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A Comprehensive Analysis of Demand Prediction Models in Supply Chain Management

Hamid Badr, Waqar Ahmed

Department of Industrial Engineering, King Abdulaziz University, Jeddah, Saudi Arabia
Email: wahmed@kau.edu.sa

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Abstract

The capacity to provide accurate demand projections is essential for supply chain management to work well. Because their projections influence important choices at every stage of the supply chain, including sourcing raw materials, manufacturing, transportation, and inventory management, the demand team bears a great deal of obligation. Precise demand projections greatly impact customer satisfaction and organizational efficiency in general, ultimately saving money and effort. Even though they are essential, historical demand and sales statistics frequently fall short. Traditional statistical models neglect to account for complex variables and do not have the necessary accuracy. In demand forecasting, advertisements are often underutilized while being a significant source of complexity. Forecast accuracy is improved by combining time series approaches with expert opinion and data from unique occurrences. This research aims to develop a thorough grasp of demand planning and offer workable methods to improve supply chain oversight. Our technique includes both quantitative and qualitative study design methodologies developed from comprehensive data obtained through published examination of secondary sources and critical observation. The collected data is analyzed, and conclusions are drawn from our data analysis using a variety of data analysis methodologies, such as statistical, thematic, and content assessment. Not only are different approaches to model construction highlighted, but study comparisons and recommendations are also examined, along with a review of the literature gathered from various academic publications and papers. The study recognizes the inherent difficulties in demand planning, such as the requirement for sophisticated ideas and applications, a trained labor force, and the coordination of deliberative techniques with supply chain and logistical procedures. In conclusion, this paper seeks to improve logistical and supply chain operations by tackling current issues, offering insights into demand factors, refining demand forecasting models, and presenting helpful suggestions to companies on maximizing demand planning procedures to increase operational effectiveness and satisfaction among consumers. In addition, it offers a thorough study of the several techniques used to project future sales, gauge forecast accuracy, and enhance the demand planning procedure as a whole. It also thoroughly assesses the fundamental ideas and tactics involved in demand planning. Furthermore, it emphasizes the value of considering demand planning from various angles in addition to statistical techniques, as well as the individual contributions of every workforce.

Keywords

Demand Forecasting, Supply Chain Management, Promotions, Time Series, Demand Planning

1. Introduction

In supply chain management, demand forecasts are essential because they have an impact on choices regarding logistics, production planning, warehouse management, and replenishment planning. Forecasts that are accurate increase customer satisfaction and operational effectiveness. High-accuracy projections require historical sales or demand data, but simple statistical models are inaccurate. Promotions like marketing campaigns and notable holidays are frequently disregarded yet have the potential to boost sales at the expense of higher costs or revenue loss. Higher-accurate projections may be produced by analyzing previous data using time series methods and skilled human judgment. The cost of promotions must be systematically analyzed to see whether they are worthwhile.

2. Research Problem

Supply chain management relies on reliable demand forecasts, which can be challenging due to consumer behavior, market dynamics, and external factors like natural disasters or economic shifts. Inaccurate forecasts can lead to overstocking, understocking, increased operational costs, customer dissatisfaction, and lost opportunities, affecting businesses and customers alike.

3. Research Objective and Importance

The main goals of this research are:

- To improve this crucial component of supply chain management by developing a thorough grasp of demand planning and offering workable solutions.
- Enhance the utilization of creative forecasting techniques.
- Enhance the integration of data from several sources.
- Enhance the overall integration of numerous ideas in a company to assist demand planning.
- To improve the demand planning procedures' overall efficacy, precision, and flexibility by considering these elements.

3.1. Research Questions

In our quest to contribute to the field of supply chain and logistics, the following research questions guide our investigation:

- How does the complexity of the demand planning system impact overall supply chain and logistics performance?
- What is the pace of improvement in the overall performance of supply chain and logistics systems within the context of demand planning?
- What are the key factors influencing the integration of advanced forecasting techniques into supply chain and logistics operations?
- How does the implementation of enhanced demand planning impact the efficiency and effectiveness of current logistics and supply chain operations?

3.2. Expected Findings

The study aims to enhance the effectiveness of supply chain and logistics systems by addressing demand planning challenges, benefiting companies, and ensuring consumer satisfaction. Here are some of the expected findings:

- This study explores advanced forecasting techniques and data integration in demand planning, aiming to understand the impact of demand planning on supply chain and logistics efficiency.
- This study aims to develop a comprehensive demand planning framework using literature review ideas, enhancing demand forecasting precision beyond conventional statistical models. This will improve supply chain and logistics efficiency and effectiveness.
- The study aims to identify critical variables influencing the integration of advanced forecasting methodologies and an organization's overall demand forecasting process.
- The research suggests that companies can enhance their demand planning procedures, enhancing client satisfaction and operational efficiency. This, in turn, positively impacts the overall effectiveness of supply chain and logistics systems.

4. Literature Review

4.1. Background

Supply Demand planning is a tactical procedure that assists businesses in meeting consumer demand while minimizing the impact on inventory and supply chain interruptions. It boosts profitability, boosts client happiness, and gives you a competitive edge. For this ongoing process to run well and maintain profitability, it is necessary to hire skilled personnel. Businesses must examine sales patterns, previous sales data, and seasonal effects to maximize demand planning. To accomplish this, management should integrate sales forecasting, supply chain management, and inventory management technologies. Data from internal and external sources is gathered to make judgments on operations strategies, raw material needs, and product manufacture to satisfy customer demand (Adhikari, Domakonda, & Chandan, 2018).

4.2. Importance of Demand Planning

Demand planning is crucial for a company's strategic planning, balancing inventory levels and customer demand. It requires coordination across all parts and can significantly impact profitability and operations (Chase, 2013). Excessive inventory can lock up working capital, increase costs, and lead to lower prices. Poor planning can cause supply chain disruptions, product shortages, raw material shortages, stockouts, high costs, and customer dissatisfaction.

Demand planning is a thorough procedure that aids businesses in satisfying consumer demand, enhancing the effectiveness of the supply chain, and maximizing profit margins. Businesses may exploit market possibilities and boost sales by concentrating on client demand and profitability (Bhattacharyya, 2014). Advanced demand and supply planning are essential for businesses to achieve sales growth that is above standard. Demand planning improves product sales projections, increases supply chain scheduling, optimizes labor management, and ensures effective cash flow management. It also helps control inventory levels and guarantee a smooth supply chain flow. Proper demand planning aids in controlling manufacturing processes, warehousing, shipping, and handling activities, as well as adequately projecting sales. Getting in touch with suppliers and sales teams at once also helps to minimize shortages and lost revenues (Oey, Wijaya, & Hansopaheluwakan, 2020). In conclusion, companies must manage their cash flow effectively to prevent sales deficits and preserve liquidity. According to Ren, Chan, & Siqin (2019), accurate sales forecasts aid in controlling inventory levels in response to changes in demand or sales, preventing excess stock or shortages.

4.3. Elements of Demand Planning

1) *Product Portfolio Management:* Product portfolio management entails preparing new product lines, assessing their effects on current ones, and comprehending price-demand correlations in order to enhance the product mix, maximize profitability, and expand market share (Gansterer, 2015).

2) *Statistical Forecast:* Advanced algorithms are used in statistical forecasting to examine and make sense of previous sales data, assisting in the generation of precise sales projections.

