Addis Ababa University
College of Health Sciences, School of Pharmacy PhD Program in Social and Administrative Pharmacy

Configuring Forecasting Techniques and Supply Chain Strategies to Enhance Resilience and Minimize Pharmaceutical Shortages in the Ethiopian Public Supply Chain

Arebu Issa Bilal

Dissertation submitted in partial fulfillments for the Doctor of Philosophy Degree in Social and Administrative Pharmacy (Health Supply Chain Management Track)

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Presented in partial fulfillment for the Degree of Doctor of Philosophy in Social and Administrative Pharmacy (Health Supply Chain Management Track)

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Declaration

This is to certify that the dissertation prepared by Arebu Issa Bilal, titled *" **Configuring Forecasting Techniques and Supply Chain Strategies to Enhance Resilience and Minimize Pharmaceutical Shortages in the Ethiopian Public Supply Chain"*** submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy (PhD) in Social and Administrative Pharmacy, complies with the regulations of the University and meets the accepted standards for originality and quality.

Signed by the Examining Committee:

External Examiner ___________________________ Signature_____________Date___________

Internal Examiner _____________________________Signature____________Date___________

Advisor Prof Teferi Gedif Fenta Signature______________Date___________

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Chair of the department ____

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List of Original Papers

This PhD dissertation is based on the four papers listed below.

I. **Bilal, A.I**.; Bititci, U.S.; Fenta, T.G. Challenges and the Way Forward in Demand-Forecasting Practices within the Ethiopian Public Pharmaceutical Supply Chain. Pharmacy 2024, 12, 86. https:// doi.org/10.3390/pharmacy12030086

II. **Bilal, A.I**.; Bititci, U.S.; Fenta, T.G. Effective Supply Chain Strategies in Addressing Demand and Supply Uncertainty: A Case Study of Ethiopian Pharmaceutical Supply Services. Pharmacy 2024, 12, 132. https://doi.org/10.3390/ pharmacy12050132

III. **Bilal, A.I**.; Bititci, U.S.; Fenta, T.G. Forecasting Accuracy and Performance of Pharmaceutical Demand forecasting in Ethiopian Pharmaceutical Supply Services (Manuscript accepted for publication EPJ).

IV. **Bilal, A.I**.; Bahman Rostami-Tabar; Harsha Halgamuwe Hewageb; Bititci, U.S.; Fenta, T.G. The missing puzzle piece: Contextual insights for enhanced pharmaceutical supply chain forecasting. (Manuscript submittedfor IJPR)

Academic conferences papers presented

I. **Bilal, A.I**.; Bititci, U.S.; Fenta, T.G Effective Supply Chain Strategies in Addressing Demand and Supply Uncertainty: A Case Study of Ethiopian Pharmaceutical Supply Services. 6th African Conference on Operations and Supply Chain Management (ACOSCM). 7-18 September 2024 Bishkek, Kyrgistan **(Awarded Third best paper and third best presentation)**.

II. **Bilal, A.I**.; Bititci, U.S.; Fenta, T.G Enhancing Forecast Accuracy in the Pharmaceutical Supply Chain: Exploring Models and Strategies for Improved Decision-Making.The 5th African Conference on operations and supply chain management. 5th ACOSCM (5th African Conference on Operations and Supply Chain Management). 6-7th September, 2023 Kampala Uganda.

Abstract

Configuring Forecasting Techniques and Supply Chain Strategies to Enhance Resilience and Minimize Pharmaceutical Shortages in the Ethiopian Public Supply Chain

Arebu Issa Bilal

Addis Ababa University, 2025

Introduction: The availability of essential medicines is a cornerstone of a functional healthcare system, directly influencing health outcomes and healthcare quality worldwide. Accurate demand forecasting plays a critical role in ensuring that medicines are consistently available where and when needed, preventing stockouts and minimizing wastage. In Ethiopia, the pharmaceutical supply chain faces considerable challenges, including frequent medicine shortages, long procurement lead times, and data quality issues. These problems are exacerbated by the lack of skill and training of workforce in advanced forecasting methods. Given the dynamic nature of healthcare demands and the complexity of supply chains, advanced forecasting techniques, including machine learning, are becoming indispensable for improving accuracy and resilience. This PhD study aims to explore how forecasting techniques and other supply chain strategies can be configured to improve demand forecasting practices within Ethiopian Pharmaceutical Supply Services (EPSS), with the ultimate goal of enhancing supply chain performance and ensuring reliable access to essential medicines.

Methods: This study adopted a pragmatic philosophical paradigm, emphasizing practical solutions and the integration of diverse perspectives to address complex problems. A sequential explanatory mixed-method case study design was utilized, consistent with the pragmatic approach. The study employed a mixed-methods approach, incorporating both qualitative and quantitative data collection**.** The quantitative phase involved a five-year retrospective analysis of issue data to evaluate forecast accuracy. The process began with the application of simple forecasting methods, followed by advanced machine learning models enhanced with domain knowledge. Forecast accuracy was assessed using established metrics, including Mean Absolute Scaled Error (MASE)**,** Root Mean Squared Scaled Error (RMSSE)**,** and Continuous Ranked Probability Score (CRPS)**.** The qualitative phase complemented the quantitative findings through structured questionnaires and stakeholder interviews. This phase explored challenges and strategies for improving demand forecasting, providing contextual insights into supply chain uncertainties. By integrating quantitative analysis with qualitative insights, this comprehensive approach offers both empirical depth and practical relevance, advancing the understanding of complexities in demand forecasting and enhancing supply chain resilience.

Findings: Key challenges identified in forecasting within the Ethiopian Pharmaceutical Supply Service (EPSS) include financial constraints, workforce shortages, technology gaps, lack of coordination, and data quality issues. Financial uncertainties delay procurement, leading to stockouts, while workforce limitations and data inaccuracies hinder reliable forecasting. Analysis of EPSS_s existing methods revealed significant inaccuracies, where only 13 of the 33 products (40%) had MAPE values below 50%. Several high-priority items exhibited particularly high MAPE and RMSE values, indicating low forecasting reliability. Furthermore, MASE values suggested that most forecasts performed worse than naïve benchmarks, raising concerns about the robustness of existing methods. To explore alternatives, three basic forecasting models Naïve, Mean, and 3-Year Moving

Average were tested. The 3-Year Moving Average model consistently achieved the lowest MAPE values for the majority of products, demonstrating its potential to enhance forecast accuracy. Incorporating domain knowledge into forecasting models significantly enhanced accuracy for both point and probabilistic forecasts. LSTM models achieved the highest probabilistic accuracy, while regression models performed the worst. Models utilizing domain insights consistently outperformed those relying solely on historical data, emphasizing the value of contextual understanding in addressing forecasting challenges. Expert interviews highlighted successful strategies for mitigating medicine shortages, such as improved communication, regular stock status assessments, supportive supervision, streamlined procurement processes, and enhanced supplier management. Less effective strategies included rationing, redistribution, and emergency procurement. The study found that proactive measures, such as supplier development and contingency planning, are critical for prevention, while reactive strategies, including safety stock and capacity buffers, provide resilience in responding to unforeseen supply chain disruptions. A balanced interaction between proactive and reactive strategies is essential to effectively address supply chain uncertainties. The research underscores the importance of adopting a holistic systems approach to supply chain challenges rather than examining components in isolation. Addressing forecasting alone is insufficient; integrating forecasting techniques with broader supply chain strategies is vital to effectively mitigate medicine shortages. Incorporating domain knowledge into forecasting models bridges the gap between theoretical approaches and real-world challenges, improving accuracy and ensuring practical applicability. Finally, the study highlights the transformative potential of Large Language Models (LLMs) and other advanced technologies for developing countries. These tools make sophisticated forecasting methods accessible even in resource-constrained settings with limited infrastructure and expertise, offering significant opportunities to revolutionize supply chain research and practice.

Conclusions and recommendations: Addressing inaccuracy and unreliability in the pharmaceutical supply chain should be a top priority. EPSS_s forecasting methods should be revised, incorporating a mix of approaches tailored to the unique characteristics of pharmaceutical products. By doing so, EPSS can enhance demand predictions, reduce shortages, and ensure consistent medicine availability. Improved forecasting accuracy has the potential to positively impact healthcare delivery and patient outcomes. A balanced approach combining proactive and reactive strategies is essential, as neither strategy alone is sufficient. Key success factors include improving data quality, implementing advanced technology, leveraging automation, and increasing supply chain visibility, while addressing barriers such as communication challenges and data quality issues. The effectiveness of these strategies depends on aligning them with EPSS_s overall supply chain goals and addressing specific uncertainties. Incorporating hybrid forecasting models that blend judgment-based point forecasts with probabilistic machine learning models could significantly improve predictive performance. Training EPSS staff in foundational time series models, data interpretation, and data collection processes will strengthen workforce capabilities and promote informed decision-making. Replicating this study in diverse healthcare settings and performing comparative analyses could validate the adaptability and relevance of these findings across different contexts. Additionally, it is recommended that pharmaceutical supply services systematically collect and maintain detailed records of events that may impact consumption, alongside standard consumption data. This practice is essential for refining demand models and improving forecast accuracy.

Key words: Forecasting, Accuracy, Simple forecasting methods, Machine learning, Active strategies, Proactive strategies

List of ABBREVIATIONS AND ACRONYMS

AICc	Akaike_s Information Criterion
AI	Artificial Intelligence
ARIMA	AutoRegressive Integrated Moving Average
ARIMAX	AutoRegressive Integrated Moving Average with eXogenous variables
	BTO
CPFR	Collaborative Planning, Forecasting, and Replenishment
EFDA	Ethiopian Food and Drug Authority
EPSA	Ethiopian Pharmaceutical Supply Agency
EPSS	Ethiopian Pharmaceutical Supply Services
ETS	Exponential Smoothing State Space Model
FMOH	Federal Ministry of Health
HSTP	Health Sector Transformation Plan
KPI	Key Performance Indicator
LSTM	Long Short-Term Memory neural network
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Scaled Error
MdRAE	Median Relative Absolute Error
MLR	Multiple Linear Regression
MMR	Mixed Method Research
MOH	Ministry of Health
MSE	Mean Squared Error
PI	Principal Investigator
PSTP	Pharmaceuticals Supply Transformation Plan
RDF	Revolving Drug Fund
RF	Random Forest
RHBs	Regional Health Bureaus
RMSE	Root Mean Squared Error
SDGs	Sustainable Development Goals
SMA	Simple Moving Averages
SVR	Support Vector Regression
UHC	Universal Health Coverage

List of appendices

GLOSSARY OF TERMS AND CONCEPTS USED IN THE STUDY

Demand forecasting: is about predicting the future as accurately as possible, given all the information available, including historical data and knowledge of any future events that might impact the forecasts (Hyndman and Athanasopoulos, 2021).

Simple forecasting methods: Some forecasting methods are extremely simple and surprisingly effective among the simple forecasting methods are Naïve, moving averages, and Seasonal naïve method (Hyndman and Athanasopoulos, 2021; Svetunkov, 2023).

Traditional forecasting methods: Traditional forecasting methods involve using historical data to draw conclusions about future outcomes. These methods are widely used, but they have their limitations. For instance, traditional forecasting models assume that past trends and patterns will continue into the future. However, this is not always the case, as external factors such as natural disasters, pandemics, and economic recessions can significantly impact outcomes. These include Exponential Smoothing and regression analysis.

Machine learning: machine learning can be defined as a part of artificial intelligence that explains the fact that machines can learn on their own when given the right data thereby solving a specific problem (Schuld et al., 2015). With the help of mathematics and statistics, machine learning can Perform intellectual tasks independently that are always generally performed by human beings (Srivastava et al., 2015). Machine learning is a part of computer science that emanated from the study of pattern recognition and computational learning theory all in artificial intelligence. Algorithms are used to make predictions on data (Learned-Miller, 2014).

Supply chain strategies refer to the approaches and plans organizations use to manage the flow of goods, services, information, and finances from suppliers to customers efficiently. These strategies aim to optimize supply chain performance, reduce costs, meet customer demands, and create a competitive advantage.

Drug shortages: A **drug shortage** occurs when the supply of a pharmaceutical drug is insufficient to meet the current or projected demand at a patient care level. It can affect prescription medications, over-the-counter drugs, or essential medical supplies, potentially disrupting healthcare services and impacting patient treatment. drug shortage as ―a situation in which the total supply of all clinically interchangeable versions of an FDA regulated drug product is inadequate to meet the projected demand at the user level‖ (Schwartzberg et al., 2017).

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CHAPTER 1: INTRODUCTION

1.1. Introduction to dissertation

Supply chain resilience refers to the capacity of a supply chain to anticipate, prepare for, respond to, and recover from unexpected disruptions while maintaining operational continuity and minimizing adverse impacts. It involves developing flexible and adaptive processes capable of responding quickly to shocks such as natural disasters, economic fluctuations, pandemics, or other external events (Fiksel et al., 2015; Pettit et al., 2010). In pharmaceutical supply chains, resilience is particularly vital due to the critical nature of ensuring the continuous availability of life-saving medicines, even during disruptions.

One of the primary strategies to enhance supply chain resilience is the improvement of forecasting practices, which are essential to effective supply chain management (Moon et al., 2003). Accurate forecasting facilitates better planning and resource allocation, helping to mitigate risks (Sekhri et al., 2007). However, in low-income countries like Ethiopia, there is limited empirical evidence on the specific forecasting challenges and effective mitigation strategies within pharmaceutical supply chains. This study addresses this gap by exploring how improved forecasting practices can contribute to strengthening supply chain resilience in the Ethiopian context.

This dissertation focuses on improving demand forecasting accuracy and enhancing resilience within the Ethiopian Pharmaceutical Supply Services (EPSS). A mixed-method, cross-sectional case study design was adopted, integrating both qualitative and quantitative data collection and analysis approaches.

The dissertation is organized into six chapters. Chapter one introduces the study, including its background, problem statement, and significance. Chapter two provides a comprehensive review of the literature and presents the conceptual framework. Chapter three outlines the research objectives and questions. Chapter four describes the research philosophy, methodology, and ethical considerations. Chapter five presents the study‘s findings, while chapter six offers a discussion of the findings, practical and policy implications, conclusions, and recommendations for future research.

This dissertation is submitted in partial fulfillment of the requirements for the Doctor of Philosophy degree under the *PhD by publication* format. The research is titled Configuring Forecasting Techniques and Supply Chain Strategies to Enhance Resilience and Minimize Pharmaceutical Shortages in the Ethiopian Public Supply Chain. The body of work includes a series of peer-reviewed articles—published, under review, or submitted—that address various aspects of the overarching research objectives.

Figure 1 below presents a mapping of each article to the corresponding components of the dissertation, illustrating how each contributes to the overall research aim and conclusions.

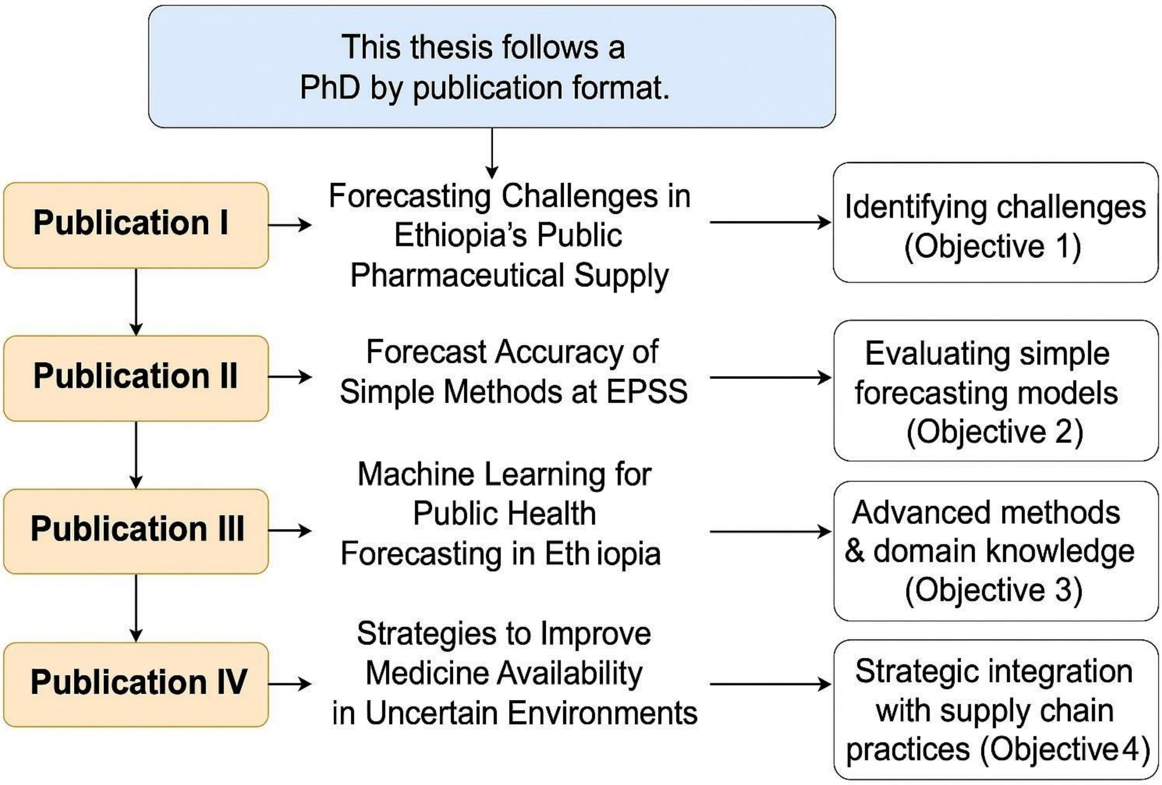


Figure 1: Thesis structure

1.2. Background

Universal Health Coverage (UHC) aims to ensure that all individuals have access to the healthcare services they need without financial hardship. Essential to achieving UHC is the availability of essential medicines and health technologies, forming the backbone of effective healthcare delivery. This principle is also embedded in the Universal Declaration of Human Rights, which asserts in Article 25 that "everyone has the right to a standard of living adequate for the health and well-being of himself and his family, including food, clothing, housing, and medical care" (UN, 1948). Ensuring universal access to quality healthcare is not only a matter of human rights but also vital for health equity and strengthening global health systems (WHO, 2004, 2007, 2015). Achieving these goals aligns directly with Sustainable Development Goal (SDG) 3, which aims to "ensure healthy lives and promote well-being for all at all ages" (UN, 2015). Without universal access to health services, achieving the SDGs becomes exceedingly difficult (WHO, 2015a; Wilkinson and Hulme, 2015).

Achieving SDG 3 requires overcoming substantial barriers to accessing essential medicines, especially in low- and middle-income countries, where disparities are most acute. Despite the global emphasis on the importance of essential medicines, access gaps remain, challenging progress toward UHC and health-related SDGs (Quick, 2003; WHO, 2003). In many regions, especially in Africa and Asia, barriers such as high costs, inefficient supply chains, regulatory challenges, workforce shortages, poor inventory management, and limited local production capacity restrict access to essential medicines (Yenet et al., 2023; Droti et al., 2019; WHO, 2004). On the supply side, challenges include limited geographic accessibility, shortages of qualified staff, restricted operating hours, and fragmented services. High service costs, informal payments, and a lack of transparency further hinder accessibility. On the demand side, issues such as indirect costs, lack of health awareness, and cultural stigmas deter people from seeking care (Jacobs et al., 2012; Ensor and Cooper, 2004). Together, these barriers exacerbate healthcare inequities, disproportionately affecting vulnerable populations.

Even in high-income regions, such as North America and Europe, medicine shortages disrupt patient care, compromise treatment outcomes, and increase healthcare costs through alternative therapies, rationing, and administrative burdens (Kaakeh et al., 2011; GAO, 2016). The root causes of these shortages are multifaceted, involving globalization, manufacturing challenges, geopolitical issues, regulatory requirements, and events like natural disasters and disease outbreaks (Tucker, 2020; Vann Yaroson et al., 2024). The COVID-19 pandemic further exposed the fragility of global supply chains, highlighting the need for resilient strategies to ensure continuous access to essential healthcare products (Jagtap et al., 2022; Kent and Haralambides, 2022).

Pharmaceutical products are integral to healthcare delivery, playing a crucial role in achieving favorable health outcomes. However, consistent availability is often compromised due to weak supply chains, insufficient investments, regulatory challenges, and high procurement costs (Sakthivel, 2005). A well-functioning pharmaceutical supply chain must deliver medicines in appropriate quantities, quality, and locations, at optimal costs. Failures in this process lead to shortages, wastage, and compromised patient safety (Schneider et al., 2010; Merkuryevaa et al., 2019). Strengthening the pharmaceutical supply chain demands a comprehensive approach to address system-wide weaknesses. A resilient pharmaceutical system encompasses structures, people, resources, and processes within the health system to ensure equitable access to safe, effective, and quality medicines (Hafner et al., 2016). This picture is even more pronounced in developing countries such as Ethiopia, ensuring consistent availability of essential medicines requires a robust supply chain capable of withstanding various pressures, from funding limitations to unexpected health crises. One critical aspect of a resilient supply chain is demand forecasting, which anticipates future needs for medicines and supplies to prevent stockouts and excess inventory. Effective forecasting enables better planning, resource allocation, and reduced operating costs. However, forecasting is inherently uncertain, with accuracy decreasing as forecasts extend further into the future. Additionally, forecasting is more reliable at a general level than for specific details, such as individual items or daily demand (Kerkkänen, 2010). In healthcare, forecasting involves estimating the types, quantities, and timing of medicines required (Sekhri et al., 2007). Despite its importance, demand forecasting is underutilized in the health sector, especially in developing countries, where data limitations, skills gaps, and resource constraints hinder effective forecasting practices (Lee and Billington, 1992; Kraiselburd and Yadav, 2013). The healthcare supply chain is dynamic, shaped by fluctuating demand, disease patterns, evolving regulations, and advancing medical technologies. External factors like disease outbreaks, economic shocks, and socio-political instability further complicate forecasting, increasing uncertainty and risk. In developing countries, additional challenges include limited disease data, fragmented infrastructure, cultural diversity, and financial constraints (Hermes et al., 2020).

Ethiopia, located in the northeastern part of Africa (the Horn of Africa), shares borders with Sudan and South Sudan to the west, Eritrea and Djibouti to the northeast, Somalia to the east and southeast, and Kenya to the south. It spans 1.1 million km², including 7,444 km² of water bodies. The country's diverse geography features rugged mountains, flat-topped plateaus, deep gorges, and river valleys shaped by erosion, volcanic activity, and tectonic movements. More than half of Ethiopia's land area lies above 1,500 meters, with the highest point at Ras

Dashen (4,620 meters) and the lowest at the Danakil (Dallol) Depression (148 meters) (HSTP II). Ethiopia is one of Africa_s fastest-growing economies, with an average annual growth rate of 10% between 2004 and 2014. However, it remains a low-income country, with a GDP per capita of $1272 in 2023 and a gross national income per capita of $1,020 (World Bank, 2024). Significant economic growth has not eliminated widespread poverty (HSTP II).

Ethiopia is home to over 80 languages and is characterized by rapid population growth (2.6%), a youthful population, and a high rural-urban divide. The total fertility rate is 4.6 births per woman (2.3 in urban areas and 5.2 in rural areas), with a crude birth rate of 32 per 1,000 people (2016). The average household size is 4.6. With a projected population of 109 million in 2024, Ethiopia is the second-most populous country in Africa after Nigeria, with 77% of its population residing in rural areas (ESS, 2024). Administratively, Ethiopia is divided into 12 regional states and two city administrations, which are further subdivided into zones, districts (woredas), and kebeles. Children under 15 years account for 47% of the population, individuals aged 15–65 years make up 49%, and 4% are over 65 years. Life expectancy at birth rose from 58 years in 2007 to 65.5 years in 2017 (HSTP II). However, Ethiopia_s per capita health expenditure was only $36.30 in 2019/20, well below the $43 average for low-income African countries and the $86 recommended by the WHO for essential health services in 2015 (MOH, 2022).

Ethiopia_s health system is decentralized and structured into three tiers (Figure 2). At the primary care level, the woreda-based system includes primary hospitals, health centers, and health posts. Secondary care is provided by general hospitals, while tertiary care is offered by teaching and specialized hospitals. By 2024 the country has 404 public hospitals, 3907 health centers, and 15,531 health posts, alongside more than 5,000 private and not-for-profit health facilities offering preventive and curative services (MOH, 2025).

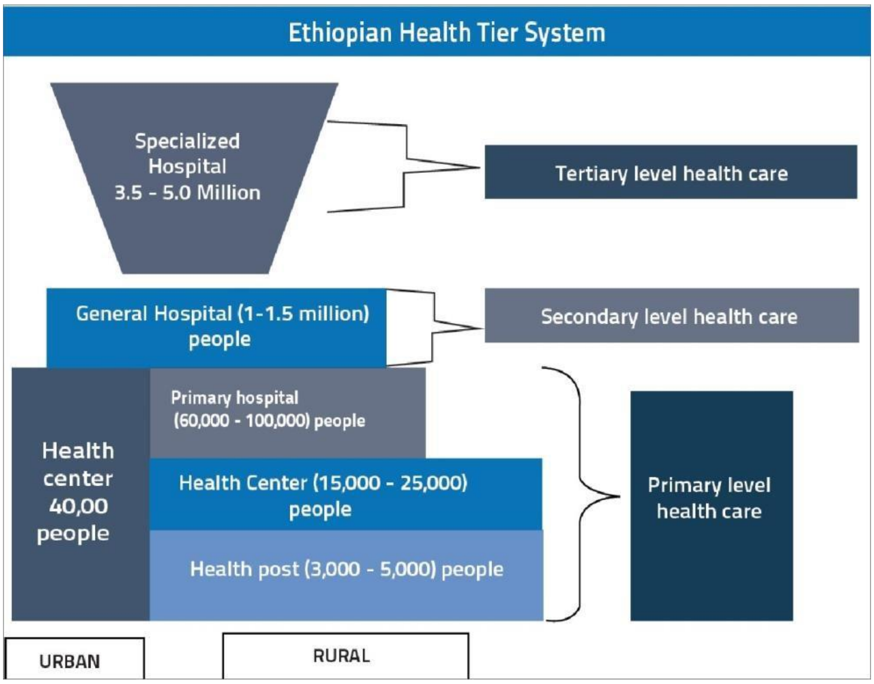


Figure 2: Ethiopian healthcare Tier System

Ethiopia's pharmaceutical supply chain involves public and private actors, including some domestic manufacturers. The main players in the supply chain are manufacturers, wholesalers, and distributors who deliver medicines to health facilities (Figure 3). To secure access to essential medicines, the Ethiopian Pharmaceutical Supply Services (EPSS) was established under the Ministry of Health. EPSS_s mandate is to ensure the reliable supply of quality medicines and health technologies to public health facilities. Its responsibilities include procurement, modern storage management, and direct delivery of pharmaceuticals to hospitals and health centers through an extensive transportation network. EPSS has been working to improve access to affordable, quality-assured medicines and promote their rational use (EPSA, 2015; EPSA, 2020(A); MOH, 2015).

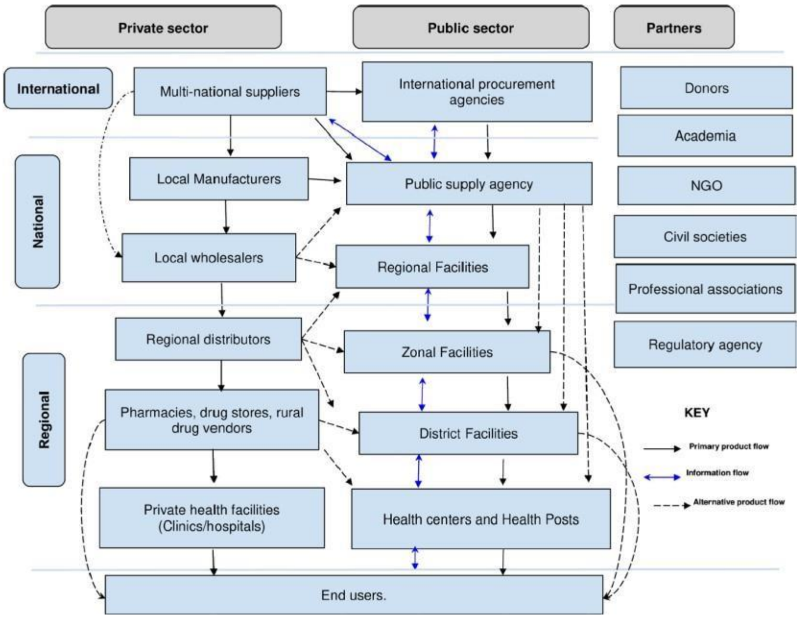


Figure 3: Pharmaceutical Supply Chain Map of Ethiopia (Sources: MSH, 2012)

Despite these efforts, EPSS faces significant challenges, including weak infrastructure, high forecast errors, inefficient procurement practices, regulatory hurdles, and limited local production capacity, which contribute to frequent shortages and stockouts. Ethiopia_s reliance on imported medicines further exposes the supply chain to global market fluctuations. To address these issues, the government has implemented reforms such as the Health Sector Transformation Plan (HSTP-II) and the Pharmaceuticals Supply Transformation Plan (PSTP), aimed at enhancing procurement, storage, and distribution systems (FDRE, 2020; MOH, 2022).

This dissertation investigates current demand forecasting practices at EPSS, focusing on strategies to improve accuracy and resilience in the pharmaceutical supply chain. It identifies gaps in forecasting methods, explores the causes of errors, and proposes innovative solutions to integrate forecasting techniques with supply chain strategies. By addressing these critical issues, the research aims to strengthen Ethiopia_s pharmaceutical supply chain; ensuring essential medicines are consistently available where they are needed.

1.3. Statement of the research problem

The need for this research arises from four key factors. First there is a widespread shortages of essential medicines. Second, there are significant challenges associated with forecasting practices in the study area. These challenges necessitate the identification, categorization, and targeted resolution of issues to improve the accuracy and relevance of forecasting. Third, the lack of expertise in forecasting presents a major barrier, especially given the wide range of available techniques, from simple methods to advanced machine learning-based approaches. These methods require both technical expertise and domain knowledge, making it critical to identify the most suitable forecasting techniques for EPSS. Without the contextual understanding provided by experts, these techniques are often ineffective. Fourth, forecasting practices, when conducted in isolation, have a limited impact on overall supply chain performance. To address this limitation, it is essential to explore the integration of forecasting techniques with supply chain strategies to enhance the availability of essential medicines within EPSS. Despite the significance of these challenges, there is a notable gap in the literature addressing the intersection of forecasting techniques and supply chain strategies. This lack of empirical research leaves organizations without clear guidance on addressing these interconnected issues. This research aims to bridge that gap by investigating these challenges and proposing solutions to improve both forecasting practices and supply chain outcomes.

1.3.1. Empirical Evidence of Pharmaceutical Shortages in Ethiopia

Pharmaceutical supply chains play a critical role in ensuring consistent and equitable access to essential medicines. In Ethiopia, persistent challenges in demand forecasting and supply chain performance have led to widespread medicine shortages, threatening public health and the effectiveness of the healthcare system.

A growing body of evidence confirms the depth of the problem. A systematic review by Tewuhibo et al. (2021) found that the average availability of essential medicines in public facilities across Ethiopia ranged from 41.9% in the Tigray region to 98.5% in Addis Ababa, with the national average falling below WHO‘s recommended 80%. Private facilities fared similarly, with availability between 31.5% and 98.2%. This highlights stark regional disparities and underlines a systemic issue in medicine availability.

For example, Berassa and Worku (2023) reported that only 65.3% of essential medicines were available at Tikur Anbessa Specialized Hospital in Addis Ababa again below the WHO benchmark. In Eastern Ethiopia, Sisay et al. (2021) also noted persistent stockouts and suboptimal availability, pointing to broader supply chain fragility, particularly in remote or resource-limited settings.

The COVID-19 pandemic further strained the system. A comparative study by Melaku et al. (2024) showed that the availability of selected generic medicines declined from 67.4% before the pandemic to 43.3% during it, reflecting the health system's vulnerability to external shocks.

In terms of stock-out duration, Tefera et al. (2022) found that primary health care facilities experienced an average stock-out period of 99.2 days, with some regions such as Benishangul Gumuz reaching 139 days—a critical delay for life-saving medicines. For pediatric medicines, Sado and Sufa (2016) found that availability of the lowest-priced medicines in public facilities was only 43.0%, with the highest-priced products barely available (1.2%), indicating severe access issues for children‘s treatments.

Multiple studies identify underlying factors contributing to this problem, including poor demand forecasting, weak data systems, transportation challenges, inefficient procurement, and limited human and financial resources (Tefera et al., 2022). These issues result in not only frequent medicine shortages, but also reliance on emergency procurement, increased patient out-of-pocket expenses, and adverse health outcomes.

Despite these challenges, there is limited empirical research in Ethiopia that explores how improved forecasting especially when informed by domain knowledge and supported by integrated supply chain strategies can enhance availability and supply chain resilience. This study aims to fill that gap by evaluating current forecasting practices, testing advanced forecasting models, and identifying practical strategies to minimize pharmaceutical shortages in Ethiopia‘s public health system.

1.3.2. The challenges in the pharmaceutical forecasting

Medicines are not ordinary items of commerce; they are essential for patient care and must be available in a timely manner, particularly for drugs with significant clinical consequences when doses are missed, such as antipsychotics, antiepileptic‘s, immune suppressants, and anticancer medications. A medicine shortage is a critical issue in any health system, as it directly impacts patient health. Unlike production industries where insufficient supply results in customer dissatisfaction, in healthcare, it can compromise patient outcomes. Hospitals, while serving the public, also face the challenge of balancing financial sustainability with ensuring adequate supply. Lost sales in this context translate to lost treatment opportunities. Simultaneously, healthcare systems aim to minimize excess capacities and reduce costs (Ivanov et al., 2021).

Pharmaceutical shortages are often caused by disruptions in fragile supply chains (GAO, 2016), compounded by complex contributing factors and persistent unpredictability (Tucker, 2020). The lack of timely and accurate information exacerbates planning difficulties for healthcare professionals (Batista et al., 2019). To address shortages effectively, robust supply chain management, including accurate demand forecasting, is essential.

Accurate demand forecasting is critical for managing inventory, scheduling orders, and ensuring efficient supply chain operations in the pharmaceutical sector. It optimizes inventory levels, reduces costs, and guarantees timely access to essential medicines, ultimately saving lives. Moreover, demand forecasting impacts not only inventory but also clinical decisions and health policy. However, unique challenges such as short product shelf lives, regulatory requirements, and strict quality standards make forecasting in this industry particularly complex (Gupta et al., 2000; Makridakis, 2020). Drug shortages can result in delayed treatments, reliance on costly alternatives, and compromised patient care (Alspach, 2012; Kaakeh et al., 2011).

Global health supply chains face numerous challenges, including fragile last-mile delivery, human resource constraints, limited research and development, and inefficient resource utilization. In Africa, these issues are exacerbated by stock-outs, corruption, product diversion, poor last-mile delivery, and fragmented leadership. This lack of accountability creates strong incentives for corruption and hinders access to essential health commodities (Yadav, 2015).

In Ethiopia, the Ethiopian Pharmaceutical Supply Services (EPSS), which manages 80% of the country‗s pharmaceutical supply, encounters significant challenges in demand forecasting and inventory management. A USAID (2016) study revealed an average forecast error of

27.8% for program commodities, exceeding the acceptable threshold of 25% (FMOH, 2019). Forecasting errors for critical items such as HIV/AIDS and malaria treatments were even higher, at 31.71% and 37.25%, respectively. These inaccuracies, combined with long procurement lead times averaging 137.3 days, further exacerbate availability issues. Additional challenges include poor data quality, incomplete consumption reports, and communication gaps (Boche et al., 2022; Eshetu & Gebena, 2020).

Inaccurate forecasts lead to disruptions such as changes in schedules, higher costs for inbound materials, increased transportation expenses, and excessive inventory levels (Kerkkänen, 2010). A SWOT analysis of EPSS highlighted systemic weaknesses, including low customer satisfaction, poor inventory management, inadequate distribution planning, and the absence of a robust track-and-trace system (FDRE, 2020). The organization also struggles with financial limitations, untrained staff, and an inefficient organizational culture. These challenges underscore the urgent need for coordinated efforts to improve forecasting accuracy, streamline procurement processes, enhance data quality, and strengthen supply chain management. Addressing these issues is critical to ensuring medicine availability, improving supply chain resilience, and ultimately enhancing health outcomes in Ethiopia.

1.3.3. Forecasting techniques

Forecasters frequently face the challenge of selecting the most suitable forecasting method from a range of alternatives, particularly when dealing with a large number of time series. This decision is influenced by the problem context, the characteristics of the data, and the available resources (Fildes & Petropoulos, 2015; Armstrong, 2001; Ord & Fildes, 2013). Various forecasting methods have been proposed in the literature, ranging from simple techniques, such as Simple Exponential Smoothing (SES) (Hyndman & Athanasopoulos, 2018), to advanced methods like regression models (Seyedan & Mafakheri, 2020), machine learning approaches, and mathematical modeling (Cerna et al., 2016).

Simple forecasting methods, such as aggregate selection, apply a single forecasting model across all-time series without accounting for the unique characteristics of each series. These methods are computationally less intensive, making them easier to implement, but they often sacrifice accuracy when the time series exhibit diverse traits, such as trends or seasonality (Fildes, 1989; Fildes & Petropoulos, 2015).

In contrast, complex forecasting methods involve selecting the best model for each time series based on its specific characteristics. This individual selection approach can enhance accuracy, particularly when time series can be segmented into sub-populations with similar attributes and when the performance of methods remains stable over time. However, complex methods require greater computational resources, sophisticated systems for data management, and sufficient historical data, making them more demanding to implement (Fildes & Petropoulos, 2015).

