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Enhancing supply chain efficiency: a holistic examination of hybrid forecasting models employing mode and PERT technique as deterministic factors

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ABSTRACT
Inaccurate forecasts can cause severe financial consequences and disrupt supply chain operations for organisations. This study focuses on the pharmaceutical industry, renowned for its complex supply chain and diverse data attributes. It proposes a novel approach to identify the optimal combination of demand forecasting models that enhance accuracy by leveraging deterministic factors using Mode and PERT. By refining model selection in the pharmaceutical industry, this research aims to improve both forecasting precision and supply chain efficiency. A four-level framework based on deterministic factors is proposed to evaluate the extent of hybrid modelling in demand forecasting, empowering practitioners to make informed decisions even in challenging circumstances. The findings offer decision-makers flexibility in selecting suitable forecasting models and assist in tailoring methods to specific conditions. Furthermore, this research highlights the industry's ability to leverage digital technologies and transform existing forecasting methodologies, ensuring uninterrupted business operations during disruptions such as the COVID-19 pandemic.

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Hybrid forecasting; Demand forecasting; Pharmaceutical supply chain; Forecasting accuracy; Inventory optimization; Advanced forecasting techniques

Introduction

In the twenty-first century, where data and technology drive processes, the organisations that exhibit adaptability and resiliency and consider people, processes, and technology in their main agenda are the market leaders (Accenture 2023; Azmat, Ahmed, and Mubarik 2022). The paradigm of competition has changed drastically in this era of modern science and technology. Their performance in the supply chain has replaced the traditional rivalry among organisations to gain a competitive edge (Siddiqui et al. 2021). One such example could be inventory management, which has always been a primary concern for manufacturing, distribution, or retail organisations. A large amount of capital has been exhausted in the form of inventory, adversely affecting firms' financial performance (Cruz, Torres, and Ibañez 2019; Vries 2007), which seriously impacts the ability of an organisation to recover quickly from difficulties. Literature related to inventory management has shown that approximately 20% to 40% of a firm's assets have been consumed due to inefficient inventory

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management (Farooq 2019; Li et al., 2015), signifying that the profitability of the firm and its resilience depends on adequate management of the inventories and remain vigilant on the driving factors related to it such as demand forecasting.

Similarly, applying appropriate forecasting techniques is an essential element that saves an organisation from the bullwhip effect or stock-out situation (Barwa 2015; Mbohwa 2016). Zhu et al. (2021) argue that to overcome the external pressure from the government and the public to provide cost-effective drugs, adopting advanced demand forecasting technologies and inventory management is critical for many aspects of the pharmaceutical supply chain efficiency. According to Xue, Dou, and Shang (2021), digital technologies can help save energy, connect people globally, and inform decisions through big data, artificial intelligence, and blockchain. Digital technologies resolve supply chain collaboration challenges, create business value, mitigate risks, and improve efficiency (Dhruman Gohil 2021).

Since the early 2000s, substantial efforts have been made to improve forecasting accuracy in the supply chain. In a similar context, Siddiqui et al. (2021) emphasised the hybrid demand forecasting model, coupling their application with integrated systems specifically for pharmaceutical manufacturers. The pharmaceutical industry is fragile, so coping with the demand is essential (Salam and Khan, 2018; Fildes and Goodwin 2021); uncertain demand has a positive linear relationship with excessive inventory (Siddiqui et al. 2021; Vries 2007); concentrated on using hybrid forecasting method instead applying a single model that increases forecast accuracy. For forecasting purposes, the Mean Absolute Error (MAPE) of the hybrid model developed by (Munim and Schramm 2020; Munim and Schramm 2017) has a reasonable reduction in forecast error.

To increase the accessibility of the products, improve forecasts, and maintain the balance between supply and demand, a globally appropriate forecasting mechanism is necessary (WHO 2016) devised a tool for forecasting the demand for antiretroviral therapy (ART) for Human Immunodeficiency Virus (HIV) patients. The consolidated forecast arrangements can reduce the error rate from 5% to 9% (Irem Islek 2017). Thus, this research aims to find the best combination of models out of 25 combinations against therapeutic classes and brands. Therefore, refining and redefining the demand forecasting methodology is the objective of this research.

According to Hinings, Gegenhuber, and Greenwood (2018), A scenario analysis tool is the need of the hour along with the analyst while forecasting in an uncertain and complex environment. Furthermore, the forecasting applications' role is critical while managing the electronic supply chain for healthcare services (Debashri Dey 2013). Subsequently, (Radhakrishnan et al. 2011; Rees 2011) elaborated on the impact of the pharmaceuticals supply chain due to globalisation proscribed the need for intelligent information and communication systems for data collection, processing, analysis and drawing inferences. Furthermore, forecasting the demand through integrated systems with accurate data would enable an organisation to optimise its inventory levels (Erkayman 2018; Tiwari 2020), whilst integrated systems decrease the gap between the actual and forecast (Aytac and Wu 2017; Hinings, Gegenhuber, and Greenwood 2018).

Additionally, predictive and prescriptive approaches are intertwined for value achievement through big data analysis that contributes to better demand management and order fulfilment by appropriately utilising key enablers such as people, processes, and technology (Barbosa et al. 2018). Disruptive technologies such as big data analytics play a vital role in translating enormous amounts of data into meaningful information for handling demand volatility, inventory management, effective demand management, and efficient decision-making (Wang et al. 2016). Hence, it requires a robust technological infrastructure to realise the benefits of digital technologies. Due to globalisation and the customer's ever-changing needs, it becomes very difficult for the organisation to manage its supply chains without taking advantage of information technology (Ahmed et al. 2021).

More importantly, the purpose of this research is to identify the best combination of hybrid models with the utilisation of deterministic factors that enable practitioners to make informed decision-making, specifically in the pharmaceutical industry. Subsequently, the research will define the previous research on the application of technology in forecasting practices, hybrid models and their applications, the limitations of using a single forecasting model, and the need to redefine the forecasting model in normal conditions and turbulent times. Similarly, the problem statement section sheds light on the pressing challenges due to inappropriate forecasting. The methodology section will define the construction of hybrid models and identify the deterministic factors. In the empirical analysis and findings section, the results of the calculations will be presented in the figures and tables, along with the solutions to the problems. Lastly, these will be commented on, and a summary of the results will be presented in the discussions and conclusion section.

