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Comparative Analysis of Demand Forecasting Methods to Optimize Supply Chain Efficiency in PharmaHealth Group

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ABSTRACT: PharmaHealth Group encounters significant challenges in its supply chain distribution due to the pharmaceutical industry's demand for rapid responsiveness and the high risk of demand fluctuations, particularly during events like the COVID-19 pandemic. Additional complexities include the short shelf-life of pharmaceutical products and extensive quality control processes mandated by strict regulations. This study compares advanced demand forecasting methods to address these issues and optimize supply chain efficiency.

The research examines three forecasting techniques: Holt-Winters, ARIMA (Autoregressive Integrated Moving Average), and the hybrid ARHOW (ARIMA & Holt-Winters additive) model. The Holt-Winters method, effective for time series data with trends and seasonal patterns, improves supply chain management but has limitations in inventory forecasting. ARIMA, known for its simplicity and effectiveness in capturing trends and seasonality, faces challenges with non-linear data and the need for stationarity. The hybrid ARHOW model combines the strengths of both Holt-Winters and ARIMA, offering enhanced forecasting accuracy and efficiency. By analyzing these methods, the study highlights the potential of hybrid approaches like ARHOW to address PharmaHealth Group's unique supply chain challenges, leading to improved inventory management and overall supply chain performance.

KEYWORDS: ARHOW Model, ARIMA, Demand Forecasting, Holt-Winters Method, Hybrid Forecasting, Pharmaceutical Industry

I. INTRODUCTION

In the current pharmacy industry, supply-demand forecasting faces several challenges that impact the efficient management of pharmaceutical stock and overall supply chain performance. Forecasting errors have led to shortages and fluctuations in demand and supply, affecting pharmaceutical stock control in hospital pharmacy departments (Angula, 2024). These errors have implications for inventory management and supply chain performance, as accurate demand forecasting is crucial to ensure zero stockouts and to withstand fluctuations in demand and supply (George & Elrashid, 2023). The pharmacy industry is undergoing transformations, but there is a need for significant changes to address the existing imbalances in supply and demand (Lebovitz & Eddington, 2019).

While efforts have been made to moderate shortages through changes in pharmacy practices and the utilization of technology, concerns persist regarding the adequacy of future supply to meet the expected demand (Knapp & Cultice, 2007). Pharmacy departments in hospitals often maintain high levels of safety stock to mitigate uncertainties such as daily demand fluctuations and supply bottlenecks, emphasizing the importance of accurate demand forecasting in inventory management (Bhakoo & Singh, 2012). Inaccurate forecasts can lead to imbalances in supply and demand, affecting the overall efficiency of the supply chain (Polater & Demirdöğen, 2018).

Demand forecasting accuracy is crucial for supply chain management in the pharmacy industry, as it directly influences logistics costs and helps in planning physical and human resources effectively (Mirčetić et al., 2016). Forecasting errors can result in inventory backlogs, highlighting the significance of precise demand forecasting in reducing costs and improving supply chain management (Xiao et al., 2021).

PharmaHealth Group, a pharmaceutical holding company, is focused on enhancing its supply chain distribution by improving its forecasting system. Recently, the branches face challenges such as low fulfillment rates despite maintaining high inventory levels. This has led to significant amounts of dead stock remaining unsold for over a year, posing a burden due to product expiration dates.

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Additionally, deliveries outside of branch regions have resulted in increased transportation costs. Addressing these issues requires advanced supply-demand forecasting methods to optimize inventory management and enhance overall supply chain efficiency.