3) *Trade Promotion Management:* Trade promotions are marketing techniques that use discounts, in-store promotions, and freebies to raise consumer demand and product recognition (Lapide, 2014). Consequently, they set a company's brand apart from rivals through efficient coordination and solid client relationships. Offering clients a price break and other activities to boost product exposure and optimize returns are significant components of promotions that are used to change the statistical forecasting model. These mechanisms, which increase sales, include promotional, exhibition, marketing, and special events.

4.4. Importance of Forecasting in Business

In order to assure product availability, eliminate uncertainty, and minimize stockouts, waste, and profits, forecasting is essential in corporate planning. On the basis of demand projections, accurate predictions assist producers in ensuring adequate supplies of raw materials and packaging materials (Nissi et al., 2021). Results can be enhanced by using advanced statistical techniques and human judgment. Although forecasting accuracy is excellent, the planning process must take error into account. A cost-effective strategy is advised to reduce forecasting mistakes rather than allocating additional resources effectively. Cannibalization, promotions, and weather patterns may all be predicted using sophisticated forecasting techniques like machine learning and regression analysis.

4.5. Business Forecasting and Models Involved

Predicting future business occurrences while taking into account both past and present business events is known as business forecasting (Shila, 2021). It tries to lessen management decision-making uncertainty in reference to profitability, price, production, capital expenditure, and sales. It is a crucial component of business planning since it enables businesses to examine past, present, and future operations while concentrating on future product demand and organizational needs.

4.5.1. Forecast Maturity Model matrix

Organizations utilize the maturity model in demand forecasting to gauge progress toward a specific objective. It concentrates on figuring out the process, organizational structures, measurements, and the scope and emphasis of projections (Hopkinson, 2017). Choosing the procedure, organizational systems and metrics to apply are common criteria for maturity model implementation. This model is consistent with the findings made by Arunachalam, Kumar, and Kawalek (Arunachalam, Kumar, & Kawalek, 2018). They asserted that a firm's capacity to advance along the maturity curve is determined by its processes and systems.

4.5.2. Forecast Evaluation and Measurement

Forecasting accuracy, acceptance levels, poor demand, and service levels can be used to measure and evaluate forecasts.

1) Forecasting Accuracy: When assessing a forecasting model's effectiveness, forecasting accuracy is a crucial parameter to consider (Zhang, 2016). The dissimilarity between the predicted and the actual value, articulated as a proportion of the actual value, is what this term refers to. The Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE), as well as Mean Squared Error (MSE) are prominent forecasting methodologies. Forecasters can also use a range of qualitative and quantitative techniques. According to Blasco, Moreno, and Abad, MAPE should be used in forecasting (Blasco et al., 2013). Hence, MAPE models employ precise percentages that are computed across time and are therefore regarded as acceptable in predicting. The MAPE method is thus frequently chosen in retail organizations because it can precisely measure the difference between actual and forecasted sales. It is helpful when comparing numerous projections as it provides a more logical measure of accuracy and is often more straightforward to comprehend than MAE and MSE. According to the literature, prediction accuracy metrics, including bias, mean absolute error, as well as mean absolute percentage error, remain the most crucial ones to take into account when evaluating and measuring forecasts (Bobby, Jones, & Smith, 2020). These metrics show the forecast's overall accuracy and can be used to pinpoint forecasting inaccuracies.

2) Acceptance Levels: Different predicting accuracy thresholds are taken into account in various businesses, according to evidence from earlier research. For exponential smoothing models, Makridakis, Wheelwright, and Hyndman discovered that the standard for excellent forecast accuracy is often about 25% (Makridakis, Wheelwright, & Hyndman, 2008). Additionally, the acceptable accuracy level in the retail sector is often between 20 and 30 percent, but in the banking sector, it is typically between 10 and 20 percent (Makridakis, Wheelwright, & Hyndman, 2008). Hence, models with lower measures of error, below 10%, would be regarded as adequate. Analysts in this situation must think about what would be acceptable in their particular professions.

3) Poor Demand Models: Demand forecasting and operational planning are both done using forecast models. Demand projections might be erroneous as a result of a subpar demand model (Agarwal & Womack, 2009). This is because a flawed model might not be able to make precise forecasts or accurately capture the underlying trends in the data. The conclusions of Agarwal and Womack are consistent with those of Wang, Gershman, and Srinivasan, who claimed that it is difficult for an organization to select the right amounts of stock when there is a poor demand model (Agarwal & Womack, 2009; Wang, Gershman, & Srinivasan, 2014). Because the decision-making process in the scenario mentioned above is based on incorrect models, poor planning follows.

4) Service Level Improvement: In their 2005 article, Holzmann and Platt stress the significance of demand models in informing pricing and supply chain decision-making, adding that "improving the accuracy and quality of the demand models can lead to significant improvements in service levels and cost savings." Heikkinen's findings concur with those of Holzmann and Platt in that it is vital to make sure that adopted models are continuously refined to increase accuracy (Heikkinen, 2016; Holzmann & Platt, 2005). This is because demand forecast models have an impact on a firm's overall performance. Heikkinen suggests a number of methods for enhancing service levels, one of which is to take the seasonality of the items that are in demand into account (Heikkinen, 2016). Those mentioned above would guarantee that the model accounts for changes in the external environment that can impact demand. Results from a few research show several methods for evaluating the precision of demand forecasting models. Hofmann and Rutschmann provide the following formula to calculate

MAPE.

$$\text{MAPE} = (|\text{actual value} - \text{forecasted value}|)/100 \quad (1)$$

The accuracy of demand forecast models is evaluated using Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), as well as Root Mean Squared Error (RMSE), with MAPE being more appropriate due to its capacity to measure differences between actual and anticipated sales precisely (Hofmann & Rutschmann, 2018; Hyndman, 2014). The study explores the concept of MAPE and its distinction from MAE, utilizing data from Wang and Wei, with **Table 1** providing an illustration (Wang & Wei, 2016).

Table 1 show somewhat higher MAPE values than MAE, potentially as a result of MAPE being inflated due to lower predicted and actual data values.

As stated by Prayudani et al., the precision of the forecast for this research ought to be at least 95% (Prayudani et al., 2019). This aspect suggests that these models capture actual findings more effectively.

Table 1. Results of calculating MAPE and MAE for the same set of data.

	Forecast (Units)	Actual Data (Units)	MAPE	MAE
Period 1	11	13	18.18	3.8
Period 2	27	33	22.22	4
Period 3	18	25	38.89	3.75
Period 4	16	23	43.75	3.29
Period 5	9	10	11.11	2.67
Period 6	10	12	20	3
Period 7	20	18	10	3.25
Period 8	20	24	20	3.67
Period 9	25	22	12	3.5
Period 10	23	19	17.39	4

4.6. Demand Model Evaluation

4.6.1. Generating ABC/XYZ Classifications

Based on the Pareto principle, the ABC/XYZ categorization system divides data into clearly understandable groupings (Pandya & Thakkar, 2016). It aids in data comprehension and decision-making for organizations. Class A products are those that generate 80% of revenue, Class B products 10%, and Class C products the remaining 20% (Bulinski, Waszkiewicz, & Buraczewski, 2013; Pandya & Thakkar, 2016). In the retail sector, this strategy is beneficial for managing inventory and choosing which product categories to concentrate on.