Fildes and Petropoulos (2015) emphasize the trade-offs between simplicity and complexity in forecasting. While simple methods are easier to use and require minimal computational effort, complex methods often yield superior accuracy. However, these advanced methods pose challenges in settings with limited expertise, as they require trained professionals capable of managing the intricacies of complex forecasting techniques. For countries with a shortage of skilled forecasting professionals, balancing simplicity and accuracy becomes particularly critical. In such contexts, developing capacity for using more advanced methods while leveraging simpler techniques in the interim can help address forecasting challenges effectively.

1.3.4. Limited empirical research linking forecasting techniques and supply chain strategies

Managing supply chains effectively is increasingly complex due to expanding product variety, shorter product life cycles, globalization, increasing outsourcing, and continuous advancements in information technology (Lee, 2002). Forecasting, as a foundational activity in supply chain management (SCM), plays a critical role in initiating all SCM actions and driving decision-making at both organizational and enterprise levels (Habib, 2011). Accurate forecasting informs key decisions such as capacity building, resource allocation, and supply chain integration, making it indispensable for professional and efficient operations (Albarune & Habib, 2015).

Despite its importance, existing literature on forecasting often focuses on isolated aspects, such as methodologies, tools, or software, without exploring their integration into broader supply chain strategies. Makridakis and Hibon (2000) emphasized that predictions remain the foundation of all science, yet the identification of the most suitable forecasting techniques for specific contexts remains a persistent challenge (Fildes & Makridakis, 1995). Current research predominantly examines point forecasts, neglecting the full distribution of forecast data, which could better capture demand uncertainties and support risk management in supply chains.

Forecasting is not merely a statistical exercise or a software-driven process; it is a management process that requires domain expertise and strategic alignment (Moon, 2018). While companies can invest in tools to facilitate forecasting, true excellence depends on integrating these tools with organizational processes and domain knowledge. Unfortunately, many existing forecasting systems primarily collect transactional data, such as consumption, without capturing events influencing demand variability—critical information for building reliable forecasting models.

In pharmaceutical supply chains, effective forecasting alone cannot resolve the complex challenges of shortages. These challenges require a holistic approach that combines advanced forecasting techniques with appropriate supply chain strategies. Despite significant investment in logistics systems, there is limited research addressing how domain expertise can enhance pharmaceutical forecasting accuracy or how forecasting techniques can align with supply chain strategies to mitigate shortages.

This study aims to address these gaps by exploring which forecasting techniques, combined with appropriate supply chain strategies, can effectively minimize pharmaceutical shortages within the Ethiopian public health supply chain. The research will apply both simple and advanced forecasting methods, incorporate domain expertise, and evaluate how these methods perform in the Ethiopian Pharmaceutical Supply Services (EPSS) context. By doing so, it seeks to identify approaches that improve forecast accuracy and enhance supply chain resilience.

1.3.5. Problem statement

Considering the three problems discussed in this chapter so far, the broad research problem addressed in this dissertation is stated as follows:

The Ethiopian Pharmaceutical Supply Services (EPSS) faces persistent challenges in achieving demand forecasting accuracy, aligning forecasting expertise with operational needs, and integrating forecasting techniques with supply chain strategies. These challenges contribute to inefficiencies in inventory management, high forecast errors, prolonged lead times, and limited availability of essential medicines, ultimately compromising patient care. Despite the critical role of forecasting in optimizing supply chain operations, existing methods often fail to address the unique complexities of the pharmaceutical sector, including variability in demand, short product shelf lives, and regulatory constraints. Moreover, the lack of empirical research exploring how advanced forecasting techniques can be effectively integrated with supply chain strategies further exacerbates these issues. This research seeks to address these interconnected challenges by identifying effective forecasting methods, incorporating domain expertise, and aligning forecasting practices with supply chain strategies to enhance supply chain resilience and improve the availability of essential medicines in Ethiopia.

1.4. Significance of the study

This study is critical for improving the pharmaceutical supply chain in Ethiopia, particularly within the EPSS. It addresses a significant gap in demand forecasting accuracy, which is essential for ensuring the availability of vital medicines. By focusing on the unique challenges of Ethiopia_s pharmaceutical sector, the research aims to develop and implement advanced forecasting methodologies tailored to local conditions. These methodologies will leverage machine learning techniques and domain expertise, overcoming the limitations of traditional forecasting approaches that often rely on qualitative judgments and simplistic time-series methods.

Moreover, this study highlights how effective forecasting can be integrated with supply chain strategies to alleviate pharmaceutical shortages in EPSS. By employing advanced forecasting techniques, organizations can better anticipate demand fluctuations, thereby optimizing procurement and inventory management. Improved forecasting accuracy would help reduce stockouts and ensure that essential medicines are available when needed—an urgent requirement in Ethiopia, where frequent shortages have severely impacted healthcare delivery and patient outcomes.

The findings of this research have numerous practical implications. Enhanced forecasting accuracy can lead to better alignment of supply with patient needs, ultimately strengthening the resilience of the supply chain. This is particularly vital in a context where healthcare challenges are exacerbated by the unpredictability of medicine availability.

Additionally, the study would provide valuable insights for policymakers, healthcare professionals, and supply chain managers. It identified systemic weaknesses in the current pharmaceutical supply chain management system and recommend actionable strategies for improvement. The outcomes could inform national healthcare policies, guide the development of training programs for supply chain professionals, and promote the adoption of innovative, data-driven approaches within the EPSS.

On a broader scale, this research has the potential to contribute to the global discourse on pharmaceutical supply chain management, particularly in low-income countries facing similar challenges. The innovative approaches and solutions proposed can be adapted and applied in other nations with comparable healthcare and supply chain environments, fostering international collaboration to tackle the pervasive issue of drug shortages. Ultimately, by enhancing demand forecasting and integrating it with supply chain strategies, this study aims to support the availability of affordable and reliable medicines, thereby improving public health and healthcare outcomes in Ethiopia and beyond.

1.5. Structure of the dissertation

This introductory chapter initiated this research, presenting the need for understanding about the challenges in forecasting and supply chain resilience. Figure 4 demonstrates the structure of this thesis.

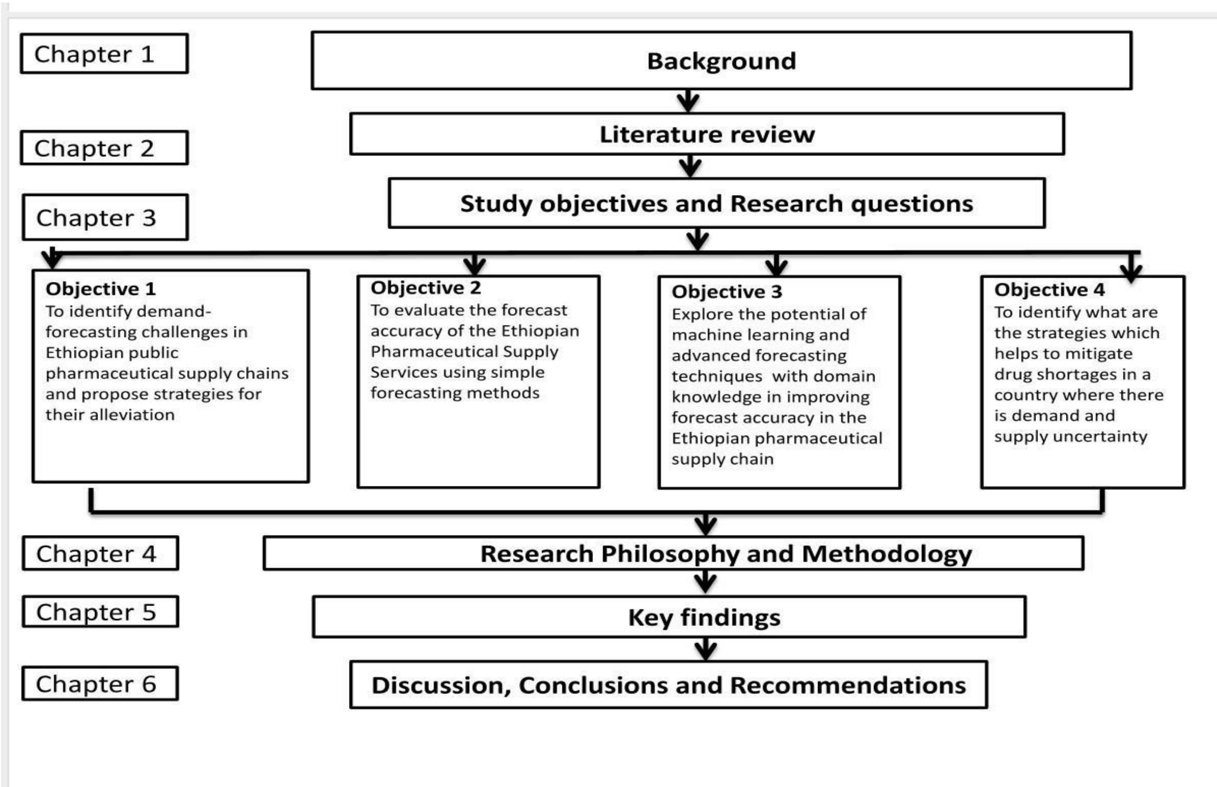


Figure 4:Structure of the dissertation

Chapter 1 introduces the dissertation by presenting the background, statement of the problem, and significance of the study.

Chapter 2 provides a comprehensive literature review, covering key topics including the challenges in pharmaceutical forecasting, simple forecasting methods, and forecasting accuracy measures. Additionally, it addresses the integration of domain knowledge with advanced forecasting methods, discusses effective supply chain strategies for managing uncertainty, and concludes with the conceptual framework that guided the study.

Chapter 3 outlines the study objectives and research questions, following the literature review and conceptual framework.

Chapter 4 discusses the philosophical foundation of the research, which is underpinned by pragmatism. Pragmatism recognizes multiple ways of interpreting reality, but prioritizes the practical implications of research over theoretical interpretations.

Chapter 5 presents the main findings derived from the four research papers that form the core of the study.

Chapter 6 discusses the key findings of each paper, providing conclusions and recommendations. This chapter also addresses the strengths and limitations of the research, practical and policy implications, and suggests areas for future research.

The dissertation concludes with the appendices, which include each published article along with its abstract, background, methods, results, discussion, conclusions, and references.

Conclusion to Chapter 1

This introductory chapter has set the context for the dissertation by outlining the research problem and highlighting the significance of the study. The following chapters will present a thorough review of the literature and the conceptual framework that guided the design of the research.

CHAPTER 2: LITERATURE REVIEW

This chapter presents a review of the related literature, focusing on three key areas: the challenges in forecasting, Simple Forecasting Methods and Forecast Accuracy Measures, Integrating Domain Knowledge and Advanced Forecasting Methods, Effective Supply Chain Strategies for Managing Uncertainty, the advantages and disadvantages of various forecasting techniques, and the integration of forecasting methods with other supply chain strategies. The primary objective of this review is to synthesize existing knowledge on these topics to identify gaps and inform the research.

A systematic literature search was conducted using a combination of terms such as *"forecasting challenges," "forecasting techniques," "simple forecasting techniques," "advanced forecasting techniques," "machine learning,"* and *"domain knowledge."* These were further combined with terms like *"supply chain strategies," "demand forecasting," "demand planning," "quantification," "health commodity," "health supply chain,"* and *"health products."* Searches were conducted in the Embase and PubMed databases, which collectively provide extensive coverage of journals relevant to these topics. This approach ensured a comprehensive exploration of the literature to address the study's objectives.

2.1. Challenges in Pharmaceutical Forecasting

Demand forecasting for health commodities is a significant weak point in global health supply chains, with numerous challenges that impede accuracy. Accurate demand forecasts are essential for market viability, production capacity, and financial planning. National governments and international donors depend on these forecasts for budgeting, while health programs and implementing partners use them to organize supply chain logistics (Subramanian, 2021). In Africa, demand forecasting in public health systems faces additional hurdles, such as limited funding, inadequate infrastructure, and a shortage of skilled personnel, which hamper the implementation and maintenance of forecasting systems (Lugada et al., 2022). Another critical issue is unreliable data—often due to incomplete or inaccurate records, lack of standardized data collection methods, and restricted access to real-time information. These data challenges make accurate forecasting difficult. Forecasting for new health commodities poses further difficulties due to the uncertainities surrounding the acceptance of breakthrough technologies and products by consumers (Subramanian, 2021). Additionally, the collection of information to guide procurement and supply decisions is inadequate.

Most health facilities collect data on products, but this information often consists of distribution records from one point to another rather than reflecting actual consumption. As a result, it lacks a comprehensive product history, including the reasons for spikes in distribution at specific times, making it challenging to use for accurate forecasting and future demand predictions. Even when some facilities track real-time demand, this information is frequently recorded in paper-based systems and is not effectively shared across different levels of the supply chain, limiting its utility (Privett & Gonsalvez, 2014). Consequently, much of the data fails to provide an accurate picture of actual consumption, focusing instead on distribution patterns.

Leadership engagement and support across various levels of the health system are vital for the successful implementation of demand-forecasting systems in Africa. A lack of accountability and fragmented leadership can create significant challenges in forecasting and overall supply chain management (Yadav, 2015). The current health delivery system is often siloed and uncoordinated, further complicating forecasting efforts (Privett & Gonsalvez, 2014). Additionally, the shortage of qualified personnel results in high workloads, low performance, and unaddressed critical duties. There is often an insufficient number of trained supply chain staff at warehouses and health facilities to carry out even basic tasks (Privett & Gonsalvez, 2014; Sridhar et al., 2008). Poor working conditions, lack of training, inadequate facilities, and low pay not only affect employees' performance but also contribute to low morale and high turnover rates.

The quality of forecasting tools also plays a critical role in gathering adequate data on future demands and trends (Subramanian, 2021). The dynamic nature of disease burdens, shifting patient needs, and new products in global markets add layers of complexity to the forecasting process (Hermes et al., 2020). Other factors such as stockouts, corruption, and product diversion further complicate forecasting efforts and negatively impact health outcomes (Sued et al., 2011).

In resource-constrained settings, logistical challenges make forecasting even more difficult (Subramanian, 2021). Limited information on how risks are shared and incentives are aligned among stakeholders can adversely affect demand forecasting. Additionally, healthcare organizations often operate under tight budget constraints, making it challenging to accurately predict and meet the demand for medical technologies (Levine et al., 2008). The robustness of health forecasting tools is also a notable concern (Zhu et al., 2021).

In the pharmaceutical industry, forecasting frequently relies on basic statistical methods using historical data, which fail to account for complexities such as economic conditions, regulatory changes, market competition, special contracts, and media influence. Addressing these factors requires more sophisticated models that incorporate extensive data and expert industry knowledge (Chase, 2013). Demand sensing has emerged to address these complexities, highlighting the need for advanced forecasting techniques (Maroun et al., 2019). Traditional time series models, which assume future demand is solely based on past trends, do not adequately capture multifaceted influences. Maroun et al. categorized forecasting challenges into internal and external factors. Internal challenges arise within the organization and include employee issues, management practices, communication barriers, and cultural factors that hinder information sharing and collaboration, affecting forecasting accuracy. External challenges are driven by market forces such as customer behavior, market dynamics, and supplier relationships, which introduce uncertainties and market fluctuations (Browning et al., 2023).

Post-2020, traditional statistical models like exponential smoothing have proven inadequate in the face of volatile and dynamic environments. The complexity of forecasting in such settings is often described as a "wicked problem" (Churchman, 1967; Rittel & Webber, 1973; Estrin et al., 2020). Unpredictable events, such as the COVID-19 pandemic, can disrupt forecasting accuracy, leading to inventory shortages or excesses (Peysakhovich & Karmarkar, 2016). Despite advances in analytics and artificial intelligence (AI), quantitative models struggle with the complex and evolving data requirements. While machine learning techniques offer valuable insights, human interpretation, context awareness, experience, intuition, and creativity are still essential for identifying non-trivial patterns in forecasting (Brooks, 2024; Sanders & Ritzman, 2001). This illustrates "Moravec_s Paradox," where the strengths and limitations of human judgment and analytical methods complement each other

(Sanders, 2000; Sanders, 2017; Fildes & Goodwin, 2007; Moritz et al., 2014; Brynjolfsson & Mitchell, 2017; Sanders & Wood, 2022). An ideal forecasting approach integrates both judgmental and statistical methods, leveraging collective intelligence to improve accuracy (Fildes & Goodwin, 2007; Taylor-Phillips & Freeman, 2022; Soyiri & Reidpath, 2013). Demand uncertainty, characterized by small variations in patient needs at health clinics, can lead to significant fluctuations in order quantities across the supply chain, resulting in stockouts or excess inventory. Inaccurate forecasting during procurement planning can exacerbate these issues, causing stockouts or product expiration (Yadav, 2015).

2.2. Simple Forecasting Methods and Forecast Accuracy Measures

Various demand forecasting methods have been developed, ranging from simple techniques to advanced machine learning and mathematical modeling (Hyndman, 2018; Cerna et al., 2016; Seyedan and Mafakheri, 2020). Simple forecasting methods, such as mean, naïve, and moving averages, are straightforward yet surprisingly effective for several reasons. First, they can provide quick and uncomplicated statistical forecasts. Second, they offer a baseline for comparing more complex methods. Third, simple methods often perform well (Chaman and Malehorn, 2006). These methods can deliver reasonable accuracy in some cases, as supported by evidence from Armstrong (1984) and Schnaars (1984), who found naïve forecasts to be as accurate as other more sophisticated models.

In the pharmaceutical industry, forecasting methods span traditional statistical models, like ARIMA and exponential smoothing, to machine learning approaches such as Support Vector Regression (SVR) and Random Forest (RF) (Zahra and Putra, 2019; Khalil Zadeh et al., 2014). Metrics for evaluating forecast accuracy include Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Despite their usefulness, traditional models often struggle with complexities like seasonality and external influences (Sanders and Graman, 2009). Hybrid models, combining linear and nonlinear techniques, have shown improved accuracy in capturing diverse data patterns. For instance, integrating downstream information in machine learning models has significantly enhanced accuracy, as evidenced by reductions in MSE and RMSE (Van Belle et al., 2021). Forecasting in healthcare faces additional challenges, including fluctuating patient needs, resource allocation constraints, and disease burdens. The choice of forecasting tools depends on factors such as data availability, demand volatility, and product maturity (Huff and Sultan, 2014). Simple methods offer advantages like ease of use, computational efficiency, and adaptability to different data types. They also provide robust baseline models for comparing advanced techniques, making them valuable for both practitioners and learners (Hyndman and Athanasopoulos, 2018; Kolassa et al., 2023). However, these methods may fail to capture complex data relationships, necessitating the use of more sophisticated models for higher accuracy.

This study evaluates simple forecasting models to improve demand forecasting accuracy in Ethiopia, a country challenged by frequent pharmaceutical shortages and forecasting difficulties (Bilal et al., 2024, Gutesa et al., 2024; Melaku et al., 2024; Tefera et al., 2022; Kefale and Shebo, 2019). Forecast accuracy is assessed using various error metrics, each with strengths and limitations (Davydenko and Fildes, 2016). These metrics include:

- **Scale-dependent errors:** Mean Absolute Error (MAE) and RMSE are popular for their simplicity but can be difficult to interpret (Hyndman, 2018).
- **Percentage errors:** MAPE is widely used for comparing performance across data

series, but it becomes less reliable when actual values approach zero (Hyndman, 2014).

- **Relative errors:** Metrics like the Median Relative Absolute Error (MdRAE) provide comparisons against benchmark methods.
- **Scale-free errors:** The Mean Absolute Scaled Error (MASE) accounts for limitations in other measures, scaling errors based on in-sample MAE from a naïve forecast (Hyndman and Koehler, 2006).

2.3. Integrating Domain Knowledge and Advanced Forecasting Methods

Demand forecasting for pharmaceutical supply chains is complex, impacted by factors such as data quality, funding uncertainties, supply chain structure, workforce shortages and external drivers like market trends (Bilal et al., 2024; Schneider et al., 2010). While traditional forecasting often relies on quantitative data, incorporating domain knowledge adds value by accounting for factors such as clinical guidelines, disease outbreaks, and local policies not evident in raw data alone. Combining, statistical and judgmental forecasting and using it these approaches has been discussed by some as the best way to obtain a more reliable forecast (Armstrong and Green, 2005; Fildes et al., 2009; Lawrence et al., 2006; Wright et al., 1996) .

Domain knowledge is any information relevant to the forecasting task other than the time series i.e., non-time series information. In its very simplest case, this could be an awareness of the nature of the time series. For example, knowledge that a downward trending time series is related to daily interest rates rather than sales of a product may (arguably) contain valuable information that may change the way in which a person forecasts the variable (Lawrence et al., 2006). The most common situation in which a judgmental forecaster finds himself/herself is one where there is both contextual knowledge (knowledge of the nature of the time series) and some additional irregular knowledge that can be useful in either explaining the past behaviour of the series or in predicting the future (or both). Sometimes the impact of this information can be quite minor, but sometimes it can be quite important and can have a major influence on the behaviour of the variable. In any event, the distinguishing characteristic of such domain knowledge is that it represents an un-modelled component of the time series. This un-modelled component is a necessary characteristic if it is capable of being modelled by a statistical method, it can be incorporated into the statistical forecast. For example, knowledge that a fixed and known marketing promotion will occur regularly in a particular month would not represent domain knowledge, since such regularity could be modelled as a seasonal component by a statistical method (Lawrence et al., 2006).This is crucial in the pharmaceutical industry, where accurate sales forecasting affects inventory management and healthcare delivery.

Despite the advancements in forecasting methods, several gaps remain, particularly in addressing uncertainty and incorporating domain knowledge into the modeling process. Most existing studies focus on point forecasts, which may not fully capture the range of possible outcomes in pharmaceutical demand. This limitation is critical, given the high stakes of inventory management in this industry. Moreover, there is a lack of research on the impact of integrating domain knowledge—such as insights from experienced professionals—into forecasting models. This integration could potentially improve model accuracy and reliability, especially in complex and rapidly changing environments. In summary, the literature on pharmaceutical forecasting has evolved from traditional statistical models to advanced machine learning techniques, each offering unique insights and capabilities. However, there is still room for improvement, particularly in addressing uncertainty and incorporating domain knowledge. Future research should focus on developing probabilistic forecasting models and exploring ways to integrate expert insights into the forecasting process. These advancements could significantly enhance decision-making and operational efficiency in the pharmaceutical supply chain (Rostami et al., 2022).

2.4. Effective Supply Chain Strategies for Managing Uncertainty

Drug shortages are a significant global issue, affecting countries of all income levels and leading to severe health and economic crises worldwide (Shukar et al., 2021; Dill and Ahn, 2014; Dave et al., 2018). The impact of these shortages is particularly detrimental to patients, who may face increased monitoring requirements, suboptimal treatment with alternative drugs, delayed care, transfers to other institutions, prolonged hospitalization, readmission due to adverse events or treatment failure, and in severe cases, even death (McLaughlin et al., 2013; Rider et al., 2013; Souliotis et al., 2014; Blaine et al., 2016; Yang et al., 2016; Alruthia et al., 2017).

This issue is especially challenging in low- and middle-income countries, where research is limited and policies to address drug shortages are often lacking. Studies have reported stockouts of essential medicines in Malawi, Egypt, and Uganda (Alsirafy and Farag, 2016; Khuluza and Heide, 2017), along with shortages of TB drugs, ketamine, and HIV medications in various African countries (Seunanden and Day, 2013; Gray, 2014; Addo et al., 2018; Wall and Bangalee, 2019). In Ethiopia, frequent shortages of essential medicines have been documented, but detailed strategies for managing these shortages are rarely discussed (Gutesa et al., 2024; Melaku et al., 2024; Tefera et al., 2022; Kefale and Shebo, 2019).

Effective supply chain strategies are crucial for addressing these challenges, particularly in healthcare, where demand and supply uncertainties have serious repercussions (Begen et al., 2016). Fisher (1997) and Lee (2002) categorized supply chains as efficient or responsive based on demand predictability and supply uncertainty, emphasizing the need for mechanisms like robust supplier relationships and real-time tracking.

The complexities of modern supply chains have increased due to shifting customer demands, disruptions, and global events. The COVID-19 pandemic, geopolitical conflicts, and economic turbulence have highlighted the need for resilient strategies to manage these uncertainties. In Ethiopia, addressing supply chain issues like stockouts and long lead times remains critical. Despite efforts through initiatives like the Pharmaceutical Logistics Master Plan, medicine shortages continue to be a pressing issue (Haileselassie et al., 2019; Tewuhibo et al., 2021).

Pharmaceutical supply chains face unique risks such as regulatory challenges, sourcing constraints, and manufacturing disruptions. Effective solutions involve clear communication, standardized practices, and proactive shortage management strategies (Fox et al., 2014). For low-income countries, essential strategies include transparent redistribution, careful management of limited stock, and robust reporting systems to mitigate the impact of drug shortages on healthcare delivery. Shukar et al. (2021) noted that countries adapt their shortage-mitigation strategies to their specific contexts, and Ethiopia_s pharmaceutical supply chain, with its distinct features, similarly requires tailored strategies to address drug shortages effectively.

2.5. Summary of Literature Review

The literature review highlights the critical role of accurate demand forecasting in the pharmaceutical industry, as it significantly affects inventory management, healthcare service delivery, and patient outcomes. However, in resource-limited settings like Ethiopia, the effectiveness of traditional forecasting methods is hampered by high demand variability, limited data, and frequent supply chain disruptions. These challenges often result in stock imbalances, impacting the availability of essential medicines and overall healthcare delivery. Current models, from basic time-series techniques to advanced machine learning, often struggle to adapt to these local complexities, indicating a gap in the existing approaches.

2.6. Gaps in knowledge

The literature review highlighted several critical gaps. First, while various challenges in forecasting have been identified, there is a notable absence of studies that integrate advanced forecasting methods with domain knowledge, particularly in the context of pharmaceutical supply chains. Second, limited research explores the application of forecasting techniques in combination with supply chain strategies, leaving a significant gap in understanding how these two elements can work together to mitigate pharmaceutical shortages effectively. Additionally, there is insufficient evidence on how this integration could address shortages not only in the study area but also in similar low- and middle-income country settings. Addressing these gaps could play a vital role in enhancing supply chain resilience and ensuring consistent medicine availability in resource-constrained contexts.

Building on this literature review, the research question was defined as: *"**How best can forecasting techniques and supply chain strategies be configured to minimize pharmaceutical shortages in the Ethiopian public supply chain?**"* Consequently, the aim of this research is to investigate how the integration of forecasting techniques with supply chain strategies can be optimized to address these challenges within the Ethiopian public supply chain.

2.7. Conceptual model

The conceptual framework aims to enhance forecast accuracy and supply chain resilience in pharmaceutical services by addressing four key components. First, it highlights the demand forecasting challenges, such as data quality issues, communication barriers, budget constraints, and limited expertise among professionals. These factors complicate the forecasting process, potentially leading to inaccuracies and less effective supply chain planning. The second component focuses on forecasting methods, comparing simple approaches with more advanced techniques. The choice of forecasting method plays a crucial role in determining forecast accuracy, as advanced techniques can better handle complex data and address existing challenges, ultimately improving the reliability of forecasts.

Drug shortages, the third component, are directly influenced by forecast accuracy. Inaccurate demand forecasts can create supply imbalances, leading to drug shortages that disrupt healthcare delivery. Enhancing forecast accuracy is therefore critical to minimizing the risk of shortages and ensuring a consistent supply of essential medications. The fourth component involves supply chain strategies, which include both proactive and reactive measures aimed at increasing resilience. Proactive strategies anticipate demand fluctuations, while reactive strategies adapt to unexpected changes. Together, these strategies help mitigate the impact of drug shortages and respond effectively to supply chain disruptions. The framework integrates these elements to improve forecast accuracy and strengthen supply chain resilience in pharmaceutical services (Figure 5).

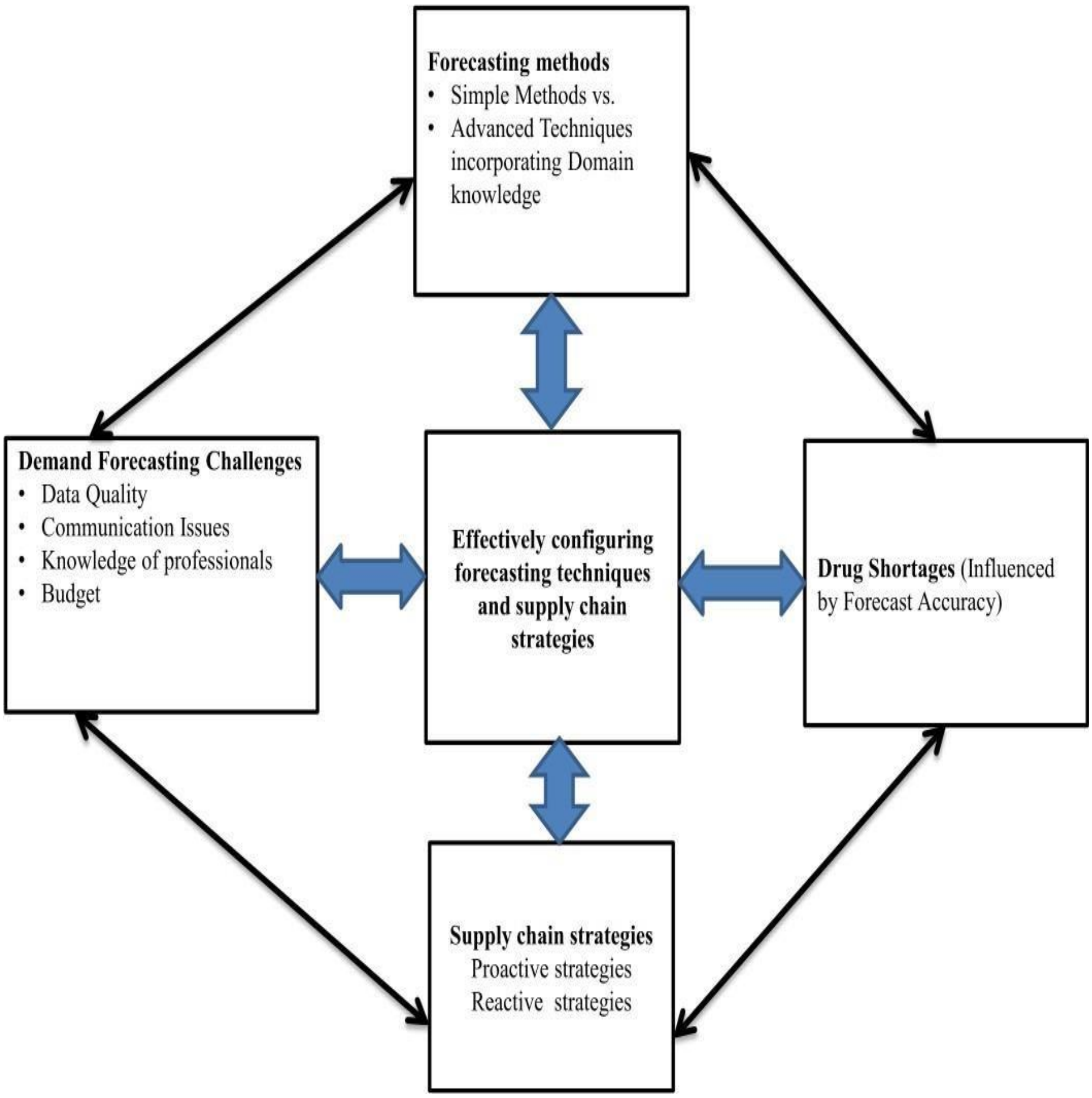


Figure 5: Conceptual framework

CHAPTER 3: STUDY OBJECTIVES AND RESEARCH QUESTIONS

3.1. General objective

The general objective of this PhD research is to explore how forecasting techniques and other supply chain strategies can be effectively configured to improve demand forecasting practices and address forecasting inaccuracies within the Ethiopian Pharmaceutical Supply Chain.

3.2. Specific objectives

1. To identify demand forecasting challenges in Ethiopian public pharmaceutical supply chains and propose strategies for their alleviation
2. To evaluate the forecast accuracy of the Ethiopian Pharmaceutical Supply Services using simple forecasting methods.
3. To explore the potential of machine learning and advanced forecasting techniques along with domain knowledge in improving forecast accuracy in the Ethiopian pharmaceutical supply chain.
4. To identify the strategies which help mitigate drug shortages in Ethiopia where there is a demand and supply uncertainties.

3.3. Research questions

The primary question of this PhD research seeks to answer as to how demand forecasting accuracy and supply chain resilience be improved in the Ethiopian pharmaceutical supply chain? and the specific research questions were:

1. What are the key challenges in demand forecasting within the Ethiopian public pharmaceutical supply chain?
2. How accurate are the current forecasting methods used in Ethiopian Pharmaceutical Supply Services, and how do simple forecasting models perform in this context?
3. What is the potential of advanced forecasting techniques, such as machine learning, in improving demand forecasting accuracy for the Ethiopian pharmaceutical supply chain?
4. What strategies can be developed to mitigate drug shortages in the presence of demand and supply uncertainties within the Ethiopian pharmaceutical sector?

CHAPTER 4: RESEARCH PHILOSOPHY AND METHODOLOGY

4.1. Introduction to chapter

This chapter outlines the philosophy and methodology guiding this research, providing a comprehensive overview of the research process. Figure 6 illustrates the research design, aligning with the framework proposed by Saunders, Lewis, and Thornhill (2019), which aids in visualizing the study_s methodological positioning. The figure's components are discussed throughout the chapter, starting with the research philosophy's ontological, epistemological, and axiological foundations, and the theoretical lens adopted (Section 4.2).

The methodology is divided into two main parts: a qualitative component and a quantitative component. The qualitative approach focuses on exploring the challenges in demand forecasting practice and finds strategies for mitigating drug shortages in the pharmaceutical supply chain, while the quantitative approach aims to analyze forecasting methods by incorporating domain knowledge and advanced machine learning techniques. The integration of these approaches provides a comprehensive understanding of the research problem, allowing for a more robust analysis of the challenges and opportunities in pharmaceutical demand forecasting. The methodological choice and justification for the case study approach are elaborated in Sections 4.3 and 4.5, respectively. Subsequent sections (4.6 to 4.8) detail the study setting, design, data collection, and analysis techniques for both qualitative and quantitative methods, describing how the findings from each were synthesized to generate insights (Section 4.7). The ethical considerations underlying the study are presented in Section 4.8, followed by the conclusion in Section 4.9.

Saunders_ Research Onion were selected for this research because it aligns well with the study's applied nature, offering both depth (philosophical considerations) and breadth (strategies and methods) necessary for tackling supply chain challenges in healthcare. Creswell and other alternatives were considered but deemed less suitable for the specific needs of this research, which required a structured yet flexible framework like Saunders.

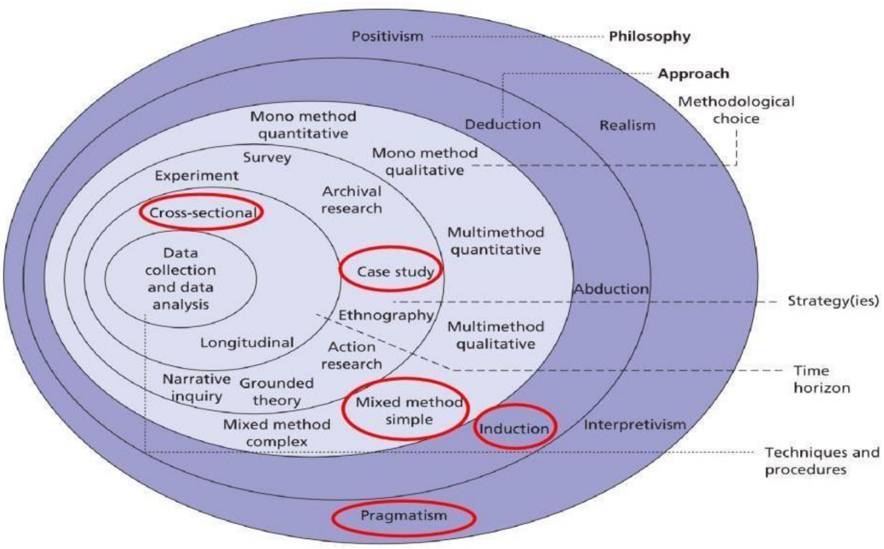


Figure 6: Research _onion' (Saunders, Lewis and Thornhill, 2019)

4.2. Philosophy

Research philosophy refers to a system of beliefs about how knowledge is developed, involving ontological, epistemological, and axiological considerations (Saunders, Lewis, & Thornhill, 2019). In social science research, these considerations shape the study_s design, data collection methods, and interpretation of findings.

Ontology addresses the nature of reality and whether it is objective and external or constructed by individuals. In social sciences, perspectives on ontology range from **objectivism**, where reality is considered independent of human perception, to **subjectivism**, which posits that reality is shaped by individual experiences and social interactions (Burrell & Morgan, 1979). These differing views influence how social phenomena are studied, with objectivists focusing on observable, measurable facts and subjectivists emphasizing social constructs and multiple realities.

Epistemology pertains to the nature and validity of knowledge. It affects the research process, including the questions posed, data collection methods, and the interpretation of results (Johnson & Duberley, 2000). In social sciences, **positivism** and **interpretivism** represent two ends of the epistemological spectrum. Positivism seeks to establish universal truths through empirical observation and measurement, similar to the natural sciences, while interpretivism focuses on understanding the subjective experiences and cultural meanings behind social phenomena.

Axiology considers the role of the researcher_s values in the study, influencing how data is interpreted and what is considered valuable knowledge. Understanding the researcher's position within these philosophical dimensions is crucial for ensuring consistency between the research question, objectives, and methodological approach.