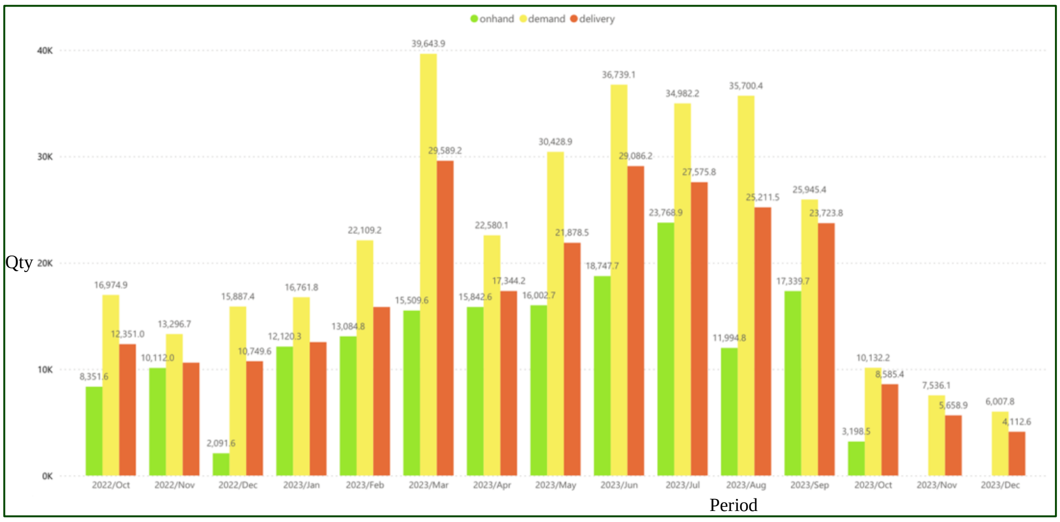

Figure 1. On-hand, Demand, and Delivery data of PharmaHealth Group

II. LITERATURE REVIEW

Demand forecasting methods effectiveness could vary depending on the requirement of the demands inside the industry. Accurate demand forecasting enables businesses to efficiently manage various aspects such as production, inventories, finances, and market positioning, contributing to improved supply chain management (She, 2023). Some of the common methods used for demand forecasting in a supply chain environment includes traditional demand forecasting, machine learning demand forecasting, and hybrid model demand forecasting.

A. *Traditional Demand Forecasting*

Traditional demand forecasting involves using established methods such as statistical models to predict future demand based on historical data. These methods are commonly applied in scenarios where early sales data is limited (Li et al., 2021). Examples of traditional demand forecasting methods include using linear regression, exponential smoothing, and other statistical models to predict flight bookings based on factors like day of the week and current data collection points (Fan et al., 2023). Moreover, traditional time-series forecasting methods like Simple Exponential Smoothing and Moving Average are still widely used in practice for intermittent demand forecasting (Thummathid, 2020). These methods play a crucial role in supply chain management by helping in predicting future demand accurately (Singh, 2024). When demand patterns are smooth and continuous, historical demand data can be effectively used for forecasting (Wu, 2010).

B. *Machine Learning Demand Forecasting*

Machine learning forecasting in the supply chain involves the application of machine learning techniques to predict various aspects related to supply chain management within the industry. Machine learning has been successfully utilized in supply chain management for tasks such as demand forecasting, backorder prediction, cost optimization, inventory management, and supply chain risk assessment (Wang, 2023). These techniques enable accurate forecasting of multiple aspects such as demand, sales, revenue, production, and backorders, contributing to improved decision-making processes within the supply chain (Islam & Amin, 2020).

Deep learning, a subset of machine learning, has also been increasingly applied in supply chain forecasting, including demand prediction, production prediction, and price prediction, showcasing the versatility and effectiveness of advanced machine learning techniques in optimizing supply chain operations (Ma et al., 2023). Additionally, the integration of machine learning in inventory optimization models has been demonstrated to improve demand forecasting accuracy, leading to more informed decision-making processes and enhanced strategic planning within the pharmaceutical supply chain (Nasution et al., 2022).

C. Hybrid Model Demand Forecasting

Hybrid forecasting in the context of supply chain management involves the integration of multiple forecasting methods or models to enhance the accuracy and reliability of demand predictions. This approach combines different techniques to leverage their individual strengths and mitigate their weaknesses, ultimately leading to more robust forecasts (Wang et al., 2017). Hybrid forecasting models often incorporate various techniques such as neural networks, time-series methods, and machine learning algorithms to handle different aspects of demand variability and intermittency (Fu et al., 2018). These models have been shown to improve forecast accuracy, particularly in industries with sporadic or unpredictable demand patterns like the semiconductor supply chain (Fu et al., 2018).

