not only sheds light on the crucial role of forecasting within 3PL logistics but also paves the way for future research into the integration of hybrid forecasting models. Such research could further revolutionize supply chain management, offering 3PL enterprises the agility and precision required to thrive in the digital age.

6. Conclusions

The insights gleaned from the research presented in this article serve to significantly enrich our existing knowledge of third-party logistics (3PL) companies. They not only shed light on the evolving and ever-expanding role of 3PL in the global economy but also underscore their critical importance from a competitive standpoint. These findings hold substantial relevance for businesses, both those currently engaged with 3PL providers and those considering such partnerships. By offering a comprehensive exploration of 3PL operations, this research equips companies with invaluable knowledge for optimizing their collaboration with logistics service providers. It delineates the potential advantages and challenges associated with logistics outsourcing, helping businesses make informed decisions in a rapidly changing economic landscape. While this article delves deeply into the world of 3PL, it's important to acknowledge that several aspects still beckon for further investigation. Future studies could hone in on specific industry sectors, dissect regional variations in 3PL utilization, or closely examine the technological metamorphosis within the sector. The research underscores that technology is poised to be a linchpin in the evolution of 3PL, presenting an avenue for firms to bolster their efficiency and competitiveness. Embracing and integrating new technologies may well be the key to thriving in this dynamic field. The implications of these research findings extend beyond the corporate sphere. They resonate profoundly with strategic-level decision-makers, including policymakers and regulators. A nuanced comprehension of the dynamics governing 3PL is indispensable for formulating policies and strategies that foster an environment conducive to the growth of this sector. As 3PL increasingly takes on a more vital role in global supply chains, these findings can inform the development of regulations and infrastructure, creating an environment where 3PL companies can thrive and contribute effectively to economic growth.

The studies encapsulated in this article provide indispensable insights into the role and significance of 3PL in the current economic landscape. These insights have the potential to shape the decisions of managers, investors, and policymakers alike, influencing their strategies and investments in the 3PL sector. As the world of logistics continues to evolve and become increasingly complex, the knowledge derived from this research equips stakeholders with the tools they need to navigate the challenges and seize the opportunities presented by the dynamic world of third-party logistics. The study's focus on the ARIMA_PLUS model underscores the significance of adopting advanced statistical tools in improving forecast accuracy within 3PL operations. This emphasis is further substantiated by the study's findings, which demonstrate a direct correlation between technological advancements and the precision of demand and supply predictions. This correlation is particularly evident in the context of smaller order volumes, where the model's limitations become more pronounced. These findings suggest a potential avenue for further research, particularly in enhancing the model's capability to handle smaller logistic units more effectively. The exclusion of external factors such as market trends, customer behaviors, and broader economic indicators, which can significantly impact demand and supply dynamics, indicates a need for a more holistic approach in future research. Integrating these external regressors could provide a more comprehensive understanding of the factors influencing

3PL forecasting accuracy. In addition to the technical aspects of forecasting, the study opens up discussions on the practical applications of these forecasts in the operational management of 3PL companies. Understanding how these predictions are utilized in real-time decision-making, resource allocation, and strategic planning is crucial. It would be beneficial for subsequent research to explore the operational impact of forecast accuracy, examining how close alignment with actual demand and supply figures translates into operational efficiency and financial performance.

Research papers findings have significant implications for the broader logistics industry, especially in the context of increasing reliance on e-commerce and the need for agile supply chain management. The ability of 3PL operators to adapt their forecasting models to rapidly changing market conditions is essential for maintaining competitiveness and meeting customer expectations in a dynamic business environment. This study makes a valuable contribution to understanding the forecasting capabilities of 3PL operators and the effectiveness of the ARIMA_PLUS model, it also highlights several areas for future research. These include the need for more comprehensive data integration, enhancing the model's handling of smaller logistic units, and exploring the practical application of forecasts in operational management. As the logistics industry continues to evolve, the role of advanced forecasting in maintaining a competitive edge becomes increasingly crucial.

Additionally, the study suggests the potential for leveraging machine learning and artificial intelligence technologies to refine forecasting models further. These advanced technologies could offer new insights into complex data patterns, enabling more nuanced and adaptive forecasting approaches that can keep pace with the rapidly evolving e-commerce sector. The research underscores the vital role of advanced forecasting capabilities for 3PL companies, particularly within the e-commerce context. As these companies continue to navigate the challenges and opportunities presented by digital marketplaces, their ability to predict and adapt to changing market conditions will be a key determinant of their success. This study not only contributes to a deeper understanding of the strategic importance of predictive capabilities in 3PL operations but also opens the door for further exploration into how these capabilities can be enhanced and effectively applied to meet the demands of a dynamic global marketplace. The evolution of forecasting techniques and their application in the logistics industry remains a critical area for ongoing research and development, promising to shape the future of supply chain management in the digital age.

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