State of the art

This section contributes to the existing body of literature focusing on demand forecasting practices in pharmaceutical supply chain management, as accurate demand forecasting is critical for supply chain efficiency. According to Zhu et al. (2021), since the mid-2000s, significant effort has been made to improve forecast accuracy in the supply chain. In this vein, numerous measures have been taken, such as applying different statistical methods and hybrid forecasting mechanisms and developing and adopting various software and technologies for demand forecasting.

Demand forecasting in pharmaceutical supply chain

(Neelam 2006; Omar Gala´rraga et al. 2007; Rees 2011) they have emphasised on adequate demand forecasting, as inappropriate demand forecasting for health products may cost lives. Before the 2000s and early 2000s, pharmaceutical companies did not pay much attention to demand forecasting or supply chain efficiency (Angell 2004). In a pharmaceutical industry survey, C. Jain (2003) highlighted the widely practised models of forecasting, which are the basic exponential smoothing, moving averages, and regression. However, in recent times, to gain a competitive advantage, pharmaceutical companies have a strong focus on demand forecasting (Galina, Valberga, and Smirnov 2019; Kiely 2004). (Charles W. Chase 2013; Chase 2016) concentrated on demand-driven pharmaceutical forecasts.

In addition, Weller and Crone (2012) mentioned that the basic exponential smoothing, moving average, and naive methods had been widely used for forecasting in pharmaceuticals. On the one hand, pharmaceutical companies deal with many active pharmaceutical ingredients (API) and different therapeutic classes. On the other hand, due to the complex and volatile nature of the industry and its product, collaboration among the supply chain network enhances forecasting accuracy (Papageorgiou 2009; Suzanne, Roy, and Ari-Pekka 2003; Walters 2006; Whewell 2009). (Cook 2016) suggested obtaining the forecast against the transformed data. Subsequently, Nikolopoulos et al., for the demand forecasting of branded drugs and their generic equivalent, eleven different methods used to forecast drug time series, including but not limited to Diffusion models, Autoregressive Integrated Moving Average (ARIMA), Holts Winter, Exponential Smoothing, Naïve, and Regression methods. On the other hand, forecasting through the statistical model's human/expert judgment is appropriate in cases such as new product launches and promotions (Arvan et al. 2019).

Importance of data in demand forecasting

For informed decision-making, data quality is essential; when inaccurate data is used for computation purposes, results invoke the phrase garbage in – garbage out (Mazurek, Szeleszczuk, and Pisklak 2020). Historic sales data are the most frequently used data for statistical forecasting (Weller and Crone 2012). (Nasiri et al. 2020; PWC 2016) data collection through external and internal collaborations is more accurate and drives better forecast results (Galina, Valberga, and Smirnov 2019). Mentioned the underlying challenges regarding data usage and accessibility, i.e. different data formats and lack of data integration tools. Supply chain dynamics are greatly affected by inconsistent data (Fildes, Goodwin, and Önkal 2019). Demand estimates can also be derived from the patient's consumption data (Salam and Khan 2018). Fatal consequences occur due to inappropriate demand forecasting against the patient data, leading to loss of lives (Rees 2011).

Role of technology in demand forecasting

The COVID-19 pandemic has highlighted the application of digital technologies in manufacturing essential drugs; integrated and distributed manufacturing will shape critical medicine manufacturing and increase decision-making precision (Ashok and Aravind 2021; Webb et al. 2022). Understanding supply-demand imbalances, responding with agility against disruptions, gaining a competitive advantage, and enhancing advanced analytical capabilities by leveraging digital technologies are critical for operational excellence (Accenture 2023; Kolkova et al., 2022). In addition, increased access to essential drugs heavily relies on the quality, availability of the data, variability in the studied population, and inconsistent data; a sound inventory management system improves reproductive health (Alkema et al. 2013).

According to (Kamar et al. 2021; Socal, Sharfstein, and Greene 2021), the production and distribution network of pharmaceutical products encountered unprecedented shifts in demand for regular as well as new drugs to catapult the shortage situation and increase supply chain resilience, enforcing implementation of the federal drug shortage surveillance system on a regional or local level to cope up the demand uncertainties. Advanced technologies enable specialised data analysis methods when dealing with large data sets recorded over multiple variables (Casian et al. 2022); in this vein, Nemaa and Aswed (2021) mentioned that the European Medicines Agency and Food and Drug Authority (FDA) jointly proposed a framework for analytical development, system suitability, and analytical life-cycle management in the pharmaceutical industry.

For demand forecasting purposes, various software provides ease to the forecaster, including but not limited to SAP, Oracle, R, Excel, etc. (Chase 2016; Cook 2016). However, vast room is available for improvements, as supply chain and information technology are relatively new fields compared to Maths, Physics, Statistics, etc. (Candan and Harun Yazgan 2014). According to (Fordyce 2009; Jharkharia and Shankar 2005), the technology's adaptability is emphasised to enhance supply chain performance. For example, Mohan (2003) outlined the surveyed response of Indian Pharmaceuticals and rated demand forecasting through integrated systems 4.22 out of 5, resulting in a better forecast.

Enhancing demand forecasting capabilities for turbulent times

The COVID-19 pandemic has emphasised the importance of businesses updating their forecasting methods to ensure continuity during disruptions. One approach is the decomposition-based data curation model proposed by Ashok and Aravind (2021). Kolkova and Rozehnal (2022) applied hybrid models, such as Theta and Forecasthybrid, to an e-shop dataset before and after the pandemic, finding that they performed well during unprecedented times. Nikolopoulos et al. (2021) presented a methodology for combatting the negative impact of COVID-19 on demand forecasting, utilising models such as Decision Tree, Random Forests, and Support Vector Machines and comparing results from other indicators and calculators, such as WHO COVID-19 ESFT and CHIME, can aid in managing essential supplies during the pandemic (Kamar et al. 2021).