4.6.2. The Use of ABC/XYZ Classifications in Forecasting

The definition of classification, according to Guevara and Gómez-González and Bridgewater and Williamson, is the grouping and categorization of data

(Bridgewater & Williamson, 2014; Guevara & Gómez-González, 2016). Different techniques, including clustering, decision trees, and linear regression, can be used to accomplish this. Forecasts may be produced using classifications by examining the data and seeing trends. Applying algorithms to the data can help you find patterns that can be utilized to generate predictions. Forecasts for various areas, including sales, demand, and consumer behavior, may be produced using this method. Classifications may offer precise and timely projections, which can assist organizations in making better decisions and staying one step ahead of the competition, according to Guevara and Gómez-González and Bridgewater and Williamson (Bridgewater & Williamson, 2014; Guevara & Gómez-González, 2016). Therefore, the estimates would be crucial for companies in the retail sector, particularly in inventory management.

According to Stojanovi and Regodi, the ABC/XYZ categories are created based on a product's worth and demand (Stojanović & Regodić, 2017). When it comes to retail planning, Zenkova and Kabanova note that products that contribute the highest revenue are assigned to the first class (Zenkova & Kabanova, 2018). To assess the contribution of each product, the calls mentioned above on firms to use appropriate inventory management. Identifying variances in demand is the next stage in creating classes. The following is a description of the demand variation formula. Analysts eventually mix ABC and XYZ to get the following combinations: AX, AY, AZ, BX, BY, BZ, CX, CY, and CZ. The combinations mentioned above help when classifying items according to their worth or unpredictability.

ABC/XYZ classifications in forecasting involve determining demand variations using the formula:

$$\text{Average Demand} = \sum\nolimits_i^n \left(\text{Demand}_i\right) \div n \tag{2}$$

where n represents the number of products in demand (Stojanović & Regodić, 2017).

Similarly, forecasting starts by defining the things to be predicted and figuring out the coefficient of variance. After calculating the coefficient of variations, the elements are grouped as shown in **Figure 1** below (Zenkova & Kabanova, 2018).

Organizations should ultimately think about AX-based goods as being the most practical.

4.6.3. Performance Measurement and KPIs

1) Forecast Bias: Since forecasting accuracy directly affects profitability and customer happiness, it is essential for effective integrated retail operations. According to Chien, the majority of forecasting models work to lessen forecast bias or the discrepancy between expected and actual values (Chien & Hung, 2013). To lessen the likelihood of prejudice, it might be essential to have a distinct baseline. Hence, there is no one method for doing this. Analysts should utilize the best-fit strategy to look at bias. However, it is essential to carefully assess the data and models utilized in predicting.

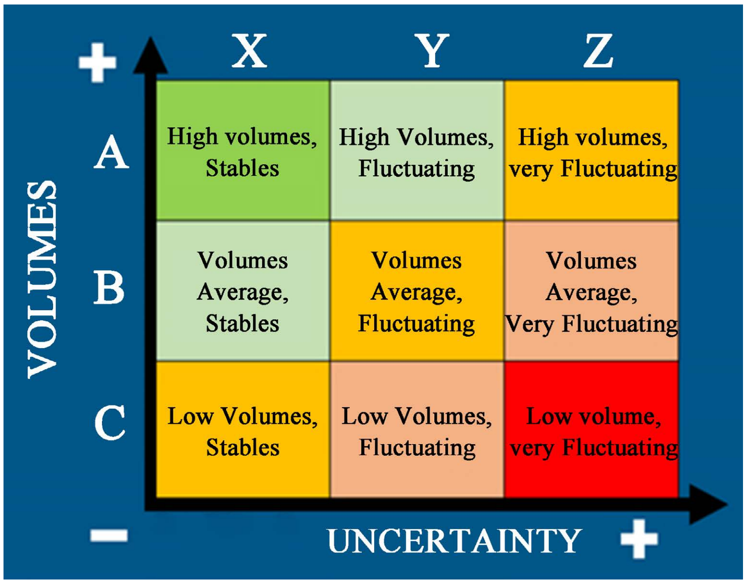

Figure 1. ABC/XYZ (Source: (Zenkova & Kabanova, 2018)).

2) KPI and Performance: According to Gardiner and Soltani, financial analysts are always looking for different ways to improve the accuracy of forecasting (Soltanali et al., 2021). One such way is by determining appropriate metrics and KPIs that could be applied in demand forecasting. One of the KPI measures identified by Chien is the mean absolute percent error (MAPE) method (Chien & Hung, 2013). The KPI is appropriate in determining the % error associated with products under demand. This measure would be appropriate, especially when some products are considered to be more important (Chien & Hung, 2013). The application of these measures means that planners are able to increase visibility and efficiency across the supply chain.

The following formula could be used to calculate or determine the forecast bias:

$$\text{Forecast Bias} = \frac{(\text{Forecast Value} - \text{Actual Value})}{(\text{Forecast Value} + \text{Actual Value})} \tag{3}$$

For instance, if the forecasted demand value for a product in the retail industry is \$11 and the actual price is \$13, the forecast bias would be calculated as follows;

$$\text{Forecast Bias} = \{(11-13) \div (11+13)\} = -0.08 \tag{4}$$

The negative above is an indication of under-forecasting. In this case, such elements of bias could be reduced by continuously testing the models to examine their accuracy.

3) KPI and Measures: The study identifies several KPI measures that could be used in determining the accuracy of forecasting in forecast models. Among the measures is the MAPE. The measure represents the percentage error and would be calculated as follows:

$$\text{MAPE} = \sum(\text{Forecast error time } t \div \text{Actual Sales } t) \div \text{No. of Forecast Errors} * 100) \tag{5}$$

For more accurate forecasting, Chien and Hung recommend the use of Weighted Mean Absolute Percentage Error (Chien & Hung, 2013). This would be calculated as follows:

$$\text{WMAPE} = \sum(\text{Actual sales time } t - \text{Forecast sales time } t) \div \text{Actual sales time } t \quad (6)$$

The method ensures that products with more weight are accorded the proper emphasis. The application of these measures improves the accuracy of forecasting and demand planning, which affects the overall performance of the business.

4) Forecast Model: This model has two primary methods applied in statistical forecasting.

a) *Moving Average*: The moving average approach, which forecasts trends in a dataset using historical data, has been examined by Nau (Nau, 2014). With this approach, analysts are able to concentrate on long-term trends rather than short-term temporal fluctuations. Wang and Wei contend that this approach is appropriate for the retail sector because it can accommodate cyclical changes (Wang & Wei, 2016). However, Nau disagrees, arguing that choosing a period for the moving average might be challenging, particularly when indicators like sales have ambiguous tendencies (Nau, 2014). The formula for this method is as follows:

$$\text{MA} = \left(A_1 + A_2 + A_3 + \cdots + A_n\right)/n \quad (7)$$

To explain this aspect further, according to the information in **Table 2** below, a 12-period moving average in the retail sector would use the most recent twelve data points for a particular variable, such as demand or sales. Hence, the average of the past 12 points is 55.42.

Table 2. Data on demand patterns (source: (Yuen, 2022)).