Major Philosophical Approaches

1. **Positivism**: Emphasizes empirical observation and the formulation of universal laws based on measurable facts. Originating in the 19th century, it aligns with an objective ontology, where reality is considered external and independent of human perception (Collis & Hussey, 2009). Critics argue that applying positivism to social sciences oversimplifies complex human behaviors by treating them as immutable (Raworth, 2017).
2. **Interpretivism**: Opposes the positivist view, asserting that social reality is constructed by individuals. This approach focuses on understanding the context-specific meanings behind social actions, recognizing that multiple realities may coexist (Crotty, 1998). Interpretivists prioritize the perspectives of participants to gain insights into social processes and behaviors.
3. **Postmodernism**: Takes a more radical stance, rejecting the notion of objective truth entirely. Postmodernists argue that reality is a subjective mental construct, challenging the legitimacy of universal knowledge claims (Parker, 1995). Their research often critiques established norms and values rather than seeking to establish new truths.
4. **Pragmatism**: Acknowledges the existence of multiple perspectives but emphasizes practical solutions. Pragmatists focus on addressing real-world problems and consider knowledge valuable if it supports action and problem-solving (Kelemen & Rumens, 2008). This approach balances between objective

and subjective perspectives, prioritizing practical outcomes over theoretical debates.

5. **Critical Realism**: Combines elements of both positivism and interpretivism by recognizing an external reality while acknowledging that our understanding of it is mediated by social experiences. Critical realism contends that while social structures exist independently of individuals, they can only be understood through human perceptions (Easton, 2010).

In summary, choosing a research philosophy involves aligning the ontological and epistemological assumptions with the study_s objectives. While positivism emphasizes objectivity and measurable outcomes, interpretivism seeks to understand the subjective nature of social phenomena. Pragmatism and critical realism offer middle-ground approaches. The researcher _s own interpretation of the ontological and epistemological assumptions within each philosophical research position is summarized in Table 1.

Table 1:Summary Table: Philosophical Foundations and Research Paradigms

Philosophical Paradigm	**Ontology (Nature of Reality)**	**Epistemology (Nature of Knowledge)**	**Axiology (Role of Values)**	**Approach/Methods**
Positivism	Objective, external reality exists	Knowledge through empirical observation and measurement	Value-free, objective	Quantitative (e.g., experiments, surveys)
critical Realism	Objective reality exists, but knowledge is imperfect and theory-laden	Knowledge through empirical investigation and understanding of deeper mechanisms	Value-laden, but researcher strives for objectivity	Mixed methods (quantitative and qualitative)
Pragmatism	Dynamic reality that depends on context	Knowledge through practical experience; what works	Value-laden; focus on solving practical problems	Mixed methods (choosing the best method for the problem)
Interpretivism	Reality is socially constructed and subjective	Knowledge through understanding human experiences and meanings	Value-laden; researcher interacts with subjects	Qualitative (e.g., interviews, case studies)
Postmodernis m	Fragmented, relative reality shaped by language and power	Knowledge is constructed through language, power, and discourse	Value-laden, influenced by power dynamics	Qualitative (e.g., discourse analysis, narrative approaches)

So far in this chapter, the ontological and epistemological assumptions of this dissertation have been discussed, as well as its theoretical lenses. Since the purpose of this research is to bring practical and actionable outcomes the researcher believe that pragmatism is the best approach moreover the researcher are not starting with a pre-established theory and our research involves a practical mix of both qualitative and quantitative methods, Pragmatism aligns well. It allows us to focus on solving real-world problems through a flexible approach, emphasizing practical outcomes over rigid adherence to any single research method or theoretical framework. Pragmatism will give the freedom to use the most effective tools available, whether they come from qualitative or quantitative traditions, ensuring the research addresses the actual challenges in pharmaceutical supply chain forecasting and resilience.

Pragmatism acknowledges that there are multiple ways of interpreting reality; however, researchers are less concerned about how reality is interpreted and more preoccupied with what the practical value of the research is. Having evolved since the 19th century and sitting in the middle of the continuum between objective and subjective ontologies, a pragmatist approach starts with a problem and argues that concepts are only relevant if they support action and the application of problem-solving ideas (Kelemen and Rumens, 2008). While postmodernists would be preoccupied with criticizing previous research based upon the values of the researcher, pragmatists would not engage in such debate focusing instead on the usefulness of their results to the applied world. Notwithstanding, a criticism is that such usefulness of pragmatism is constrained to the specific context studied without providing much opportunity for theorizing and generalising (Easton, 2010).

Pragmatism asserts that concepts are only relevant where they support action (Kelemen and Rumens 2008). Pragmatism originated in the late-nineteenth–early-twentieth century USA in the work of philosophers Charles Pierce, William James and John Dewey. It strives to reconcile both objectivism and subjectivism, facts and values, accurate and rigorous knowledge and different contextualized experiences. It does this by considering theories, concepts, ideas, hypotheses and research findings not in an abstract form, but in terms of the roles they play as instruments of thought and action, and in terms of their practical consequences in specific contexts. Reality matters to pragmatists as practical effects of ideas, and knowledge is valued for enabling actions to be carried out successfully.

For a pragmatist, research starts with a problem, and aims to contribute practical solutions that inform future practice. Researcher values drive the reflexive process of inquiry, which is initiated by doubt and a sense that something is wrong or out of place, and which recreates belief when the problem has been resolved (Elkjaer and Simpson 2011). As pragmatists are more interested in practical outcomes than abstract distinctions, their research may have considerable variation in terms of how objectivist‗or subjectivist‗it turns out to be. If a research problem does not suggest unambiguously that one particular type of knowledge or method should be adopted, this only confirms the pragmatist‗s view that it is perfectly possible to work with different types of knowledge and methods. Pragmatists recognize that there are many ways of interpreting the world and undertaking research, that no single point of view can ever give the entire picture and that there may be multiple realities. This does not mean that pragmatists always use multiple methods; rather they use the method or methods that enable credible, well-founded, reliable and relevant data to be collected that advance the research (Kelemen and Rumens 2008). In the next section will provide clarity on its methodological choice, justifying the use of mixed method case studies.

4.3. Approach to theory development

In research, it is essential to clarify the assumptions regarding how knowledge and theories are generated. This is often referred to as the "logic of inquiry" or "logical reasoning," and it can be categorized into inductive, deductive, or adductive approaches.

In an inductive approach, a phenomenon is studied without preconceived assumptions, and data collection serves as the basis for developing a theory. This approach is primarily exploratory, where the researcher identifies patterns emerging from the data, examines the relationships between variables or constructs, and generalizes the findings from a sample to a broader population of interest (Woo, O_Boyle, and Spector, 2017). The outcome of inductive research is typically a theory derived from empirical data, which is considered likely to be true. And in this research, the researcher have used an inductive approach.

4.4. Strategies

Once the philosophy of the research has been established, Saunders, Lewis and Thornhill (2019) argue that the first methodological choice pertains to the choice between qualitative, quantitative or mixed methods approaches.

According to Bell, Bryman and Harley (2019), a quantitative strategy involves an objectivist conception of social reality, usually underpinned by a positivistic epistemology and deductive reasoning logic. A quantitative approach is appropriate for a researcher who has deduced hypotheses from the literature and wants to test them empirically, for example through data collected from surveys, questionnaires, structured observations, and structured interviews. Key concerns pertaining to quantitative studies are the validity of any causality inferred; the quality of the sampling techniques used to assess the generalization of the findings; and the transparency and replicability of the research (Bell, Bryman and Harley, 2019).

There are several data collection methods that are appropriate in quantitative research. A survey technique involves firstly sampling either randomly or through a non-probability approach (such as convenience and quota). Subsequently, it can involve data collection through self-completion questionnaires or diaries and/or structured interviews. When conducting these quantitative approaches, researchers need to be aware of the limits to generalization (external validity), as findings – even for studies that used random or probabilistic sampling methods – are ultimately only generalizable to the population studied (Bell, Bryman and Harley, 2019). Additionally, structured observation can be utilized as a quantitative data collection approach. However, it focusses on observed behaviour rather than any intentions underpinning behaviour. Once data is collected, in a quantitative approach the data is analyzed with the purpose of accepting or rejecting the prior hypotheses. As hypotheses had not been created through the literature review, a quantitative approach was not considered the most appropriate method for this research.

By contrast, qualitative research strategies are mostly (but not necessarily) underpinned by constructionist ontologies, starting from a general research question, followed by collection of data, and only then the creation of a conceptual or theorical framework (Bell, Bryman and Harley, 2019). Ethnography, action research, and grounded theory are qualitative approaches. LeCompte and Goetz (1982) suggested that, in qualitative studies, the researcher should be concerned with external reliability (the degree to which a study is transparent and can be replicated); internal reliability (having inter-observer consistency); internal validity (providing a good match between observations and theoretical ideas developed for example through data triangulation); and external validity (the degree to which findings can be generalized across social settings).

Ethnography refers to the practices of writing (graphy) about people and cultures (ethnos) and has provided organizational researchers with the ability of studying the cultural norms, values, and behavioral patterns in the workplace (Bell, Bryman and Harley, 2019). It usually involves fieldwork, observations and analysis of the employees view of reality. Action research is somewhat like ethnography, although in this methodology the researcher can be a part of the organization to be studied and therefore could have a higher degree of participation and interference with the phenomenon being studied (Coghlan and Brannick, 2005). Both ethnography and action research are strictly interpretivist approaches (Remenyi et al., 1998), and therefore their inherent emphasis in the worldview of participants was not considered appropriate for this research.

Grounded theory is another qualitative approach where theory derives from data, which is systematically collected and analyzed (Strauss and Corbin, 1998). It starts from a general research question, but rather than being followed by a review or creation of a conceptual framework, the researcher will move straight to the sampling of participants or incidents. Data are subsequently collected, coded, and analyzed through an interactive back-and-forth process (Bell, Bryman and Harley, 2019). Although it is one of the most utilized methods in qualitative research, grounded theory has been criticized by researchers who are skeptical of the possibility of collecting data without a previous awareness of relevant theories and concepts (Bulmer, 1984). Eisenhardt (1989) suggested that the approach proposed by grounded theory is impractical, since the study‗s purpose, site selection, and data gathering require some rationale or preconceived ideas. As the design of this research was influenced by a long and careful literature review process, grounded theory was not considered an appropriate approach.

Although arguably quantitative and qualitative paradigms carry distinct ontological and epistemological assumptions, it is possible to conduct mixed-methods research. Case study is a method that can be quantitative, qualitative, or mixed. In case studies, there is an emphasis in data triangulation – a process in which different data are compared to each other to increase the internal validity of the study. As qualitative single case studies are argued to be an appropriate method for this research, they will be discussed in detail in the next two sections.

4.4.1. Case-studies

A case-study involves the in-depth study of a single example of whatever the researcher wishes to investigate (Chapman and McNeill, 2005). This may be an individual, a group, an event or an institution. Such studies, normally involve the researcher using a range of research methods. Case-studies make no claim to representativeness because the essence of the technique is that each subject studied is treated as a unit on its own. However, what all these researchers maintain is that a vividly told story can make an important contribution to our knowledge and understanding of aspects of social life such as crime, educational under-achievement, strikes and policing. Such case-studies may prompt further, more wide-ranging research, providing ideas to be followed up later, or it may be that some broad generalization is brought to life by a case-study (Chapman and McNeill, 2005).

4.4.2. Study area and setting

The Ethiopian Pharmaceutical Supply Services (EPSS) is a governmental institution operating under the Federal Ministry of Health (FMOH) in Ethiopia. Its primary mandate is to ensure a consistent and reliable supply of medicines and health technologies, as outlined in the national health policy. EPSS's responsibilities encompass establishing procurement and distribution systems for pharmaceuticals, implementing modern storage management practices, and supplying essential medicines that meet quality, safety, and efficacy standards. The agency also manages the delivery of pharmaceuticals directly to hospitals and health facilities through an extensive transportation network. In addition, EPSS coordinates sector-wide initiatives to enhance the availability of affordable, quality-assured pharmaceuticals and promote their rational use (EPSA, 2015; EPSA, 2020(A); MOH, 2015).

Since its establishment in 1947, EPSS has undergone several restructurings to better address the evolving healthcare needs of the population (EPSA, 2015; EPSA, 2018). The agency's current mission focuses on ensuring a sustainable supply of quality-assured pharmaceuticals to health facilities at reasonable prices. This objective is supported by strategies such as demand-driven procurement, effective inventory management, efficient financial practices, and a well-integrated management information system, along with efforts to attract and retain a skilled workforce (EPSA, 2020(A); MOH, 2015). EPSS operates within the broader Ethiopian healthcare system, which prioritizes decentralization and the expansion of primary healthcare. The system encourages the participation of multiple stakeholders in the National Health Sector Development Programme, which spanned two decades. Following 2015, Ethiopia launched the Health Sector Transformation Plan (HSTP-I), a five-year strategy aimed at enhancing the quality and equity of health services, progressing towards universal health coverage (UHC). The ongoing HSTP-II (2020/2021–2024/2025) continues to focus on improving population health and advancing UHC (MOH, 2021). According to the most recent National Health Accounts report, Ethiopia's total health expenditure (THE) is approximately \$3.63 billion, representing around 6.3% of the GDP, with a per capita health expenditure of \$36.4—below the regional average of \$38.0. The government covers 32% of THE, while 31% comes from out-of-pocket spending and 34% from development partners. Given these resource limitations, HSTP-II emphasizes efficiency gains through strategic purchasing and performance-based financing to achieve UHC (MOH, 2022).

EPSS is responsible for the centralized forecasting, procurement, warehousing, and distribution of pharmaceuticals across the country. The agency operates 19 branches throughout Ethiopia, strategically positioning central medical stores to serve all regions. It procures medicines and supplies through competitive bidding to ensure high-quality products at affordable prices. Using information systems and logistics management tools, EPSS strives to optimize inventory management and improve distribution efficiency, thereby reducing stockouts and minimizing wastage. Additionally, it collaborates with the Ethiopian Food and Drug Authority (EFDA) to ensure that all procured items meet the required quality standards.

EPSS also partners with international organizations, donors, and development partners to strengthen its capacity and continuously improve pharmaceutical supply chain practices. The agency plays a crucial role in enhancing access to essential medicines, especially in underserved and remote areas.

4.5. Study design

A mixed methods research (MMR) design was selected for this study to gain a comprehensive understanding of the challenges in demand forecasting and ways to enhance supply chain resilience. The choice of MMR is particularly relevant in the Ethiopian context, where limited literature exists on these critical issues, and most studies have only provided a brief overview without delving deeply into forecasting challenges and resilience strategies. MMR was suitable for capturing participants' beliefs, thoughts, and experiences through qualitative data, while also using quantitative data to identify patterns in demand forecasting within the study setting. Mixed methods research involves integrating both quantitative and qualitative approaches in a sequential, concurrent, or transformative manner to mitigate the limitations associated with each method when used alone (Creswell, 2014). It employs both inductive and deductive reasoning at different stages, incorporating multiple research paradigms (Teddlieand Tashakkori, 2009).

The strengths of MMR include the ability to leverage the benefits of both qualitative and quantitative data, enhance generalizability, and produce more robust findings (Johnson & Onwuegbuzie, 2004; Teddlie and Tashakkori, 2009; Creswell, 2014; Bryman, 2016). However, it also poses challenges, such as potential researcher errors due to incomplete familiarity with both methodologies, difficulties in analysis because of philosophical complexities, and information overload from excessive data collection (Johnson & Onwuegbuzie, 2004; Teddlie and Tashakkori, 2009; Creswell, 2014; Bryman, 2016). The following section will detail how the mixed methods approach was applied in this study (Figure 7).

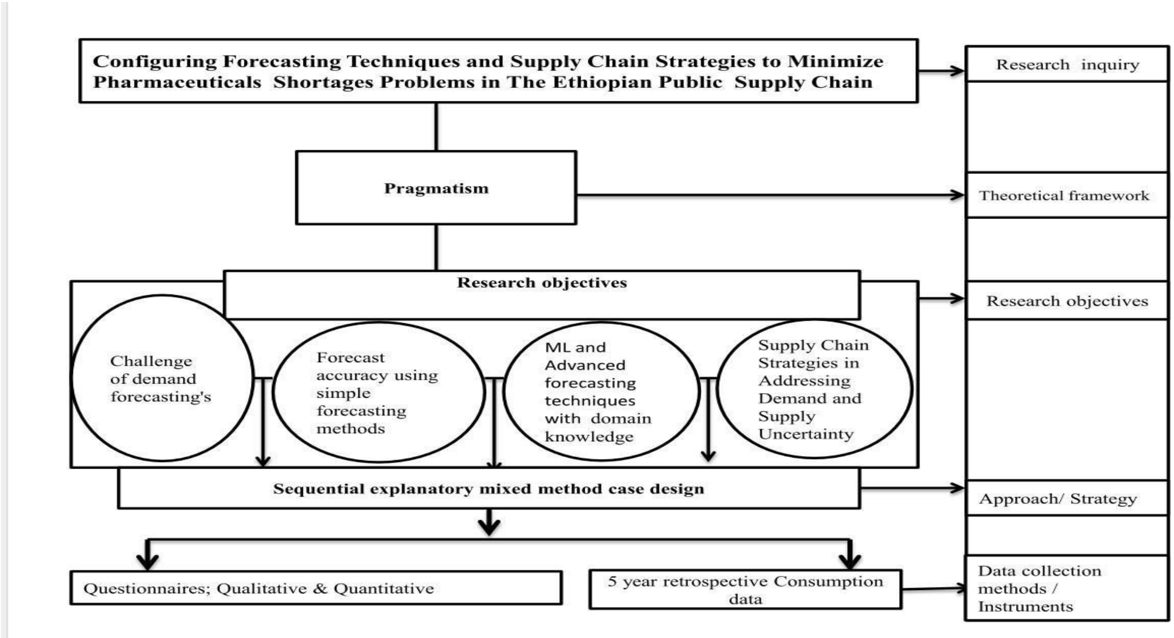


Figure 7:Summarizes the research design and process

4.6. Part 1: Qualitative approach

A qualitative research design was chosen for the present research to get a detailed understanding of the challenges regarding demand forecasting_s and supply chain resilience_s.

4.6.1. Sampling and recruitment

Participants for this study were supply chain experts from EPSS, experts from Ministry of Health, Supply chain coordinator from regional health bureau, pharmacy directors from hospitals and health center. The inclusion criteria for this study were. Maximum variation sampling method was considered to recruit a representative number of participants from all regions of the country. Health professionals and top management members involved in health supply chain services, forecasting, and decision- making at the hospital level as well as the regional level were purposely selected to ensure that appropriate informants would provide rich study data. Participants were chosen based on their roles, ensuring a comprehensive representation across all departments within EPSS.

Once a preliminary selection was made, the researcher followed up by contacting each potential study participant to begin the recruitment process. A brief self-introduction was followed by additional information about the study such as the general purpose of the study he or she would be informed about it and further information provided that was available in the information and consent form (Appendix 1). For those individuals who were found to be eligible, still further information about the study was given in the form of a verbatim reading of the study information including more detail about their required participation, short description of measures that would be taken to ensure privacy, anonymity and confidentiality (Appendix 1). Following this it was assessed whether each individual was still interested in the study or learning more about the study. In the end of this exercise, time was taken to respond to any inquiries that the individual may raise before they could move forward. Once participants who could potentially be involved in the study were identified and their eligibility was determined, they were asked to sign the informed consent form (Appendix 1). This was followed by arranging an initial meeting date at a location that was mutually acceptable to conduct the first in-depth interview.

In this manner, a total of 51 participants who fulfilled the study criteria were approached of which 17 were for objective one and 34 participants for Objective four. Although a pre-determined sample size was not set when entering the field, the final sample size was reached based on the concept of data saturation described as, _the point where you have identified the major themes and no new information can add to your list of themes or to the detail for existing themes_ (Creswell 2012). Inclusion and exclusion criteria for the respondents are listed below (Table 2).

Table 2:Inclusion and exclusion criteria of respondents for the qualitative part of the research.

Inclusion criteria	Exclusion criteria
EPSS staff working in contract management, quantification and market shaping, tender management, and warehouse/inventory management	Professionals not working at EPSS
Professionals working in the Federal Ministry of Health related to forecasting	Administrative staff at EPSS
Professionals in non-governmental organizations involved in forecasting	
Professionals working in regional health bureaus related to forecasting	
Supply chain personnel, pharmacists, forecasting specialists, and EPSS managers	
At least 1 year of experience in pharmaceutical forecasting or logistics	
Available and willing to participate in interviews or provide quantitative data	
Pharmacy professionals in a leadership role within regional	

health bureaus

4.6.2. Data collection instruments and procedure

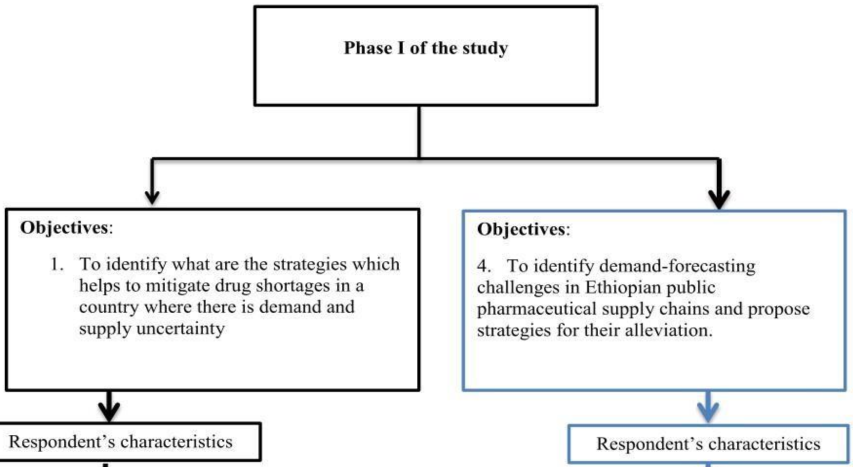
Data collection for this study comprised of key informant interviews with individual participants. The key informant interviews were prepared after conducting a thorough literature review. See Appendix II and Appendix III for the key informant interview guide. These set of questions aimed to understand and capture challenges of demand forecasting methods.

Questionnaire Development and Validation

The semi-structured interview guides and data collection tools were developed based on a thorough review of the literature and national pharmaceutical logistics frameworks. The process involved multiple steps to ensure validity and reliability:

- **Step 1**: A literature scan was conducted to identify key thematic areas relevant to pharmaceutical forecasting and supply chain resilience.
- **Step 2**: A draft tool was developed with open-ended questions for qualitative interviews and structured templates for quantitative data extraction.
- **Step 3**: The tools were reviewed by three subject-matter experts (including a senior EPSS official, an academic from AAU and Heriot Watt University to ensure content validity.
- **Step 4**: The finalized questionnaire incorporated changes to improve clarity, flow, and alignment with study objectives.

Following identification and consent, informants were approached on the scheduled dates to freely share their opinions. At times, participants shared their experience over the course of the study with the researchers. They were also amicably informed that they would be part of this investigation as appropriate personnel in the healthcare setting. The phenomenon of interest in this study was the challenges of forecasting practice in the Ethiopian public supply chain system. The following questions were asked: ―*How do you see the health supply chain in Ethiopia and in particular in EPSS", ―What are the factors which affect the availability of pharmaceuticals in Ethiopia and in particular with EPSS?*(Appendix II and III). One-to-one interviews with key informants were conducted during the specified period and lasted 40–60 min. All interviews were digitally audio-recorded and transcribed verbatim. Data collection was conducted until a point of theoretical saturation (Figure 8).



Gender	Frequency	Percentages
Male	14	82.4
Female	3	17.6
Age		
25-35	7	41
> 35	10	59
Years of experience		
3 -10	7	41
>10	10	59
Level of education		
Degree	3	17.6
Masters	14	82.4

Gender	Frequency	Percent
Female	16	32
Male	34	68
Age in years		
25-30	16	32
30-35	19	38
Year of experience		
1 -5	16	32
Greater than 5	34	68
Profession		
Pharmacist	37	74
Laboratory	8	16
Biomedical engineer	5	10
Level of education		
Degree	31	62
MSc	19	38
Current working department		
Contract management	6	12
Quantification market shaping	13	26
Tender management	12	24
Warehouse inventory management	19	38

Figure 8:Summary of the data collection for phase I of the study

4.6.3. Data analysis

Data Analysis The transcribed data were cleaned and imported to NVIVO 14 Qualitative Data Analysis software. Analysis was conducted following the steps stipulated by Braun and Clarke (2006). First, we repeatedly read the textual transcriptions for familiarization; then, initial codes of relevant data were generated. Related codes were then merged into themes, which were reviewed for coherence and data support, which led to condensed themes. On this basis, we defined the final themes and produced a composite description of the essence. Themes were modified and refined inductively from the data in Microsoft Excel through a thematic content analysis. The validity of the findings was verified by employing various methods. These included undertaking a thorough literature search, following steps that ensure a trustworthy thematic analysis as suggested by Brien et al. (2014), bracketing of the researchers_ experience of the phenomenon from the participants_ view, and crosschecking of contents among the researchers (O'Brien et al., 2014).

4.6.4. Researcher's position and reflexivity

Reflexivity has become increasingly important in qualitative research, particularly in the fields of health care research and education. It involves acknowledging and using the researcher_s own subjectivity as part of the research process (Rolfe et al., 2001). Reflexivity can be understood as the ability to reflect on oneself and adjust one's actions and thought processes accordingly (West, 1994), and as the practice of considering oneself as an object of inquiry (Schon, 1987). Positionality, which refers to how aspects of a researcher_s identity (such as age, gender, profession, and social class) influence research interactions and outcomes (Hopkins, 2007), was an important consideration throughout this study. I remained aware of how my roles and background could shape the research process, including the framing of questions, interview settings, and data interpretation.

Several aspects of my positionality influenced this research. As a healthcare professional, my deep understanding of the healthcare environment provided valuable insights for interpreting the data. However, this familiarity also risked leading to assumptions about shared experiences with participants, which I actively checked during analysis to maintain objectivity. Additionally, my dual role as both a PhD student and a peer to some respondents created a dynamic where participants could perceive me as either a colleague or someone still in training, potentially influencing their responses. I remained conscious of this dynamic and took steps to minimize its impact. Pre-existing relationships with some participants through professional networks, conferences, or academia could have also affected their responses, possibly encouraging openness or leading to bias and social desirability. To address this, I maintained neutrality by using standardized interview questions to ensure consistency. My experience in the pharmaceutical supply chain, particularly from the private sector, provided insights into its complexities and allowed for a more nuanced analysis. However, this insider knowledge carried the risk of influencing how I viewed the data, potentially leading to preconceived interpretations. I actively worked to balance my perspectives as both a researcher and business owner. Throughout the research, I communicated my dual roles openly to participants, ensured neutrality in my interactions, and applied standardized procedures to maintain consistency. These measures helped minimize bias and contributed to the reliability and validity of the findings.

4.6.5. Reliability

Reliability in qualitative research can be addressed in different ways including the use of detailed field notes, audio recording the interview for subsequent transcription, the use of computer software in the analysis of the data and intercoder agreement use of multiple coders to analyze transcribed data (Creswell 2007). In the present study, reliability was maintained by taking e, all the interviews were audio recorded, transcribed in MS Word and then analyzed with the support of a computer software for qualitative data analysis, NVivo version 14.

4.6.6. Ethical considerations

This research was approved by the Institutional Review Board of the College of Health Sciences, Addis Ababa University (protocol number 010/22/SoP, see Appendix 5). Following this approval, EPSS also gave permission for the conduct of this study.

4.6.7. Informed Consent Process, Privacy and Confidentiality

All the participants recruited for this study were provided with adequate information about the study and their participation before they were requested to consent in written form (Appendix 1). They were further told that their involvement was voluntary, and that their identity would be held in the strictest confidence and that anonymity maintained in the research reports. Audio-recording was done after informing participants who were told that they can request that it be stopped at any time or the interview for that matter. All material identifying the participants in the study, including audio-recordings of interviews and interview transcripts, and any others were stored in locked files at the investigator_s office at the School of Pharmacy, Addis Ababa University and were accessible only to himself, and his graduate supervisors. Audios, reports based on this research and all paper files were anonymized – with no names attached, as all identifying information were removed, except a code number or pseudonym--prior to analysis of data or storage of it. All computer files were password protected, and data collected is kept indefinitely in an appropriate database. No reports from this study have or will not identify any single individual. With regards to all written reports as well as other future forms of presentations where verbatim quotes will be used, it was noted in the information sheet and consent form that anonymity would be maintained in cases excerpts from the interview were or would be used.

4.6.8. Risks and Benefits

The study is assumed to have entailed minimal risk to the study participants. In the conduct of the study the principal investigator did not detect any major problems, physical or emotional. Furthermore, the organization will benefit in the future if some changes are made to the health services to improve the situation as a result of the reports emanating from this study and further engagements by the research group. Participants were free to decline to have their interviews audio-recorded, to decline to discuss issues that they find uncomfortable, to request that components of their interviews not be audio-recorded; or to stop participating in the study at any time.

4.7. Part 2: Quantitative approach

4.7.1. Study Design

A cross-sectional retrospective study design was used to select key pharmaceuticals. All forecasting and consumption data from January 2015 to December 2021 were included in the study, for determining the forecasting accuracy.

4.7.2. Sampling techniques

The key pharmaceuticals for this study were selected using heterogeneous sampling techniques. The initial list of key pharmaceuticals was obtained from the Ethiopian Ministry of Health, which is considered representative of the trends in the country. Moreover, discussions were held with experts in EPSS regarding which pharmaceuticals need to be included in the list. From the pharmaceuticals procurement list of EPSS, we further narrowed the selection by including only those drugs with complete data available. Since the study required five years of forecast data, drugs with data for the previous five years were included. It was clarified that EPSS had data available for five years. Additionally, to optimize the selection, we considered certain criteria. Drugs that had a high value in the total budget were given priority. Expert opinions and the organization's interest in specific drugs were taken into account during the selection process, allowing us to include particularly relevant and impactful pharmaceuticals. The selected pharmaceuticals were essential products for priority health programs and represented diverse categories, including adult, pediatric, cold chain, and critical disease products. By adhering to these criteria, we ensured a representative sample of key pharmaceuticals that play a vital role in the healthcare supply chain managed by EPSS (Appendix 4).

Furthermore, we gathered domain knowledge, we contacted experts from the Ethiopian Pharmaceuticals Supply Service (EPSS) who work in the distribution unit. Five experts with over 10 years of experience in managing the distribution of the pharmaceuticals in EPSS agreed to participate. The researchers, along with these experts, examined the electronic bin cards of selected pharmaceuticals. A bin card is a physical or electronic record used to track the inventory levels of individual items in a storage location, such as a warehouse or stockroom. The term 'bin' refers to the specific storage location for an item. Information typically recorded on a bin card includes the Item ID, unit of measure, product description, account details, date, references, beginning balance, manufacturer, batch number, expiry date, quantity received, quantity issued, and balance. In summary, a bin card is a fundamental tool in inventory management, especially in environments where physical stock tracking is essential. It provides a straightforward and immediate way to monitor item quantities, helping to ensure effective inventory management.

4.7.3. Data collection

We meticulously traced sales data for the past five years, triangulating graphs with bin card records to identify predictors influencing demand for each product. The expert uses their domain knowledge and experience to identify about the distribution characteristics of the specific products and sometimes when they assume that they do not have enough history or do not remember about that specific products they call to other experts who remember specific issues and decide whether the specific predictors affect the distribution and if all of them agree the include it as predictors. The data collection process took more than a month. We downloaded and analyzed over 100 bin cards per product. Dates on the bin cards were converted from the Ethiopian calendar to the Gregorian calendar for accuracy. Transactions due to storage or warehouse changes within EPSS were excluded. After cleaning the data, and discussing with the experts we identified the following key predictors affecting distribution and sales: stock replenishment, stock outs, COVID-19, fiscal year counting, conflict, and malaria seasonality summarized in (Figure 9).

4.7.4. Collaborative expert review to identify factors affecting consumption

To incorporate expert knowledge into time series forecasting in a structured and replicable manner, we developed a multi-step process involving expert engagement, collaborative data review, and operational validation. In partnership with the Forecasting and Market Shaping Directorate at EPSS, we identified six experienced professionals from the Warehouse and Inventory Management Directorate with deep operational knowledge of pharmaceutical logistics (Figure 9).

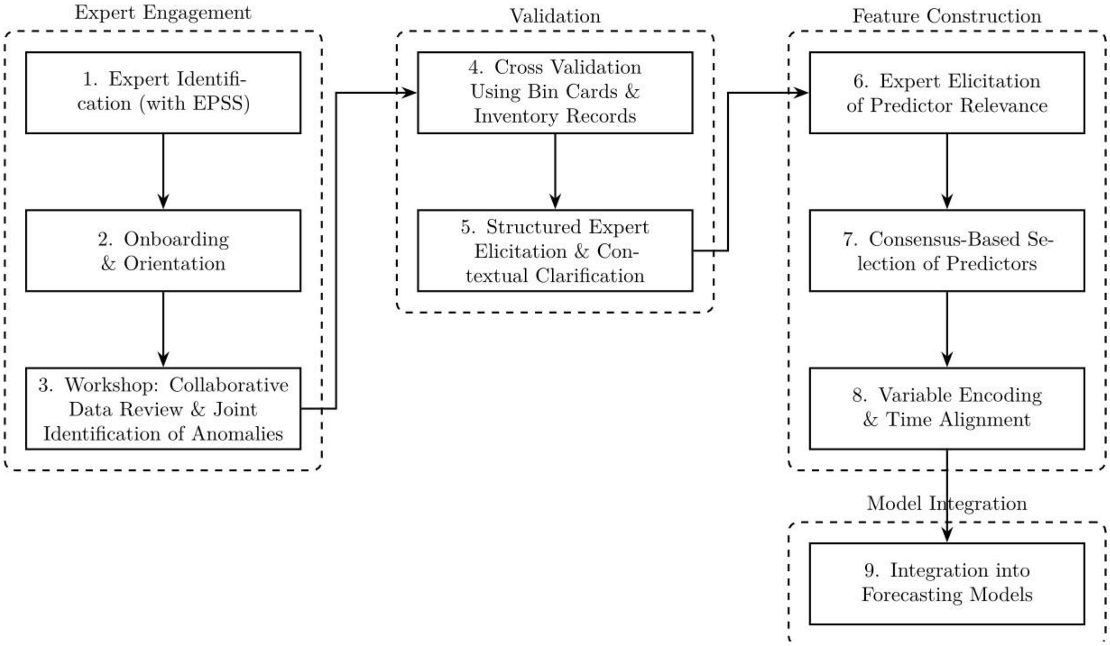


Figure 9: Presents a visual overview of the end-to-end approach, highlighting each major stage of the process from expert engagement to model integration

Through a facilitated half-day workshop, these experts reviewed five years of monthly consumption data for 33 pharmaceutical products. Anomalous patterns—such as consumption spikes, prolonged lows, and erratic fluctuations—were jointly identified and interpreted in light of operational events (e.g., emergency distributions, inventory cycles). These insights were cross-validated against bin cards and warehouse records, and internal transfers were excluded to isolate externally relevant events. Dates were standardized to the Gregorian calendar.

Predictor variables were defined through expert consensus, with inclusion contingent on agreement among all six core participants regarding the operational relevance and causal validity of each factor. The final predictors included binary indicators for stock replenishment events, categorical variables for fiscal year inventory counts, and dummy variables for malaria seasonality. A further description of these variables are summarized as followings:

- Stock replenishment: refers to the process of restocking or refilling inventory to ensure that there are sufficient quantities of products or materials available to meet demand. Whenever there was stock replenishment at the central EPSS, consumption and distribution to hubs and health facilities increased. This increase was attributed to the need to restock depleted inventories and the push from central EPSS to manage space constraints.

- Physical fiscal year inventory counting: refers to the process of manually counting and verifying the actual quantities of pharmaceutical products available in stock at a specific location. The process is critical for maintaining the accuracy of inventory records, ensuring that medicines are available when needed, and preventing stockouts or overstocking. Physical inventory counting periods also influenced consumption. Stores closed during these periods, halting transactions. We observed increased con- sumption before inventory counting periods, as hubs and facilities stocked up. July and August were identified as physical counting periods each year.

- Malaria seasonality: Refers to the predictable patterns and fluctuations in malaria incidence through- out the year, typically influenced by climate and environmental conditions. In many regions, malaria transmission peaks during and shortly after the rainy season, when conditions such as stagnant water pools create ideal breeding sites for the Anopheles mosquitoes that transmit the disease. Conversely, malaria cases often decline during the dry season when mosquito breeding sites are reduced. During peak malaria seasons, there is a significant surge in the demand for antimalarial drugs and other re- lated treatments. Malaria seasonality was another significant predictor. Certain pharmaceuticals, like Artemether + Lumefanthrine and Rapid Diagnostic Test kits, were affected by malaria outbreaks. We identified epidemic periods affecting consumption: September to December 2017, March to May 2018, September to December 2018, March to May 2019, September to December 2019, March to May 2020, September to December 2020, March to May 2021, September to December 2021, and March to May 2022.

These predictors, encoded with known historical and future values, were added to the modeling dataset. This approach ensured consistent integration of expert-informed contextual variables across both point and probabilistic forecasting models.