Hybrid forecasting methods

Zhu et al. (2021) introduced various grouping schemes, proposed a framework of multiple modelling possibilities, and comprehended that the consolidated machine learning models for demand forecasting show promising results. Similarly, Siddiqui et al. (2021) presented a hybrid forecasting methodology for demand forecasting and proposed a model ARHOW, a combination of ARIMA and Holts Winter. The ARHOW forecast's empirical analysis exhibits significant results compared to other forecasting methods. Subsequently, linear extrapolation and historical demand data have been used for consolidated forecasting (WHO 2016) for HIV diagnostics. The consolidated forecast arrangements can reduce the error rate from 5% to 9% compared to forecasting through a single model (Irem Islek 2017).

Additionally, higher forecast accuracy can be achieved by using machine learning tools rather than using a single model to forecast demand (Thomson et al. 2019; Y.-J. Zhang and Zhang 2018). Ideal estimates can be achieved by combining the results of independent forecasts (Chase 2016). Similarly, (Caiado 2010; Chan and Pauwels 2018; Munim and Schramm 2020; Wei and Yang 2012) mentioned that combined forecasting techniques derived better results in other industries. Thus, this research aims to optimise the hybrid forecasting technique and devise a mechanism that reduces forecast error and improves forecast accuracy in the context of the pharmaceutical industry.

Limitations and implications of using single model demand forecasting models

Tailoring the demand forecasting models and practices with respect to data enables the forecaster to make more informed decisions as different data features can be associated with advanced, sophisticated, or simpler extrapolation methods to help in building resilience in the value chain (Petropoulos et al. 2014). Similarly, Siddiqui et al. (2021) mentioned the limitation related to the application of consolidated forecasting practices: no forecasting/integrated/enterprise-wide system provides functionality to obtain hybrid forecasts. Subsequently, PWC (2016) highlighted a need to explore and develop the mechanism in the available technologies and systems for computing demand forecasting functionality to increase supply chain efficiency.

The Mean Absolute Error (MAPE) of the hybrid model developed by (Munim and Schramm 2020; Munim and Schramm 2017) for forecasting purposes has a reasonable reduction in forecast error compared to the MAPE of ARIMA and ARCH models independently. Moreover, forecasting demand through the single model has low or less predictive capabilities that mislead practitioners and forecasters in anticipating demand during turbulent times such as the COVID-19 pandemic. In this vein, machine learning, deep learning and hybrid forecasting models are more efficient and derive better results (Nikolopoulos et al. 2021).

Another challenge mentioned by Tian, Wang, and Erjiang (2021) which cannot be handled by using a single model of forecasts, i.e. an intermittent demand with a high percentage of zero values. (Tian, Wang, and Erjiang 2021) urge the use of combined methods to cope with the underlying challenges. According to Kolkova et al. (2022), when there is high volatility in the data, results are insignificant by applying a single forecasting model such as ARIMA, Theta, Naïve, exponential smoothing, etc., compared to the combination of models. Thus, the hybrid forecasting technique derives better results.

Summary of the state of the art

Furthermore, reviewing and analysing the literature presented in this study provides solid credence to enhancing the capabilities of existing technologies used for forecasting. Table 1 below provides evidence of different forecast combination approaches in the pharmaceutical industry. Before the Covid-19 pandemics, very little attention was paid to adopting new models for demand forecasting (Singh et al. 2023). Weller and Crone (2012) mentioned that 82.1% of pharmaceutical companies used simple methods for forecasting demand. Similarly, 5% of the companies utilised hybrid forecasting methodology (Chaman L Jain 2005). Therefore, the proscribed methodology for computing the forecast allows the forecaster to select either the best model or identify and choose the model among the different combinations as per the given situation. There is not extensive literature available for demand forecasting in the particular industry; however, the authors have made significant

Table 1. Highlights the approaches used in hybrid forecasting.

Authors	Machine Learning-Based Combination Approach	Statistical Modelling – Based Combination Approach	Combination of Machine Learning and Statistical Modelling Approach
(Ashok and Aravind 2021)	-	-	α
(Nikolopoulos et al. 2021)	α	α	α
(Kamar et al. 2021)	-	α	-
(Siddiqui et al. 2021)	-	α	-
(Irem Islek 2017)	α	-	-
(Rees 2011)	α	-	-
(Cook 2016)	-	α	-
(Candan et al., 2014)	α	-	-
(Nikolopoulos, Buxton, Khammash, & Stern, 2016)	-	α	-

contributions to enlightening the adoption of the hybrid forecasting technique. Table 1 below exhibits the author and year-wise modelling methodology.

Table 1 illustrates that the most commonly practised hybrid forecasting approach is the statistical modelling-based combination approach, followed by the machine learning-based combination approach. In contrast, the combination of machine learning and statistical modelling approach is also gaining traction for research purposes.

However, in this era of globalisation, organisations cannot make informed decisions unless they have good-quality data and systems that can transform data into meaningful information. Moreover, the authors emphasised leveraging digital technologies in computing demand and re-engineering the forecasting models to enhance forecast accuracy. Subsequently, adequate training is essential for practitioners to understand data flow, system computational mechanisms, and the application of hybrid forecasting techniques to achieve the organisation's goal of competitiveness. Indeed, establishing a cohesive and balanced relationship between people, processes, and technology is crucial in demand forecasting for pharmaceutical products. The synergy among these three elements drives supply chain innovation that creates efficiency throughout the supply chain as people drive the process, utilising their expertise to design and execute effective forecasting processes. Technology supports and automates these processes, handling the data and calculations efficiently. The process ensures that the workflow is structured and consistent. Additionally, to take full advantage of the hybrid/consolidated forecasting technique, enhancing the resources' capabilities and building coherence among them is critical to the organisation's success.