Period (Months)	Demand (units)
January	40
February	45
March	50
April	40
May	50
June	55
July	60
August	50
September	70
October	65
November	60
December	80
Sum	665
Average	55.42

Figure 2 below shows data from Table 2 with the moving average extrapolated to provide the forecast for the following period.

Moving average extrapolation is a forecasting method that uses the average of past values to predict future values. It is a simple but effective method for forecasting trends and cyclical patterns.

To extrapolate a moving average, first calculate the moving average for a certain number of periods. For example, to calculate a three-period moving average, you would add the values for the current and two previous periods and divide by three. Once you have calculated the moving average, you can extrapolate it into the future by assuming that the trend will continue.

In the example of Figure 2, the moving average is calculated using the following formula:

$$\text{Moving average for January} = (80 + 60 + 65)/3 = 68.33 \text{ units}$$

To extrapolate the moving average, we simply continue the trend into the next period. In this case, the forecasted demand for the next period (January) is 68.33 units.

b) *Exponential Smoothing*: An exponential smoothing forecasting technique creates parameters using weighted averages of past observations (Sidqi & Sumitra, 2019). There are three different kinds of it: single exponential smoothing, which is used when there is no trend or seasonality, and double exponential smoothing, which employs two weights. A number between 0 and 1 should be used to represent the factor, with a value closer to 1 indicating quicker smoothing (Gustriansyah et al., 2019). Triple exponential smoothing accounts for changes in the dataset by focusing on three parameters: stationery, trend, and seasonal components.

- *Single Exponential Smoothing:* Tratar, Mojškerc, and Toman provided the following formula for single exponential smoothing:

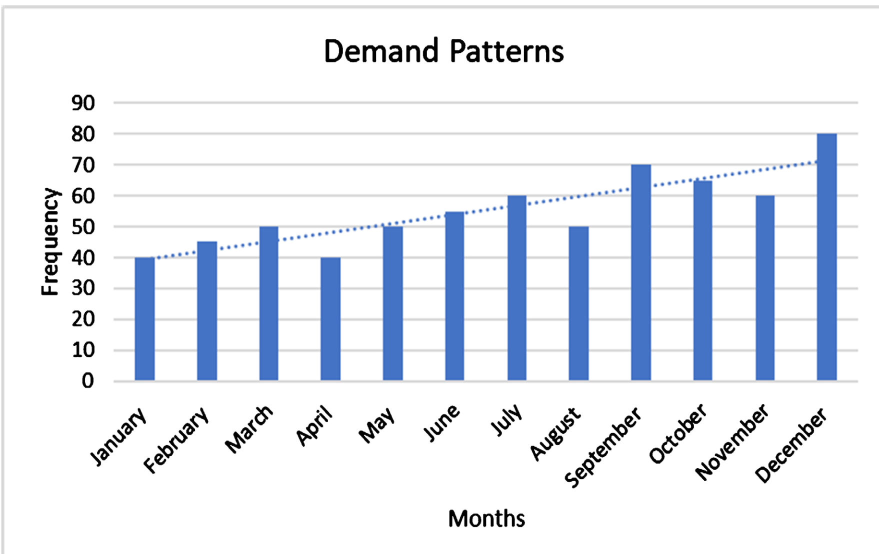

Figure 2. Moving average.

$$F_t = P_{t-1} + \alpha(B_t - P_{t-1}) \tag{8}$$

where F_t is the forecast value, α is the weight attached to the model; B_t represents the actual value, while P_{t-1} represents the previous smoothed value (Tratar, Mojškerc, & Toman, 2016).

- *Double Exponential Smoothing:* The method of forecast integrates two weights (level weight and trend weight). As a result, it is appropriate in situations where there is a trend but no seasonal component (Tratar, Mojškerc, & Toman, 2016). The first step in the analysis would be to determine the level weight, which would be calculated as follows:

$$L_t = \alpha B_t + (1-\alpha)[L_{t-1} + T_{t-1}] \tag{9}$$

In this formula, α represents the weight at that level, and B_t represents the data value at time *t*. After calculating the level weight, the next step would be to consider the trend. The formula for determining the trend is as shown below:

$$T_t = C[L_t - L_{t-1}] + (1-C)T_{t-1} \tag{10}$$

In the formula above, *C* represents the weight of the trend. After computing the level weight and the trend, a combined forecast using the method is shown below.

$$Y_t = L_{t-1} + T_{t-1} \tag{11}$$

An essential factor to consider in this context is the calculation of level weight and trend weight shown by α and *C* as described above. According to Lima, Gonçalves, and Costa, the weights assigned must result in the lowest possible value of MSE (Ghalehkhondabi et al., 2017). Besides MSE, the calculation of forecast values through the approach above would also require the determination of MAPE, MAD, and MSD (Ghalehkhondabi et al., 2017).

- *Triple Exponential Smoothing:* The three critical components of the technique are the seasonal, stationery, and trend components. Both additive and multiplicative techniques may be used in this situation. As a result, multiplicative models are used in exponential seasonality, whereas additive models are used in linear seasonality. The following formula would be used if we were considering a multiplicative model. As shown below, the formula starts by figuring out the seasonal component:

$$S_t = \alpha \times (X_t - C_{t-L}) + (1-\alpha) \times (S_{t-1} + \Phi \times T_{t-1}) \tag{12}$$

where α represents the smoothing factor, and Φ is the damped smoothing factor.

The trend factor would be calculated as follows:

$$T_t = \beta \times (B_t - B_{t-1}) + (1-\beta) \times \Phi \times T_{t-1} \tag{13}$$

In this formula, *T* is the trend, *B* represents smoothed observations, and β is the trend smoothing factor. The last formula represents the stationarity components and is represented as follows:

$$C_t = \gamma \times (X_t - S_t) + (1-\gamma) \times C_{t-L} \tag{14}$$

Based on the above, the following formula is for forecasting under the approach.

$$F = S_t + T_t + C_t \tag{15}$$

Moving averages and exponential smoothing are the two primary techniques used in the study to make statistical forecasts. Findings suggest that the technique only offers an average of the datasets for a certain period when it comes to moving averages. The study concentrated on single, double, and triple exponential under exponential smoothing. Findings under a single exponential show that the main emphasis is the computation of predictions directly using the past smoothed values. The technique lacks the seasonality and trend components that increase predicting accuracy.

5. Summary

The literature analysis highlights the importance of examining past sales data, seasonal effects, and sales and customer patterns to optimize a company's capacity to satisfy consumer demand efficiently. Demand planning includes product portfolio management, statistical forecasting, and trade promotion management. It also includes improving product sales focus, increasing supply chain schedules, optimizing labor management, ensuring efficient cash flow management, managing inventory levels, and creating value. COVID-19 has impacted demand planning, with changes in business tracking patterns, purchasing channels, and product shifting leading to economic strain. The literature emphasizes the importance of improving forecast accuracy using ERP. the enterprise resource planning (ERP) system has greatly improved the availability and accuracy of data (Ni, Peng, Peng, & Liu, 2022). Ghalehkhondabi et al. identified common forecasting approaches like Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), as well as Mean Squared Error (MSE) (Ghalehkhondabi et al., 2017). MAPE is easier to interpret than MAE and MSE, especially when dealing with extensive data. However, there is a gap in forecast demand models, particularly in using MAPE and determining adequate benchmark levels. Limited evidence exists for using ABC/XYZ classifications for demand planning in the retail industry, and future studies will address this gap by focusing on items that cannot be forecasted. The study discusses focus bias and forecast bias in KPI and performance measurement, focusing on the impact of different forecasting models on forecast accuracy. It also highlights the role of managers in forecasting demand levels, communication, and prioritization. However, there is limited evidence on how a clear structure can improve forecasting by eliminating unnecessary adjustments and errors. The difference between demand planning and forecasting is also highlighted, but a gap exists in understanding this. Kahn and Chase outline steps for setting up a demand model for forecasting new items, including the Bayesian method for determining uncertainty (Kahn & Chase, 2018). The literature review also discusses statistical forecasting methods, including the moving average and exponential smoothing. However, there is a gap in the best model for the retail industry, necessitating further research. The literature review highlights the need for a comprehensive approach to forecasting new items, addressing challenges, and providing a more accurate forecast.