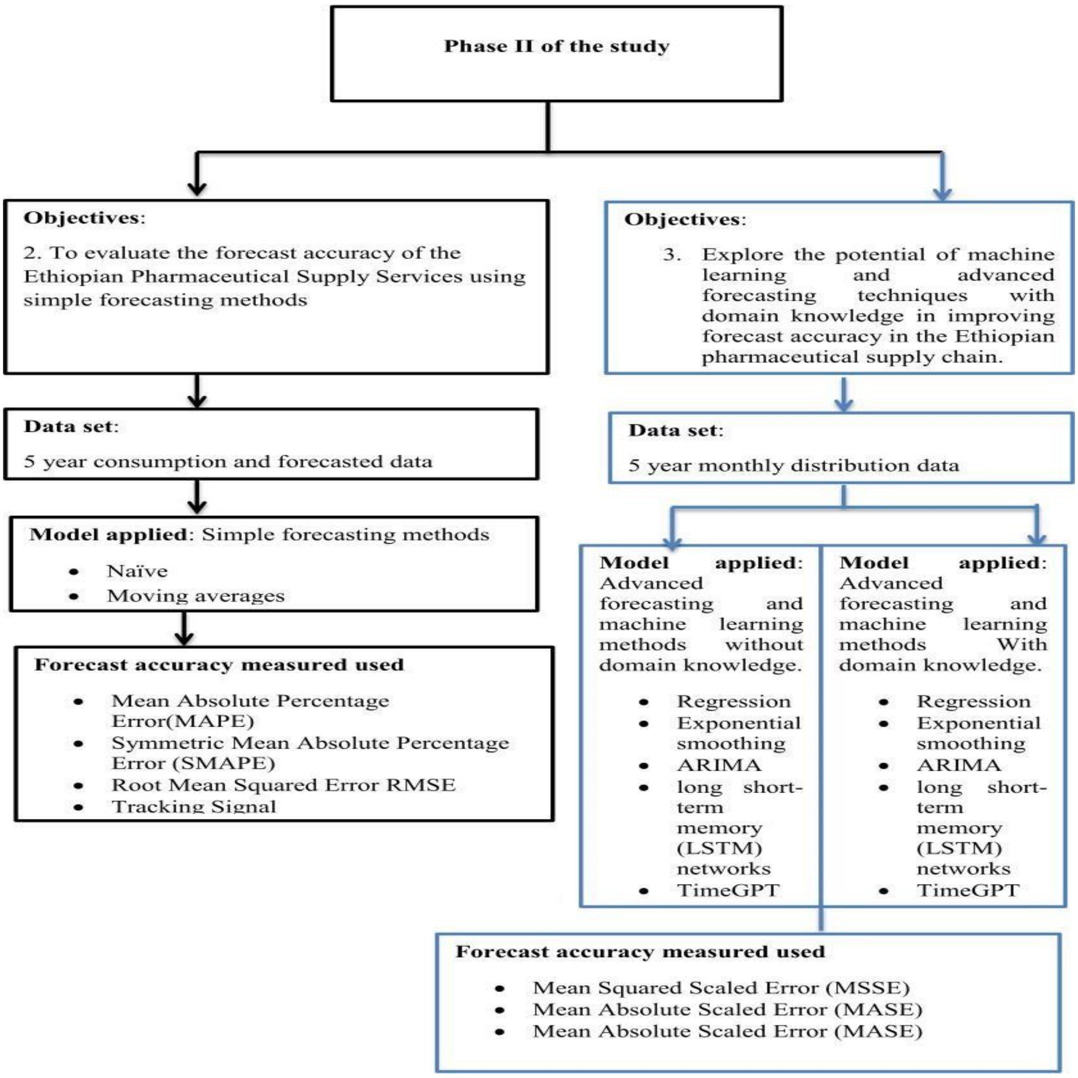


Figure 10: Summary of the data collection for phase II of the study

4.7.5. Forecasting methods applied

We applied simple forecasting methods and saw how the results changed. Further we applied advanced forecasting models with machine learning and domain knowledge collected from experts In the introduction, we clarified why we applied simple forecasting techniques and advanced ones. In the following sections, we briefly discuss forecasting models.

The naive forecast, also known as the no-change or random walk forecast, predicts future values by simply using the last observation. It assumes that the best predictor for tomorrow is today_s value, ignoring all previous history (Nau, 2014). This method is easy to understand and implement. However, it results in forecasts that can change significantly with each new observation, showing "high adaptivity" or "high variance." Whether this variability is seen as a benefit or drawback depends on the specific forecasting context (Kolassa et al., 2023).

The Simple Moving Average (SMA) model offers a middle ground between two forecasting extremes: the mean model, which predicts future values based on the average of all past data, and the random walk model, which uses only the most recent observation to forecast the next. Instead of relying on all past data or just the last observation, the SMA takes the average of a specified number of recent values, providing a "moving" perspective of past behavior (Nau, 2014). This approach allows the model to better adapt to cyclical patterns compared to the mean model, while being less sensitive to random shocks than the random walk model. There are various methods to calculate a moving average, but the simplest is to average the most recent m values for a chosen integer m. This simple approach gives the SMA equation for predicting the value of Y at time t+1 based on data up to time t.

$$\dot{Y}t_{+1} = \frac{F_t + F_t - 1 + \cdots + F_{t-m} + 1}{m}$$

The SMA model has key properties: each of the past m observations is weighted equally (1/m), so as m increases, recent observations have less impact, smoothing the forecasts. The data used in the forecast has an "average age" of (m+1)/2, causing forecasts to lag behind trends or turning points. For example, with m=5, the lag is about 3 periods (Kolassa et al., 2023). SMA remains popular in practice; a survey found it to be the most commonly used quantitative forecasting technique in U.S. corporations (Sanders & Manrodt, 1994), and it has been shown to help reduce inventory costs (Sani & Kingsman, 1997). We evaluate a range of univariate models and their counterparts that include predictors, spanning from simpler methods like regression, exponential smoothing, and ARIMA to more complex models such as long short-term memory (LSTM) networks and advanced foundational time series forecasting models. Below, we provide a brief overview of these approaches. Detailed implementation codes in R and Python are available in a GitHub repository and accessible for public.

Exponential Smoothing State Space model (ETS): ETS models, as described by Hyndman and Athanasopoulos (2021), combine trend, seasonality, and error components in time series using different configurations that can be additive, multiplicative, or mixed. The trend component can be specified as none (―N‖), additive (―A‖), or damped additive (―Ad‖); the seasonality can be none (―N‖), additive (―A‖), or multiplicative (―M‖); and the error term can be additive (―A‖) or multiplicative (―M‖). To forecast consumption, we use the ETS() function from the fable package in R, which automatically selects the optimal model for each time series based on the corrected Akaike_s Information Criterion (AICc). In our study, an automated algorithm determines the best configuration for trend, seasonality, and error components across each time series, leveraging the ets() function_s use of AIC to identify the optimal model. Given the high volume of time series (1530), manual selection of components is impractical, so the algorithm customizes model forms for each series based on its unique characteristics. This results in a tailored combination of additive or multiplicative components, adapting to the specific patterns of each time series.

Multiple Linear Regression (MLR): We use Multiple linear regression to model the relationship between a consumption and potential variables influencing its variation. In our first model, we use multiple linear regression with a trend component to capture the underlying progression over time, i.e., regression. We also incorporate dummy variables for each month to account for seasonal fluctuations, without including any additional predictors, i.e., regression_reg. This approach helps us establish a baseline model focused soley on temporal trends and seasonal patterns. We then extend this model by introducing additional predictors that include variables such as replenishment cycles, fiscal year indicators, and periods with malaria prevalence. These additional predictors allow the model to see if capturing external factors can provide a better understanding of the factors influencing the consumption and result at enhanced accuracy. We produce forecasts using TLSM() function from the fable package in R.

ARIMA and ARIMA with regressors: ARIMA (AutoRegressive Integrated Moving Average) is a powerful statistical model designed to forecast time series by capturing temporal dynamics and are widely used in time series forecasting due to their ability to model complex trends and patterns over time without relying on external predictors. ARIMAX (AutoRegressive Integrated Moving Average with eXogenous variables) extends ARIMA by incorporating external variables, or exogenous predictors, into the model. This modification allows to include relevant information from external factors such as malaria season, and fiscal year period that may explain variations in the series beyond its internal time dynamics, we refer to this in the result as arima_reg. By adding these predictors, ARIMAX combines the strengths of ARIMA_s time-series structure with the flexibility of regression models. In our study, we use an automated algorithm to determine the optimal configuration for ARIMA components, following the approach outlined by Hyndman and Athanasopoulos (2021) and We use the ARIMA() function from the fable package in R.

Long Short-Term Memory neural network (LSTM): The LSTM model is a specialized form of recurrent neural network (RNN) used to model sequential data by capturing long-term dependencies (Graves and Graves, 2012). Unlike traditional RNNs, LSTMs can learn to retain information for longer time periods due to their unique architecture, which consists of several gates that control the flow of information. This makes LSTMs particularly effective for time series forecasting. In our implementation, we used a sequential model architecture, comprising one LSTM layer with 50 units, followed by dense layers, with the final output being a single linear unit. The Adam optimizer was employed to minimize the mean squared error, and the model was trained for 100 epochs using the keras_model_sequential() function from the Keras package in R. We use LSTM models both with and without predictors, referring to the LSTM model with predictors as lstm_reg.

TimeGPT: TimeGPT is the first pre-trained foundational model designed specifically for time series forecasting, developed by Nixtla (Garza et al., 2023). It uses a transformer-based architecture with an encoderdecoder configuration but differs from other models in that it is not based on large language models. Instead, it is built from the ground up to handle time series data. TimeGPT was trained on more than 100 billion data points, drawing from publicly available time series across various sectors, such as retail, healthcare, transportation, demographics, energy, banking, and web traffic. This wide range of data sources, each with unique temporal patterns, enables the model to manage diverse time series characteristics effectively. Furthermore, TimeGPT supports the inclusion of external regressors in its forecasts and can generate quantile forecasts, providing reliable uncertainty estimation. We use TimeGpt models both with and without predictors, referring to the model with predictors as timegpt_reg.

4.7.6. Data analysis

To evaluate the performance of the various forecasting approaches, we have used different point forecast measures, namely the Mean Absolute Percentage Error (MAPE) and the symmetric Mean Absolute Percentage Error (sMAPE). While we acknowledge. Disadvantages of these error measures (see, for example, Goodwin and Lawton, 1999; Hyndman & Koehler, 2006), we believe that their inclusion is necessary given their popularity in practice. The formula used to compute MAPE was as follows as it was proposed by (Hyndman and Athanasopoulos, 2018):

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{Actuals_t - Forecasted\_t}{Actuals_t} \right|$$

Where **n** is the number of times forecasting and actual demand are compared for an item. Based on the Lewis MAPE scale of judgment for forecast errors, forecasts with MAPE of 0- 10% were considered highly accurate, 11-20% good, 21-50% reasonable, and 51% Inaccurate (Lawrence et al., 2009) . Forecasting accuracy was calculated by Subtracting MAPE from 100. For items with negative forecasting accuracy results, forecasting accuracy is assumed to be zero.

The Symmetric Mean Absolute Percentage Error (SMAPE) is a measure commonly used to evaluate the accuracy of forecasting models. SMAPE provides a symmetric and percentage- based measure of the forecast error, making it suitable for comparing forecast accuracy across different time series data sets. It is particularly useful when dealing with data that contains zero or near-zero values, as it avoids division by zero issues that can occur with other error metrics. SMAPE values typically range from 0% to 200%, where a lower SMAPE value indicates better forecast accuracy, with 0% representing a perfect forecast.

Interpretation:

- SMAPE values below 10%: Considered excellent, indicating a high level of accuracy in the forecasts.
- SMAPE values between 10% and 20%: Generally acceptable for many forecasting applications.
- SMAPE values above 20%: May suggest that the forecasts have significant errors and room for improvement.

To calculate the SMAPE, we use the formula it was proposed by (Hyndman and Athanasopoulos, 2018):

$$sMAPE = (200|Yt - Ft\,|/(Yt + Ft\,))$$

We have also applied Root mean squared error: it was proposed by [13] root mean squared error is the most common standard of goodness-of-fit, penalizes big errors relatively more than small errors because it squares them first; it is approximately the standard deviation of the errors if the mean error is close to zero (Nau, 2014).

Where the formula for RMSE is

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n} ei^2}$$

The error metrics presented here consider a forecasting horizon denoted by by j, which represents the number of time periods ahead we are predicting, with j ranging from 1 to 6 months in our study. Point forecast accuracy is measured using the Mean Squared Scaled

Error (MSSE) and the Mean Absolute Scaled Error (MASE). The Mean Absolute Scaled Error (MASE) (Hyndman and Koehler, 2006; Hyndman and Athanasopoulos, 2021) is calculated as follows:

$$\mathrm{MASE} = \mathrm{mean}(|q_j|),$$

where

$$q_j = \frac{e_j}{\frac{1}{T-m}\sum_{t=m+1}^{T}|y_t - y_{t-m}|},$$

and ej is the point forecast error for forecast horizon j, m = 12 (as we have monthly seasonal series), yt is the observation for period t, and T is the sample size (the number of observations used for training the forecasting model). The denominator is the mean absolute error of the seasonal naive method in the fitting sample of T observations and is used to scale the error. Smaller MASE values suggest more accurate forecasts. Note that the measure is scale-independent, thus allowing us to average the results across series. Here, ej represents the point forecast error for forecast horizon j, with m = 12 (since we are dealing with monthly seasonal data). The term yt denotes the observation at time t, and T is the sample size, or the number of observations used for training the forecasting model. The denominator in the MASE formula is the mean absolute error of the seasonal naive method over the training sample of T observations, providing a basis for scaling the forecast error. Lower MASE values indicate more accurate forecasts. Notably, this measure is scale-independent, allowing us to average results across different series for broader performance comparison.

A related measure is MSSE (Hyndman and Athanasopoulos, 2021; Makridakis et al., 2022), which uses squared errors rather than absolute errors:

$$\mathrm{MSSE} = \mathrm{mean}(q_j^2),$$

where,

$$q_j^2 = \frac{e_j^2}{\frac{1}{T-m}\sum_{t=m+1}^{T}(y_t - y_{t-m})^2},$$

Again, this is scale-independent, and smaller MSSE values suggest more accurate forecasts.

To measure the forecast distribution accuracy, we calculate the Continuous Rank Probability Score (Hyndman and Athanasopoulos, 2021). It rewards sharpness and penalizes miscalibration, so it measures overall performance of the forecast distribution.

$$\mathrm{CRPS} = \mathrm{mean}(p_j),$$

where

$$p_j = \int_{-\infty}^{\infty} \left(G_j(x) - F_j(x)\right)^2 dx,$$

where $Gj(x)$ is the forecasted probability distribution function for forecast horizon j, and (x) is the true probability distribution function for the same period.

CHAPTER 5: KEY FINDINGS

5.1. Introduction

This study has contributed to an understanding of on how we can improve demand Forecasting Accuracy and Supply Chain Resilience in Ethiopian Pharmaceutical Services. The study identified what are the challenges in EPSS and what can be done for solving the problem furthermore the study identified different strategies for managing drug shortages in countries like Ethiopia. Furthermore the study also tried to see different forecasting methods from simple forecasting_s to advanced forecasting methods. In this chapter, an overview of the main findings from the four papers that constitute this PhD study will be presented.

5.2. Overview of the main findings

The main findings from Phase I of this study, which investigates the challenges of pharmaceutical forecasting practices within the EPSS, reveal several critical issues affecting forecasting accuracy and effectiveness. In this study, two main theme and ten sub themes were developed from the content analysis.

The first theme was: challenges related with forecasting in EPSS and the sub-themes were (1) Finance related (2) workforce related (3) data quality related (4) technology related (5) Coordination collaboration and leadership support related. The second theme were strategies for improving forecasting and the sub–themes were (1) responsibilities and attention for forecasting_s (2) Improvements regarding the data quality (3) workforce and capacity building related (4) finance related (5) stakeholders role related (Figure 11).

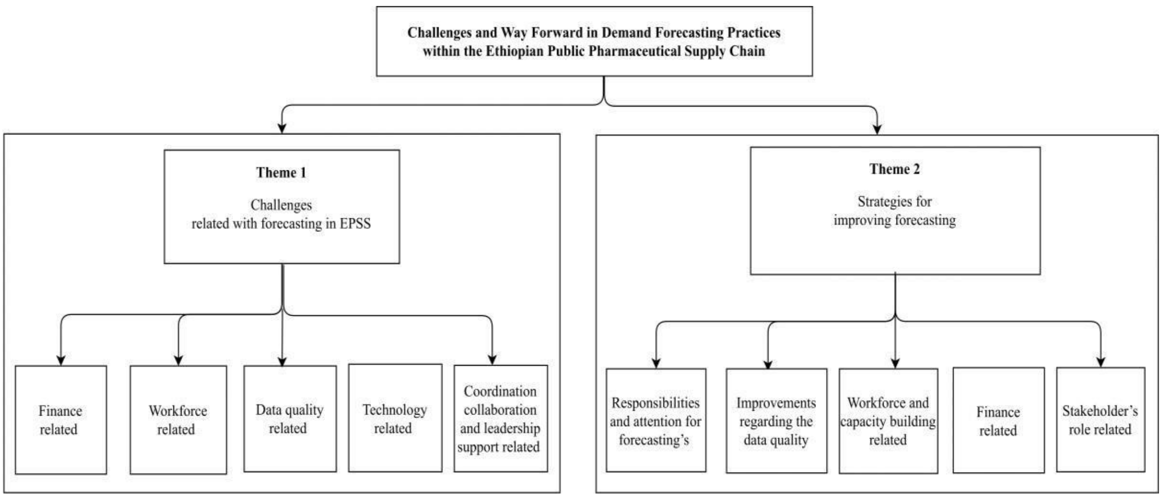


Figure 11:The main themes and subthemes of the thematic analysis

Financial constraints emerged as a significant challenge, with respondents reporting widespread shortages for procuring pharmaceuticals, compounded by delayed budget releases. Inadequate data quality and availability were also identified as major barriers to accurate forecasting, as unreliable data undermines the ability to predict pharmaceutical needs. Additionally, workforce-related challenges, such as a lack of trained personnel and insufficient capacity-building efforts, were highlighted, further diminishing the effectiveness of forecasting activities. Technological limitations, including insufficient infrastructure and a lack of advanced tools for data analysis and forecasting, were found to hinder the accuracy of predictions. Moreover, weak communication and collaboration among stakeholders involved in the supply chain were cited as significant coordination gaps, contributing to fragmented forecasting efforts.

To address these challenges, the study proposed several strategies. Improving data quality by implementing measures to enhance the accuracy, completeness, and reliability of forecasting data is crucial. Capacity building through workforce training and development is necessary to improve skills in forecasting and supply chain management. Addressing financial constraints requires better budget planning, timely allocation, and improved financial oversight. Additionally, fostering better communication and collaboration among stakeholders would strengthen coordination and information sharing, leading to more efficient supply chain management.

Overall, the findings underscore the importance of addressing these challenges and implementing the proposed strategies to enhance the availability of pharmaceuticals within Ethiopia's public pharmaceutical supply chain. By doing so, the healthcare delivery system in Ethiopia could see significant improvements in efficiency and effectiveness.

5.3. Forecast Accuracy by Using Simple Forecasting Methods

The main findings from Phase II, which focused on forecast accuracy within the Ethiopian Pharmaceutical Supply Services (EPSS), revealed several critical insights.

Figure 10 displays time series plots comparing forecasted and issued quantities for nine pharmaceutical items (out of a total of 33) between the years 2010 and 2014 (Ethiopian Calendar). The products are grouped by programme type: *RDF* (Revolving Drug Fund) and *Programme*, with quantities disaggregated by year. The red line represents forecasted quantities, while the blue line depicts issued quantities.

The visualization highlights a recurring mismatch between forecasted and actual issued quantities across multiple products and years. For instance, in *Malaria Rapid Diagnostic Test*, and *Artemether + Lumefantrine*, issued quantities sharply exceeded forecasts, particularly in the earlier years, suggesting substantial under-forecasting. Conversely, products like Oxytocin, Ringer‘s *Solution* and *Magnesium Sulphate* exhibit consistent over-forecasting, where forecasted quantities surpass the quantities issued. The plots also reveal considerable inter-annual fluctuations, such as in *Lidocaine Injection* and *RHZ*, where issued quantities spike in certain years compared to relatively stable forecasted values, pointing to sudden surges in demand not captured by forecasts. In contrast, *Amoxicillin* and *Amlodipine* show moderate trends with closer alignment between forecasts and actuals, although discrepancies still persist (Figure 12).

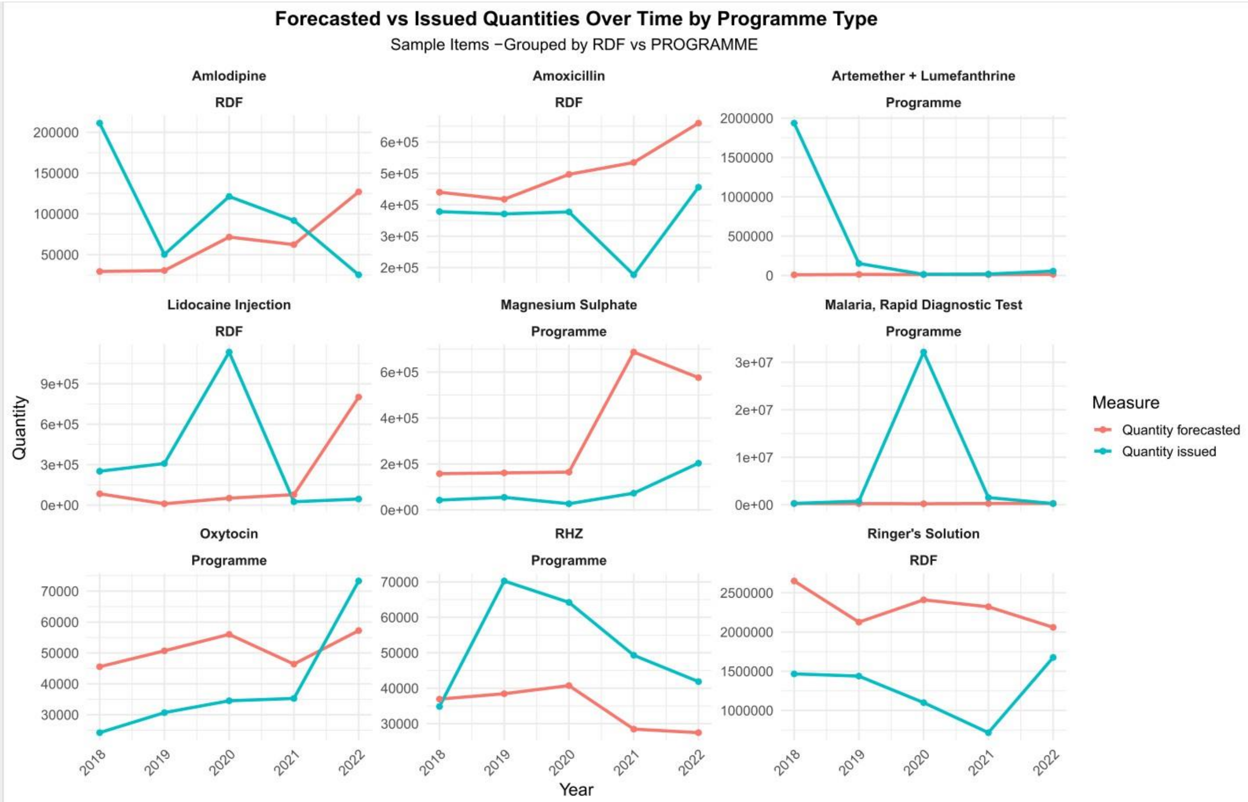


Figure 12:Time Series of Forecasted vs Issued Quantities for Selected Pharmaceuticals by Programme Type (2010–2014 E.C). The panels display data from nine products to give a glimpse of the forecasted and issued quantity patterns.

Difference between Issued and Forecasted Quantities by Year and Programme Type

Figure 13 displays a series of bar charts illustrating the annual differences between issued and forecasted quantities for 33 pharmaceuticals over a five-year period (2010–2014). Each subplot represents a specific pharmaceutical, showing whether the product was over- or under-forecasted in each year. Positive values on the vertical axis indicate under-forecasting, where the quantity issued exceeded the forecast, while negative values indicate over-forecasting, where less was issued than anticipated. The red bar representing program drugs and blue indicating those under the RDF. The visualization reveals considerable variation in forecasting accuracy. Pharmaceuticals such as Ferrous Sulphate + Folic Acid, and Metronidazole were significantly under-forecasted across multiple years, suggesting persistent underestimation of demand. In contrast, drugs like Magnesium Sulphate, Omeprazole Injection, and Medroxyprogesterone Acetate show consistent over-forecasting, indicating recurring overestimation.

A few drugs, such as Amoxicillin and Sodium Chloride, display fluctuating patterns, alternating between over- and under-forecasting. Notably, Propylthiouracil and Pentavalent show substantial discrepancies, reflecting major forecasting errors for these high-priority items. Overall, the figure highlights systemic challenges in accurately predicting pharmaceutical demand within EPSS, with potential consequences for both stockouts and overstocking (Figure 13).

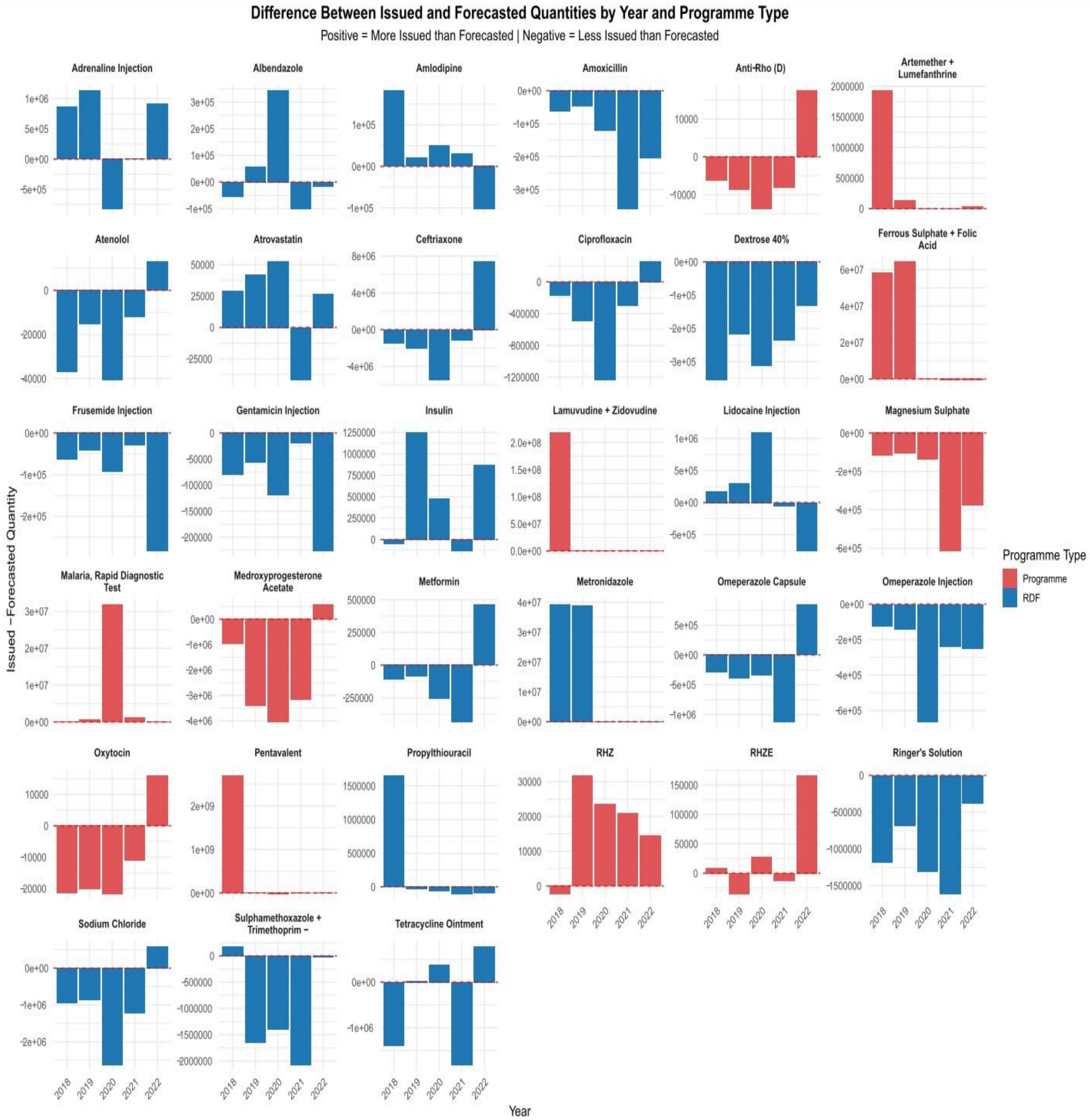


Figure 13:Forecasted and Issued pharmaceuticals Quantities for Selected Pharmaceuticals in EPSS from 2010–2014 EC.

Forecast Accuracy Analysis across Products

Table 3 summarizes forecast accuracy metrics for each of the 33 pharmaceutical items assessed over a five-year period. The metrics include MAPE, sMAPE, MASE, and RMSE, which provide complementary perspectives on forecast performance (Table 3).

Table 3:Forecast accuracy measures of Key Pharmaceuticals for the year 2018-2022 in EPSS.

Item	RMSE	MAPE	sMAPE	MASE
Sodium Chloride	1434833	23	26	1.3
Medroxyprogesterone Acetate	2795159	23	27	0.7
Amoxicillin	194942	29	38	1.3
Tetracycline Ointment	1090070	32	40	0.7
Anti-Rho (D)	11578	33	36	0.9
Oxytocin	18441	35	42	1.5
Atenolol	26557	36	45	1.2
Ceftriaxone	4282272	36	38	0.8
RHZE	77283	39	28	0.6
Ringer's Solution	1124067	44	59	2.4
Ciprofloxacin	623837	46	66	1.0
Sulphamethoxazole + Trimethoprim	1338894	47	77	0.8
Metformin	312540	49	58	0.9
RHZ	21016	54	41	1.2
Omeperazole Capsule	681884	55	75	0.9
Omeperazole Injection	345532	64	101	4.0
Gentamicin Injection	122550	70	116	6.5
Dextrose 40%	261630	72	119	3.8
Frusemide Injection	138203	73	118	11.6
Magnesium Sulphate	334703	75	123	5.0
Atrovastatin	39386	84	58	0.7
Albendazole	163524	116	92	0.5
Insulin	712739	163	60	0.8
Amlodipine	97134	176	85	0.9
Adrenaline Injection	838807	218	90	1.0
Propylthiouracil	743866	425	76	0.9
Lidocaine Injection	611069	1099	150	0.9
Malaria, Rapid Diagnostic Test	14297183	3052	90	0.4
Artemether + Lumefanthrine	864791	5075	110	0.9
Ferrous Sulphate + Folic Acid	38737634	5490	111	1.4
Pentavalent	1209729219	5556	62	0.8
Lamuvudine + Zidovudine	97449671	5670	59	0.8
Metronidazole	24736898	7604	132	1.6

An in-depth evaluation of the forecast accuracy across 33 pharmaceutical items was conducted using four standard metrics: Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (sMAPE), Root Mean Square Error (RMSE), and Mean Absolute Scaled Error (MASE). The results reveal considerable variability in forecasting performance across different products. Notably, MAPE values, which measure the average magnitude of forecasting errors as a percentage, vary widely. The lowest MAPE value were obtained for Sodium chloride solution and Medroxyprogesterone Acetate with the MAPE value of 23%.And those products with MAPE value of less than 50% were 13(40%). In contrast, items like Metronidazole and Ferrous Sulphate + Folic Acid exhibited extremely high MAPE values, suggesting persistent over- or under-forecasting.

The RMSE values further underscore the magnitude of absolute forecasting errors. High-volume items, including Pentavalent vaccines, Metrondazoe capusles and Malaria, Rapid Diagnostic Test, showed particularly large RMSE values, indicating that the models failed to capture actual demand fluctuations accurately. The sMAPE values, which provide a balanced view of forecast accuracy by accounting for both forecasted and actual values, also varied considerably. For example, products like Nevirapine and Zinc Sulphate exhibited sMAPE values below 50%, suggesting relatively balanced and symmetric forecasting performance, while others like Metronidazole showed values well above 100%, indicative of extreme disparities between forecasted and actual values.

MASE was used to compare the performance of the forecasting models against a naïve baseline forecast. Values below 1 indicate that the model performed better than a simple naïve approach. Only a few products, including Nevirapine and Zinc Sulphate, achieved MASE values below 1. The majority of items had MASE values greater than 1, revealing that the forecasting approaches applied may not have consistently outperformed naive models, thereby calling into question the robustness of current methods.

Application of simple forecasting methods

In this analysis, three simple forecasting methods—Naïve, Mean, and 3-Year Moving Average (MA3) were applied to the data set, with forecast accuracy assessed using the Mean Absolute Percentage Error (MAPE). The results demonstrate that the 3-year moving average method consistently outperformed the other two methods in most cases, yielding the lowest MAPE values for a majority of the products. For instance, Sodium Chloride, Oxytocin, and Frusemide Injection showed MAPE values of 9%, 11%, and 11% respectively under MA3, significantly lower than the errors produced by the naïve and mean methods. This suggests that the moving average method is particularly effective for items with stable or gradually changing demand patterns (Table 4).

Table 4: Mean Absolute Percentage Error of Key Pharmaceuticals for 2018-2022 in EPSS using Naïve, Mean and 3 years Moving Average Forecasting Models.

Item	Naïve MAPE	Mean MAPE	3 year moving averages MAPE
Sodium Chloride	17	23	9
Oxytocin	22	33	11
Frusemide Injection	31	25	11
RHZ	27	25	12
Medroxyprogesterone Acetate	44	23	13
RHZE	46	34	13
Anti-Rho (D)	31	52	15
Atenolol	45	33	16
Insulin	53	36	17
Tetracycline Ointment	45	52	17
Atrovastatin	55	45	20
Amoxicillin	45	28	20
Ringer's Solution	36	28	21
Ceftriaxone	40	51	21
Ciprofloxacin	67	74	22
Metformin	49	75	24
Magnesium Sulphate	64	81	27

Amlodipine	169	95	45
Adrenaline Injection	114	67	51
Omeprazole Injection	140	65	58
Sulphamethoxazole + Trimethoprim	221	193	66
Dextrose 40%	122	105	73
Gentamicin Injection	280	177	129
Propylthiouracil	648	334	172
Omeprazole Capsule	424	437	208
Albendazole	815	298	298
Lidocaine Injection	1161	429	546
Malaria, Rapid Diagnostic Test	670	1258	1017
Artemether + Lumefanthrine	572	1291	1074
Pentavalent	7956	5080	2384
Ferrous Sulphate + Folic Acid	2591	3789	2647
Lamivudine + Zidovudine	10340	10375	4882
Metronidazole	6626	19449	15082

The performance of the naïve and mean methods varied depending on the item. In certain cases, such as RHZ and Medroxyprogesterone Acetate, the mean method showed better accuracy than the naïve approach. In contrast, for items like Amoxicillin and Atenolol, the naïve methods yielded better results.

However, a number of items displayed very high MAPE values across all three methods, indicating erratic and unpredictable demand patterns. For example, Pentavalent , Ferrous Sulphate + Folic Acid, Lamuvudine + Zidovudine and Metronidazole had exceptionally high MAPE values, even with the moving average method, suggesting that these products are influenced by complex factors such as programmatic interventions, stockouts, or irregular supply schedules. For such products, simple forecasting methods are inadequate, and more sophisticated techniques such as exponential smoothing, ARIMA models or machine learning approaches may be necessary to improve forecast accuracy. Overall, while the 3-year moving average method generally offered the best accuracy among the simple methods.

The analysis uncovered significant inaccuracies in the current forecasting methods used by EPSS for essential pharmaceuticals, indicating that existing practices fall short in meeting the demand for these vital health commodities. The study further demonstrated that the use of simple forecasting models, such as moving averages and naïve models, could substantially improve forecast accuracy compared to the methods currently employed by EPSS. This finding suggests that simpler forecasting approaches may be more effective in the Ethiopian supply chain context.

5.4. Application of advanced forecasting methods with domain knowledge

In this section, we compare the forecasting performance of various approaches, examining models that incorporate expert identified business context predictors versus those that rely solely on historical consumption data. Point forecast performance is reported using MASE and RMSSE, while probabilistic forecast accuracy is reported using CRPS.

The forecasting performance is reported in Figure 14, in which the average forecast accuracy over forecast horizon and across all products is calculated for each origin. We report the distribution of accuracy metrics across all rolling origins. This shows how models varies in providing accuracy across different origins. The y-axis displays models sorted by their MASE and RMSSE values, with the model exhibiting the lowest error positioned at the bottom. This model is the LSTM model, followed by ARIMA, which incorporate exogenous variables. Additionally, Figure 13 indicates that predictors obtained through interactions with domain experts enhance point forecast accuracy across most models. This underscores the critical importance of systematically collecting such expert-informed data alongside transactional consumption data.