Problem statement

The selection of the combination of models is considered an arduous task that enhances forecast accuracy and supply chain efficiency, particularly in the pharmaceutical industry. Inventory management is the biggest threat adversely affecting the supply chain's overall performance (Adeyemi and Salami 2017; Atnafu and Balda 2018). Higher inventory levels are a significant supply chain risk leading to the organisation's bankruptcy (Weller and Crone 2012). One of the main reasons for inadequate inventory management is inappropriate forecasting (Neelam 2006; Omar Gala´rraga et al. 2007; Rees 2011). Challenges in the supply chain can be handled by accurately forecasting the demand. Therefore, based on the current academic work, the following challenges need to be addressed:

- Conceptualisation, analysis, and application of advanced forecasting technique
- Improve forecast accuracy by reducing forecast error
- Inventory management challenges due to low-quality data and in appropriate forecast
- Data volatility challenges, integration and involvement of people, process, and technology for demand forecasting purposes.

Methodology

This paper introduces a novel approach based on multiple criteria for selecting a hybrid model with slight changes in the basics of the Mode and Programme Evaluation Review Technique (PERT), unlike their application in different sectors for analysis purposes (Liu et al. 2022; Zhang and Hong 2021). Nevertheless, in this study, the two are considered deterministic factors in model selection for demand forecasting and to get the optimal forecast result. Thus, this allows the forecaster to select the model concerning the practitioner or organisation's given situation and risk appetite. Moreover, PERT is widely used in Project Management for time estimation (Nemaa and Aswed 2021; Sun et al. 2020; Liu et al. 2018).

Methodological process flow

The methodological process flow in Figure 1 below sets the basis for decision-making that improves modelling and addressing customisation abilities for complex forecasting problems. It offers access to various hybrid demand forecasting models and helps select the best one for a given situation with greater accuracy. Additionally, this process flow considers deterministic factors and descriptive statistics to fine-tune results and make informed decisions to gain a competitive edge.

The introduction of deterministic factors such as PERT and Mode has a critical role in appropriate decision-making. These tools enable identifying the best models for demand forecasting, creating a significant differentiation from other research in the domain. According to Petropoulos et al. (2014), identifying the best method for data is very difficult. Our proposed methodology is capable of suggesting the best method and model against specific data for the pharmaceutical industry.

Data and technique

In this empirical research, the authors used sales data of the six therapeutic classes of six pharmaceuticals in Pakistan. The sample consists of 34 brands with different formulations such as

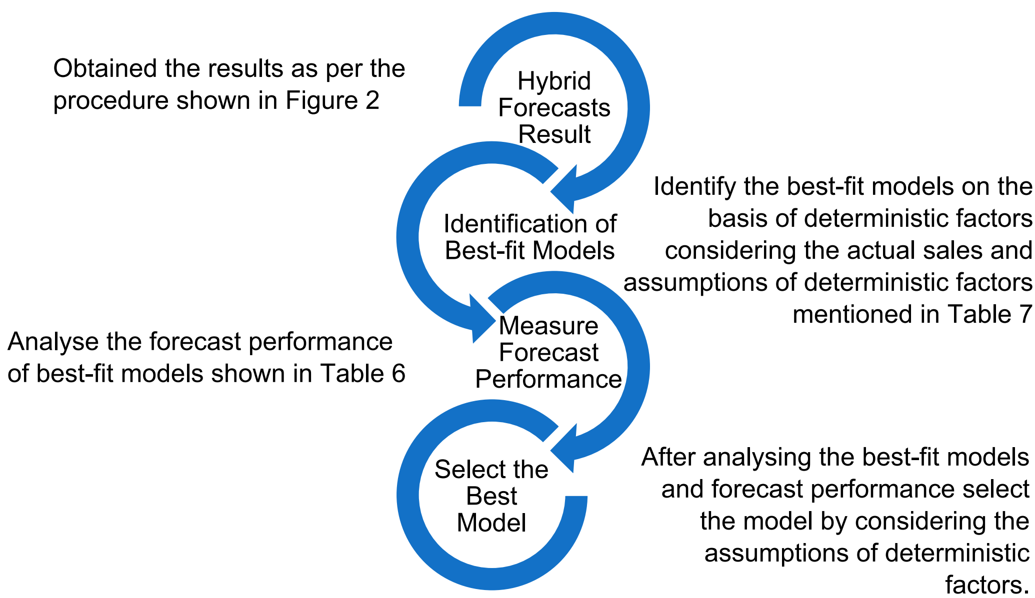

Figure 1. illustrates the conceptual framework for selecting the best model.

Injections, Tablets, Capsules, Suspensions, and different potencies such as 1gm, 10, 20, 250, and 400 mg. This adds breadth and depth to the research that justifies the model's robustness in any given scenario. Actual sales data have been collected from the selected pharmaceuticals from Quintiles (formerly known as the IMS-health) database, as shown in Table 2.

Five years of actual sales data consisting of 60 months taken for computational purposes, 43 months of data is considered a training set, whereas 15 months is a test set. The therapeutic classes are also selected for the research used to treat gonorrhoea, pelvic inflammatory disease, gastroesophageal reflux disease (GERD), meningitis, pneumonia, seasonal allergies, bronchitis, mycobacterium avium complex, typhoid fever, infectious diarrhoea, asthma, gastrointestinal problems, and other bacterial infections.

This study extends our previous research by Siddiqui et al. (2021), 'A hybrid demand forecasting model for greater forecasting accuracy: the case of the pharmaceutical industry'. Thus, a similar methodology is used to compute the demand. In addition, however, significant differentiation in computing, modelling, and inference methodology is introduced. Furthermore, this research not only expands the scope by introducing more combinations for forecast than a single combination, such as ARHOW, but also adds deterministic factors alongside a consolidated forecast matrix that allows the forecaster to make an informed decision. Figure 2 below illustrates an adapted and adjusted step-by-step methodology for forecasting hybrid demand.