6. Methodology

6.1. Research Design

This segment highlights the research methodology used for this investigation. Our main area of interest was the case study of a well-known Fast-Moving Consumer Goods (FMCG) firm in the Saudi retail industry. According to Pukdesree (2017), research design is a strategy that outlines what information needs to be gathered, from which individuals, how and when it should be collected, and how it will be analyzed to meet the study's goals. Since the study's aims are descriptive to a certain extent and could also involve attending to numerous realities that are anticipated to be encountered in the context. According to Allan (2020), a qualitative investigation is a method for studying human behavior that depends on narrative analysis of information to evaluate the significance of the acts from the viewpoint of those involved in their particular social environment. Besides, as Allan (2020) defined, qualitative research is to thoroughly examine, comprehend, and analyze interpersonal events in the context of their surroundings. Consequently, we were able to collect more thorough data and have a deeper grasp of the issues, scenarios, or events by using a qualitative research technique. More importantly, we were able to look into the scenarios where and when it may have happened as well as its why and how by employing a qualitative technique. Asenahabi (2019) asserts that the technique is simple to administer and control. The problem's scope and pace were also determined using the quantitative approach. It was important to focus on gathering information from the chosen samples. A visual summary and description of the available data were thus provided.

6.2. Data Collection

In this section, I describe the method used to gather data for the case study. Published analysis of secondary data, in addition to critical observation, served as the tools employed in the data-collecting process. Historical sales data, seasonal patterns, marketing initiatives, item age classifications, authorized, verified predictions, and KPI metrics, including Forecast Error (MAPE), Forecast Accuracy, and Forecast Bias, are all included in the dataset that was gathered. Please take note that I describe the method used to gather data for the case study, with a focus on choosing essential data points from the FMCG Company's Enterprise Resource Planning (ERP) system. Historical sales data, seasonal patterns, marketing initiatives, item age classifications, authorized, verified predictions, and KPI metrics, including Forecast Error (MAPE), Forecast Accuracy, and Forecast Bias, are all included in the dataset that was gathered. For the secondary data used in this research, any data gathered from other researches are clearly mentioned above the tables.

6.3. Data Analysis

The many approaches and strategies used for data analysis are described in this subsection. An essential part of this research remains to be data analysis, which is analyzing and drawing conclusions from the gathered data. In order to examine the data, which mainly consists of an accounting of the data gathered, the research employed statistical, thematic, and content evaluation. The data came from both secondary and primary sources. While previous research materials and other publications pertaining to the research topic comprise the secondary data, the primary data source comprises information gathered in a cross-sectional way from both new and old things as well as from various items included in ABC classes.

6.4. Results and Discussion

With the Category Manager and Category Assistant managing demand forecasting, the business lacks a demand planning team structure. Their correctness and conformity with the desired team structure are called into doubt by this absence of a committed team. The maturity level of the present demand model is evaluated, highlighting strengths, limitations, and a path for development. Research recommendations are contrasted with the company's Triple Exponential Smoothing model, and Bayesian forecasting is investigated for new item forecasting. Examining the ABC classification and discussing the advantages of switching to the ABC/XYZ categorization is also undertaken. According to study suggestions, this change might enhance service levels and accuracy, operational efficiency, and customer happiness. The goal of the research is to offer a plan for enhancing the business' demand planning system.

6.4.1. Existing Team Structure

Rather than having a specific Demand Planning team responsible for creating forecasts, the company's organizational structure spreads out responsibilities across several positions. The Category Manager and Category Assistant, who have marketing credentials rather than competence in statistical quantitative forecasting, are mainly in charge of the company's demand forecasting. Their methodology primarily focuses on qualitative evaluations and judging procedures, which is essential for determining how their strategies would affect overall predicting accuracy. However, there is a glaring mismatch when compared to the suggestions made by the study for the best team structure. According to the report, companies rely on people with marketing expertise who essentially use qualitative forecasting techniques, as opposed to specialist Demand Planners with strong quantitative forecasting credentials. This aspect emphasizes the demand for a more well-rounded method of forecasting.

6.4.2. The Current Demand Model's Maturity Level

Understanding an organization's Demand Planning maturity is essential to creating a successful forecasting approach, and Gartner's 5 Stages of Maturity, adapted from Gartner research, may be used as a helpful framework. To solve supplier availability and fulfillment difficulties, the organization has to move towards Stage #4 from Stages #2 and #3 of the maturity matrix. In order to do this, suppliers and retailers will need to work more closely together, sharing predictions, manufacturing capacity, and availability dates. Several efforts have been put in place to advance the maturity level of demand forecasting, bridging the gap between the present stage and the targeted Stage #4 maturity in order to increase the accuracy of demand planning.

- Establishing forecast sharing process: The business has initiated a cooperative strategy with its top five suppliers, who account for over 40% of its sales volume, to enhance supplier cooperation and forecast accuracy, thereby boosting sales volume.
- Developing the vendor portal: The Vendor Portal is a cutting-edge platform that enables suppliers to access crucial data, including predictions, real-time stock levels, and open purchase orders, encouraging transparency and cooperation. It was created in conjunction with IT, System Design, Supply Chain, Commercial, and Buying divisions.
- Joint ownership of KPIs: KPIs should be jointly owned by the retailer and suppliers, who should also share responsibility for fulfillment and new product partnerships. This notion is consistent with Stage #5 of maturity, in which both sides share performance and client happiness.

In an effort to reach Stage #4 maturity, the organization is putting strategic plans into action to increase the Demand Model's maturity and develop better supplier connections.

6.4.3. Current Statistical Model Findings

The Category Manager and Assistant employ a growth factor based on previous peak sales to project future sales of products using the company's existing forecasting methodology. This process entails multiplying the previous sales amount by the growth factor between the historical peak month and the desired predicted month. However, this strategy is incorrect because it ignores the fundamentals of statistical forecasting, seasonal fluctuations, and the introduction of new items, which can result in errors, overstocking, and stockouts and pose severe operational difficulties. This aspect is illustrated in **Table 3** below:

Based on **Table 3**, suppose the November sales plan for the entire category is SR10,000, and the actual March sales for that category were SR8,000.

Based on the current method, the growth factor calculation is as follows:

Growth Factor = (November Sales Plan − March Actual Sales)/March Actual Sales

$$\text{Growth Factor} = (\text{SR}10{,}000 - \text{SR}8{,}000)/\text{SR}8{,}000 = 0.25\% \text{ or } 25\% \tag{14}$$

Applying this growth factor to the peak sales in March:

Forecast for November using the Current Method:

$$\text{Forecast for November} = \text{March Peak Sales} \times (1 + \text{Growth Factor})$$

Table 3. Sales unit and sales plan on category level in value.