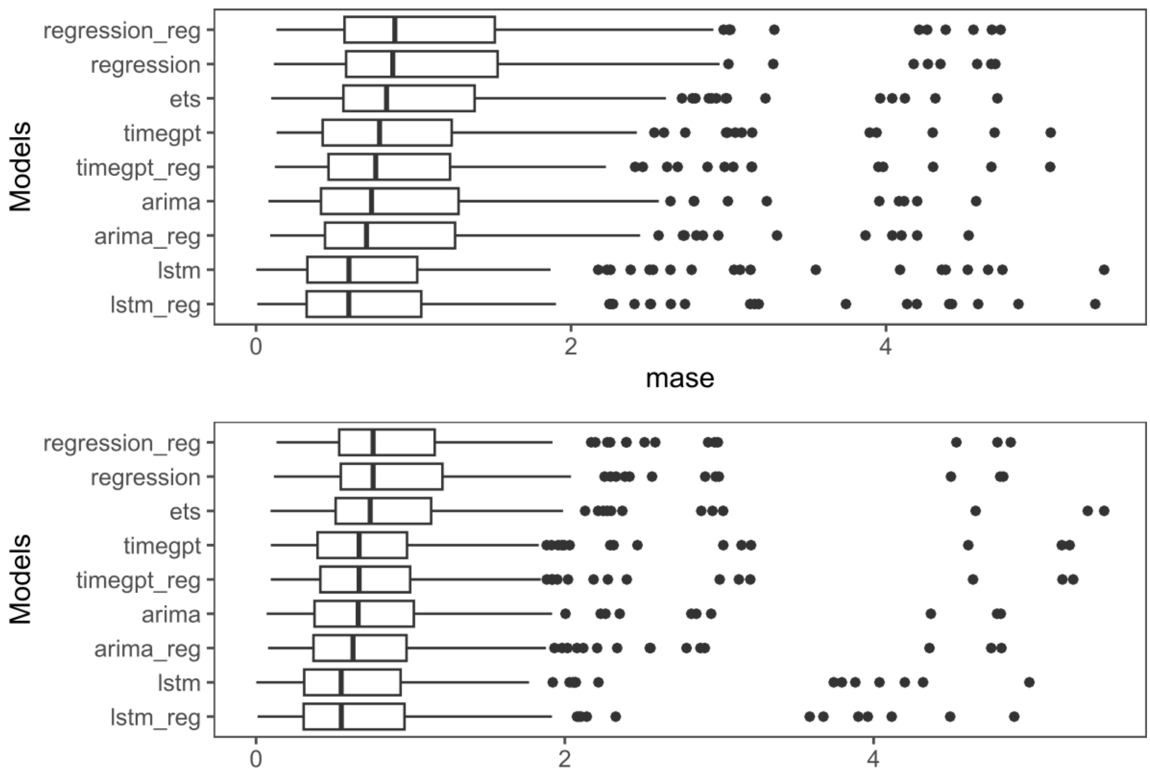


Figure 14: Distribution of point forecast accuracy across different origins, averaged across the forecast horizon and all products

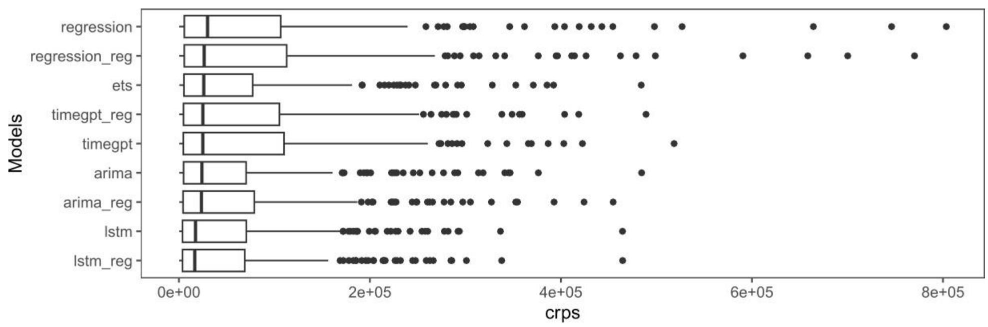


Figure 15:Distribution of probabilistic forecast accuracy across different origins, averaged across the forecast horizon and all products

Figure 15 illustrates the forecast distribution accuracy measured by CRPS, which evaluates both forecasting calibration and interval sharpness. A smaller CRPS value indicates better overall performance. We observed that incorporating domain knowledge improved forecast accuracy for most models, enhancing not only point forecasts but also probabilistic forecasts. Notably, LSTM and ARIMA yielded the most accurate probabilistic forecasts when identified predictors were incorporated. This aligns with the findings related to point forecast accuracy, reinforcing the earlier explanations for these results.

The findings emphasize the importance of incorporating relevant domain knowledge into forecasting models. In pharmaceutical supply logistics administration systems, data often consists solely of transactional records on consumption and distribution. Including exogenous variables such as administrative procedures, seasonal patterns, or conflicts, or any other relevant factor that could be identified by those with domain knowledge proved essential for reducing forecast errors. This approach improved both point and probabilistic forecast accuracy, enabling a more confident assessment of uncertainty. Therefore, the systematic collection of information about significant events and their impact on consumption is vital. Recording details of events such as policy changes, administration procedures, conflicts, and incorporating this information into forecasting models creates a comprehensive understanding of consumption. This practice enhances modeling reliability and allows institutions in developing countries and humanitarian organizations to better forecast demand, allocate resources effectively, and respond proactively. Establishing robust data collection systems is thus a critical step for strengthening forecasting capabilities and operational resilience.

Computational efficiency and resource considerations

In addition to forecast accuracy, it is also important to consider the computational efficiency of each model, particularly in settings where computational resources and technical expertise are limited.

Table 5 shows the total runtime required to train and generate forecasts across all 33 pharmaceutical product time series for each method for all origins. All models were implemented using R, except TimeGPT, which was run via Google Colab using a T4 GPU backend. All other models were executed on a local machine with 7 CPU cores (11th Gen Intel(R) Core(TM) i5-1135G7 @ 2.40 GHz and 8 GB RAM)

Table 5:Computation time required for training and generating forecasts for each model across all products.

Model	Runtime (Seconds)	Runtime type	category
LSTM	6892.30	CPU with 7 cores	high
LSTM with regressors	7234.00	CPU with 7 cores	high
Regression	27.48	CPU with 7 cores	low
Regression with regressors	47.38	CPU with 7 cores	low
ARIMA	96.27	CPU with 7 cores	low
ARIMA with regressors	138.08	CPU with 7 cores	medium
TimeGPT	2.57	Colab T4 GPU	low
TimeGPT with regressors	3.72	Colab T4 GPU	low
ETS	75.71	CPU with 7 cores	low

As shown in Figure 13 and 14, models that incorporated expert-informed regressors generally achieved better forecast accuracy compared to their univariate versions. This trend was most evident in classical models such as ARIMA and regression, where the inclusion of regressors led to a noticeable shift toward lower and more concentrated error distributions. However, this improvement came with an increase in computational cost. In all cases, the addition of regressors increased runtime—by 72% in the regression model (from 27.48 to 47.38 seconds) and by 43% in ARIMA (from 96.27 to 138.08 seconds). TimeGPT also showed a slight increase in runtime (from 2.57 to 3.72 seconds), although the total processing time remained extremely low overall. Moreover, LSTM exhibited the largest increase in runtime when regressors were added, rising from 6,892 to 7,234 seconds. This sharp increase reflects the sensitivity of neural networks to input configuration, especially in contexts with limited data, irregular demand, and noisy signals. These results underscore the importance of balancing model performance with implementation cost. While deep learning models such as LSTM offer strong potential when well-tuned, they demand significantly more computational resources and may be less robust when integrating static or weakly aligned contextual features. By contrast, TimeGPT, a foundational model pretrained on large-scale time series data, provides a compelling alternative. It required less than 4 seconds to forecast all products, offered competitive accuracy, and required no tuning or retraining—making it well-suited for practical use in low-resource environments.

An illustration of probabilistic forecast for Pharmacuitical product consumption

In this section, we present an illustrative example of a probabilistic forecast for future consumption of Sodium Chloride (Normal Saline) product. Due to the complexity of including such visualizations for all products, only one example is shown here. However, it is feasible to generate these plots for all products if needed.

In practice, point forecasts are commonly used despite their limitations, but they do not account for the inherent uncertainty associated with forecasts. The future is inherently uncertain, and effective planning re- quires considering alternative scenarios. Probabilistic forecasts offer a comprehensive approach by assigning likelihoods to a range of possible outcomes, recognizing that different consumption levels may occur with varying probabilities. The goal is to maximize the sharpness of these predictive distributions—i.e., how con- centrated the forecasts are—while maintaining calibration, meaning that the predicted probabilities align well with actual outcomes (Gneiting and Katzfuss, 2014). This approach allows decision-makers to fully leverage available information, incorporating uncertainty in a structured and measurable way. The primary purpose, as illustrated in Figure 15, is to quantify and communicate uncertainty. This figure displays the forecast distribution of consumption over a 6-month horizon using a density plot. For each month within the forecast period, a separate distribution is generated. The plot also includes the point forecast alongside 80% and 90% prediction intervals to illustrate potential variability.

Probabilistic forecasts enhance planning and decision-making by offering a comprehensive view of potential future outcomes and their likelihood, rather than relying on a single point estimate. A probabilistic forecast takes the form of a predictive probability distribution over future quantities or events of interest.

It is important to note that while point forecasts and prediction intervals can be derived from probabilistic forecasts, the reverse is not true. A single-point forecast cannot inherently provide the probabilistic context needed to capture the range of possible outcomes. Although prediction intervals can indicate a range of potential values, they do not convey the detailed probabilities of low or high consumption. This distinction highlights the value of probabilistic forecasting in supporting informed decision-making by offering a clearer view of future uncertainties.

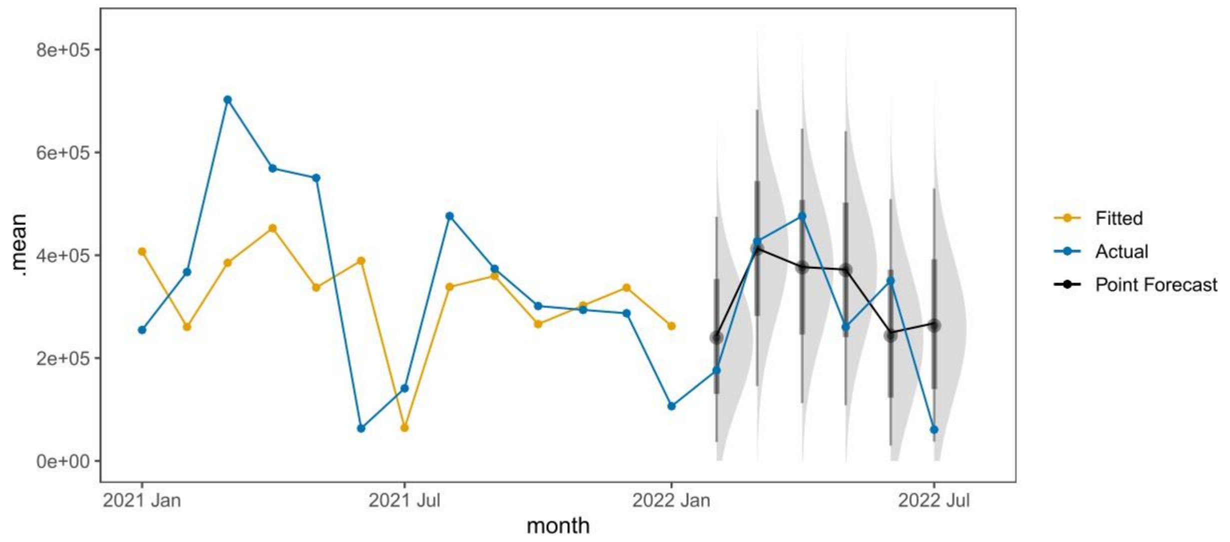


Figure 16:A graphical illustration of the forecast distribution of a pharmaceutical product (i.e. total incidence attended) for the SB health board for a horizon of six month. For each month, we display the point forecast (black point), the histogram, and 80% (thick line) and 90% (thin line) prediction intervals. It also shows a portion of a historical time series as well as its fitted values.

To further illustrate the practical relevance, we consider an illustrative case where the mean forecasted consumption for the next month is 1,000 units, with a 90% prediction interval ranging from 850 to 1,150 units. Table 6 summarizes the decision outcomes under each approach.

Under a traditional approach, inventory decisions would rely solely on the point forecast. Based on the mean prediction of 1,000 units, the store manager would order precisely that quantity, assuming it would meet the expected demand. However, this approach does not incorporate any adjustment for uncertainty, potentially leading to stockouts if actual demand exceeds 1,000 units, or excess inventory if consumption is lower.

In contrast, utilizing the full probabilistic forecast allows the decision-maker to take variability into account. If a higher service level is required, for example 95%, the inventory policy may be adjusted by stocking closer to the upper bound of the 90% prediction interval (e.g., 1,150 units). If inventory holding costs are a major concern and the organization can tolerate a modest risk of shortage, the order quantity could remain closer to the median forecast of 1,000 units.

Table 6: Comparison of ordering decisions under point and probabilistic forecasts - an illustrative example.

Forecast Type	**Ordering Quantity**	**Risk Consideration**
Point Forecast Only	1,000 units	No explicit consideration of uncertainty
Probabilistic Forecast (95% service level)	1,150 units	Adjusts inventory to account for demand variability

This illustrative comparison indicates that point forecasts provide a single estimate without adjusting for forecast uncertainty, while probabilistic forecasts allow decision-makers to explicitly align inventory decisions with risk tolerance and service level requirements. This is particularly important for pharmaceutical products, where the consequences of stockouts or overstocking can be significant both operationally and clinically.

5.5. Effective Supply Chain Strategies in Addressing Demand and Supply Uncertainty

From the qualitative interview the respondents we identified several strategies which can be used for mitigating drug shortages from Phase I. First, several successful strategies were identified, including regular communication and stock status assessments at both central and hub levels, which are critical for optimizing planning and preventing stockouts or overstocking. Supportive supervision and training for staff were also shown to be effective in reducing drug shortages and enhancing employee motivation. Streamlining procurement processes, such as providing early notifications for tenders, helps expedite supply acquisition, reduce lead times, and improve responsiveness in the supply chain. Additionally, enhancing supplier relationship management through strong collaboration and coordination proved to be beneficial during supply disruptions.

On the other hand, some strategies were found to be less successful. Rationing, while helpful in managing supply allocation during shortages, is viewed as a temporary solution that does not address the root causes of the problem. Similarly, product redistribution between hubs, although sometimes necessary, is often costly and time-consuming, requiring efficient communication and coordination to be effective.

The study also identified key success factors for effective supply chain management, including the importance of data quality, technology integration, and strong supplier relationships in enhancing supply chain resilience. However, several barriers to effectiveness were noted, such as poor data quality, inadequate communication, and regulatory constraints, all of which hinder smooth supply chain operations. Finally, the study highlighted context-specific challenges faced by the EPSS in a resource-limited environment, offering valuable insights into the dynamics of pharmaceutical supply chains in developing countries. Overall, the findings stress the need for a comprehensive approach that integrates various strategies to effectively address drug shortages and improve the resilience of Ethiopia_s pharmaceutical supply chain (figure 17).

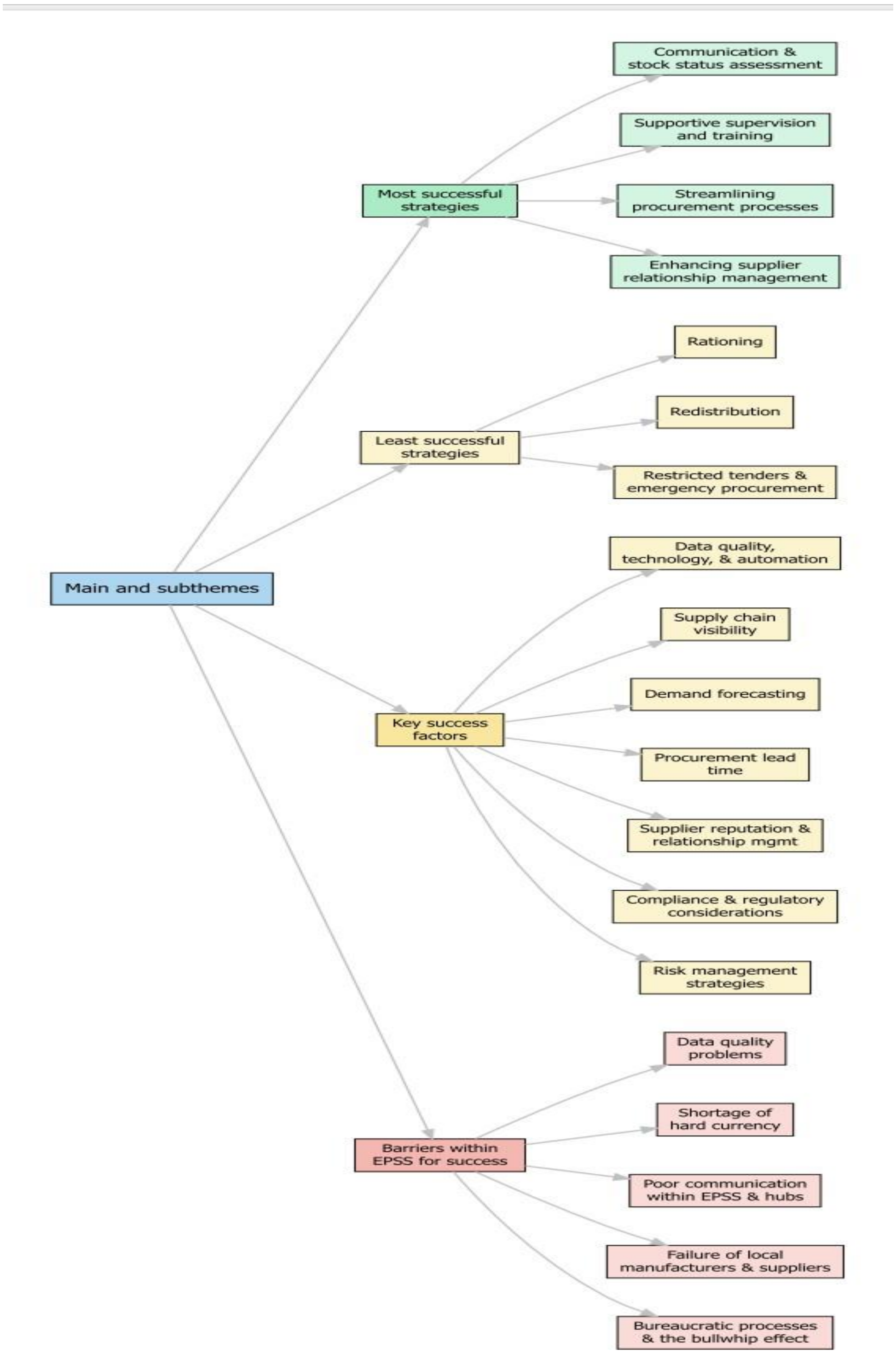


Figure 17:The main themes and sub-themes of the thematic analysis.

CHAPTER 6: DISCUSSION, CONCLUSIONS AND RECOMMENDATIONS

The key research findings emerging from both parts of this research are discussed in detail below, followed by an examination of the study's strengths and limitations. The discussion will then cover the implications of the findings, followed by conclusions and recommendations. The chapter will conclude with suggestions for future research directions.

6.1. Challenges of pharmaceutical forecasting practices within the EPSS

The Ethiopian pharmaceutical supply chain faces issues like lack of financing, work-force skills, poor coordination, data quality problems, and lack of end-to-end visibility. These factors create a systemic problem requiring an integrated solution. Bititci (2015) suggests that organizations perform better when working towards a common goal with collaboration and shared learning, enhancing problem-solving and innovation. This requires open communication, trust, and reflection (Bititci, 2015).

This study emphasizes the importance of responsibility and attention to forecasting to mitigate sector challenges. Gurzawska also highlights that responsible and sustainable SCM requires innovative technology, political solutions through multi-stakeholder partnerships, and ethical responsibility across supply chain tiers, necessitating a systemic approach (Gurzawska, 2020). To improve forecasting, responsible bodies should focus on technology, ensure end-to-end data visibility, and develop forecasting tools and databases. Digitalizing supply chains fosters communication and collaboration among stakeholders, but technological innovations alone are not enough without strong coordination (Gurzawska, 2020). Supply chains are multitier, involving manufacturers, intermediaries, end-users, governments, and communities. Effective SCM relies on stakeholder engagement and multi-stakeholder approaches (CSSPs) to achieve responsibility and sustainability (Doh et al., 2010; Van Huijstee and Glasbergen, 2010; Ritvala et al., 2014; Vurro et al., 2009). This approach, rooted in stakeholder theory, asserts that a company_s success depends on sustainable relationships within its stakeholder network (Van Opijnen and Oldenziel, 2011; Tencati and Zsolnai, 2009).

Freeman (1984) defines stakeholders as groups affecting or affected by an organization_s purpose (Freeman, 1984). The multi-stakeholder approach in SCM stems from the concept of collaborative enterprises, where companies build long-term, mutually beneficial relationships with stakeholders to create sustainable value (Tencati and Zsolnai, 2009). This enhances relationships through better coordination with suppliers, customers, and other stakeholders, improving social outcomes and generating win-win solutions. Thus, a company_s sustainability depends on its stakeholder relationships (Tencati and Zsolnai, 2009; De Bakker and Nijhof, 2002). This multi-stakeholder approach addresses collaboration, communication, and power distribution challenges in the supply chain. Collaborative initiatives enable better monitoring and tracing of supply chain activities, which individual companies may lack resources for the societal and environmental impacts of its activities (Clarkson, 1995). However, developing these deep relationships requires time (Klassen and Vereecke, 2012). Non-state actors can enhance supply chain responsibility and sustainability by effectively gathering, collating, and providing information on policy issues and problem areas (Hood et al., 2001; Hutter, 2006).

This paper highlights the interplay between technology, politics, and stakeholder involvement. Solutions like end-to-end data visibility, political will, and collaboration among supply chain actors could alleviate forecasting challenges. Non-state actor initiatives use technologies for data sharing via multi-stakeholder digital platforms, enhancing compliance through mutual control (Gurzawska, 2020). These platforms also promote transparency, cooperation, and trust, as well as reduce power abuse, requiring oversight for ethical decisions (Ferrell et al., 2013). Effective governance involves multi-stakeholder collaboration for credibility, combining technological, political, and ethical solutions to address SCM challenges.

6.1. Forecast Accuracy by Using Simple Forecasting Methods

EPSS was established to ensure a sustainable supply of quality-assured essential pharmaceuticals to health facilities at affordable prices for Ethiopian citizens (FDRE, 2022). However, there have been challenges in making these pharmaceuticals accessible to the people of Ethiopia (FDRE, 2022). Moreover, EPSS faces issues such as lack of financing, workforce skills, poor coordination, data quality problems, and end-to-end visibility (Bilal, et al., 2024). These problems largely stem from data quality issues, leading to poor forecasting. Demand forecasts form the basis of all logistics and supply chain management decisions. Demand forecasting is the starting point for all planning activities and execution processes. All supply chain activities, including procurement, production, transportation, and operations, require demand forecasts to plan necessary levels of activity and inventory, with customer demand data being the starting point (Merkuryeva, et al.,2019).

The findings highlight a substantial gap between forecasted and actual issued quantities, with wide ranging discrepancies observed across product types, program categories, and years. These patterns of under and overestimation suggest that the current forecasting methods are insufficiently responsive to demand variability. The forecast accuracy metrics indicated that there is high forecast errors for a majority of products. Only 13 out of 33 items had MAPE values below 50%, a commonly used benchmark for acceptable forecast performance in health supply chains. The RMSE values for high-volume items such as Pentavalent and malaria commodities further underscore the magnitude of absolute errors in the system. These errors are not merely statistical anomalies—they represent real operational risks in terms of stockouts, wastage, or delayed treatment in the healthcare system.Such kind of high forecast error was also reported by other studies conducted in EPSS (Adane and Ensermu, 2019; Tibebu et al., 2022). Overall, the inconsistency in demand forecasting accuracy, with both underestimation and overestimation observed across product types and programme categories. If such discrepancies, unaddressed, could lead to supply chain inefficiencies including stock outs or overstocking, particularly within essential medicines and public health programmes.

Additionally, the MASE values suggest that for most items, the applied forecasting approaches did not outperform a naïve baseline forecast. This is a critical finding, as it questions the value added by existing forecasting techniques and signals the need for a shift toward more robust and adaptive models. Moreover, the disparity in forecast performance between RDF items and program drugs suggests that governance and data flow differences across procurement mechanisms may influence forecasting accuracy. The application of three simple forecasting methods (Naïve, Mean, and 3-Year Moving Average) to the data set indicated that a 3-Year Moving Average method consistently achieved lower MAPE values for most of the pharmaceuticals, particularly for products such as Sodium Chloride and Oxytocin. However, this method still performed poorly items like Ferrous Sulphate + Folic Acid and Metronidazole, suggesting that simple historical averaging alone is insufficient for managing these items. Similar findings were also reported by Tibebu et al. (2022), where moving average methods produced more accurate forecasts, with 86.7% of items having better forecast accuracy. Collectively, the results demonstrate substantial inconsistency in forecast accuracy across products and suggest the need for differentiated forecasting strategies. Items with high usage volumes and those with wide seasonal or programmatic variability may benefit from tailored models that incorporate disease burden trends, stockout history, and contextual programmatic shifts. These findings highlight the importance of improving data inputs, applying advanced modeling techniques, and strengthening forecast governance to ensure better alignment between projected and actual pharmaceutical needs.

6.2. Application of advanced forecasting methods with domain knowledge

In this study, we conducted an extensive analysis of pharmaceutical demand forecasting within the EPSS. Using five years of consumption data for 33 key pharmaceutical products, along with additional information gathered through collaboration with domain experts at EPSS, our goal is to contribute to enhancing the demand forecasting process and emphasize the importance of integrating domain knowledge into model building. This step is critical, as the phase of understanding the data and incorporating valuable contextual information is often overlooked. Too frequently, forecasting efforts rely solely on consumption data, leading to building models with little relevance to reality. Our approach highlights the necessity of including domain insights to construct more accurate and effective forecasting models.

Our findings highlight the importance of collecting and incorporating domain knowledge when building forecasting models. We evaluated both point and probabilistic forecasts using a range of models, from simple univariate approaches like ARIMA to complex models such as LSTM. We demonstrated that while the use of complex models may improve forecast accuracy in the pharmaceutical supply context, this comes at the cost of significantly increased computational time an important consideration for resource-constrained settings in low- and middle-income countries (LMICs). Additionally, our research indicates that newly developed foundational time series forecasting models hold promise, particularly in settings with limited computational infrastructure and constrained access to advanced analytical expertise, as often seen in pharmaceutical supply chains in developing countries.

To advance forecasting practices further, exploring additional predictor variables such as public health campaigns, disease outbreaks, and economic indicators could provide valuable insights into demand dynamics. Improving the granularity of historical consumption data, through finer temporal intervals and geographic differentiation, also holds potential for more precise predictions. Additionally, hybrid forecasting models that combine judgmental point forecasts with probabilistic machine learning models could enhance predictive performance. Empowering EPSS staff through training in foundational time series models, data interpretation, and collection will enable informed decision-making and strengthen workforce capabilities. Replicating this study across diverse healthcare settings and conducting comparative analyses would help validate the adaptability and applicability of the findings. Additionally, it is recommended that pharmaceutical supply services systematically collect and maintain detailed records of events that may influence consumption, alongside consumption data. This practice is essential for refining demand models and enhancing forecast accuracy.

6.3. Supply Chain Strategies in Addressing Demand and Supply Uncertainty

The primary aim of this research was to comprehend the risks within EPSS supply chains and identify strategies for mitigating the risk of drug shortages. Building on the literature review, the study explored various shortage-mitigating strategies through a survey and participant interviews. The findings highlighted successful and less successful strategies, key success factors, and barriers within the EPSS concerning drug shortages. This study_s contributions are twofold. First, it advances our theoretical understanding by exploring proactive and reactive supply chain strategies for mitigating drug shortages within the pharmaceutical supply chain. Second, it sheds light on key success factors crucial for overcoming drug shortages in resource-limited countries, providing practical insights.

The literature review emphasized the dichotomy of proactive and reactive strategies in supply chain risk management. Proactive strategies involve anticipatory and preventive actions to address potential challenges before they occur, while reactive strategies respond to challenges after they have manifested (Zsidisin and Ritchie, 2008). These strategies include supplier development, supply chain contracts, contingency planning, and disaster management (Ghadge et al., 2012). Studies from various contexts have identified specific strategies such as establishing information systems, imposing public service obligations, influencing trade rules, and forming committees to collaboratively tackle shortages (Bochenek et al., 2018). The EPSS study aligns with these findings, offering insights into the effectiveness of such strategies within a developing country_s pharmaceutical supply chain (Figure 18).

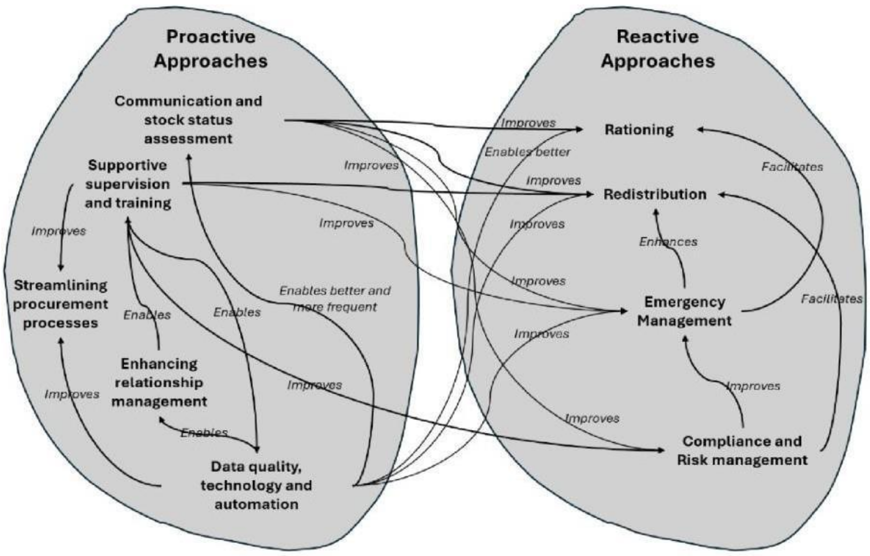


Figure 18:How the different strategies interact to aid improved management of supply chain performance under demand uncertainties

Additionally, the research provides a unique perspective by delving into specific proactive strategies employed by EPSS, such as communication, stock status assessment, supportive supervision and training, and streamlining procurement processes. Resource sharing through strategic alliances was also identified as a proactive resilience strategy (Vann Yaroson et al., 2024). Reactive strategies discussed in the literature, such as safety stock, capacity buffers, and supplier backups, were found to be used in response to uncertainty in the pharmaceutical supply chain (Van Kampen et al., 2010). It is important to understand that both proactive and reactive strategies do not stand alone as single entities; they interact with each other. This interaction is illustrated in Figure 2. For instance, data quality, technology, and automation enable better and more frequent communication and stock status assessment, which in turn improves rationing, redistribution, emergency management, compliance, and risk management. The role of data quality, technology, and automation also helps us to easily communicate and address information.

Furthermore, our findings reveal that supportive supervision and training are crucial when dealing with uncertainty of demand and supply, and this was evident in one of the studies conducted by Bilal et al., which emphasized the pivotal role of training in fostering workforce competence and motivation. While short-term training interventions were deemed crucial for immediate skill enhancement, participants emphasized the long term imperative of elevating the quality of education programs, including degree-level education, in cultivating a pipeline of skilled professionals.

The study adds depth by examining how the EPSS utilizes these strategies to address medicine shortages. Furthermore, the study acknowledges the scarcity of research on supply chain risk management in developing countries. This gap is critical because of the heightened uncertainty in such regions, emphasizing the study_s relevance to a more fragile economic and political structure.

In terms of managerial implications, the study underscores the importance of a responsive supply chain structure for mitigating risks effectively. It highlights the need for a nuanced approach, understanding that certain strategies may not be effective in isolation and that a combination of proactive and reactive strategies may be necessary. Managers are encouraged to focus on key success factors, including data quality, technology, automation, and supply chain visibility while addressing barriers like data quality problems and communication issues. The success of reactive and proactive strategies hinges on their alignment with the company_s overall supply chain goals and the particular uncertainties encountered. Combining both strategies in a balanced manner can create a more resilient supply chain that effectively handles uncertainties. In essence, although reactive and proactive strategies have distinct roles, their interaction is vital for optimal supply chain flexibility. Companies that effectively merge these approaches can boost their responsiveness to uncertainty and advance long-term enhancements in their supply chain design and operations.

6.4. The interplay between the forecasting methods and supply chain strategies

Pharmaceutical shortages demand a multifaceted approach that combines forecasting techniques with supply chain strategies, tailored to the specific context of the shortage. In emergency situations (Scenario I), where immediate action is required, forecasting is not typically utilized. Instead, reactive strategies which were employed after shortages occurred and these strategies were rationing, redistribution, and emergency risk management take center stage. These strategies focus on quickly reallocating available resources to minimize the impact of the shortage. For example, rationing ensures equitable distribution of limited supplies, while redistribution allows for the transfer of stock from central or hub locations to areas facing critical shortages. The effectiveness of these reactive strategies depends on accurate stock visibility, well-coordinated communication systems, and a robust supply chain foundation, but they do not rely on real-time forecasting.

In contrast, forecasting plays a pivotal role in Scenario II, where time and data are available for planning. Under these conditions, proactive strategies are deployed to prevent shortages before they occur. Simple forecasting methods are especially important when quick results are needed, or when skilled human resources for advanced forecasting are unavailable. These methods provide rapid insights and serve as a benchmark for advanced forecasting techniques. When more time and expertise are available, advanced forecasting methods, enriched with domain knowledge from pharmaceutical experts, can predict demand, identify potential supply chain bottlenecks, and guide timely procurement and distribution decisions. These advanced methods significantly benefit from real-time product information, which is why investing in data quality, technology, automation, and effective stock status assessment is critical. Moreover, supportive supervision and training help equip supply chain teams with the skills necessary to leverage these advanced forecasting tools effectively. By integrating these proactive strategies, forecasting informs decision-making and fosters continuous improvement through feedback loops (Figure 19).

Figure legend Arrows reflect:

- **Black (solid)** → Must be there
- **Red (dotted)** → Improves
- **Green (solid, thick)** → Impacts

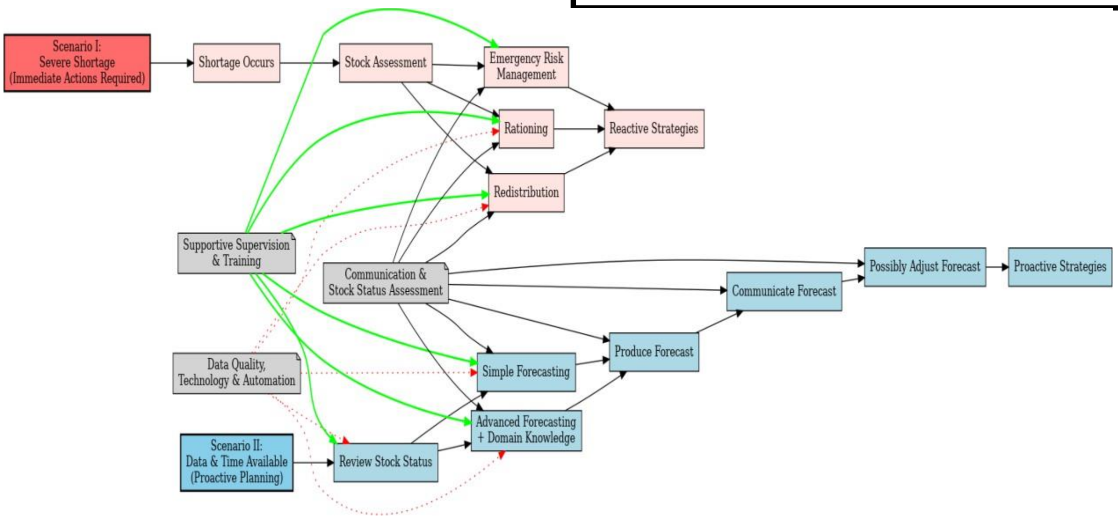


Figure 19: Summary of contributions to theory

The synergy between forecasting techniques and supply chain strategies becomes evident in how proactive planning strengthens the execution of reactive strategies. While forecasting is not directly applied during emergencies, the groundwork laid through proactive strategies ensures that reactive measures can be implemented more effectively. A well-structured supply chain, with clear data visibility and established communication channels, allows for quicker and more efficient redistribution during crises. This integration shows how forecasting indirectly contributes to the success of reactive strategies by enhancing the overall supply chain infrastructure.

Ultimately, the combined use of forecasting techniques with supply chain strategies creates a comprehensive framework for managing pharmaceutical shortages. Reactive strategies address immediate needs during emergencies, while proactive strategies, guided by forecasting, help build resilience and prevent future shortages. Together, these approaches form a dynamic system that not only responds to crises but also reduces their frequency and severity over time. This integrated approach underscores the importance of aligning forecasting methods with strategic interventions to ensure the continuous availability of essential pharmaceuticals.

6.5. Strengths and limitations of the study

6.5.1. Strengths of the study

This study on pharmaceutical forecasting practices within the Ethiopian Pharmaceutical Supply Services (EPSS) demonstrates several significant strengths. A primary strength lies in its adoption of a sequential explanatory mixed-methods design, which allowed for an in-depth examination of forecasting challenges through the integration of both quantitative and qualitative data. This design enriched the analysis by combining empirical performance evaluation with contextual understanding, thereby enhancing the study‘s internal validity and practical relevance. Another notable strength is the innovative incorporation of domain-specific knowledge, into forecasting models. This integration proved critical in improving both point and probabilistic forecast accuracy, especially in low- resource environments where data is often limited. The study not only evaluated simple statistical models (e.g., naïve, moving averages) but also tested advanced machine learning techniques including ARIMA, Random Forest, and TimeGPT, providing robust empirical comparisons. Importantly, the research found that models enriched with domain knowledge significantly outperformed those relying solely on historical data, highlighting the value of contextual insights in health supply chain forecasting.