Table 3 indicates the forecast results of the brand 'Oxidil' obtained by running the procedure shown in Figure 2 against the therapeutic classes and their related brands shown in Table 2. A summary of the hybrid forecast of a brand is shown in Table 4. A training data set is used to obtain the individual estimates of models 1 and 2. Following is the model equation for obtaining the multiple combinations of the hybrid forecasts.

$$\text{Hybrid} \quad \text{Forecast} = \beta_o * \text{Modell} \quad \textit{Forecast} \quad + \beta_1 * \text{Model2} \quad \textit{Forecast} \tag{1}$$

Where β_0 = Weight of Model 1

β_1 = Weight of Model 2

Nonetheless, the statistical package 'R' is used for computing the demand of the individual models. Subsequently, Microsoft Excel is used to determine weights, consolidate the forecast results, and calculate the descriptive statistics, identify and obtain the deterministic factors. Finally, the forecast package of 'R' and other functions related to forecasting is used to get the result of forecasts of the individual models, i.e. ARIMA, Holts Winter, ETS, and Theta proposed and suggested by (Bokde et al. 2017; Coghlan 2015; Dhamo and Puka 2010; Dufour and Neves 2019; Hyndman 2020); and using the forecast functions in 'R', i.e. 'auto.arima', 'forecast.arima', 'forecast. holt winters, '[forecast {fit(ets(data), forecast period}], and 'thetaf(data, forecast period)'.

Empirical analysis and findings

The steps proposed in Figure 2 have been carried out in this section, and forecast results obtained through it have been discussed and presented. Then, to provide ease to the forecasters, this paper

Table 2. Companies, formulation, potency, and brands selected for the research.

Company Name/ Product	Ceftriaxone (Inj. 1gm)	Clarithromycin (Tab. 250 mg)	Ciprofloxacin (Tab.250 mg)	Cefixime (Cap. 400 mg)	Omeprazole (Sus. 20 mg)	Montelukast (Tab. 10 mg)
GETZ	Getofin	Claritek	Novidate	Cefiget	Risek	Montiget
SAMI	Oxidil	Rithmo	Ciplinz	Caricef	Teph	Montika
BOSCH	Cefxone	Maclacin	Inoquin	Cebosch	Omezol	Beasy
BARRETT HODGSON	Inocef	Megaklar	Ciproquine	Cefspan	Losec	Aerokast
MACTER	Titan	Ultima	Cycin	Maxima	Sante	Mntk
HIGH-Q	Hizone	Pylocar	–	–	Ruling	Freehale

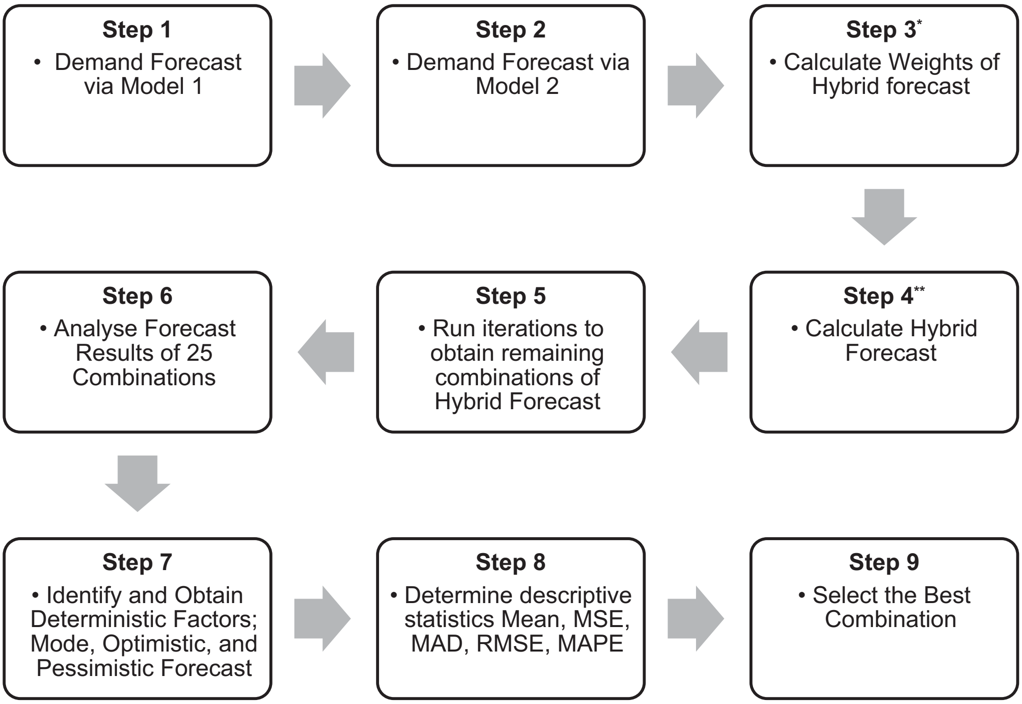

Figure 2. Step by Step procedure to obtain combinations of hybrid forecasting models. *Compute weights, i.e. β_0 and β_1 of hybrid forecast model. (Various methods and techniques are used to optimise weights for combination, but a right-hand side equation is developed to compute forecast based on regression shown in Equation#01. For this instance, therapeutic class sales data is taken as the dependent variable. Therefore, the estimates obtained from Model 1 and Model 2 is considered an independent variable). **Insert the results from the first, second, and third steps in forecast equation (1) to get the hybrid forecast against the test data set.

proposes a novel idea for the first time in the pharmaceutical industry for forecasting demand, with multiple criteria for selecting a hybrid model based on Mode and PERT estimations. Table 3 below exhibits the result of a hybrid forecast of a brand of the therapeutic class.

Table 4 exhibits the summary of the forecasts obtained after running the procedure mentioned in Figure 2, extracted from Table 3, thus bringing the 25 different combinations of the hybrid forecast of a brand.

The average sales of the brand are 8,161; by analysing Table 4, the best combination which provides the closest result for this brand is ARIMA-HW and its reciprocal HW-ARIMA. However, there are other models which provide the most comparable results, which are ARIMA-ETS, ETS-ARIMA, and NAÏVE-ARIMA.

Furthermore, Table 5 provides evidence of a differentiating factor among all the research done so far, specifically in the pharmaceutical industry, as mentioned in the literature. Mode and PERT are used for estimation purposes in different sectors (J. Liu et al. 2022; Y. Liu et al. 2018; Nemaa and Aswed 2021; Sun et al. 2020; Z. Zhang and Hong 2021). For the first time, applied them as a tool in drawing inferences for choosing the best model among the various models in the pharmaceuticals. Alternatively, it allows forecasters to select the model according to the company's risk appetite and profile.