Month	Sales (units)	Sales Plan (Category Level Value)
January	300	6200
February	200	5000
March	500	8000
April	450	7800
May	350	6500
June	400	6800
July	330	6000
August	460	7500
September	350	7000
October	?	8600
November	?	10,000
December	?	6700

$$\text{Forecast for November} = 500 \text{ units} \times (1 + 0.25) = 625 \text{ units} \quad (15)$$

This approach is flawed because it ignores seasonal trends, does not take into account new product releases, and fails to adhere to statistical forecasting standards. Prediction errors, overstocking of certain goods, and stockouts of others ensue, which presents operational difficulties.

6.4.4. Introduction of the Triple Exponential Smoothing Model

With the help of the Excel Forecast Sheet function, as seen in **Figure 3**, the business has switched from its previous forecasting technique to the Triple Exponential Smoothing model.

As a result, the business is able to utilize the Triple Exponential Smoothing model prior to integrating the sophisticated RDF tool created by Oracle. The IT team is presently implementing the RDF tool, which enables complex statistical computations and extensive forecasting capabilities. This proactive strategy coincides with the study goal of improving demand planning to maximize customer happiness and operational efficiency while also addressing present forecasting shortcomings.

6.4.5. The Introduction of the RDF (Retail Demand Forecasting) Tool

The RDF tool from Oracle is a sophisticated forecasting tool that improves demand planning. To examine seasonal changes for each product, Triple Exponential Smoothing, and historical data are used. This strategy guarantees that projections are responsive to dynamic changes, producing more precise predictions. RDF also uses cutting-edge data-cleaning methods to remove outliers and smooth demand changes in order to produce trustworthy baseline projections. In order to guarantee that the baseline projection accurately represents actual

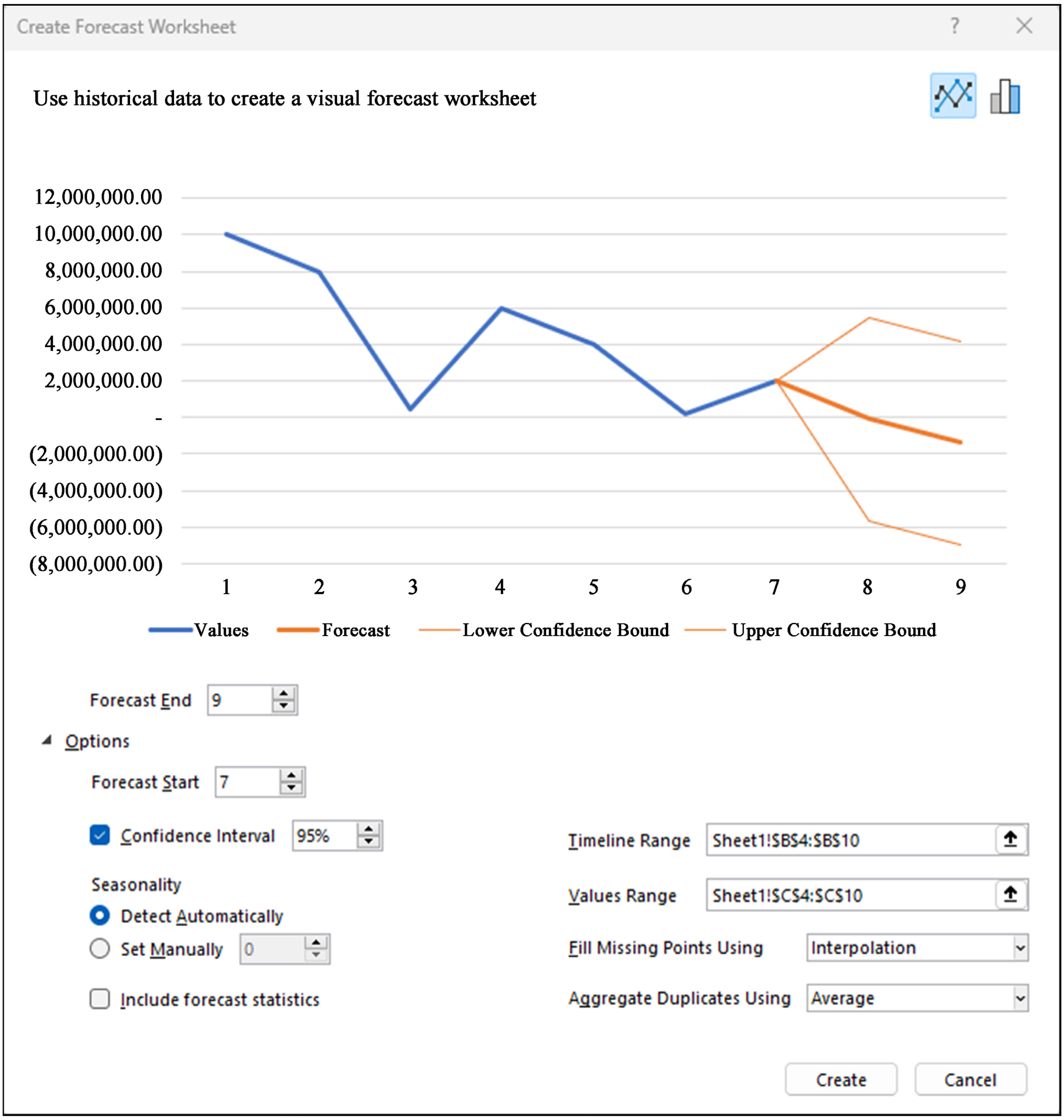

Figure 3. Excel forecast sheet.

demand patterns, it additionally includes "out of stock" signs. As illustrated in Figure 4 below, these methods improve the forecast's stability and accuracy, laying a solid basis for future forecasting.

With the help of RDF, which evaluates historical data on products, it is possible to determine prior marketing campaigns and their effects on sales. When a similar advertising flag is found in the future, it will take this information into account to make precise sales spike projections. This cutting-edge method outperforms conventional forecasting methods by offering a more exact and flexible solution that fits a company's unique objectives, especially in circumstances when promotional activities are essential for sales.

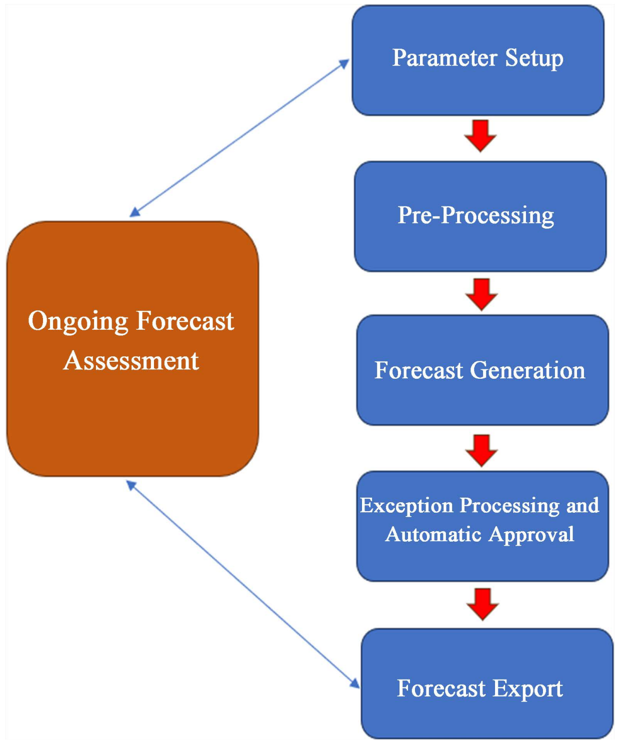

Figure 4. RDF high-level process flow.