The study also benefits from its context-specific focus on Ethiopia a low-income country with unique health system constraints. This setting enhances the applicability and usefulness of the findings for local policymakers and practitioners. Furthermore, the study draws on a broad and diverse set of stakeholder perspectives, including those from supply chain managers, health officials, and EPSS experts. This diversity of input adds depth to the qualitative findings and ensures the challenges identified such as financial constraints, workforce shortages, and weak coordination‘s are holistically captured. The alignment of the research with national health strategies such as the Health Sector Transformation Plan (HSTP-II) and the Pharmaceuticals Supply Transformation Plan (PSTP) reinforces its policy relevance. The study goes beyond analysis by offering practical, actionable recommendations to improve forecasting accuracy and supply chain resilience particularly through a balanced integration of proactive and reactive strategies. Lastly, the research makes a meaningful contribution to the global literature on health supply chain management in resource-constrained settings. By addressing a largely underexplored area forecasting in low-income health systems the study bridges a critical gap and serves as a model for similar contexts.

6.5.2. Limitations of the study

While this study provides important insights into pharmaceutical forecasting and supply chain strategies within the Ethiopian Pharmaceutical Supply Services (EPSS), several limitations should be acknowledged.

First, the study‘s context-specific focus on EPSS, although valuable for local relevance, may limit the generalizability of the findings to other countries or health systems with different organizational structures, technological capabilities, or regulatory environments. The case study design, while enabling in-depth exploration of real-world practices, inherently limits broad extrapolation without appropriate contextual adaptation.

Second, the quantitative component relied on retrospective distribution (issued) data as a proxy for actual medicine consumption, due to the challenges of obtaining real-time consumption data from health facilities. While commonly accepted in low-resource settings, this substitution may not fully capture actual demand behavior, particularly in settings affected by stockouts or supply interruptions. Furthermore, the use of historical administrative data carries risks related to incomplete records, inconsistent reporting, and human errors during data entry, all of which can affect the precision and reliability of forecasting performance evaluation.

Third, although the qualitative phase successfully identified thematic challenges and strategic insights, the study did not explore inter-theme relationships—that is, how identified themes (e.g., data quality issues, communication breakdowns, procurement delays) interact or reinforce each other in shaping forecasting outcomes. The lack of analysis on the interconnectedness between themes may limit the study's depth in explaining systemic dynamics within the forecasting and supply chain context. For instance, data quality problems may be closely linked to training deficiencies or governance issues, yet such relationships were not formally evaluated. This omission may have constrained a more nuanced interpretation of the qualitative findings and their broader implications for intervention design.

Lastly, while the study proposed several potential strategies to mitigate pharmaceutical shortages and improve forecasting, it did not conduct a formal impact evaluation to test the effectiveness or scalability of these interventions in practice. Implementation research or longitudinal studies would be required to assess how these strategies perform over time and under varying operational conditions. Future research should aim to address these limitations by incorporating mixed-method triangulation, evaluating the interrelationships between qualitative themes, improving data granularity, and piloting interventions in real-world settings to assess their measurable impacts.

6.6. Implications of the study

The findings of this study have a number of practice and policy implications. Some of the major ones will be discussed.

6.6.1. Implication to research

The findings of this study have significant implications for researchers focusing on supply chain strategies and pharmaceutical management. First, it underscores the importance of adopting a holistic systems approach rather than examining supply chain components in isolation. Researchers should study inaccuracies and supply problems within the broader context of the supply chain to develop comprehensive solutions. Addressing forecasting in isolation is insufficient; integrating forecasting techniques with supply chain strategies is essential to mitigate medicine shortages effectively. Additionally, this study highlights the value of incorporating domain knowledge into forecasting models. The involvement of domain experts improves forecast accuracy by contextualizing data and ensuring the models reflect real-world nuances. This approach bridges the gap between theoretical forecasting methods and practical supply chain challenges. The research also demonstrates that Large Language Models (LLMs) and other advanced technologies offer transformative opportunities for developing countries. By making advanced forecasting methods more accessible, even in resource-constrained settings with limited expertise or infrastructure, these technologies have the potential to revolutionize supply chain research and practice.

Finally, this study addresses a critical gap in the literature by integrating domain expertise with machine learning-based forecasting models a previously underexplored area in pharmaceutical supply chain studies. Future research should build on these findings by exploring the scalability and adaptability of such integrated models in diverse healthcare settings.

6.6.2. Practice implications

The study highlights several practical implications for improving supply chain management and addressing drug shortages. First, practitioners are encouraged to adopt integrated strategies that combine both proactive and reactive approaches, improving communication, conducting regular stock assessments, and optimizing procurement processes to prevent shortages. Continuous training and capacity building for staff involved in supply chain management is essential to equip them with the skills necessary to address shortages and enhance overall performance. Moreover, improving data quality and leveraging technology are crucial for enhancing decision-making, visibility, and responsiveness to supply chain disruptions. Strengthening relationships with suppliers and stakeholders can improve communication and coordination, fostering greater supply chain resilience. Policymakers are also advised to develop regulatory frameworks tailored to the pharmaceutical sector, addressing constraints that may hinder effective management. Additionally, implementing monitoring and evaluation systems will allow organizations to assess the effectiveness of their strategies and make data-driven improvements. Addressing barriers such as poor data quality and communication issues is vital for the success of these strategies. Encouraging collaborative planning and forecasting with stakeholders can further enhance the efficiency of the supply chain and reduce the risk of shortages. Lastly, adopting advanced technology and innovative forecasting techniques, such as machine learning, can improve demand forecasting accuracy, ensuring better access to essential medicines. By addressing these implications, the study provides actionable steps to enhance the resilience, efficiency, and responsiveness of Ethiopia's pharmaceutical supply chain.

6.6.3. Policy implications

This study suggests several policy implications to enhance supply chain management and mitigate drug shortages. First, investing in robust data management systems is essential. This includes implementing technology for efficient data collection and analysis, alongside mechanisms for gathering product-specific information to support more accurate and effective forecasting models. Policies should also prioritize human resource development by establishing training programs that build capacity in supply chain management.

Developing crisis management policies, including contingency plans, will better prepare the supply chain to handle drug shortages. Establishing governance structures and accountability mechanisms is critical to ensuring effective policy implementation and maintaining transparency.

Promoting research and development in supply chain practices and drug shortage solutions can support evidence-based policymaking. Public awareness campaigns are also valuable, fostering collaboration and emphasizing the importance of effective supply chain management. Finally, implementing frameworks for monitoring and evaluating supply chain policies and practices will enable continuous improvement, helping Ethiopia build a more resilient and efficient pharmaceutical supply chain.

6.7. Conclusions and recommendations

6.7.1. Conclusions

Findings from the present study have revealed that. The study highlight the significant challenges EPSS faces in forecasting, such as financial constraints, poor data quality, inadequate workforce, technological limitations, and weak stakeholder coordination. These issues hinder effective supply chain management, directly impacting healthcare delivery. The studies stress the need for strategic improvements, including better data management, workforce training, financial planning, and enhanced collaboration, all of which are essential for improving forecast accuracy and reliability.

The research also underscores the potential of simple forecasting models, like moving averages, and the importance of adopting a mixed-method approach tailored to the unique characteristics of pharmaceutical products to enhance accuracy and supply chain performance. Our findings highlight the importance of collecting and incorporating domain knowledge when building forecasting models. Proactive strategies, such as communication, stock assessments, and streamlined procurement, are crucial for preventing shortages, while reactive measures like safety stock are seen as temporary solutions. A balance between proactive and reactive approaches is recommended to ensure long-term supply chain resilience.

The studies call for further research to assess the effectiveness of these strategies and their impact on improving healthcare outcomes. For policymakers, prioritizing forecasting improvements is seen as critical to enhancing healthcare delivery. The conclusions emphasize that continuous evaluation and adaptation of strategies are necessary for overcoming drug shortages, improving supply chain management, and ultimately strengthening Ethiopia's healthcare system. We demonstrated that employing complex models does not necessarily lead to more accurate forecasts in the pharmaceutical supply context. Additionally, our research revealed that newly developed foundational time series forecasting models have potential applicability, particularly in environments where advanced analytical skills and knowledge are limited, as often seen in pharmaceutical supply chains in developing countries.

6.7.2. Recommendations

Based on the key findings and discussions, the following recommendations are made to improve forecasting and supply chain management in EPSS:

1. **Enhance Data Accuracy and Leverage Advanced Tools**: Implement real-time tracking tools at health facilities to improve data quality, and adopt advanced forecasting models, such as machine learning, along with domain knowledge integration. Utilizing sophisticated information systems and recording product history can further enhance forecasting accuracy and support better decision-making.
2. **Invest in Capacity Building and Collaboration**: Strengthen efforts to train healthcare professionals in forecasting, data management, and inventory control, while also fostering a coordinated approach among stakeholders. This will build a skilled workforce capable of addressing supply chain challenges and improve communication throughout the supply chain.
3. **Improve Financial Management and Policy Support**: Strengthen budget planning, ensure timely release of funds, and address financial constraints to support effective procurement. Advocate for policies that prioritize health supply chains, ensuring resources and support for sustainable improvements.
4. **Adopt Proactive and Contingency Strategies**: Implement proactive measures such as regular stock assessments, and establish clear contingency plans to mitigate potential shortages and disruptions in the supply chain.
5. **Continuous Monitoring and Feedback**: Establish ongoing assessment and adaptation of strategies, with active feedback mechanisms among stakeholders, to enhance responsiveness and optimize forecasting processes.
6. Pharmaceutical supply services systematically collect and maintains detailed records of events that may influence consumption, alongside consumption data. This practice is essential for refining demand models and enhancing forecast accuracy

6.7.3. Directions for further research

Based on the findings, we propose the following areas for future research to improve forecasting and supply chain management in the healthcare sector:

1. **Long-Term Impact and Comparative Analysis of Forecasting Strategies**: Conduct longitudinal studies to assess the long-term effects of different forecasting strategies on supply chain performance. Additionally, comparative studies with other countries facing similar challenges can help identify best practices that can be adapted to the Ethiopian context.

2. **Integration of Advanced Technologies and Crisis Management**: Explore how advanced technologies, such as artificial intelligence (AI) and machine learning, can enhance forecasting accuracy and supply chain resilience.
3. **Developing intelligent systems that incorporate domain-specific knowledge into model building**: Future research could focus on developing intelligent systems that incorporate domain-specific knowledge into model building. This would involve creating algorithms capable of identifying relevant domain insights and integrating them effectively into model training processes. Such tools would bridge the gap between purely data-driven approaches and expert-knowledge-enhanced modeling, leading to more robust and contextually informed forecasts.
4. **Exploring more granular forecasts**: While current study focuses on monthly aggregate consumption at the organizational level, there is potential in exploring more granular forecasts. Future research could investigate daily or weekly forecasting and examine the impacts at hierarchical levels, such as specific sites or health facilities. Investigating how fine-grained temporal and hierarchical forecasts influence inventory management and operational efficiency could yield valuable insights for reducing stockouts, minimizing costs and reducing waste.
5. **Training Programs and Stakeholder Collaboration Models**: Study the effectiveness of training programs designed to improve healthcare professionals' skills in forecasting, data management, and inventory control, and evaluate how these programs impact supply chain performance. Additionally, research models of stakeholder collaboration to identify best practices for enhancing communication and coordination across the supply chain.
6. **Financial Management and Supply Chain Effectiveness**: Investigate the relationship between financial management practices, such as budget planning and fund allocation, and their impact on forecasting accuracy and overall supply chain performance. This can inform strategies to improve financial management for better forecasting outcomes.
7. **Link between Forecasting Accuracy, Patient Outcomes, and Resilience**: Research the direct relationship between forecasting accuracy and patient outcomes, focusing on the availability of essential medicines. Additionally, study how forecasting improvements can enhance resilience in the supply chain during disruptions.

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PAPER I

Forecasting Accuracy and Performance of Pharmaceutical Demand forecasting in Ethiopian Pharmaceutical Supply Services

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Abstract

Background: Accurate forecasting is critical to ensuring that life-saving medicines are delivered to those in need. Dynamic and precise forecasting enables evidence-based planning and supports effective decision-making within pharmaceutical supply chains. Objective: This study aimed at assessing the forecast accuracy of pharmaceuticals within the Ethiopian Pharmaceutical Supply Services (EPSS). Methods: A retrospective time series analysis was conducted using five years of historical data (2018–2022) on forecasted and issued quantities of pharmaceuticals. Thirty-three essential pharmaceuticals were sampled purposively for analysis: 25 identified as key products by the Ethiopian Ministry of Health and 8 additional products chosen in consultation with EPSS experts. All selected items were included in the EPSS procurement list and had complete data records. Forecast accuracy was evaluated using point forecast metrics, including Root Mean Squared Error (RMSE), Symmetric Mean Absolute Percentage Error (sMAPE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Scaled Error (MASE). Results: The analysis revealed significant forecast inaccuracies across the selected products. Only 13 of the 33 products (40%) had MAPE values below 50%. Several high-priority items exhibited high MAPE and RMSE values. Furthermore, The MASE results revealed that 13 products (39.4%) exhibited forecast accuracy inferior to that of the naïve benchmark, indicating suboptimal model performance for those items. To explore alternatives, three basic forecasting models Naïve, Mean, and 3-Year Moving Average were tested. The 3-Year Moving Average model consistently achieved the lowest MAPE values for 18(54.54%) of the products, demonstrating its potential to enhance forecast accuracy. Conclusion: The study revealed that there were high forecast errors in the demand forecasting system of EPSS. The high degree of variability in forecast errors, along with limited model performance compared to naïve methods, underscores the urgent need for more data driven, context-sensitive, and methodologically advanced forecasting approaches.

Keywords: Forecasting, Naïve, Moving Average, Pharmaceuticals, Ethiopian

Introduction

Accurate demand forecasting is critical in health supply chains to ensure timely access to essential medicines and reduce stockouts and wastage. Forecasts support evidence-based planning, resource allocation, and inventory management, especially in resource constrained settings (Subramanian, 2021; Dey and Nath, 2013; Merkuryeva et al., 2019). Demand forecasting involves estimating future needs for products and serves as a foundation for operational decisions (Armstrong, 2001; Guo et al., 2017). Forecast accuracy is essential, as errors directly affect inventory systems and service delivery (Babai et al., 2019; do Rego and De Mesquita, 2015; Wang and Petropoulos, 2016).

Various forecasting methods exist from simple approaches like naïve and moving averages to advanced techniques such as exponential smoothing, regression, and machine learning (Hyndman and Athanasopoulos, 2018; Cerna et al., 2016; Seyedan and Mafakheri, 2020). Simple methods are often effective, serve as useful baselines, and are particularly valuable in low-resource settings due to their ease of use and interpretability (Kolassa et al., 2023). Forecasting performance is influenced by internal factors (e.g., staff capacity, system integration) and external factors (e.g., seasonality, uncertainty) (Merkuryeva et al., 2019; Candan et al., 2014). Poor forecasting contributes to stockouts, inefficiencies, and access barriers, particularly in developing countries with fragmented supply chains like Ethiopia (Yadav, 2015; Steele et al., 2019; Bilal et al., 2024).

In Ethiopia, the Ethiopian Pharmaceutical Supply Service (EPSS) manages national forecasting using centralized and decentralized methods. However, challenges persist, and studies focusing on forecasting accuracy within such settings remain limited (Adane & Ensermu, 2019; Tibebu et al., 2022). Forecast accuracy metrics assess how closely forecasts match actual demand. These include scale-dependent metrics (MAE, RMSE), percentage errors (MAPE, sMAPE), relative errors (MdRAE, GMRAE), and scale-free metrics like MASE (Hyndman & Koehler, 2006; Davydenko & Fildes, 2016). Each has advantages and limitations, and selecting the appropriate metric is context dependent. Simple forecasting methods are especially useful in environments with limited technical capacity. They are easy to implement, interpret, and adapt, making them suitable for pharmaceutical supply chains in low income countries. However, they may fall short when capturing complex patterns. The objectives of the study were to assess the forecast accuracy of various pharmaceuticals within the EPSS and to compare the performance of simple forecasting methods, namely naïve, mean, and moving average approaches.

Methods

Study design

This study employed a retrospective time series analysis to evaluate the forecast accuracy of selected pharmaceuticals within the EPSS. The analysis was based on five years of historical data, specifically the forecasted quantities and issued quantities of pharmaceuticals from 2018 to 2022.

Dataset and Sampling

This study included a total of 33 pharmaceuticals. The initial 25 key items were identified by the Ministry of Health based on their relevance to national assessments. An additional 8 pharmaceuticals were incorporated through consultations with EPSS experts; selected for their high importance, budget impact, and alignment with organizational priorities. Only products with complete data for the past five years (2018–2022) were included. All selected pharmaceuticals were, listed in EPSS procurement records, and had complete five-year data for both forecasted and issued quantities. The final selection covered a wide range of categories, including adult and paediatric medicines, cold chain products, and treatments for priority diseases.

Data Collection and Pre-processing

Forecast data (2018–2022) were obtained from EPSS quantification reports, while issued quantities were sourced from bin cards in the Health Commodity Management Information System (HCMIS). Stock-out days were also recorded. Data consistency and completeness were verified through cross-checks during transfer and entry. Quality control measures were applied throughout data collection, processing, and analysis.

Data Cleaning and Processing

Data were cleaned to resolve inconsistencies such as date formats and range alignment. Standardization to a uniform date format (yyyy-mm-dd), filtering by year, and removal of erroneous entries were performed. Product units were also standardized. The cleaned data were merged into a unified dataset, combining forecasted and issued quantities along with stock-out days for each product. And data were visualized and analysed by using R studio.

Forecasting methods

We applied simple forecasting methods namely Naïve forecast, Mean method, and 3 year moving averages.

The naive forecast

The *naive forecast*, also called the *no-change* or *random walk* forecast, forecasts the last observation across the future. The random walk model assumes that the best predictor of what will happen tomorrow is what happened today, and all previous history can be ignored (Nau, 2014). This is very simple and easy to understand and execute. Such a forecast will vary more daily than the historical mean: each time we see a new observation, the naive forecast can change radically. In contrast, the historical mean will be much less influenced by a single new observation. You can call this property of the naive forecast "high adaptivity‖ and consider it a feature or call it ―high variance‖ and consider it a bug – which perspective is more helpful depends on your forecasting environment (Kolassa, et al., 2023).

Mean method

Here, the forecasts of all future values are equal to the average (or ―mean‖) of the historical data. If we let the historical data be denoted by $y_1,,,,, y_T$, then we can write the forecasts as

$$\hat{y}_{T+h|T} = \bar{y} = (y_1+\ldots\ldots+y_T)/T$$

The notation $\hat{y}_{T+h|T}$ is a short hand for the estimate $\hat{y}_{T+h}$ based on the data $y_1,,,,, y_T$ (Hyndman and Athanasopoulos, 2018).

SIMPLE MOVING AVERAGES

The mean model assumes that the best predictor of what will happen tomorrow is the average of everything that has happened up until now. The random walk model assumes that the best predictor of what will happen tomorrow is what happened today, and all previous history can be ignored. Intuitively, there is a spectrum of possibilities between these two extremes. Why not take an average of what has happened in some window of the recent past? That is the concept of a "moving" average (Nau, 2014). A moving-average model is likely superior to the mean model in adapting to the cyclical pattern and superior to the random walk model in not being too sensitive to random shocks from one period to the next. There are several different ways in which a moving average might be computed, but the most obvious is to take a simple average of the most recent m values for some integer m. This is the so-called simple moving average model (SMA), and its equation for predicting the value of Y at time t+1 based on data up to time t is:

$$\dot{Y}t_{+1} = \frac{Y_t + Y_t - 1 + \cdots + Y_{t\_m} + 1}{m}$$

The SMA model has the following characteristic properties. First, each of the past m observations gets a weight of 1/m in the averaging formula, so as m gets larger, each observation in the recent past receives less weight. This implies that larger values of m will filter out more period-to-period noise and yield a smoother-looking series of forecasts. Second, the first term in the average is "1 period old" relative to the point in time for which the forecast is being calculated, the second term is two periods old, and so on up to the third term. Hence, the "average age" of the data in the forecast is (m+1)/2. This is how the forecasts will lag in following trends or responding to turning points. For example, with m=5, the average age is 3, so that is the number of periods by which forecasts will tend to lag what is happening now. Interest is resurgent, and the use of the simple moving average (SMA) has become apparent. Sanders and Manrodt surveyed forecasting practices in US corporations and found moving averages to be the most familiar and used quantitative technique (Sanders and Manrodt, 1994). Sani and Kingsman found that SMA may lower inventory costs (Sani and Kingsman, 1997).

Performance evaluation

To evaluate the performance of the various forecasting approaches, we have used different point forecast measures, as that of Scaled errors, scale dependent errors and Percentage error namely the Mean Absolute Percentage Error (MAPE) and the symmetric Mean Absolute Percentage Error (sMAPE). We also used scale dependent error measures like that of RMSE and scaled error measures like that of MASE. While we acknowledge the disadvantages of these error measures as MAPE can be problematic when actual values are close to zero, leading to skewed distributions, (Hyndman and Koehler, 2006; Goodwin and Lawton, 1999) we believe that their inclusion is necessary given their popularity in practice. The formula used to compute MAPE was as follows as it was proposed by (Hyndman and Athanasopoulos, 2018)

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n} \left|\frac{Actuals_t - Forecasted\_t}{Actuals_t}\right|$$

Where **n** is the number of times forecasting and actual demand are compared for an item.
Based on the Lewis MAPE scale of judgment for forecast errors, forecasts with MAPE of 0-10% were considered highly accurate, 11-20% good, 21-50% reasonable, and 51% Inaccurate (Lawrence, et al .,2009). Forecasting accuracy was calculated by Subtracting MAPE from 100. For items with negative forecasting accuracy results, forecasting accuracy is assumed to be zero.

The Symmetric Mean Absolute Percentage Error (SMAPE) is a measure commonly used to evaluate the accuracy of forecasting models. SMAPE provides a symmetric and percentage-based measure of the forecast error, making it suitable for comparing forecast accuracy across different time series data sets. It is particularly useful when dealing with data that contains zero or near-zero values, as it avoids division by zero issues that can occur with other error metrics. SMAPE values typically range from 0% to 200%, where a lower SMAPE value indicates better forecast accuracy, with 0% representing a perfect forecast.

Interpretation:

- SMAPE values below 10%: Considered excellent, indicating a high level of accuracy in the forecasts.
- SMAPE values between 10% and 20%: Generally acceptable for many forecasting applications.
- SMAPE values above 20%: May suggest that the forecasts have significant errors and room for improvement.

To calculate the SMAPE, we use the formula it was proposed by (Hyndman and Athanasopoulos, 2018).

$$sMAPE = mean(200|Yt - Ft\ |/(Yt + Ft\ ))$$

Scale-dependent errors

The forecast errors are on the same scale as the data. Accuracy measures that are based only on et are therefore scale-dependent and cannot be used to make comparisons between series that involve different units.

The most commonly used scale-dependent measures are based on the absolute errors or squared errors: We have also applied Root mean squared error: it was proposed by (Hyndman and Athanasopoulos, 2018) root mean squared error is the most common standard of goodness-of-fit, penalizes big errors relatively more than small errors because it squares them first; it is approximately the standard deviation of the errors if the mean error is close to zero Where the formula for RMSE is

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n} ei^2}$$

Consequently, the RMSE is also widely used, despite being more difficult to interpret (Hyndman and Athanasopoulos, 2018).

The Mean Absolute Scaled Error (MASE) is a measure of forecast accuracy proposed by Hyndman and Koehler in the paper. It is calculated as the mean of the absolute values of scaled forecast errors.

Specifically, the forecast errors are scaled by the in-sample mean absolute error (MAE) obtained from a naïve forecasting method, typically a one-step naïve forecast. This scaling makes MASE interpretable and comparable across different time series, even if they have different scales or contain zeros or negative values.

Scaled errors

Scaled errors were proposed by Hyndman & Koehler (2006) as an alternative to using percentage errors when comparing forecast accuracy across series with different units. They proposed scaling the errors based on the *training* MAE from a simple forecast method. For a non-seasonal time series, a useful way to define a scaled error uses naïve forecasts:

$$q_t = \frac{e_t}{\frac{1}{n-1}\sum_{i=2}^{n}|Y_i - Y_{i-1}|}$$

Because the numerator and denominator both involve values on the scale of the original data, qj is independent of the scale of the data. A scaled error is less than one if it arises from a better forecast than the average one-step naïve forecast computed on the training data. Conversely, it is greater than one if the forecast is worse than the average one-step naïve forecast computed on the training data.

The Mean Absolute Scaled Error is simply

$$\text{MASE} = \text{mean}(|q_t|).$$

RESULTS

Figure 1 displays time series plots comparing forecasted and issued quantities for nine pharmaceutical items (out of a total of 33) between the years 2010 and 2014 (Ethiopian Calendar). The products are grouped by programme type: *RDF* (Revolving Drug Fund) and *Programme*, with quantities disaggregated by year. The red line represents forecasted quantities, while the blue line depicts issued quantities.

The visualization highlights a recurring mismatch between forecasted and actual issued quantities across multiple products and years. For instance, in *Malaria Rapid Diagnostic Test*, and *Artemether + Lumefantrine*, issued quantities sharply exceeded forecasts, particularly in the earlier years, suggesting substantial under-forecasting. Conversely, products like Oxytocin, Ringer's *Solution* and *Magnesium Sulphate* exhibit consistent over-forecasting, where forecasted quantities surpass the quantities issued. The plots also reveal considerable inter-annual fluctuations, such as in *Lidocaine Injection* and *RHZ*, where issued quantities spike in certain years compared to relatively stable forecasted values, pointing to sudden surges in demand not captured by forecasts. In contrast, *Amoxicillin* and *Amlodipine* show moderate trends with closer alignment between forecasts and actuals, although discrepancies still persist (Figure 1).

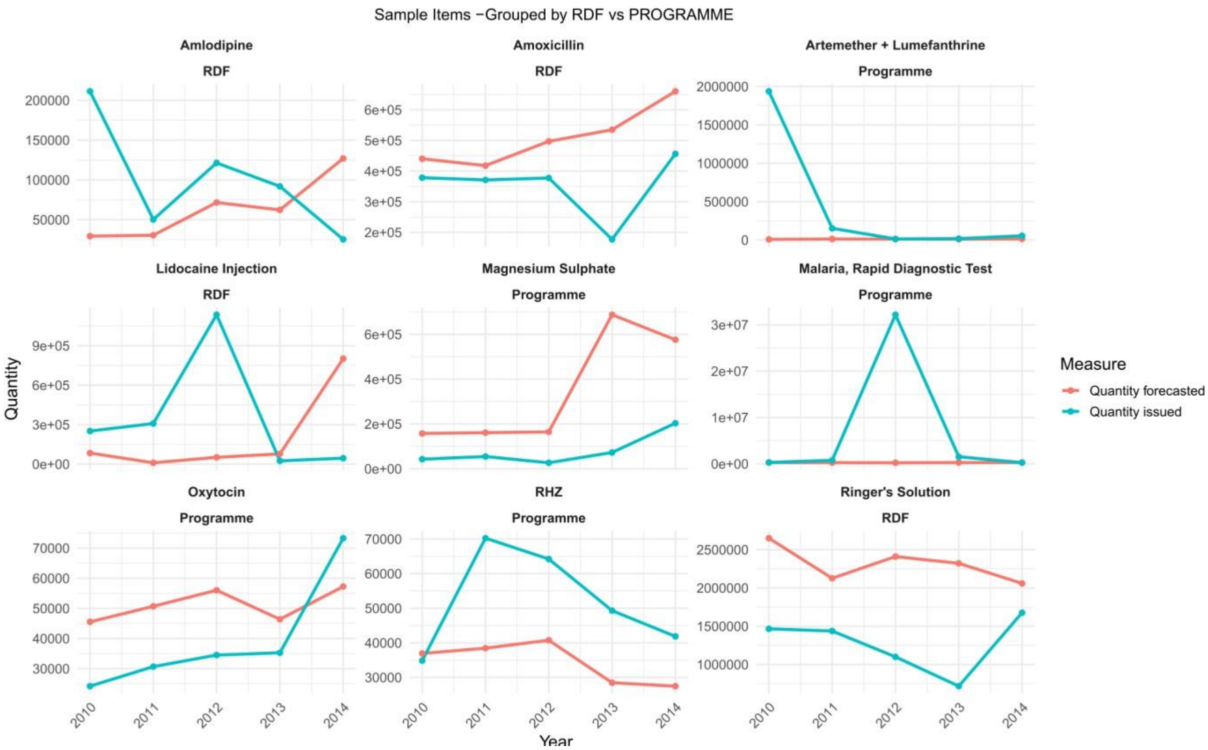

Figure 1: Time Series of Forecasted vs Issued Quantities for Selected Pharmaceuticals by Programme Type (2010–2014 E.C). The panels display data from nine products to give a glimpse of the forecasted and issued quantity patterns.

Difference between Issued and Forecasted Quantities by Year and Programme Type

Figure 2 displays a series of bar charts illustrating the annual differences between issued and forecasted quantities for 33 pharmaceuticals over a five-year period (2010–2014). Each subplot represents a specific pharmaceutical, showing whether the product was over- or under-forecasted in each year. Positive values on the vertical axis indicate under-forecasting, where the quantity issued exceeded the forecast, while negative values indicate over-forecasting, where less was issued than anticipated. The red bar representing program drugs and blue indicating those under the RDF. The visualization reveals considerable variation in forecasting accuracy. Pharmaceuticals such as Ferrous Sulphate + Folic Acid, and Metronidazole were significantly under-forecasted across multiple years, suggesting persistent underestimation of demand. In contrast, drugs like Magnesium Sulphate, Omeprazole Injection, and Medroxyprogesterone Acetate show consistent over-forecasting, indicating recurring overestimation.

A few drugs, such as Amoxicillin and Sodium Chloride, display fluctuating patterns, alternating between over- and under-forecasting. Notably, Propylthiouracil and Pentavalent show substantial discrepancies, reflecting major forecasting errors for these high-priority items. Overall, the figure highlights systemic challenges in accurately predicting pharmaceutical demand within EPSS, with potential consequences for both stockouts and overstocking (Figure 2).

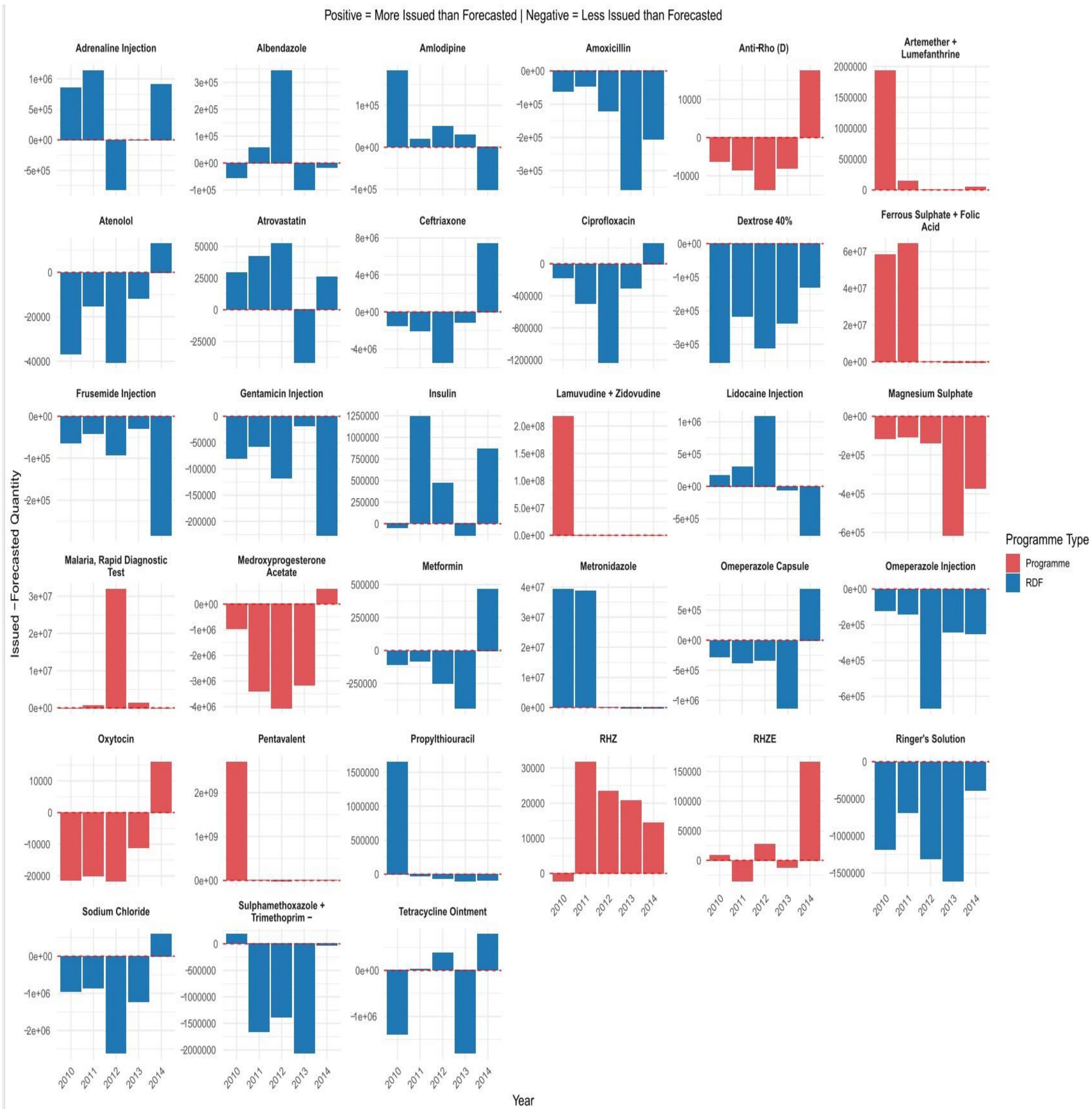

Figure 2: Forecasted and Issued pharmaceuticals Quantities for Selected Pharmaceuticals in EPSS from 2010–2014 EC.

Forecast Accuracy Analysis across Products

Table 1 summarizes forecast accuracy metrics for each of the 33 pharmaceutical items assessed over a five-year period. The metrics include MAPE, sMAPE, MASE, and RMSE, which provide complementary perspectives on forecast performance (Table 1).

Table 1: Forecast accuracy measures of Key Pharmaceuticals for the year 2018-2022 in EPSS.

Item	RMSE	MAPE	sMAPE	MASE
Sodium Chloride	1434833	23	26	1.3
Medroxyprogesterone Acetate	2795159	23	27	0.7
Amoxicillin	194942	29	38	1.3
Tetracycline Ointment	1090070	32	40	0.7
Anti-Rho (D)	11578	33	36	0.9
Oxytocin	18441	35	42	1.5
Atenolol	26557	36	45	1.2
Ceftriaxone	4282272	36	38	0.8
RHZE	77283	39	28	0.6
Ringer's Solution	1124067	44	59	2.4
Ciprofloxacin	623837	46	66	1.0
Sulphamethoxazole + Trimethoprim	1338894	47	77	0.8
Metformin	312540	49	58	0.9
RHZ	21016	54	41	1.2
Omeperazole Capsule	681884	55	75	0.9
Omeperazole Injection	345532	64	101	4.0
Gentamicin Injection	122550	70	116	6.5
Dextrose 40%	261630	72	119	3.8
Frusemide Injection	138203	73	118	11.6
Magnesium Sulphate	334703	75	123	5.0
Atrovastatin	39386	84	58	0.7
Albendazole	163524	116	92	0.5
Insulin	712739	163	60	0.8
Amlodipine	97134	176	85	0.9
Adrenaline Injection	838807	218	90	1.0
Propylthiouracil	743866	425	76	0.9
Lidocaine Injection	611069	1099	150	0.9
Malaria, Rapid Diagnostic Test	14297183	3052	90	0.4
Artemether + Lumefanthrine	864791	5075	110	0.9
Ferrous Sulphate + Folic Acid	38737634	5490	111	1.4
Pentavalent	1209729219	5556	62	0.8
Lamuvudine + Zidovudine	97449671	5670	59	0.8
Metronidazole	24736898	7604	132	1.6

An in-depth evaluation of the forecast accuracy across 33 pharmaceutical items was conducted using four standard metrics: Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage

Error (sMAPE), Root Mean Square Error (RMSE), and Mean Absolute Scaled Error (MASE). The results reveal considerable variability in forecasting performance across different products. Notably, MAPE values, which measure the average magnitude of forecasting errors as a percentage, vary widely. The lowest MAPE value were obtained for Sodium chloride solution and Medroxyprogesterone Acetate with the MAPE value of 23%.And those products with MAPE value of less than 50% were 13(40%). In contrast, items like Metronidazole and Ferrous Sulphate + Folic Acid exhibited extremely high MAPE values, suggesting persistent over- or under-forecasting.

The RMSE values further underscore the magnitude of absolute forecasting errors. High-volume items, including Pentavalent vaccines, Metrondazoe capusles and Malaria, Rapid Diagnostic Test, showed particularly large RMSE values, indicating that the models failed to capture actual demand fluctuations accurately. The sMAPE values, which provide a balanced view of forecast accuracy by accounting for both forecasted and actual values, also varied considerably. For example, products like Nevirapine and Zinc Sulphate exhibited sMAPE values below 50%, suggesting relatively balanced and symmetric forecasting performance, while others like Metronidazole showed values well above 100%, indicative of extreme disparities between forecasted and actual values.

MASE was used to compare the performance of the forecasting models against a naïve baseline forecast. Values below 1 indicate that the model performed better than a simple naïve approach. Only a few products, including Nevirapine and Zinc Sulphate, achieved MASE values below 1. The majority of items had MASE values greater than 1, revealing that the forecasting approaches applied may not have consistently outperformed naive models, thereby calling into question the robustness of current methods.