Application of deterministic factors

In this empirical research, Mode and the PERT tools have been considered deterministic factors for drawing inferences against each brand. Deterministic factors are obtained by considering the sales

Table 3. Hybrid Forecast results of (therapeutic class) Ceftriaxone IV (1 gm injection) Oxidil; the remaining results are presented in the Appendix section.

Oxidil						
Date	Sales in Units	ARHOW FORECAST	ARIMA – ARIMA	ARIMA – NAÏVE	ARIMA – ETS	ARIMA – THETA
01/08/2015	11,441	11,339	11,142	11,406	11,155	11,131
01/09/2015	11,036	10,951	10,760	10,723	10,818	10,770
–	–	–	–	–	–	–
–	–	–	–	–	–	–
01/09/2016	7,952	8,048	8,003	7,981	8,063	8,026
01/10/2016	7,905	7,919	7,956	7,936	8,030	7,993
Average Forecast	8,161	8,157	8,189	8,183	8,184	8,188
Date	Sales in Units	HW – ARIMA	HW – HW	HW – NAÏVE	HW – ETS	HW – THETA
01/08/2015	11,441	11,366	11,293	11,424	11,325	11,351
01/09/2015	11,036	10,977	10,906	10,888	10,919	10,940
–	–	–	–	–	–	–
–	–	–	–	–	–	–
01/09/2016	7,952	8,061	8,042	8,031	8,027	8,029
01/10/2016	7,905	7,926	7,937	7,926	7,902	7,891
Average Forecast	8,161	8,165	8,173	8,170	8,171	8,169
Date	Sales in Units	NAÏVE – ARIMA	NAÏVE – HW	NAÏVE – NAÏVE	NAÏVE – ETS	NAÏVE – THETA
01/08/2015	11,441	11,377	11,418	0	11,468	11,454
01/09/2015	11,036	10,720	10,887	10,982	10,805	10,737
–	–	–	–	–	–	–
–	–	–	–	–	–	–
01/09/2016	7,952	7,984	8,033	7,701	8,078	8,058
01/10/2016	7,905	7,939	7,927	7,633	8,055	8,060
Average Forecast	8,161	8,184	8,170	7,328	8,174	8,179
Date	Sales in Units	ETS – ARIMA	ETS – HW	ETS – NAÏVE	ETS – ETS	ETS – THETA
01/08/2015	11,441	11,155	11,325	11,487	11,163	11,282
01/09/2015	11,036	10,818	10,919	10,810	10,854	10,970
–	–	–	–	–	–	–
–	–	–	–	–	–	–
01/09/2016	7,952	8,063	8,027	8,073	8,099	8,131
01/10/2016	7,905	8,030	7,902	8,049	8,074	8,058
Average Forecast	8,161	8,184	8,171	8,173	8,180	8,167
Date	Sales in Units	THETA – ARIMA	THETA – HW	THETA – NAÏVE	THETA – ETS	THETA – THETA
01/08/2015	11,441	11,131	11,351	11,481	11,282	11,103
01/09/2015	11,036	10,770	10,940	10,745	10,970	10,795
–	–	–	–	–	–	–
–	–	–	–	–	–	–
01/09/2016	7,952	8,026	8,029	8,053	8,131	8,083
01/10/2016	7,905	7,993	7,891	8,053	8,058	8,082
Average Forecast	8,161	8,188	8,169	8,178	8,167	8,186

Table 4. Illustrates the summary of the average hybrid forecast of the brand Oxidil; the remaining results are presented in the Appendix section.

Oxidil					
Forecasting Models	ARIMA	Holts Winter (HW)	NAÏVE	ETS	Theta
ARIMA	8,189	8,157	8,183	8,184	8,188
Holts Winter	8,165	8,173	8,170	8,171	8,169
NAÏVE	8,184	8,170	7,328	8,174	8,179
ETS	8,184	8,171	8,173	8,180	8,167
Theta	8,188	8,169	8,178	8,167	8,186

as a pivotal point; hence, deterministic factors revolve around the sales value and have the following characteristics derived after the data analysis of all 34 brands used in this study.

Table 5. Illustrates the deterministic factors of the brand Oxidil; the remaining results are presented in the Appendix section.

	OXIDIL	
Deterministic Factors	Forecast Values '000	Best-fit Models
SALES	8,161	
MODE	8,184	ARIMA-ETS, ETS-ARIMA, NAÏVE-ARIMA
PESSIMISTIC	8,157	ARIMA-HW
OPTIMISTIC	8,165	HW-ARIMA
AVERAGE OF PESSIMISTIC & OPTIMISTIC	8,161	

Deterministic Factors Specifications: [1]

Following are the specifications of the deterministic factors derived from data analysis.

- Pessimistic factor value either less than the sales or equal to sales or the smallest number near to sales value
- Mode factor value either equal to the sale, lesser than or greater than the sales value
- Optimistic factor value either equal to the sale, less than or greater than the sales value
- In some cases, sales can be the most significant value out of all the deterministic factors

In the case of the brand 'Oxidil', the attributes are:

Mode is the most repeated value and shows the maximum forecast value, i.e. '8,184' concerning sales.

The pessimistic value is 8,157, which is less than the sales value.

The optimistic Value is 8,165, which is greater than the sales value. Thus, it can be comprehended as:

Mode > Optimistic > Sales > Pessimistic, and none of the deterministic factors equal to sales, i.e. (Mode/Optimistic/Pessimistic ≠ Sales); hence,

M>O>S>P & M/O/P ≠ S

The brands Getofin, Cefxone, Inocef, Claritek, and Beasy follow the same attributes.

By plotting these factors to draw the inference, higher upper bound (Mode), upper bound (Optimistic), and lower bound (Pessimistic) against the actual sales shown in Figure 3 below.

In Figure 3, the most suitable models are displayed based on deterministic factors. For Oxidil, the best HYBRID models are ARIMA-HW, HW-ARIMA, ARIMA-ETS, ETS-ARIMA, and NAÏVE-ARIMA. Practitioners can choose from these models according to their organisation's risk threshold and preference. Additionally, the results obtained can help analysts analyse the forecast behaviour of other models. However, for the most accurate forecast for this brand, it is recommended to take the average of optimistic and pessimistic deterministic factors. In this context, descriptive statistics are also helpful for selecting the appropriate model of the hybrid forecast among all the model results shown in Table 6.