Table 4. Forecast accuracy comparison between previous and improved models.

Item Class	Average Forecast Accuracy (Previous Model)	Average Forecast Accuracy (Improved Model)
Class A	77.50%	84.80%
Class B	73.70%	82.50%
Class C	72.50%	83.10%
Class D	65.50%	77.90%
Class E	55.60%	75.50%

The Triple Exponential Smoothing model closes the gap in the existing method's reliance on historical growth variables and is in line with research suggestions. This approach controls new product launches, improves demand prediction accuracy, and considers seasonality. This change brings the company's approach to demand forecasting a long way closer to the standards already used in the retail sector.

Table 4 illustrates KPI's level optimization that compares the company's previous model versus an improved model. KPIs for the company's prior demand forecasting methodology have significantly improved, especially forecast accuracy, demonstrating the revolutionary effects of the new demand planning strategy. Due to the earlier model's prioritization of Class A products because of their substantial sales impact, other classes' forecast accuracy suffered. Time restraints and staff capacity restrictions in the forecasting process were the leading causes of this unbalanced emphasis on Class A.

The organization has adopted a new strategy for demand planning that prioritizes fair treatment for all classes and lowers gaps in prediction accuracy. Modern technology that can effectively analyze massive datasets has assisted this transformation. The Demand Planning Team's workload has decreased as a result of this change, enabling more efficient resource allocation. The transition from a concentration on Class A products to a more balanced strategy highlights the significance of giving all things, regardless of classification, equal attention. It acts as a catalyst for improved demand prediction accuracy. This change demonstrates the firm's dedication to improving its demand forecasting methodology.

The organization has increased forecast accuracy by applying the proper demand planning framework, the Triple Exponential Smoothing model from RDF, and cross-functional input. The forecast quality is improved by collaboration, which significantly improves forecast accuracy. In order to improve forecast production, the organization consults stakeholders from multiple divisions, assures thorough forecast validations, and performs manual modifications. With this change in the demand forecasting methodology, the company can operate more efficiently and better fulfill consumer requests across the board. The ability to offer excellent client experiences is ensured by striking a balance between improved forecast accuracy and fair treatment of all item classes.

6.4.6. Overall Summary and Integration

The research has revealed significant findings for demand planning and forecasting, with a notable achievement in the improved Demand model. The model consistently surpasses the company's old model in forecast accuracy. This achievement is based on previous studies that establish benchmarks for forecast accuracy within forecasting models. Makridakis et al. suggest a 25% forecast accuracy level is typically considered good performance, especially for exponential smoothing models (Makridakis, Wheelwright, & Hyndman, 2008). In the retail industry, an acceptable accuracy level typically hovers around 20% - 30%. The new demand model's results fall within this range, indicating a significant leap in accuracy from the company's previous methods.

7. Conclusion and Recommendation

To effectively respond to our first research questions regarding the effects of the complexity of the existing demand planning process on supply chain performance, the paper first links this complexity to forecast bias. However, the paper processes the WMAPE formula for more accurate forecasting. To respond to our research question regarding the pace to improve the overall performance based on demand planning, the research suggests the use of a forecasting technique called exponential smoothing since it creates parameters using weighted averages of past observations, making it easy to avoid future challenges that might occur in the process. To answer the question on key factors influencing the integration of advanced forecasting techniques, the paper identified applied KPIs, focus bias, and how switching to ABC/XYZ categorization has the potential to improve accuracy and service levels in accordance with study recommendations. Lastly, our overall findings reflect our final research questions regarding the effects of implementing enhanced demand planning. Hence, the paper concludes that enhanced demand planning based on forecast accuracy within forecasting models is a significant leap in accuracy from the company's previous methods, as the accuracy level typically hovers around 20% - 30% in the retail industry. This approach impacts the efficiency and effectiveness of current logistics and supply chain operations.

Conclusively, this research focuses on addressing contemporary challenges in supply chain and logistics, explicitly enhancing demand planning and forecasting. It aims to understand the intricacies of demand planning in the modern context, unravel demand dynamics, and develop innovative methods that transcend traditional statistical models, ensuring the efficient flow of goods and services. The research has yielded significant findings for demand planning and forecasting, with one notable achievement being the improved Demand model, which consistently outperforms the company's old model in forecast accuracy. This research's meticulous development and analysis highlight the importance of accurate demand planning. The new demand model achieved a 25% forecast accuracy level, which is typically considered good performance for exponential smoothing models. This is a significant leap in accuracy from the company's previous methods, as the accuracy level typically hovers around 20% - 30% in the retail industry, a sector closely related to the focus of the study. Previous studies on forecasting models support this achievement. This research seeks to enhance demand forecasting, inventory management, and customer happiness by identifying potential future work areas. It highlights the company's dedication to ongoing development and adaptability to the changing retail environment, ensuring its demand planning procedures are improved and optimized for a competitive edge.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

Adhikari, N. C. D., Domakonda, N., & Chandan, C. (2018). An Intelligent Approach to Demand Forecasting. In S. Smys, R. Bestak, J. Z. Chen, & I. Kotuliak (Eds.), *International Conference on Computer Networks and Communication Technologies* (pp. 167-183). Springer. https://doi.org/10.1007/978-981-10-8681-6_17

Agarwal, R., & Womack, K. (2009). *Forecasting: Principles and Practice*. O'Reilly.

Allan, G. (2020). Qualitative Research. In G. Allan, & C. Skinner (Eds.), *Handbook for Research Students in the Social Sciences* (pp. 177-189). Routledge. https://doi.org/10.4324/9781003070993-18

Arunachalam, D., Kumar, N., & Kawalek, J. P. (2018). Understanding Big Data Analytics Capabilities in Supply Chain Management: Unravelling the Issues, Challenges, and Implications for Practice. *Transportation Research Part E: Logistics and Transportation Review, 114,* 416-436. https://doi.org/10.1016/j.tre.2017.04.001

Asenahabi, B. M. (2019). Basics of Research Design: A Guide to Selecting Appropriate Research Design. *International Journal of Contemporary Applied Researches, 6,* 76-89.

Bhattacharyya, S. (2014). Improving Inventory Demand Forecasting by Using the Sales Pipeline: A Case Study. *Journal of Business Forecasting, 33,* 1, 9-11.

Blasco, B. C., Moreno, J. J. M., Pol, A. P., & Abad, A. S. (2013). Using the R-MAPE Index as a Resistant Measure of Forecast Accuracy. *Psicothema, 25,* 500-506.

Bobby, P., Jones, J., & Smith, S. (2020). A Review of Forecast Evaluation and Measurement. *Journal of Operations Management, 28,* 211-220.