III. PROPOSED SOLUTIONS

PharmaHealth Group encounters significant challenges in enhancing its supply chain distribution due to the pharmaceutical industry's need for rapid responsiveness and the high risk of demand fluctuations, such as those experienced during the COVID-19 pandemic. Additionally, the short shelf-life of products, coupled with the lengthy quality control and standardization processes required by strict government regulations, worsen the risk of loss. This research compares advanced demand forecasting methods commonly used in the pharmaceutical industry and other sectors with high demand volatility.

A. Holt-Winters

The Holt-Winters method is a well-established forecasting technique widely used in various industries, including the pharmacy sector. This method is particularly useful for handling time series data that exhibit both trend and seasonal patterns (Chen, 1996). In the pharmacy industry, the Holt-Winters method can be utilized to forecast demand for pharmaceutical products based on historical data trends and seasonal variations. By incorporating both trend and seasonality components, this method can provide accurate predictions for future demand, enabling pharmacies to optimize inventory management and ensure product availability (Purwanto & Nofrisel, 2020). Additionally, the Holt-Winters method has been shown to be effective in forecasting stock levels and demand for pharmaceutical products, contributing to improved supply chain management and operational efficiency within the industry (Agusman, 2023).

The Holt-Winters method has been compared with other forecasting techniques in various studies, demonstrating its superiority in generating accurate predictions. For instance, research has shown that the Holt-Winters method outperforms other models in forecasting stock indices and returns (Ponziani, 2022), as well as in predicting cargo volume at port terminals (Nieto et al., 2021). The method has also been found to be reliable in forecasting gasoline demand and energy consumption, highlighting its versatility across different sectors (Mardiana et al., 2020).

Nevertheless, despite its advantages, the Holt-Winters method has limitations. One significant drawback is its subpar performance in inventory forecasting, particularly concerning inventory cost and service level trade-offs (Petropoulos et al., 2019). This limitation may restrict its suitability for applications where inventory management is crucial. Additionally, there are debates surrounding the method's appropriateness for predicting noisy and non-linear data, such as childhood mortality rates (Adeyinka & Muhajarine, 2020).

B. ARIMA

ARIMA (Autoregressive Integrated Moving Average) is a widely used statistical method for time series forecasting that combines autoregressive and moving average components (Fara et al., 2021). It is particularly effective in analyzing and predicting time-dependent data by incorporating historical information to forecast future trends (Faradiela et al., 2022). ARIMA models have been successfully applied in various fields such as energy production forecasting (Fara et al., 2021), cryptocurrency price prediction (Derbentsev et al., 2019), healthcare services demand estimation (Faradiela et al., 2022), and even in forecasting COVID-19 cases (Singh et al., 2020).

In the pharmacy industry, the ARIMA forecasting method have been widely used in forecasting due to their ability to capture trends, seasonality, and autocorrelation in time series data (Helmini et al., 2019). One of the key advantages of ARIMA models is their

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simplicity and interpretability, making them accessible for users without extensive machine learning expertise (Velasco et al., 2019). Moreover, ARIMA models are effective when the data has a clear linear structure and follows a stationary pattern (Fara et al., 2021). On the other hand, ARIMA models have limitations that need to be considered. These models may struggle with non-linear relationships in the data, which can lead to inaccurate forecasts when the underlying patterns are complex (Yang et al., 2013). Additionally, ARIMA models require the data to be stationary, which might not always be the case in real-world applications (Fara et al., 2021). In such instances, preprocessing steps to transform the data may be necessary, adding complexity to the modeling process (Fara et al., 2021).