Application of simple forecasting methods

In this analysis, three simple forecasting methods—Naïve, Mean, and 3-Year Moving Average (MA3) were applied to the data set, with forecast accuracy assessed using the Mean Absolute Percentage Error (MAPE). The results demonstrate that the 3-year moving average method consistently outperformed the other two methods in most cases, yielding the lowest MAPE values for a majority of the products. For instance, Sodium Chloride, Oxytocin, and Frusemide Injection showed MAPE values of 9%, 11%, and 11% respectively under MA3, significantly lower than the errors produced by the naïve and mean methods. This suggests that the moving average method is particularly effective for items with stable or gradually changing demand patterns (Table 2).

Table 2: Mean Absolute Percentage Error of Key Pharmaceuticals for 2018-2022 in EPSS using Naïve, Mean and 3 year Moving Average Forecasting Models.

Item	**Naïve MAPE**	**Mean MAPE**	**3 year moving averages MAPE**
Sodium Chloride	17	23	9
Oxytocin	22	33	11
Frusemide Injection	31	25	11
RHZ	27	25	12
Medroxyprogesterone Acetate	44	23	13
RHZE	46	34	13
Anti-Rho (D)	31	52	15

Atenolol	45	33	16
Insulin	53	36	17
Tetracycline Ointment	45	52	17
Atrovastatin	55	45	20
Amoxicillin	45	28	20
Ringer's Solution	36	28	21
Ceftriaxone	40	51	21
Ciprofloxacin	67	74	22
Metformin	49	75	24
Magnesium Sulphate	64	81	27
Amlodipine	169	95	45
Adrenaline Injection	114	67	51
Omeperazole Injection	140	65	58
Sulphamethoxazole + Trimethoprim -	221	193	66
Dextrose 40%	122	105	73
Gentamicin Injection	280	177	129
Propylthiouracil	648	334	172
Omeperazole Capsule	424	437	208
Albendazole	815	298	298
Lidocaine Injection	1161	429	546
Malaria, Rapid Diagnostic Test	670	1258	1017
Artemether + Lumefanthrine	572	1291	1074
Pentavalent	7956	5080	2384
Ferrous Sulphate + Folic Acid	2591	3789	2647
Lamuvudine + Zidovudine	10340	10375	4882
Metronidazole	6626	19449	15082

The performance of the naïve and mean methods varied depending on the item. In certain cases, such as RHZ and Medroxyprogesterone Acetate, the mean method showed better accuracy than the naïve approach. In contrast, for items like Amoxicillin and Atenolol, the naïve methods yielded better results.

However, a number of items displayed very high MAPE values across all three methods, indicating erratic and unpredictable demand patterns. For example, Pentavalent , Ferrous Sulphate + Folic Acid, Lamuvudine + Zidovudine and Metronidazole had exceptionally high MAPE values, even with the moving average method, suggesting that these products are influenced by complex factors such as programmatic interventions, stockouts, or irregular supply schedules. For such products, simple forecasting methods are inadequate, and more sophisticated techniques such as exponential smoothing, ARIMA models or machine learning approaches may be necessary to improve forecast accuracy. Overall, while the 3-year moving average method generally offered the best accuracy among the simple methods.

DISCUSSIONS

EPSS was established to ensure a sustainable supply of quality-assured essential pharmaceuticals to health facilities at affordable prices for Ethiopian citizens (FDRE, 2022). However, there have been challenges in making these pharmaceuticals accessible to the people of Ethiopia (FDRE, 2022). Moreover, EPSS faces issues such as lack of financing, workforce skills, poor coordination, data quality problems, and end-to-end visibility (Bilal, et al., 2024). These problems largely stem from data quality issues, leading to poor forecasting. Demand forecasts form the basis of all logistics and supply chain management decisions. Demand forecasting is the starting point for all planning activities and execution processes. All supply chain activities, including procurement, production, transportation, and operations, require demand forecasts to plan necessary levels of activity and inventory, with customer demand data being the starting point (Merkuryeva, et al.,2019).

The findings highlight a substantial gap between forecasted and actual issued quantities, with wide ranging discrepancies observed across product types, program categories, and years. These patterns of under and overestimation suggest that the current forecasting methods are insufficiently responsive to demand variability. The forecast accuracy metrics indicated that there is a high forecast error for a majority of products. Only 13 out of 33 items had MAPE values below 50%, a commonly used benchmark for acceptable forecast performance in health supply chains. The RMSE values for high-volume items such as Pentavalent and malaria commodities further underscore the magnitude of absolute errors in the system. These errors are not merely statistical anomalies—they represent real operational risks in terms of stockouts, wastage, or delayed treatment in the healthcare system.Such kind of high forecast error was also reported by other studies conducted in EPSS (Adane and Ensermu, 2019; Tibebu et al., 2022). Overall, the inconsistency in demand forecasting accuracy, with both underestimation and overestimation observed across product types and programme categories. If such discrepancies, unaddressed, could lead to supply chain inefficiencies including stock outs or overstocking, particularly within essential medicines and public health programmes.

Additionally, the MASE values suggest that for most items, the applied forecasting approaches did not outperform a naïve baseline forecast. This is a critical finding, as it questions the value added by existing forecasting techniques and signals the need for a shift toward more robust and adaptive models. Moreover, the disparity in forecast performance between RDF items and program drugs suggests that governance and data flow differences across procurement mechanisms may influence forecasting accuracy. The application of three simple forecasting methods (Naïve, Mean, and 3-Year Moving Average) to the data set indicated that a 3-Year Moving Average method consistently achieved lower MAPE values for most of the pharmaceuticals, particularly for products such as Sodium Chloride and Oxytocin. However, this method still performed poorly items like Ferrous Sulphate + Folic Acid and Metronidazole, suggesting that simple historical averaging alone is insufficient for managing these items. Similar findings were also reported by Tibebu et al. (2022), where moving average methods produced more accurate forecasts, with 86.7% of items having better forecast accuracy. Collectively, the results demonstrate substantial inconsistency in forecast accuracy across products and suggest the need for differentiated forecasting strategies. Items with high usage volumes and those with wide seasonal or programmatic variability may benefit from tailored models that incorporate disease burden trends, stockout history, and contextual programmatic shifts. These findings highlight the importance of improving data inputs, applying advanced modeling techniques, and strengthening forecast governance to ensure better alignment between projected and actual pharmaceutical needs.

Limitations

In this study, we used EPSS central issue data as a proxy for health facility-level consumption, as it was not feasible to collect actual consumption data from more than 4,000 facilities. We recognize that this approach may not fully reflect true end-user demand and could affect the accuracy of our findings. Additionally, a purposive (non-probability) sampling strategy was employed to select 33 pharmaceuticals based on data availability and prioritization criteria. This limits the generalizability of the findings across the entire portfolio of over 2,000 products managed by EPSS. However, we believe that the selected products provide meaningful insight into forecast accuracy for high-priority items.

The study also relied on retrospective data, which may be subject to data quality issues, including inconsistencies in recording and reporting. Despite efforts to ensure data completeness and reliability, retrospective data collection has inherent limitations. Furthermore, the analysis focused on forecasting accuracy only, without examining the underlying causes of forecast errors, such as supply chain interruptions, shifts in disease burden, or policy changes. Lastly, the study‘s scope is limited to the EPSS system and cannot be generalized to other institutions or pharmaceutical categories not included in the analysis. We recommend that future research adopt probability-based sampling and formal sample size determination methods to enhance generalizability and explore broader drivers of forecast performance.

CONCLUSIONS

In conclusion, the study revealed that there were high forecast errors in the demand forecasting system of EPSS. The high degree of variability in forecast errors, along with limited model performance compared to naïve methods, underscores the urgent need for more data-driven, context-sensitive, and methodologically advanced forecasting approaches. Strengthening both the technical and institutional components of the forecasting system is critical to ensuring reliable pharmaceutical availability and enhancing the resilience of Ethiopia‘s public health supply chain. The study recommends that EPSS revise its current forecasting methods and tailored to the specific characteristics of pharmaceutical products. By doing so, EPSS can enhance its ability to predict demand accurately, reduce the occurrence of shortages, and ensure the availability of essential medicines for the population. These improvements in forecasting accuracy have the potential to impact healthcare delivery and contribute to improved patient outcomes positively. We also recommend conducting similar research in different EPSS hubs and future research exploring advanced forecasting techniques.

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PAPER II

pharmacy

MDPI

Article

Challenges and the Way Forward in Demand-Forecasting Practices within the Ethiopian Public Pharmaceutical Supply Chain

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Abstract: This study delves into the challenges of pharmaceutical forecasting within the Ethiopian public pharmaceutical supply chain, which is vital for ensuring medicine availability and optimizing healthcare delivery. t It aims to identify and analyze key hindrances to pharmaceutical forecasting in Ethiopia, employing qualitative analysis through semi-structured interviews with stakeholders. Thematic analysis using NVIVO 14 software reveals challenges including finance-related constraints, workforce shortages, and data quality issues. Financial challenges arise from funding uncertainties, causing delayed procurement and stockouts. Workforce shortages hinder accurate forecasting, while data quality issues result from incomplete and untimely reporting. Recommendations include prioritizing healthcare financing, investing in workforce development, and improving data quality through technological advancements and enhanced coordination among stakeholders.

Keywords: challenges; data quality; finance; forecasting; workforce

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1. Introduction

Forecasting is about predicting future events based on a foreknowledge acquired through a systematic process or intuition [1,2]. Forecasting is important to ensure an uninterrupted supply of essential medicines. Demand forecasting in a health supply chain is defined as the continuing process of projecting which health commodity will be purchased, where, when, by whom, and in what quantities [3]. Demand forecasting is a well-developed scientific discipline but has not been fully used in improving health supply chains in Africa. As a result, supply chains that serve patients in Africa remain weak and ineffective, putting treatment programs at risk, and weakening the overall health system's ability to respond to the healthcare needs of the population [4–8]. Even though there has been significant support for addressing global health issues such as HIV/AIDS, malaria, and TB in developing countries during the last decade, the availability of medicines remains very poor in public health facilities [9,10].

There are many problems in global health supply chains, including fragile last-mile delivery, human resource challenges, fewer opportunities for research and development, problems in procurement and forecasting, and the lack of an accountability structure [11–13]. These problems are more exacerbated in Africa due to the inefficient use of scarce resources, stockouts, corruption, product diversion, or poor last-mile delivery, leading to reduced health outcomes. These problems are exacerbated by the lack of accountability and fragmented leadership, making it easier to pass on the blame and create strong incentives for corruption [6]. Moreover, the continent also suffers from poor forecasting skills of health supply chain professionals, requiring better allocation of resources for capacity building and development [14].

Poor demand forecasting is a key driver of stockouts and raises the risk of substandard medicines entering the health system [15]. Forecasting challenges vary based on the nature and extent of risks faced by various stakeholders of health supply chains [16]. Some of these risks are emerging features such as change in disease burdens, complicated international markets, dynamic patient needs, new products, and advanced health technologies. The asymmetry of these risks can create missed opportunities for health supply chain stakeholders and hamper access to healthcare [17]. In addition, demand forecasting of healthcare commodities depends on exogenous factors such as the availability of data on disease burden or cultural and demographic influences. Moreover, weak budgets and budgetary constraints can impact contractual obligations, especially in a resource-constrained set-up. This vulnerability will impact demand forecasting, thereby creating gaps in the scientific and financial pipeline. The uncertainty of grant approval, complexity of disbursal cycles, and the sustainability of funding health commodities are unique risks embodying health supply chains.

In the decision-making process, forecasts could be considered the cornerstones of effective strategies, since the data gathered from them scan either enhance or thwart the organization's survival. There are multiple models of forecasting, and the various stakeholders must seriously consider which approach will provide the best information and the right guidance towards implementing that information successfully. Also, the quality of forecasting tools impacts the ability to gather adequate data about the future demands and trends [18]. The healthcare sector is continually evolving, which presents both opportunities and threats. It is difficult to standardize forecasting tools since health demands often differ due to factors such as patient experiences, resource allocation, disease burden, leadership. Appropriate forecasting tools will determine projections based on identified business drivers, influencing factors, and business constraints [19]. Moreover, the selection of forecasting methods depends on the availability of data, volatility of demand, and maturity of products [20]. Therefore, this study tries to identify what the challenges of forecasting practice are in the Ethiopian Pharmaceutical Supply Services (EPSS) and to provide strategies for mitigating the challenges related to forecasting practice.

2. Literature Review

2.1. Challenges in Pharmaceutical Forecasting

One of the weakest links in global health supply chains is demand forecasting of health commodities. Many of the health supply chain bottlenecks impede accurate demand forecasting, and without the accurate demand forecasts, market viability, production capacity, and financial commitments become challenging. National governments and the international donor community rely on forecasts for budgeting while implementing partners and health programs depend on forecasts to plan their health supply chain logistics [18].

The challenges of demand forecasting in public health systems in Africa include limited funding, poor infrastructure, and lack of skilled personnel, which can hinder the implementation and maintenance of demand-forecasting systems [21]. Moreover, the challenges of unreliable data are also another issue; data collection for demand forecasting may be challenging in Africa due to issues such as incomplete or inaccurate data, lack of standardized data collection methods, and limited access to real-time information. Moreover, forecasting new health commodities is difficult due to uncertainties in how breakthrough healthcare technologies and products will be accepted by consumers [18]. There is a lack of information gathering to inform procurement and supply decisions. While health facilities see real demand daily, it is most often logged in a paper-based system and not shared with other levels of the supply chain [22].

The engagement and support of leadership at various levels of the health system are crucial for the successful implementation of demand-forecasting systems in Africa. A lack of accountability and fragmented leadership can create challenges in demand forecasting and supply chain management [6]. The current system of health delivery is siloed, fragmented, and uncoordinated; this lack of coordination will affect forecasting as well as the whole supply chain [22]. The lack of qualified personnel leads to high workloads and low performance while leaving key duties unattended. In fact, there are often insufficient trained supply chain staff at warehouses and health facilities to perform even basic duties [22,23]. High workloads, lack of training, deficient facilities, poor working conditions, and inadequate pay not only affect employees' ability to perform their jobs but also affect morale and turnover [22,23]. Moreover, the quality of forecasting tools impacts the ability to gather adequate data about future demands and trends [18]. Shifting disease burdens, dynamic patient needs, and new products in complex international markets contribute to forecasting challenges [17]. Challenges such as stockouts, corruption, and product diversion can lead to reduced health outcomes and impact demand forecasting [7]. Resource-constrained settings face major logistic challenges in forecasting demand for health commodities [18]. Limited information on how risks are allocated and incentives are aligned among stakeholders can impact demand forecasting in health supply chains. Healthcare organizations often operate within budget constraints, which can impact their ability to accurately forecast and meet the demand for medical technologies [24]. The robustness of health forecasting tools has also been mentioned as one of the challenges in health forecasting's [25].

The pharmaceutical industry's demand forecasting often relies on simplistic statistical methods using historical data which fail to capture complexities influenced by economic conditions, regulatory changes, market competition, special contracts, and media attention. Addressing these complexities requires advanced models incorporating extensive data and industry expertise [26]. Demand sensing has emerged to consider these factors, highlighting the need for sophisticated forecasting approaches [27]. Simple time series models assume future demand depends only on past trends, neglecting these multifaceted influences. Maroun et al. categorized forecasting challenges as internal and external. Internal challenges arise within the organization and include employee, management, communication, and cultural issues, hindering information sharing and collaboration, thus affecting forecasting accuracy. External challenges such as market dynamics, customer behavior, and supplier relationships come from outside the organization, introducing uncertainties and market fluctuations. Internal challenges impact organizational processes, while external challenges are driven by market forces and environmental factors [28].

Traditional statistical models like exponential smoothing have become inadequate in dynamic and volatile post-2020 environments. Forecasting in such uncertain settings is challenging due to the complex and evolving data requirements, often termed as a "wicked problem" [29–31]. Unforeseen events like the COVID-19 pandemic can disrupt forecasting accuracy, resulting in shortages and excess inventory [32]. Despite advancements in analytics and Artificial Intelligence (AI), quantitative forecasting models may struggle to handle the complexity of changing data requirements. While machine learning methods are valuable, human interpretation, context awareness, experience, intuition, and creativity remain essential for detecting non-trivial patterns in forecasting [33,34]. This highlights "Moravec's Paradox", where human judgement and analytics possess unique strengths and weaknesses [35–40]. An ideal forecasting methodology integrates both judgmental and statistical approaches, leveraging collective intelligence to enhance accuracy [37,41,42]. Demand uncertainty, which is small variations in patient demand at health clinics, can lead to significant fluctuations in order quantities throughout the supply chain, resulting in stockouts or excess inventory. Ineffective and limited forecasting capabilities due to imprecise forecasts in procurement planning can result in stockouts or product expiration [6].

2.2. Enablers That Can Enhance Demand-Forecasting Practices in Health Supply Chains

Enabling factors for improved demand forecasting in health supply chains encompass access to accurate consumer data, reliable sources, and data quality assurance [43]. Public–private partnerships and collaboration enhance forecasting by pooling resources and expertise [44]. Investment in skilled personnel and transparent regulatory frameworks bolsters forecasting capabilities and reduces risks [45]. Information sharing among stakeholders and utilization of technologies such as data analytics enhance efficiency and accuracy [18]. Integrated IT systems streamline processes and mitigate errors in forecasting [28].

Involving key stakeholders improves forecasting outcomes, while continuous monitoring and evaluation enhance accuracy [43]. Standardized approaches ensure consistency in health forecasting, facilitating comprehensive implementation and optimal resource utilization [22]. However, achieving coordination poses challenges due to diverse actor priorities [6,46]. Enhanced communication within organizations fosters better coordination in demand forecasting [28].

Encouraging data-driven adjustments reduces bias and enhances forecast accuracy, with past adjustments informing future decisions to minimize biases. Considering external factors enhances demand predictions, ultimately enhancing organizations' ability to forecast uncertain demand effectively and overcome challenges [28]. This study aims to identify demand-forecasting challenges in Ethiopian public pharmaceutical supply chains and propose strategies for their alleviation, addressing the following research questions: (1) identifying prevailing challenges in demand forecasting; and (2) suggesting effective strategies to mitigate these challenges.

3. Methods

3.1. Research Design

This study utilizes a cross-sectional case study research design to assess the challenges of the pharmaceutical forecasting practice in the EPSS.

3.2. The Context

EPSS plays a pivotal role in providing quality pharmaceuticals to public health facilities across Ethiopia, serving a population of 105 million through 19 branch warehouses and over 3800 health facilities [47,48]. EPSS manages an annual turnover of nearly USD 1 billion, overseeing the procurement, warehousing, and distribution of pharmaceuticals and medical supplies [48].

Despite its significance, EPSS faces challenges such as inaccurate drug forecasting, and procurement delays compounded by data quality issues and communication gaps within EPSS [49]. A study identified human, financial, infrastructure, and technological challenges within the pharmaceutical supply chain [50]. EPSS struggles with systemic weaknesses, including inadequate demand planning, equipment management, and information systems [48].

A SWOT analysis highlighted concerns such as low customer satisfaction, weak supplier relationships, inventory management issues, and distribution planning deficiencies. Addressing these challenges necessitates efforts to enhance forecasting, procurement, data quality, and overall supply chain management. EPSS operates two pharmaceutical supply streams: the Revolving Drug Fund (RDF) and program pharmaceuticals. RDF quantification begins at health facilities, with requirements consolidated at EPSS branches and centrally. Program commodities are quantified centrally, with supply plans based on forecasting outputs [48].

3.3. Reflexivity

All authors of this study were not part of the EPSS. Three of team members (A.B., T.G., and U.S.) had extensive experience and expertise in qualitative research methodology. The interviews were conducted by one of the local authors (A.B.). The authors had previous training in and a good understanding of the study context and values; they performed the transcription and crosschecked the contents embedded in the translation. An initial analysis of potential informants was discussed by the authors, and schedules were created to carry out the interviews at the participants' offices.

3.4. Participants

A maximum variation sampling method was considered to recruit a representative number of participants from all regions of the country. Health professionals and top management members involved in health supply chain services, forecasting, and decision-making at the hospital level as well as the regional level were purposely selected to ensure that appropriate informants would provide rich study data. A total of 17 interviews were conducted with professionals from different sectors which have a direct or indirect relation to pharmaceutical forecasting practices. Accordingly, nine in-depth interview participants were from regional health bureaus and worked either in leadership or in health services and had direct contact with regional forecasting activities. Health facilities located in potentially eligible regions were contacted. Participants were requested to consent to being included in this study. Four interview participants were from the EPSS, where they are directly working with forecasting units and perform forecasting-related activities. Further, we included two participants form partner organizations who had direct roles in forecasting activities or supported these activities. Two interview participants were from the Ministry of Health and had a direct role in coordinating as well as monitoring forecasting activities at the Ministry of Health of Ethiopia. To ensure the anonymity of study subjects during analysis, each participant's identifier was either coded with labels or altered.

3.5. Data Collection Methods and Procedures

A semi-structured interview guide was developed and used for all the interviews. Following identification and consent, informants were approached on the scheduled dates to freely share their opinions. Interviewers had no direct connection with the interviewees, but were immersed in the situation so as to prevent interviewees from feeling evaluated, coerced, or that they were risking something by taking part in this study. At times, participants shared their experience over the course of the study with the researchers. They were also amicably informed that they would be part of this investigation as appropriate personnel in the healthcare setting. The phenomenon of interest in this study was the challenges of forecasting practice in the Ethiopian public supply chain system. The following questions were asked: "How do you see the health supply chain in Ethiopia and in particular in EPSS", "What are the factors which affect the availability of pharmaceuticals in Ethiopia and in particular with EPSS?" Further questions and probes to help participants elaborate on their views and on the facets that shaped them were also raised. Among others, these included the following: "Explain the problems in forecasting and ask why there is huge forecasting problems in EPSS? Discuss on the solutions which helps to improve on the availability of pharmaceutical in Ethiopia and in EPSS (Probe what to be done regarding forecasting problems of pharmaceuticals in EPSS). And what role does data quality and availability play in forecasting accuracy, and how are data-related challenges addressed? Can you describe the collaborative efforts and partnerships among stakeholders involved in forecasting and supply chain management for pharmaceuticals in Ethiopia?" One-to-one interviews with key informants were conducted during the specified period and lasted 40–60 min. All interviews were digitally audio-recorded and transcribed verbatim. Data collection was conducted until a point of theoretical saturation.

3.6. Ethical Approval

Ethical approval was obtained from the Institutional Review Board of Addis Ababa University, College of Health Sciences, and the Ethics Review Committee of the School of Pharmacy, Addis Ababa University (Protocol number: 010/22/SoP). Permission was also granted by EPSS Directors. Participants were assured of their right to withdraw, and written consent was obtained. Sessions were conducted in private, and pseudonyms were used to protect participant identities. Tape records and transcripts were securely stored and kept confidential.

3.7. Data Analysis

The transcribed data were cleaned and imported to NVIVO 14 Qualitative Data Analysis software. Analysis was conducted following the steps stipulated by Braun and Clarke (2006) [51]. First, we repeatedly read the textual transcriptions for familiarization; then, initial codes of relevant data were generated. Related codes were then merged into themes, which were reviewed for coherence and data support, which led to condensed themes. On this basis, we defined the final themes and produced a composite description of the essence. Themes were modified and refined inductively from the data in Microsoft Excel through a thematic content analysis approach guided by the descriptive social constructivism framework. The dynamic interactions across the professional, patient, stakeholder, institutional, and system levels that could influence providers' views of the phenomenon were described. The validity of the findings was verified by employing various methods. These included undertaking a thorough literature search, following steps that ensure a trustworthy thematic analysis as suggested by Brien et al. (2014), bracketing of the researchers' experience of the phenomenon from the participants' view, and crosschecking of contents among the researchers [52].

4. Results

Socio-Demographic Profile of Respondents

A total of seventeen participants were successfully interviewed, of which fourteen were male and three were female. Most of the participants were over 35 years of age, with more than 10 years of professional experience. More than 80% of the participants had a master's degree in the field of health supply chains (Table 1).

Table 1. Socio-demographic profiles of respondents as of 2023.

Gender	Frequency	Percentages
Male	14	82.4
Female	3	17.6
Age of the respondents in years		
25–35	7	41
>35	10	59
Years of experience		
3 to 10 years	7	41
More than 10 years	10	59
Level of education		
Bachelor's degree	3	17.6
Master's degree	14	82.4

In this study, two main themes and ten sub-themes were developed based on content analysis. The first theme was challenges related to forecasting in the EPSS and the sub-themes were (1) finance-related, (2) workforce-related, (3) data quality-related, (4) technology-related, (5) coordination-, collaboration-, and leadership support-related challenges. The second theme were strategies for improving forecasting, and the sub-themes were (1) responsibilities of and attention paid to forecasting; (2) improvements in data quality; (3) workforce- and capacity-building-related challenges; (4) finance-related challenges; (5) stakeholder role-related challenges (Figure 1).

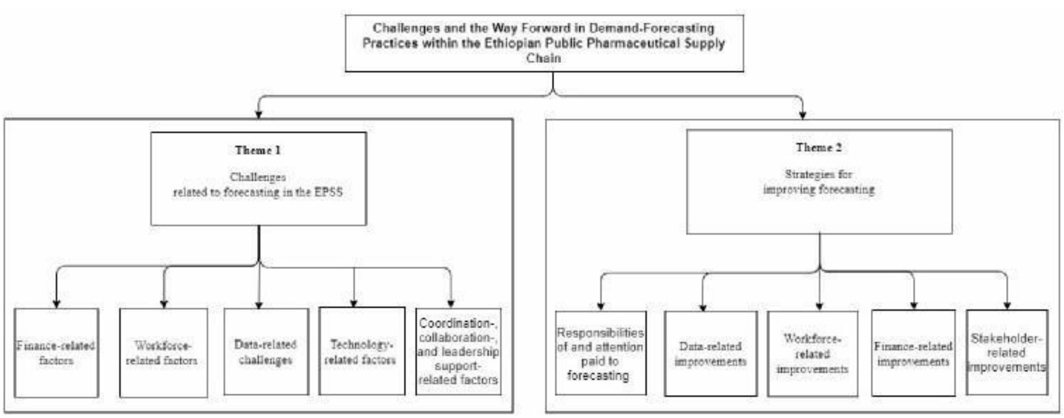

Figure 1. The main themes and sub-themes of the thematic analysis.

Theme 1: Challenges related to forecasting in the EPSS
Sub-theme 1: Finance-related factors

Participants emphasized widespread finance shortages for procuring pharmaceuticals, exacerbated by delayed budget releases post-quantification exercises. At the central EPSS level, pharmaceuticals are provided to health facilities on credit, exacerbating financial constraints. Participant 3 illustrated this as follows:

> *"Health facilities are buying the product on credit based from EPSS and the payment period is lengthened and this has created a finance shortage in EPSS where EPSS cannot be able to open Letter of Credit at the bank due to the shortages of local currency and un collected sale from the health facilities"* (Participant 3).

At the health facility level, delays in budget releases and uncertainty regarding allocated budgets for pharmaceutical procurement were common concerns. Participants noted that quantification exercises were often conducted without knowledge of the budget, leading to uncertainty in product purchases. For instance, Participant 8 illustrated this as follows:

> *"Most of the time the facilities quantify their need without having adequate budget. So the health facilities they only send their demand but they are not sure they will purchase those specific products from EPSS. Due to this EPSS may also purchase either small or big amounts of the products"* (Participant 8).

Additionally, disparities between the timing of budget releases and quantification exercises further exacerbated finance-related challenges, as stated by Participant 11:

> *"Budget shortage we don't know how much is the budget moreover the time where we conduct the quantification and the time where the budget release is different. For instances for The budget release might goes until October 2024 however the quantification is done on April 2023 and these is a major challenge"* (Participant 11).

Furthermore, shortages of hard currency for pharmaceutical imports compounded financial challenges at the central EPSS level. Nearly all participants mentioned the difficulty in obtaining sufficient hard currency due to Ethiopia's import dependency for pharmaceuticals. This issue was exacerbated by disparities between forecasted and available funds, as described by Participant 6:

> *"Capacity of the country is huge and it is not possible to get sufficient hard currency for the pharmaceuticals fund. In programme medicine we forecast on central based we have may stake holders which is good the problem is the fund for instance we forecasted for maternal health medicines around 8 million dollar however the available fund for the product is 1.8 million dollar so at that time we reconcile the forecast. You can imagine the frustration it will create"* (Participant 6).

Finance shortages were evident for both RDF and program pharmaceuticals, impacting procurement despite adequate forecasting. Participant 2 emphasized that funding shortages, rather than forecasting problems, were the main reason for national-level commodity shortages, underscoring the critical importance of addressing funding availability issues.

> *"Capacity of the country is huge and it is not possible to get sufficient hard currency for the pharmaceuticals fund". "In the health programme in my evaluation there is no forecasting problems, I am doing in HIV, Malaria, family planning Maternal and Child, and TB programme. There is a lot of investment in this area, from different funding organizations, there are well capacitated staffs in the area and I can say there is no forecasting problem at all. But what we forecasted will not be purchased due to the challenge of funding so when there are shortages of funding we will prioritized and focus on the most impactful commodities due to the shortages of funding so we cannot say that it is due to the forecasting problems rather it is due to the funding availability problems."* (Participant 2).

Similarly, Participant 16 noted finance shortages impeding RDF pharmaceutical procurement despite quantification efforts. Addressing these finance-related challenges is imperative to ensure consistent pharmaceutical availability within the Ethiopian public pharmaceutical supply chain.

> *"Even if they quantify RDF pharmaceuticals we cannot be able to purchase due to the shortage of finance"* (Participant 16).

Sub-theme 2: Workforce-related factors

Participants highlighted workforce challenges impacting forecasting, including shortages and competency issues. The attrition of skilled professionals and limited institutional emphasis worsened the situation. The scarcity of proficient forecasters was evident both locally and nationally, reflecting systemic issues. Shortages of quantification experts and lack of specialized training posed significant obstacles. Additionally, delegation of forecasting to nurses led to inconsistent data quality. Participant 17 noted supply chain workforce shortages, while Participant 13 emphasized the prevalence of low-skilled human resources, mainly nurses.

> *"There is a shortage of work force in the supply chain"* (Participant 17).

Another respondent said the following:

> *"There is low skilled human resources related with low capacity and most of them are nurses"* (Participant 13).

Participant 8 lamented the absence of pharmacy professionals equipped with the technical acumen necessary for accurate quantification. Additionally, Participant 2 identified inadequate manpower capacity as a primary impediment to timely and accurate forecasting within health facilities.

> *"There is no pharmacy professionals at the health facilities and have no the technical skills to quantification"* (Participant 8).

> *"Man power capacity, to request and report what is needed on time at the health facility is one of the main challenges in forecasting's"* (Participant 2).

Sub-theme 3: Data-related challenges

Participants highlighted challenges with data quality in the Ethiopian pharmaceutical supply chain. Poor data from health facilities, compounded by limited data visibility across the supply chain, hinder effective forecasting. Participant 8 emphasized false reporting and incomplete data, revealing a knowledge gap among health professionals on reporting protocols, complicating accuracy.

> *"There is false reporting which came from the health facility and there is a data quality problem. The data feature is not complete, as well as timely. Some of the health facility reports only when they are stock outs of the products and they have a knowledge gap as the IPLS indicated that there should be a forced reporting system to be applied even if you have the products you need to report that however most of the professionals do not comply with this methods"* (Participant 8).

Participant 2 raised concerns about inadequate information gathering and reporting practices, noting deficiencies in demand generation and commodity requesting procedures. Participant 4 also questioned the reliability of data from lower-tier health systems, impacting product availability.

> *"There is improper information gathering, improper demand generation and improper reporting and requesting of commodities at respected hubs"* (Participant 2).

> *"Challenges related with the quality of data the data is not reliable especially those data which comes from the lower health systems and these have impact on the availability"* (Participant 4).

Moreover, Participant 13 raised concerns about outdated bin card records and the absence of formal recording systems in rural health facilities, noting the reliance on assumptions in lieu of accurate data.

> *"There is a problem of data, bin card are not updated, and there is no recording system in most of the rural health facilities and most of the things are based on assumptions and these will create a problem in forecasting's"* (Participant 13).

Compensatory measures employed by experts at the EPSS were also scrutinized, with Participant 17 highlighting the tendency to over-quantify and prioritize forecasting for high-patient-load facilities. Such practices, while intended to mitigate data inaccuracies, risked distorting procurement priorities and exacerbating forecasting errors.

> *"There is a problem in the data quality for forecasting and there is over quantification beyond the budget capacity. The forecasting will not cover all the health facilities and only for the most high patient load only get focus from EPSS as well as from our side for the rest of the health facilities we do extrapolation and these action will affect the forecasting"* (Participant 17).

Participant 5 highlighted data reliability challenges, noting adjustments made due to perceived inaccuracies. Participant 3 stressed the importance of health professionals to data integrity, lamenting speculative reporting over evidence-based methods, undermining forecasting and supply chain management effectiveness.

> *"The data which comes from the health facility is a false data so what we do is we add all and we divide it by two"* (Participant 5).

> *"One of the challenges in forecasting is the emphasis that we gave for data is so poor and unable to understand the significance of data. For example EPSS collect data from the health facility and uses for forecasting if professionals working on the health facility did not understand the significance of the data and send halfhazardly since this data will have impact on the forecasting it will create a huge forecast inaccuracy. Most of the health professionals when they send their data they just guess how much they need it rather than focusing either historical data that they have. Since the data they send us is not correct that affected the whole process of the forecasting's"* (Participant 3).

Sub-theme 4: Technology-related factors

Participants highlighted challenges including inadequate technologies and a lack of data visibility affecting forecasting. At the central EPSS level, participants noted a lack of end-to-end visibility into pharmaceutical availability at health facilities, causing forecasting and availability issues. Additionally, participants mentioned using Excel-based forecasting tools, which were deemed user-unfriendly.

This was summarize as follows:

> *"Does not have a good tool for doing forecasting"* (Participant 14).

Another respondent also described this as follows:

> *"There were no standardized tools however currently we have standardized the tools at the national level"* (Participant 7).

Sub-theme 5: Coordination-, collaboration-, and leadership support-related factors

Participants emphasized the importance of coordination, collaboration, and leadership in pharmaceutical forecasting, crucial for enhancing pharmaceutical availability. Leadership engagement, especially at the political level, emerged as a key factor influencing forecasting effectiveness. Participant 16 highlighted the impact of leadership support on pharmaceutical availability and quantification, noting that inadequate political backing could hinder effective forecasting. Similarly, Participant 17 lamented the lack of attention given to supply chain management compared to other health programs, reflecting broader political disparities.

> *"Leadership level impact the on the availability as well as the quantification of pharmaceuticals, where quantification is not supported by the political leaders"* (Participant 16).

Other respondents described this as follows:

> *"The political leaders do not understand and support the pharmaceutical supply chain for example maternal and child health has a good attention every time there is reporting of how many mothers gave birth, so the supply chain do not have such attention as the other programme"* (Participant 17).

Participants noted organizational coordination challenges in managing quantification processes. Shifting responsibilities between the Ministry of Health Pharmacy Unit and the EPSS Quantification and Market Shaping Unit led to coherence and coordination issues. Participant 16 highlighted mandate-related discrepancies, noting adverse effects on forecasting accuracy due to inconsistent representation within the EPSS. The absence of EPSS representatives during quantification meetings worsened coordination challenges. Concerns were raised about the efficacy of Drug and Therapeutics Committees (DTCs) in supporting quantification exercises, as their involvement was deemed inadequate. Pharmacy professionals bore the burden of quantification, leading to various issues. Strengthened coordination, enhanced leadership support, and improved collaboration among stakeholders are needed to address these challenges in pharmaceutical forecasting within the Ethiopian public health system.

> *"There are mandate related challenges some time it the quantification exercise was conducted by EPSS some other time it comes to PMED these make lack of coordination". Those forecasting professionals who were to represent EPSS did not attend the recent quantification for the last two meetings you can imagine the impact of these"* (Participant 16).

Theme 2: Strategies for improving forecasting

The participants delineated several strategies to address the challenges associated with pharmaceutical forecasting. These strategies can be categorized into distinct themes, with the overarching goal of enhancing the management of the quantification process. The identified sub-themes encompass (1) responsibilities of and attention paid to forecasting, (2) improvements in data quality, (3) workforce and capacity-building initiatives, (4) finance-related interventions, and (5) stakeholder engagement.

Sub-theme 1: Responsibilities of and attention paid to forecasting

Participants emphasized the lack of attention given to forecasting in supply chain management, stressing the need for earnest attention from management, DTCs, and political leadership. They highlighted the imperative for heightened awareness and support for forecasting within the healthcare sector. One participant articulated the need for equitable attention to the health supply chain, akin to other programmatic initiatives, advocating for proactive consultation during instances of product stockouts and advocating for sectoral prioritization. Their perspective is encapsulated in the following statement: *"There needs to be attention given to the health supply chain just like other programs. We even consult when there are stockouts of products, and due attention should be given to the sector"* (Participant 13). Echoing this sentiment, another respondent highlighted the importance of incorporating quantification as a Key Performance Indicator (KPI) and underscored that resolving forecasting challenges necessitates commitments at higher organizational echelons. This viewpoint is elucidated by Participant 4, who emphasized, *"Including quantification as a KPI is important, and the challenges of forecasting will not be resolved with professionals alone; it requires higher-level commitments"*.

Participants noted attention disparities among pharmaceutical categories like program and RDF (Revolving Drug Fund) drugs, highlighting stakeholder engagement variations. One participant emphasized unequal support for programmatic versus RDF pharmaceuticals supply chains, urging equal focus. They stressed product availability's impact on program effectiveness, especially due to inadequate supply chain infrastructure. Participant 13 articulated this perspective, stating, *"For programs, there is high support; however,* *for the supply chain, there is no attention. Just like programs, there should be due attention for the supply chain, as without product, there is no program*". Furthermore, they underscored the adverse ramifications of inadequate supply chain frameworks, particularly within non-governmental organizations (NGOs), which often lack dedicated supply chain units, thereby exacerbating product stockouts and impeding programmatic effectiveness.