Bridgewater, A., & Williamson, D. (2014). Using Classifications for Forecasting. *International Journal of Forecasting, 30,* 51-64.

Bulinski, J., Waszkiewicz, C., & Buraczewski, P. (2013). Utilization of ABC/XYZ Analysis in Stock Planning in the Enterprise. *Annals of Warsaw University of Life Sciences-SGGW.* Agriculture (61 Agric. Forest Eng.).

Chase, C. W. (2013). *Demand-Driven Forecasting: A Structured Approach to Forecasting*. John Wiley & Sons. https://doi.org/10.1002/9781118691861

Chien, Y.-T., & Hung, C.-P. (2013). A Comprehensive Study of MAPE for Forecasting Electrical Load. *Energy and Buildings, 58,* 97-105.

Gansterer, M. (2015). Aggregate Planning and Forecasting in Make-to-Order Production Systems. *International Journal of Production Economics, 170,* 521-528. https://doi.org/10.1016/j.ijpe.2015.06.001

Ghalehkhondabi, I., Ardjmand, E., Weckman, G. R., & Young, W. A. (2017). An Overview of Energy Demand Forecasting Methods Published in 2005-2015. *Energy Systems, 8,* 411-447. https://doi.org/10.1007/s12667-016-0203-y

Guevara, M. J., & Gómez-González, J. S. (2016). Classification-Based Forecasting of Categorical Time Series. *IEEE Transactions on Neural Networks and Learning Systems, 27,* 1327-1339.

Gustriansyah, R., Suhandi, N., Antony, F., & Sanmorino, A. (2019). Single Exponential Smoothing Method to Predict Sales of Multiple Products. *Journal of Physics: Conference Series, 1175,* Article 012036. https://doi.org/10.1088/1742-6596/1175/1/012036

Heikkinen, J. (2016). Demand Forecasting and Service Level Optimization in Supply Chain Management. *International Journal of Production Economics, 173,* 228-243.

Hofmann, E., & Rutschmann, E. (2018). Big Data Analytics and Demand Forecasting in Supply Chains: A Conceptual Analysis. *The International Journal of Logistics Management, 29,* 739-766. https://doi.org/10.1108/IJLM-04-2017-0088

Holzmann, H., & Platt, F. (2005). Demand Management in Supply Chain Management. *International Journal of Production Economics, 92,* 135-148.

Hopkinson, M. (2017). *The Project Risk Maturity Model: Measuring and Improving Risk Management Capability*. Routledge. https://doi.org/10.4324/9781315237572

Hyndman, R. J. (2014). Measuring Forecast Accuracy. In *Business Forecasting: Practical Problems and Solutions* (pp. 177-183). John Wiley & Sons.

Kahn, K. B., & Chase, C. W. (2018). The State of New-Product Forecasting. *Foresight: The International Journal of Applied Forecasting, No. 51,* 24-31.

Lapide, L. (2014). Planning and Forecasting Work Hand in Hand. *Journal of Business Forecasting, 33,* 12-14. https://search.proquest.com/openview/52974d9f0d6122881052b58348eccc7d/

Makridakis, S., Wheelwright, S., & Hyndman, R. J. (2008). *Forecasting: Methods and Applications*. John Wiley & Sons.

Nau, R. (2014). *Forecasting with Moving Averages* (pp. 1-3). Fuqua School of Business, Duke University.

Ni, S. F., Peng, Y., Peng, K., & Liu, Z. J. (2022). Supply Chain Demand Forecast Based on SSA-XGBoost Model. *Journal of Computer and Communications, 10,* 71-83. https://doi.org/10.4236/jcc.2022.1012006

Nissi, J., Smaros, J, Ylinen, T., & Ala-Risku, T. (2021). *Measuring Accuracy: The Complete Guide*. Relex. https://www.relexsolutions.com/resources/measuring-forecast-accuracy/

Oey, E., Wijaya, W. A., & Hansopaheluwakan, S. (2020). Forecasting and Aggregate Planning Application—A Case Study of a Small Enterprise in Indonesia. *International Journal of Process Management and Benchmarking, 10,* 1-21. https://doi.org/10.1504/IJPMB.2020.104229

Pandya, B., & Thakkar, H. (2016). A Review on Inventory Management Control Techniques: ABC-XYZ Analysis. *REST Journal on Emerging Trends in Modelling and Manufacturing, 2,* 82-86.

Prayudani, S., Hizriadi, A., Lase, Y. Y., & Fatmi, Y. (2019). Analysis Accuracy of Forecasting Measurement Technique on Random K-Nearest Neighbor (RKNN) Using MAPE and MSE. *Journal of Physics: Conference Series, 1361,* Article 012089. https://doi.org/10.1088/1742-6596/1361/1/012089

Pukdesree, S. (2017). The Comparative Study of Collaborative Learning and SDLC Model to Develop IT Group Projects. *TEM Journal, 6,* 800-809.

Ren, S., Chan, H.-L., & Siqin, T. (2019). Demand Forecasting in Retail Operations for Fashionable Products: Methods, Practices, and Real Case Study. *Annals of Operations Research, 291,* 761-777. https://doi.org/10.1007/s10479-019-03148-8

Shila, R. (2021). *Business Forecasting*. https://www.yourarticlelibrary.com/management/forecasting/business-forecasting/99685

Sidqi, F., & Sumitra, I. D. (2019). Forecasting Product Selling Using Single Exponential Smoothing and Double Exponential Smoothing Methods. *IOP Conference Series: Materials Science and Engineering, 662,* Article 032031. https://doi.org/10.1088/1757-899X/662/3/032031

Soltanali, H., Rohani, A., Abbaspour-Fard, M. H., & Farinha, J. T. (2021). A Comparative Study of Statistical and Soft Computing Techniques for Reliability Prediction of Automotive Manufacturing. *Applied Soft Computing, 98,* Article 106738. https://doi.org/10.1016/j.asoc.2020.106738

Stojanović, M., & Regodić, D. (2017). The Significance of the Integrated Multicriteria ABC-XYZ Method for the Inventory Management Process. *Acta Polytechnica Hunga-*

rica, 14, 29-48. https://doi.org/10.12700/APH.14.5.2017.5.3

Tratar, L. F., Mojškerc, B., & Toman, A. (2016). Demand Forecasting with Four-Parameter Exponential Smoothing. *International Journal of Production Economics, 181,* 162-173. https://doi.org/10.1016/j.ijpe.2016.08.004

Wang, W., Gershman, M., & Srinivasan, S. (2014). Impact of Demand Forecasting Accuracy on Customer Satisfaction. *International Journal of Production Research, 52,* 2569-2583.

Wang, Y., & Wei, Y. (2016). Forecasting in Retail: A Review. *International Journal of Forecasting, 32,* 249-263.

Yuen, M. (2022). *Retail Trends: 2022 Retail Industry Stats, Trends, and Forecasts*. Insider Intelligence. https://www.insiderintelligence.com/insights/future-retail-trends-industry-forecast/

Zenkova, Z., & Kabanova, T. (2018). The ABC-XYZ Analysis Modified for Data with Outliers. In *2018 4th International Conference on Logistics Operations Management (GOL)* (pp. 1-6). IEEE. https://doi.org/10.1109/GOL.2018.8378073

Zhang, W. (2016). Forecasting Forecast Accuracy. *International Journal of Forecasting, 32,* 425-440.