The empirical analysis provides solid credence that the proposed methodology and the introduction of the deterministic factors in finding the best combination of a hybrid model for demand forecasting derive better results than the traditional methods of forecasting demand in the pharmaceutical industry. Furthermore, while analysing the results of a therapeutic class brand 'Oxidil' shown in Tables 3–5, and Figure 3, it is worth mentioning here that when there are lower and upper bounds available, the aggregate of the same derives the result which is almost the same as the actual sale. For this instance, the sales are 8,161, an average of optimistic and pessimistic, i.e. 8,157 and 8,165 are 8,161, the actual sales illustrated in Table 5. Moreover, the mean percentage error (MAPE), mean absolute deviation (MAD), mean square error, and root mean square error (RMSE) all are absolute '0', suggesting the average of the forecast of the best models is the best choice illustrated in Table 6.

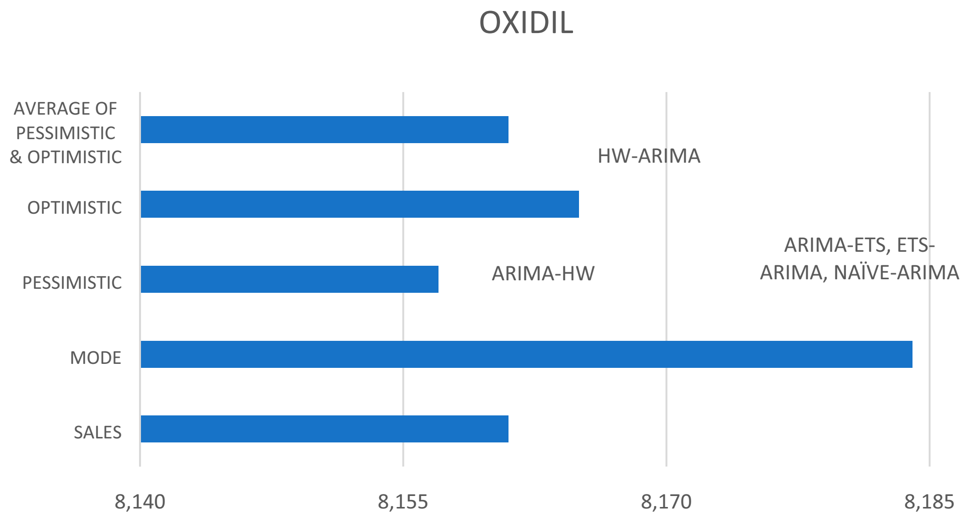

Figure 3. illustrates the level of deterministic factors against sales of the brand Oxidil; the remaining results are presented in the Appendix section.

Implications for Managerial Decision-making

To select the best combination of models out of all the hybrid models, here proposing a methodology to get an optimal demand forecast illustrated below:

- After computing the forecast in Table 3, find the best models based on Mode and PERT exhibited in Table 5.
- Subsequently, plot the results of Table 5 in Figure 3 to establish the level of the deterministic factors.
- If there is no lower bound, i.e. pessimistic value, and there are multiple best models, in that case, the combination of the model and its reciprocal is the best choice, such as ARIMA-ETS and its reciprocal model ETS-ARIMA; the related case can be seen in the appendix section.
- If all the levels are established, as shown in Table 5 and Figure 2, then the average of the Optimistic model and pessimistic model is the better choice.
- Analyse the results of the descriptive statistics shown in Table 6 and select the best combination of average forecast.

Table 6. Descriptive Statistics of the combination of hybrid forecast models of the brand Oxidil, the remaining results are illustrated in the Appendix section.

	OXIDIL				
Deterministic Factors	MEAN	MAD	MSE	RMSE	MAPE
SALES	8,161	–	–	–	–
MODE	8,184	23	529	23	0.00282
PESSIMISTIC	8,157	4	16	4	0.00049
OPTIMISTIC	8,165	4	16	4	0.00049
AVERAGE OF PESSIMISTIC & OPTIMISTIC	8,161	0	0	0	0

Assumptions of the Attributes/Conditions for Decision-making

Table 7 below highlights the summary of assumptions of the conditions obtained as a result of data analysis against all brands that will enable practitioners to make informed decisions while having a variety of forecasts in hand.

Discussions and conclusion

The pharmaceutical industry is known for its expertise in research and development, but it has not given much attention to utilising technology to improve supply chain efficiency (Etilwein 2014). To address this, we advocate for adopting the latest technologies to enhance forecasting accuracy. According to Weller and Crone (2012), the pharmaceutical supply chain is complex and relies heavily on simple forecasting methods, such as smoothing, average, and naïve methods, with an 82.1% prevalence. However, these methods can result in forecast errors of up to 40% due to the limited computational capabilities of tools like Excel (Chaman L Jain and Malehorn 2006). Enterprise Resource Planning Systems can help manage and process large amounts of data, providing accurate forecasting for future demand and enabling effective inventory management (Solutions 2023).

Table 7. illustrates the attributes/conditions for decision-making.

Attributes/Conditions	Brands	Action for Strategic Decision
$M > O > S > P$ & $M/O/P \neq S$	Oxidil | Getofin | Cefxone | Inocef | Claritke | Beasy	In this case, practitioners/forecasters have the following choices: 1. Select the average of the optimistic and pessimistic forecast values, which in most cases derived values near to forecast. OR 2. Select the model out of the four deterministic factors model concerning risk appetite and profile of the organisation.
$M > S < P < O$, OR $M = O$ & $M/O/P \neq S$	Titan | Montiget | Ciproquine | Cebosch | Omezol	In this case, practitioners/forecasters have the following choices: 1. Select the deterministic factors model whose actual and its reciprocal gave the same results, such as ARIMA-HW & HW-ARIMA.OR 2. Select the model out of the four deterministic factors model concerning risk appetite and profile of the organisation.
$M/O/P = S$, and $M = O$, $S = O$, $S = M$, $M < S$ & $P < S < O$, $P < S < M$, $P < S < O$, $M > O > S > P$	Hizone | Ultima | Cycin | Rithmo | Teph | Maclacin | Pylocar | Innoquin | Caricef | Cefspan | Maxima | Montika | Aerokast | Mntk | Freehale | Megaklar | Sante | Ruling | Ciplinz | Risek	In this case, practitioners/forecasters have the following choices: 1. Select the deterministic factors model whose deterministic factors have the same results and are equal to actual sales. OR 2. Select the model out of the four deterministic factors model concerning risk appetite and profile of the organisation.
$S > M > O > P$	Novidate	In this case, practitioners/forecasters have the following choices: 1. Select the model out of the four deterministic factors model concerning risk appetite and profile of the organisation.
$S < M = P < O$ & $M = P$	Cefiget	In this case, practitioners/forecasters have the following choices: 1. Select the model out of the four deterministic factors model concerning risk appetite and profile of the organisation.