C. ARHOW (ARIMA & Holt-Winters additive)

Hybrid forecasting methods combine different forecasting techniques to improve accuracy and performance in predicting various phenomena. One such method is the ARHOW (Autoregressive Integrated Moving Average and Holt's-Winter model) hybrid forecasting method. This method merges the Autoregressive Integrated Moving Average (ARIMA) model with the Holt's-Winter model to enhance forecasting accuracy (Siddiqui et al., 2021).

The ARHOW model computes weights for combining the ARIMA and Holt's Winter forecasts using regression, which is a common and reliable method for optimizing weights in combined forecasting models. This model is designed to provide more accurate demand predictions compared to individual forecasting models like ARIMA, Holt's Winter, Exponential Time Series (ETS), and Theta, as evidenced by the forecasted values compared to the actual unit sales.

Table I. Forecast Results of Drug Sales Data (Siddiqui et al., 2021)

Date	*Unit Sales*	*ARIMA*	*Holt's-Winter*	*ETS*	*Theta*	*ARHOW*
01/08/2015	1,187	1,186	1,174	1,186	1,186	1,152
01/09/2015	1,166	1,169	1,147	1,168	1,168	1,140
01/10/2015	1,081	1,094	1,075	1,094	1,094	1,067
01/11/2015	906	939	935	941	941	908
01/12/2015	717	767	779	771	771	734
01/01/2016	589	648	671	653	652	612
01/02/2016	591	648	683	654	654	606
01/03/2016	666	716	763	724	723	665
01/04/2016	750	792	850	801	800	732
01/05/2016	779	819	879	827	826	756
01/06/2016	765	807	862	814	813	747
01/07/2016	733	779	813	785	784	732
01/08/2016	703	752	778	758	757	712
01/09/2016	679	731	749	736	734	695
01/10/2016	658	712	729	717	715	677
Total	11,970	12,559	12,887	12,631	12,617	11,933

By combining the strengths of ARIMA and Holt's Winter models with optimized weights, the ARHOW model offers improved forecasting accuracy and efficiency, making it a preferred choice for demand prediction in various industries.

IV. CONCLUSION

PharmaHealth Group faces significant challenges in optimizing its supply chain distribution due to the pharmaceutical industry's demands for rapid responsiveness and the high risk of demand fluctuations, such as those seen during the COVID-19 pandemic. The short shelf-life of pharmaceutical products, coupled with extensive quality control and strict regulatory standards, further exacerbates these challenges. This research compares advanced demand forecasting methods commonly used in the pharmaceutical industry and other sectors with high demand volatility to address these issues.

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A. Holt-Winters Method

Widely used for handling time series data with trend and seasonal patterns, this method has shown effectiveness in improving supply chain management and operational efficiency within the pharmaceutical industry (Chen, 1996; Purwanto & Nofrisel, 2020; Agusman, 2023). Despite its advantages, it has limitations in inventory forecasting, especially concerning inventory cost and service level trade-offs (Petropoulos et al., 2019).

B. ARIMA (Autoregressive Integrated Moving Average)

This method is effective in analyzing and predicting time-dependent data and has been successfully applied in various fields, including the pharmacy industry, due to its ability to capture trends, seasonality, and autocorrelation in time series data (Fara et al., 2021; Faradiela et al., 2022; Helmini et al., 2019). However, ARIMA models may struggle with non-linear data and require the data to be stationary, which adds complexity to the modeling process (Yang et al., 2013; Fara et al., 2021).

C. ARHOW (ARIMA & Holt-Winters additive)

This hybrid forecasting method combines ARIMA and Holt's Winter models to enhance forecasting accuracy. By computing weights for combining the forecasts using regression, the ARHOW model provides more accurate demand predictions compared to individual forecasting models (Siddiqui et al., 2021). This combined approach offers improved forecasting accuracy and efficiency, making it a preferred choice for demand prediction in various industries.

While each forecasting method has its strengths and limitations, in the context of pharmacy industry, hybrid approaches like ARHOW show promise in addressing the unique challenges faced by PharmaHealth Group, potentially leading to better inventory management and supply chain efficiency.

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