Technological resources are critical to the success of a supply chain system, as they provide visibility throughout the supply chain, from suppliers to customers. A resilient pharmaceutical system and supply chain are essential for patient healthcare, especially during pandemics (Tirivangani et al. 2021). By enhancing visibility through technological advancements and predictive analytics, organisations can optimise inventory levels, improve operational efficiency, and make informed decisions about resource allocation (Delen et al. 2011, Cruz, Torres, & Ibañez, 2019). Currently, different forecasting system providers have provided the functionalities to compute demand using a single statistical model (Siddiqui et al. 2021). However, to utilise the multiple, hybrid, or consolidated modelling, advancements and customisations are required, along with the incorporation of attributes/conditions for decision-making against different pharmaceutical formulations, generics, and brands suggested by this study, is essential.

When it comes to predicting demand in the pharmaceutical industry, time-series models are the most popular method, accounting for 52% of cases, according to Chaman L Jain's (2005) research. Causal models are used in 24% of cases, while judgmental approaches comprise 19%. The remaining 5% of cases use mixed or combined forecasting models. However, despite the potential benefits of hybrid forecasting techniques, they have not been widely adopted due to various factors. This study aims to emphasise the importance of incorporating hybrid forecasting techniques in demand forecasting and address the challenges faced by the industry. The results obtained from hybrid forecasting are highly promising, providing practitioners with valuable insights and contributing to the existing literature.

The European Medical Agency has presented a reflection paper outlining best practices for demand forecasting of pharmaceutical products to avoid shortages during disruptions (Agency 2021). Predicting excess demand early during the pandemic could have significant implications for both supply chain managers and policymakers (Nikolopoulos et al. 2021). The methodology prescribed in this research provides an easy way for forecasters to select or aggregate the best models based on the situation. Shallow neural network-based demand forecasting provides better forecast results for future demand for pharmaceutical products (Rathipriya et al. 2023). Similarly, Tian, Wang, and Erjiang (2021) proposed a framework for obtaining the best forecasting method for demand forecasting based on the combination of methods. It is better to use sales data from previous historical periods to deliver shorter forecasts. Incorporating these techniques can improve resilience in the supply chain and help practitioners make informed decisions.

Nonetheless, the findings of this research have significant implications for the field of hybrid forecasting and demand forecasting, especially in the pharmaceutical industry and other relevant industries. By incorporating deterministic factors for model selection and decision-making, this study expands the current understanding and application of hybrid forecasting methods. Unlike previous studies that explored limited combinations on a single data set, this research explores 25 different combinations on 34 brands with diverse formulations and potencies. This not only enhances the breadth and depth of the research but also provides practitioners with a comprehensive understanding of patterns and trends associated with drug demand.

Managerial insights

The proposed framework for demand forecasting in the pharmaceutical industry effectively addresses the challenges faced in this area; for instance, the hybrid forecasting matrix in Table 4 allows for a comparative analysis of forecast results, while the deterministic factors in Table 5 and descriptive statistics in Table 6 provide valuable insights into demand variability. This, in turn, helps practitioners select the best-fit model for effective inventory management and improved supply chain efficiency.

The proposed framework not only reduces errors but also enhances forecast accuracy, resulting in significant financial gains and helps improve supply chain efficiency. The dynamic nature of the final model obtained through multiple iterations means that practitioners can select the best model based on the organisation's risk threshold and appetite. The appendix section provides details of the best-fit models for different therapeutic classes and brands. For instance, the best hybrid models for Oxidil are ARIMA-HW, HW-ARIMA, ARIMA-ETS, ETS-ARIMA, and NAÏVE-ARIMA, with forecast values of 8,157, 8,165, and 8,184 (ETS-ARIMA and NAÏVE-ARIMA) respectively.

Practitioners can select any model that aligns with their organisation's risk threshold and appetite. The results obtained can help analyse the forecast behaviour of other models. The most appropriate forecast result for a brand is obtained by taking the average of deterministic factors by considering the assumptions mentioned above in indication for managerial decision-making, i.e. average of optimistic and pessimistic, which is the average of forecast values 8,157 and 8,165.

Research limitations and future direction

Although this empirical study has produced significant results, it is important to acknowledge its limitations due to time and data constraints. The study focuses on a limited number of therapeutic classes and brands, and its findings are specific to the pharmaceutical industry in Pakistan. However, the study provides a foundation for developers of forecast software, integrated systems, and enterprise information management systems to create algorithms based on the proposed methodology. These advancements could greatly benefit the pharmaceutical industry and beyond, enabling more robust and sophisticated forecasting practices.

This study contributes significantly to the conceptualisation and analysis of advanced forecasting techniques, which could have potential applications beyond the pharmaceutical industry. The proposed methodology surpasses traditional forecasting methods commonly used in the pharmaceutical sector. However, there is still room for further improvement in this field. For instance, combining artificial intelligence with neural networks and machine learning, as well as integrating various statistical and machine learning models, could enhance forecasting accuracy and effectiveness.

Statement of data availability

The data that support the findings of this study are available from the corresponding author, MA, upon reasonable request.

Note

1. Deterministic Factors refer to as, throughout the study:
   Mode = M
   Sales = S
   Optimistic = O
   Pessimistic = P

Disclosure statement

No potential conflict of interest was reported by the author(s).

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