Sub-theme 2: Data-related improvements

Participants stressed the crucial need for data quality improvements, emphasizing accuracy, completeness, and timeliness. Robust data were deemed essential for informed decision-making and strategic planning. Participant 14 highlighted this, stating, "*Data quality is crucial for all decisions*". Echoing this perspective, Participant 10 advocated for the establishment of end-to-end data visibility. "*There should be end to end data visibility where it will indicate the point of sale data when there is a sell of pharmaceuticals. The data should be visible at Centre, hub and facility level*". Their assertion underscores the importance of leveraging technological advancements to ensure seamless data accessibility and integrity throughout the supply chain continuum. Similarly, Participant 15 called for improved data visibility and technological integration, expressing skepticism about data reliability from health facilities. They emphasized control mechanisms and innovative technologies for enhanced accuracy. "*We need to ensure end to end data visibility and introduce new technologies and I don't trust the data which is coming from the health facilities and we don't have any controlling system of the data coming from the health facilities. And we need to improve the use of technologies*".

Moreover, Participant 3 suggested developing tools and databases at the health facility level to track medication dispensation, enabling more accurate forecasting. Leveraging real-time data on drug utilization was deemed vital for effective forecasting. "*Developing tools and database to see the actual use dispensed to patient is important and will solve most of the challenges related with the forecasting and EPSS should know every dispensed drug at the end user level and use that information for forecasting purpose*".

Sub-theme 3: Workforce-related improvements

The participants underscored the critical necessity of a proficient and accountable workforce within the healthcare supply chain to address overarching challenges, particularly in the realm of forecasting. Participant 8 eloquently articulated the need for a structured accountability framework akin to that observed in the banking sector, advocating for rigorous auditing and monitoring mechanisms to ensure transparency and responsibility among pharmacy professionals. They emphasized the pivotal role of capacity-building initiatives in equipping professionals with essential skills in forecasting, data management, and inventory control. "*We need to have skilled human resources who is accountable just like the bank officers are accounted for each money, and there is auditing each day in the bank with the same principle there should be auditing of the pharmaceuticals and they have to be accountable as the bankers are accountable for the money they will pay for the customers, the pharmacy professionals need to have computers and other important equipment's. The professionals become reluctant because there is no auditing or check and balance*" (Participant 8).

Building upon this sentiment, Participant 15 emphasized the imperative of comprehensive capacity-building programs tailored to address skill deficiencies in RDF pharmaceutical management. They highlighted the pressing need to fortify data quality and inventory management practices at health facility levels, underscoring the pivotal role of training in fostering workforce competence and motivation. "*There should be capacity building training in RDF pharmaceuticals there are only few health facilities using bin cards so we need to improve data quality at health facilities level we need strengthen the inventory management at the health facilities*" (Participant 15). Moreover, participants unanimously emphasized the multifaceted benefits of training initiatives, not only in ameliorating skill gaps but also in bolstering workforce morale and engagement. Participant 6 underscored the transformative impact of training programs on enhancing both skill proficiency and intrinsic motivation among professionals, thereby contributing to sustained performance improvement within the supply chain domain. "*We need to provide training, which will help in solving the skill gap in forecasting but also it will increase their motivation*" (Participant 6).

While short-term training interventions were deemed crucial for immediate skill enhancement, participants emphasized the long-term imperative of elevating the quality of degree programs to cultivate a pipeline of skilled professionals. Participant 9 elucidated the dual-pronged approach of addressing immediate skill deficiencies through targeted training interventions while concurrently investing in the enhancement of academic curricula to ensure the sustained development of a competent workforce. "*In short term there should be training to improve the skill gap, in long run we need to improve the quality of the degree programme*" (Participant 9). Furthermore, the broader issue of workforce scarcity within the healthcare supply chain was acknowledged, with participants emphasizing the urgent need for comprehensive initiatives to augment both the quality and quantity of professionals in this domain. Participant 14 underscored the gravity of the challenge, highlighting the dearth of skilled professionals at the national level and advocating for concerted efforts to rectify this shortfall through strategic workforce development initiatives. "*In order to improve the problem in forecasting as well as in the health supply chain we need to work on human resources in terms of quality and quantity, the country does not have a skilled human resources in the field of forecasting at national level there are a few hand full of professionals and we need to act on these issue in order to solve the problem*" (Participant 14).

Sub-theme 4: Finance-related improvements

The participants underscored the pressing need for increased government financing in the pharmaceutical sector, recognizing the detrimental impact of financial shortages on both the supply chain and forecasting practices. This financial deficit was observed to significantly affect the procurement of pharmaceuticals, spanning both program medicines supported by external partners and the Revolving Drug Fund (RDF), where health facilities utilize a revolving budget model for pharmaceutical procurement. Central to the discourse was the imbalance between allocated financial resources and the requisite pharmaceutical quantities, prompting participants to propose various avenues for financial improvement.

Participant 10 advocated for proactive resource mobilization efforts to align forecasted pharmaceutical requirements with available financial resources, emphasizing the imperative of balancing supply projections with budgetary allocations. "*We need to mobilize the resources and we need to balance the forecasted quantity and the resources they have*".

Similarly, Participant 2 highlighted the reliance on external funding sources and urged governments to preemptively address potential funding shortfalls to mitigate disruptions in pharmaceutical procurement processes. "*We always rely on external funds if these funds reduced or stop the governments should fill the gap. So the funding problem should address in well in advance*" (Participant 2).

Moreover, participants underscored the financial strain imposed by health facilities' reliance on credit-based procurement from the Essential Pharmaceuticals Supply Services (EPSS), exacerbating financial burdens within the supply chain. Participant 10 proposed proactive measures to bolster the EPSS's financial resilience by facilitating advance resource allocation, thereby alleviating financial pressures and streamlining procurement processes. "*The health facilities purchase the products from EPSS on credit based and these issues creates a huge burden on EPSS on the financial matters so if there is a possibility EPSS obtains their resource in advance it will help the procurement process to be easy. This will increase the financial capacity of EPSS*" (Participant 10).

Sub-theme 5: Stakeholder-related improvements

Stakeholder engagement emerged as a pivotal factor in enhancing forecasting activities within the healthcare supply chain, as highlighted by the participants. They emphasized the indispensable role of stakeholders not only in the broader context of healthcare supply chain management but also specifically in forecasting endeavors. The consensus among participants was that collaborative stakeholder efforts are imperative for optimizing forecasting practices and ultimately improving pharmaceutical supply chain efficiency.

Participants stressed the necessity for stakeholders to collaborate seamlessly and extend support to forecasting initiatives. Furthermore, they underscored the importance of integrating academic institutions into the collaborative framework to leverage theoretical expertise and augment operational effectiveness at both the EEPSS and Ministry of Health (MOH) levels. Participant 8 articulated this sentiment, advocating for comprehensive stakeholder engagement involving academia, healthcare facilities, and governmental entities: "*All stakeholders should come together, with higher institutions actively contributing to healthcare facilities. Academicians should be embedded within healthcare facilities, collaborating closely with MOH teams and logistics professionals across various stakeholders. Continuous learning and knowledge exchange among EPSS, MOH, partners, and academics are essential*".

Participant 3 echoed this sentiment, emphasizing the need for stakeholder engagement in collaborative forecasting endeavors to harness expert insights and address forecasting challenges effectively. "*We need to engage stake holders and do the forecasting together these activities will improve the forecasting practice. This will help us to understand get expert opinions that will help the whole forecasting problem*" (Participant 3).

Additionally, participants highlighted the significance of stakeholder engagement in pharmaceutical supply chain management, emphasizing the importance of collaborative forecasting initiatives. Participant 4 underscored the potential benefits of involving stakeholders such as healthcare facilities and manufacturers in collaborative forecasting efforts to enhance supply chain management practices. "*To improve the Pharmaceutical supply chain management we need to engage the stakeholders like health facilities, manufacturers and other partners. It will be good if there is collaborative forecasting*" (Participant 4).

5. Discussion

The Ethiopian pharmaceutical supply chain faces issues like lack of financing, workforce skills, poor coordination, data quality problems, and lack of end-to-end visibility. These factors create a systemic problem requiring an integrated solution. Bititci (2015) suggests that organizations perform better when working towards a common goal with collaboration and shared learning, enhancing problem-solving and innovation. This requires open communication, trust, and reflection [53]. This concept can be applied to the entire supply chain, aligning with responsible innovation theory, where stakeholders anticipate problems, act responsively, and learn collectively (Figure 2).

Embracing the principles of responsible innovation, characterized by transparent and collaborative processes, can guide effective decision-making [54]. Responsible innovation, as defined by Stilgoe et al., emphasizes the importance of considering the purpose and process of innovation alongside its outcomes. Four dimensions—anticipation, reflexivity, inclusion, and responsiveness—are integral to this framework [55]. Moreover, Naughton et al. suggest that "responsible impact" is the fifth domain and output of responsible innovation, potentially serving as a natural reinforcer of the responsible innovation process [56].

Anticipation involves governance mechanisms to foresee potential societal impacts [55,57]. There are many decisions that depend on the quality of forecasts in the healthcare system, from capacity planning to layout decisions to daily schedules. In general, the role of forecasting in healthcare is to inform both clinical and non-clinical decisions. While the former concern decisions related to patients and their treatments [58], the latter involve policy/management and supply chain decisions that support the delivery of high-quality care for patients. Forecasting is also used in both national and global healthcare supply chains, not only to ensure the availability of medical products for the population but also to avoid excessive inventory. Additionally, the lack of accurate demand forecast in a health supply chain may cost lives [59] and has exacerbated risks for suppliers [24].

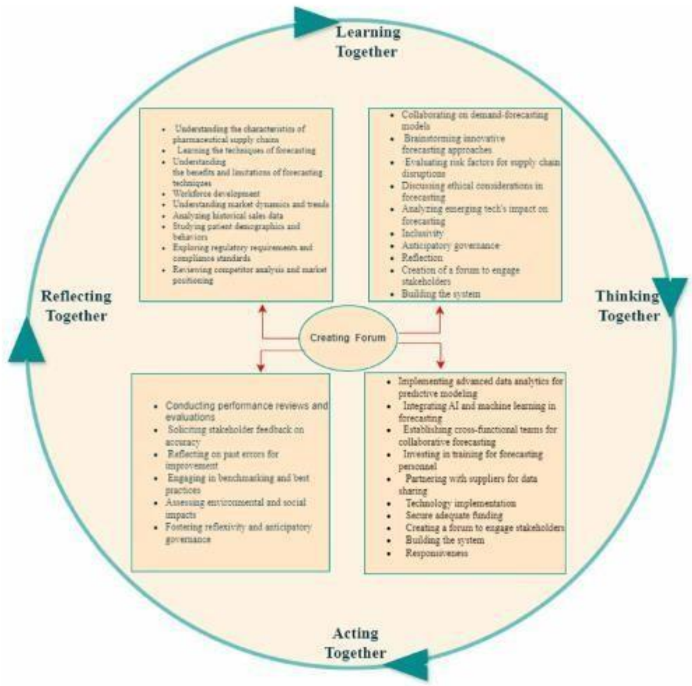

Figure 2. How EPSS can learn the forecasting process and mitigate its challenges. Sources: *Modification of Managing Business Performance: the Science and the Art*, Umit S. Bititci.

Inclusivity aims to bring relevant stakeholders and the public to the table to engage with, identify, and address unforeseen, ungoverned, or ethical issues, as well as challenge assumptions and the innovation's purpose, which is commonly the case with emerging technology and has been one of the most widely covered domains in recent years [60–68]. The issue of inclusivity is quite important in our findings, as we identified that coordination and collaboration were some of the challenges in pharmaceutical demand forecasting in the study area. Engaging relevant stakeholders is part of the problem, and working towards a common solution will improve most of the problems related to pharmaceutical forecasting.

Reflexivity is an important aspect of any innovation [57]. Stilgoe et al. describe it as holding a mirror up to oneself [55]. It is described as a process whereby one's activities, considerations, commitments, and assumptions are challenged. This issue is quite important because we have witnessed a lack of commitment, poor data, and a lack of coordination and collaboration in the workforce while conducting forecasting activities, as evidenced in this study. We believe reflexivity cannot solve the problems of forecasting by itself; however, stakeholders need to collaborate and coordinate, which would require a lot of open information sharing, and reflexivity can enable the group to reflect on the actions they have taken, their outcomes, and on what worked and what did not. Thus, they will learn as a group [53]. Responsiveness involves reactions to influencing factors, which may include political and social agendas or the thoughts and concerns of stakeholders and the public [69]. It is acknowledged that the performance of healthcare operations results in the life or death of people, whereas it is only profit or loss in other sectors. In recent years, SC management (SCM) has become prevalent in the healthcare sector because of its impact on minimizing waste and medical errors, enhancing quality of care, and improving operational efficiencies and customer satisfaction [70]. In a complex system, you need to obtain as much real-time information as possible and take action as quickly as possible (responsiveness). If you do not, the system changes quickly and the planned action will no longer be valid; thus, the cycle of collaboration, coordination, sharing data, taking action, reflecting, and learning needs to be quite fast [53].

Responsible impact refers to the positive outcomes and effects that result from responsible innovation practices within an organization or ecosystem. The concept of responsible impact emphasizes the importance of considering the broader implications of innovation beyond economic gains. It highlights the need for organizations to assess and measure the positive outcomes of their innovation efforts in terms of sustainability, ethics, social responsibility, and overall impact on stakeholders and society. Recognizing and understanding responsible impact can help organizations align their innovation practices with ethical and sustainable principles, leading to more meaningful and beneficial outcomes for both the organization and the wider ecosystem in which they operate [56].

This study emphasizes the importance of responsibility and attention to forecasting to mitigate sector challenges. Gurzawska also highlights that responsible and sustainable SCM requires innovative technology, political solutions through multi-stakeholder partnerships, and ethical responsibility across supply chain tiers, necessitating a systemic approach [71]. To improve forecasting, responsible bodies should focus on technology, ensure end-to-end data visibility, and develop forecasting tools and databases. Digitalizing supply chains fosters communication and collaboration among stakeholders, but technological innovations alone are not enough without strong coordination [71]. Supply chains are multi-tier, involving manufacturers, intermediaries, end-users, governments, and communities. Effective SCM relies on stakeholder engagement and multi-stakeholder approaches (CSSPs) to achieve responsibility and sustainability [72–75]. This approach, rooted in stakeholder theory, asserts that a company's success depends on sustainable relationships within its stakeholder network [76,77].

Freeman (1984) defines stakeholders as groups affecting or affected by an organization's purpose [78]. The multi-stakeholder approach in SCM stems from the concept of collaborative enterprises, where companies build long-term, mutually beneficial relationships with stakeholders to create sustainable value [77]. This enhances relationships through better coordination with suppliers, customers, and other stakeholders, improving social outcomes and generating win-win solutions. Thus, a company's sustainability depends on its stakeholder relationships [77,79]. This multi-stakeholder approach addresses collaboration, communication, and power distribution challenges in the supply chain. Collaborative initiatives enable better monitoring and tracing of supply chain activities, which individual companies may lack resources for the societal and environmental impacts of its activities [80]. However, developing these deep relationships requires time [81]. Non-state actors can enhance supply chain responsibility and sustainability by effectively gathering, collating, and providing information on policy issues and problem areas [82,83].

This paper highlights the interplay between technology, politics, and stakeholder involvement. Solutions like end-to-end data visibility, political will, and collaboration among supply chain actors could alleviate forecasting challenges. Non-state actor initiatives use technologies for data sharing via multi-stakeholder digital platforms, enhancing compliance through mutual control [71]. These platforms also promote transparency, cooperation, and trust, as well as reduce power abuse, requiring oversight for ethical decisions [84]. Effective governance involves multi-stakeholder collaboration for credibility, combining technological, political, and ethical solutions to address SCM challenges. This study highlights pharmaceutical forecasting challenges but has limitations. Its design may have introduced subjectivity and the small sample size limits generalizability. Data collection and interpretation biases also affect findings, making conclusions context-specific. Despite these constraints, this study is crucial for understanding and addressing forecasting challenges in resource-constrained settings.

6. Conclusions

In conclusion, this study highlights significant challenges within the Ethiopian public pharmaceutical supply chain, particularly in forecasting practices. These challenges, including finance-related constraints, workforce shortages, and data quality issues, present formidable barriers to efficient pharmaceutical procurement and distribution. Based on our discussions and the theories we covered in this paper, we believe the first priority needs to be resolving the problem of inaccuracy and unreliability in the supply chain. All stakeholders must work together as a single team to help address this problem. This will require certain incentives and disincentives to be introduced to motivate different stakeholders to collaborate and work as a team. A platform also needs to be created to enable the stakeholders to share information, communicate, and collaborate effectively in order to reinforce the cycle of thinking together, acting together, reflecting together and learning together. Finally, the learnings from this way of working need to be shared with the wider community, so that the valuable lessons and knowledge around what works well what does not work so well are not lost and continue to accumulate and improve the performance of the Ethiopian pharmaceutical supply chain. By integrating responsible innovation and impact principles into demand-forecasting practices, the EPSS can enhance the accuracy, reliability, and ethical considerations of their forecasting models. This approach can lead to more sustainable, patient-centered, and socially responsible decision-making in the pharmaceutical sector.

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Abbreviations

AI	Artificial Intelligence
EPSS	Ethiopian Pharmaceutical Supply Services
MOH	Ministry of Health
KPI	Key Performance Indicator
RDF	Revolving Drug Fund
RHBs	Regional Health Bureaus

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PAPER III

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The missing puzzle piece: Contextual insights for enhanced pharmaceutical supply chain forecasting

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The missing puzzle piece: Contextual insights for enhanced pharmaceutical supply chain forecasting

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Abstract

Accurate forecasting in pharmaceutical supply chains is critical for ensuring the continuous availability of essential medicines, particularly in developing countries where resource constraints and logistical challenges are more pronounced. Effective demand forecasting supports procurement and inventory management, which in turn could help to prevent stockouts, reduce wastage due to overstocking, and enhance overall healthcare delivery. In such settings, reliable forecasts, that acknowledge uncertainties, are essential to ensure that limited resources are used efficiently to meet health needs. Despite advancements in forecasting, significant gaps remain in effective forecasting in poor resource countries. Most existing literature on pharmaceutical supply chain forecasting focuses primarily on point estimation of consumption while neglecting the inherent uncertainty of these forecasts. Additionally, these studies often rely solely on historical consumption data without considering the broader context that influences consumption. Furthermore, many works lack rigorous methodological design, transparency, and reproducibility. This study addresses these gaps by integrating domain-specific knowledge, gathered through expert interviews and engagement with key members of the Ethiopian Pharmaceutical Supply Service (EPSS), into forecasting models. Using a dataset spanning five years (December 2017 to July 2022) from EPSS, we developed forecasting models that integrate expert-identified variables such as stock replenishment schedules, fiscal inventory counts, and disease outbreaks. Evaluation metrics including Mean Absolute Scaled Error (MASE), Root Mean Squared Scaled Error (RMSSE), and Continuous Ranked Probability Score (CRPS) are used to report forecast accuracy. The findings underscore the significance of contextual data in developing robust forecasting models that are adaptable to complex, real-world conditions. Our results also highlight the effectiveness of foundational time series models for forecasting. These models are particularly appealing for resource-constrained countries that may lack advanced analytical expertise. To promote usability, generalizability, and reproducibility, we share the complete dataset and code in R and Python, and the entire paper is written in Quarto via a GitHub repository to facilitate these practices.

Keywords: Forecasting, Pharmaceutical supply chain, Domain knowlege, Forecast accuracy, Developing countries

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1. Introduction

Universal access to essential medicines is a fundamental goal of effective healthcare systems, yet ensuring equitable availability continues to be a critical global challenge (Quick, 2003; Organization et al., 2004a). Many countries, particularly in Africa and Asia, face significant barriers to accessing these medications, often due to high costs and inefficient supply chain management (Organization et al., 2004b). A survey conducted in eight sub-Saharan African countries revealed alarmingly low availability of essential medicines. The average availability of women's priority medicines ranged from just 22% to 40%, while children's medicines were only slightly more accessible, with availability ranging from 28% to 57% (Droti et al., 2019). However, drug shortages are not limited to low-income regions; they also occur in developed areas like the United States and Europe, where they disrupt healthcare delivery and compromise the quality of patient care (Fox and Tyler, 2003; Kaakeh et al., 2011; Johnson, 2011; Huys and Simoens, 2013; Le et al., 2011).

The consequences of drug shortages extend beyond immediate healthcare delivery, impacting healthcare costs, treatment quality, and patient safety (Alspach, 2012; Kaakeh et al., 2011; Baumer et al., 2004). Such shortages can result in treatment delays, suboptimal care due to the unavailability of preferred therapies, increased reliance on costly secondary markets, and serious patient outcomes, including complications, longer hospital stays, and even deaths (Alspach, 2012). Addressing these challenges requires a resilient pharmaceutical supply chain that can ensure the timely availability of medicines. In this context, accurate demand forecasting becomes critical for effective procurement and inventory management (Subramanian, 2021).

Demand forecasting in pharmaceutical supply chains is a highly complex process, shaped by several factors. These include the quality of available data, the specific position within the supply chain, and external influences such as market trends, regulatory changes, and disruptive events such as pandemics, conflicts, flooding (Schneider et al., 2010; Hyndman and Athanasopoulos, 2018). Recently, major donors such as Bill & Melinda Gates Foundation have invested in data collection technologies in sub-Saharan Africa, recognizing the potential of data to provide valuable insights. This investment is essential and offers significant benefits for improving supply chain delivery. However, much of the data being collected focuses on transactional data, such as consumption and sale. Almost all platforms collecting data tend to overlook the critical contextual factors and events that influence these transactions—factors that are just as crucial for accurate forecasting. This presents a major barrier, as understanding the broader context, including administration procedures, local policies, disruptions, conflicts, and so on is vital for building reliable forecasting models. This gap—known as business context and domain knowledge—requires urgent attention in Pharmaceutical supply chain forecasting. Without incorporating this knowledge, any forecasting model is unlikely to produce reliable results. We must prioritize collecting and integrating this contextual information to improve the accuracy of demand forecasts in pharmaceutical supply chains. Combining statistical models with domain insights offers a more refined forecasting process, as evidenced by research that highlights the value of judgmental adjustments to enhance forecast accuracy (Fildes and Goodwin, 2007; Taylor-Phillips and Freeman, 2022; Soyiri and Reidpath, 2013). Domain knowledge enables analysts to incorporate relevant events, such as supply chain disruptions, into the forecasting model. This integration is particularly beneficial in fields like healthcare, where expert insights can align algorithms with real-world applications (Dash et al., 2022).

This study aims to bridge that gap by employing advanced machine learning models combined with domain expertise to address the distinctive characteristics of Ethiopia's pharmaceutical sector. The challenges in this sector, such as diverse product categories, limited data from service delivery points, communication issues, long lead times, forecast inaccuracies, and complex policies, necessitate tailored forecasting approaches (Bilal et al., 2024; Boche et al., 2022). Accurate demand forecasting in Ethiopia is essential for optimizing resource allocation, streamlining supply chain operations, and shaping effective healthcare policies (Rostami-Tabar et al., 2022).

This research uses consumption data from 33 health commodities, covering the period from December 2017 to July 2022, provided by the Ethiopian Pharmaceutical Supply Service (EPSS), to develop models for six-month-ahead forecasting. Initially, we implement univariate models that rely solely on consumption data. Following this, we conduct exploratory data analysis and engage in interviews with EPSS experts to gather domain knowledge on events influencing consumption patterns. Through these interviews, the experts identified three key factors collectively impacting consumption: stock replenishment period, fiscal calendar, and the seasonal malaria. We then develop forecasting models that incorporate the data gathered through the interview process and compare their performance with univariate models that rely solely on consumption data.

Our primary aims is to assess whether incorporating domain knowledge improves forecast accuracy. Moreover, we also fill a gap in the pharmaceutical demand forecasting literature by not only generating point forecasts but also producing probabilistic forecasting techniques that capture the range of potential outcomes with associated probabilities, offering a more comprehensive view of demand uncertainty than traditional methods. Model performance is evaluated using point accuracy measure including MASE, RMSSE, and probabilistic measure using CRPS.

The remainder of this paper is structured as follows: Section 2 reviews the literature and identifies gaps to position our work; Section 3 outlines the experimental design, including data sources, forecasting methods, and evaluation criteria; Section 4 presents the results and analysis; and Section 5 concludes with a summary of findings and future research directions.

2. Research background

Accurate sales forecasting is crucial in the pharmaceutical industry, where it directly impacts profit maximization, cost minimization, and the ability to respond to market changes. Forecasting in healthcare not only influences clinical decisions but also plays a pivotal role in supply chain management, ensuring that the right drugs are available when needed. The challenge lies in balancing customer demand with inventory costs, which is particularly complex in pharmaceuticals due to factors like short shelf life and quality constraints (Gupta et al., 2000; Makridakis et al., 2020).

In this review, a range of forecasting methods has been applied, from traditional statistical models to advanced machine learning techniques, with many studies using a combination of simple and advanced methods to enhance accuracy (Nikolopoulos et al., 2016; Zhu et al., 2021; Anusha et al., 2014). Some studies, such as those by Newberne and NV (2006), and Restyana et al. (2021), applied traditional forecasting methods like the Holt-Winters method, Single Moving Average (SMA), and Single Exponential Smoothing (SES), which are simpler but effective for certain applications. In contrast, other researchers explored more advanced approaches, including hybrid models and machine learning techniques, to address complex forecasting challenges, as seen in the studies by Siddiqui et al. (2022), de Oliveira et al. (2021), Kim et al. (2015), Candan et al. (2014), and Ribeiro et al. (2017).

Early research in pharmaceutical forecasting primarily focused on traditional statistical methods. These methods, including ARIMA, exponential smoothing, and moving averages, were widely used due to their simplicity and effectiveness in relatively stable environments (Zahra and Putra, 2019). These models typically assess forecast accuracy using metrics like Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). For example, Newberne and NV (2006) applied the Holt-Winters method to forecast healthcare data, focusing on prescription trends. Their findings highlighted the method's utility in short-term planning and resource management, validated through metrics like MAPE, MAD, and MSD. Similarly, Restyana et al. (2021) compared Single Moving Average (SMA) and Single Exponential Smoothing (SES) in drug demand forecasting, concluding that SES provided more accurate results, as indicated by lower MAD and MSE values.

Recognizing the limitations of traditional models, particularly in capturing the complexities of pharmaceutical demand (e.g., seasonality, external influences), researchers began developing hybrid models. These models combine linear methods like ARIMA with nonlinear techniques such as neural networks, aiming to improve forecasting accuracy by addressing diverse data patterns. Khalil Zadeh et al. (2014) introduced a hybrid model that integrated ARIMA with neural networks. Their study demonstrated that this approach significantly outperformed traditional models, especially in scenarios with limited historical data. The hybrid model's effectiveness was confirmed by improvements in key performance indicators like MAPE and RMSE.

The pharmaceutical industry's increasing complexity and the availability of large datasets have led to the adoption of advanced machine learning techniques. These methods, such as Support Vector Regression (SVR), Random Forest (RF), and Long Short-Term Memory (LSTM) networks, offer greater flexibility and predictive power. ? showed that incorporating downstream information into machine learning models, like LASSO and SVR, greatly enhances forecast accuracy. Their study on multi-echelon supply chains revealed that advanced models, particularly those integrating external variables, consistently produced lower forecast errors, as measured by AvgRelRMSE. Similarly, Rathipriya et al. (2023) compared shallow neural networks and deep learning models for drug demand forecasting. The study found that shallow models outperformed deep learning models for most drug categories, while ARIMA was more effective for the remaining categories. This suggests that no single model is universally optimal, and model selection should be context-specific.

More sophisticated models, such as Neuro-Fuzzy Systems, have emerged as powerful tools for pharmaceutical forecasting. These systems combine the learning capabilities of neural networks with the reasoning abilities of fuzzy logic, offering a balanced approach that incorporates both empirical data and expert knowledge. Deep learning models, while powerful, present challenges such as the need for large datasets and substantial computational resources. Despite these challenges, models like LSTM have shown potential in capturing long-term dependencies in time series data, as demonstrated by Sousa et al. (2019) in their study on drug distribution in the Brazilian Public Health System. Candan et al. (2014) employed an Adaptive Neuro-Fuzzy Inference System (ANFIS) to forecast pharmaceutical demand. Their study highlighted the system's ability to capture complex patterns in the data, resulting in highly accurate forecasts. The effectiveness of this approach was further validated through statistical tests, such as paired T-tests and mean difference analysis, which confirmed its superiority over traditional methods.

Nguyen et al. (2023) explore how sentiment analysis of news media can be utilized to improve demand forecasting for pharmaceutical products during disruptive events, such as pandemics and scandals. The authors employed a VARX (Vector Autoregressive with Exogenous Variables) model to forecast demand volatility. Papanagnou and Matthews-Amune (2018) investigate the impact of big data analytics, specifically through text mining, on improving forecasting accuracy for pharmaceuticals in retail pharmacies, using HMX pharmacy stores in Nigeria as a case study. They use multivariate time series analysis technique known as VARX, which incorporates customer-generated content from sources like Google, YouTube, and online newspapers to predict demand for medicines. Fourkiotis and Tsadiras (2024) focus on enhancing pharmaceutical sales forecasting through the application of both traditional statistical methods and advanced machine learning techniques. Various forecasting approaches, including traditional models like Naïve and ARIMA,Facebook Prophet, and machine learning methods such as XGBoost and LSTM neural networks are compared. The results demonstrated that machine learning models, particularly XGBoost, significantly outperformed traditional methods. Belghith et al. (2024) present a rolling forecasting framework employing moving average and three exponential smoothing methods (Brown's, Holt's, and Holt-Winters) implemented using Microsoft Power BI for enhanced data visualization.

Table 1 provides a summary of key studies in the literature on forecasting for pharmaceutical products. We identify several limitations both in the existing research and in practice, which highlight important gaps that motivate our current study. These gaps are summarized as follows:

1. Despite significant investment in data collection technologies and logistics management systems, these systems primarily collect transactional data, such as consumption. However, no data is collected on events that influence consumption variability—information that would be crucial for building reliable forecasting models. No studies to date have explored how domain expertise could enhance pharmaceutical demand forecasting.
2. Current research on forecasting for pharmaceutical supply chain predominantly focuses on generating point forecasts. There is a lack of studies that consider the entire forecast distribution of monthly

consumption, which would better capture the uncertainty of future demand and provide a valuable risk management tool for decision-makers.

3. Reproducibility remains a major challenge in this field. It is often difficult for readers to reproduce previous studies without direct assistance from the authors, limiting the practical application and validation of existing research.

Table 1: Summary of some studies on forecasting in pharmaceutical supply chain

References	data granularity	Lenth of data	Forecast variable	Horizon	Probabilistic	Method	Metric	Items	Data	Code
Current study	Monthly	60 months	Consumption of pharmaceutical products	6 months	Yes	TimeGpt (with and without predictors), LSTM (with and without predictors), Exponential Smoothing, ARIMA, Dynamic Regression (ARIMAX), Multiple Regression (with and without predictors)	RMSSE,CRIPS,MASE	33	Yes	Yes
Siddiqui et al. (2022)	Monthly	58 months	Sales of pharmaceutical products	Un known	No	ARIMA, HOLT WINTER, ETS, Theta, ARHOW	MEAN, MAD, MSE, RMSE, MAPE	31	No	No
de Oliveira et al.(2021)	Daily	365 days	Lead time	NA	No	k-NN, SVM, RF, LR, MLP	MSE	11	Yes	No
Rathipriya et al. (2023)	Weekly	260 weeks	Sales of pharmaceuticals product	Un known	No	SNN, ARIMA P_NN GR_NN RBF_NN ARIMA P_NN GR_NN RBF_NN	RMSE, Normalized RMSE	57	Yes	No
Kim et al.(2015)	Monthly	44 month	Medicines sales data	1 month	No	VARX	Prediction error rate	4	No	No
Merkuryeva et al. (2019)	Weekly	20 weeks	Sales of pharmaceuticals	1–week	No	MA, Symbolic Regression, LR	R^2, MAD	1	No	No
Nikolopoulos et al. (2016)	Yearly	21 year	Prescription records of pharmaceuticals	1–5	No	Diffusion models, ARIMA, ES, LR	R^2, ME, MAE, MSE	14	No	No
Van Belle et al.(2021)	Weekly	253 weeks	Medcine sales	1–5 weeks	No	ARIMA, ETS, MLP, SVR, RF, LR	RMSE	50	No	No
Khalil Zadeh et al. (2014)	Monthly	36 months	Sales pharmaceutical products	1 month	No	ARIMA, Graph-based analysis and ANN,	R2,MSE, MAE	217	No	No
Zhu X et al.(2021)	Weekly	520 weeks	Medcine sales	1–2 months	No	MA, LR, Clustering and RNN	NME, NMAE, NMSE	245	No	No
Anusha et al.(2014)	Monthly	36 months	Sales of pharmaceuticals	Un known	No	6 Month MA, SES, WES	MAD, MSE, MAPE	2	Yes	No
Burinskiene (2022)	Weekly	13 weeks	Medcine sales	36 days	No	SES, MA, Naïve, Holt	MAPE,MSE, U^2	8	No	No
Candan et al. (2014)	Yearly	6 years	Medcine sales	3 months	No	NF	SE Mean	1	No	No
Ribeiro et al.(2017)	Monthly	24 months	Medcine sales	3 months	No	DPM	SMAPE	357	No	No
Bon and NG (2017)	Monthly	68 months	Medcine sales	1 month	No	SMA, SES, DMA, DES, RA, HW-A, SA, HW-M, ARIMA-SM	RMSE, MSE, MAD, MAPE	1	No	No
Newberne and Mike (2006)	Monthly	36 months	Pseudoephedrine prescriptions	3 months	No	HW-M	MAPE	1	No	No
Sousa et al.(2019)	Monthly	79 months	drug distribution	quarterly	No	Naïve, Seasonal Naïve, ARIMA, DLM, LST, Recurrent Neural Network, SES, Holts linear and damped trends, HW, ES-SSM, Theta	MAE	30	Yes	Yes
Zahra and Putra (2019)	Monthly	36 months	Consumption	12 months	No	ARIMA, ES	RMSE, MAPE, MAD, MSE	1	No	No
Nguyen et al. (2023)	Un known	Un known	Pharmaceutical products	Un known	No	VARX	ME, MAE,MAPE,RMSE	Unkn wNno		No
Christos et al.(2017)	Weekly	129 weeks	Web-scraping of analgesic medcines	Un known	Yes	VARX	AIC, BIC, MSE, MAE	UnknowNno		No
Belghith et al.(2024)	Daily	1095 days	Sales of pharmaceuticals	1 year	No	Brown's method, Holt's method, and Holt-Winters method, moving average	MAD, MAPE	125	No	No
Konstantinos et al.(2024)	Weekly	260 weeks	Medcine sales	1 year	No	Naïve, ARIMA, XGBoost , LSTM, Prophet	MAPE,MSE	57	No	No

3. Experiment setup

3.1. Data

For this study, we use a dataset spanning five years (Dec. 2017- July 2022) of consumption data obtained from EPSS. Rigorous checks were conducted to ensure the consistency and completeness of the collected data. From the extensive pool of pharmaceutical products within EPSS, we selected a set of 33 key pharmaceuticals, including various programs and representing different classes of drugs.

3.1.1. Explaoratory Data Analysis with consumption data

Given the number of products in this study, we created several data plot and computed features of the time series, including the strength of trend and seasonality to better understadn data. Figure 1 shows the strength of trend versus seasonality. Each point represents one time series with the strength of trend in x-axis and the strength of seasonality in y-axis. Both measures are on a scale of [0,1]. the strength of trend and seasonality were calculated using the —STL‖ (Seasonal and Trend decomposition using Loess) decomposition method, as described by Bandara et al. (2025)

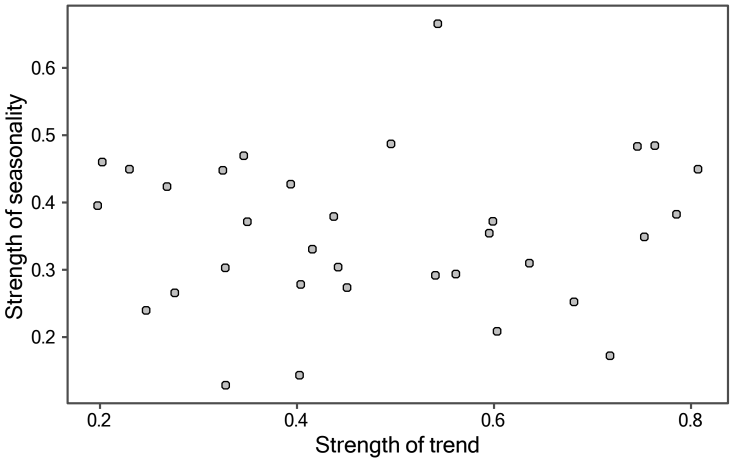


Figure 1: The strength of the trend and seasonality in the time series of pharmaceutical product consumption. The scatter plot shows 33 data points, with each point corresponding to a product.

It is evident that some time series display strong trends and/or seasonality, while the majority exhibit low trends and minimal seasonality. A number of products show pronounced trends, and only a few demonstrate clear seasonal patterns. Beyond assessing the strength of trends and seasonality, we also visualized all time series to understand data and various patterns, including trends and instances of erratic consumption behavior during certain months. For example, some series show low consumption volumes over consecutive months, followed by peak consumption in specific months, making them more volatile and difficult to forecast. This underscores the diversity of monthly pharmaceutical time series patterns within the dataset and highlights the importance of understanding the factors driving these consumption behaviors. Figure Figure 2 illustrates the time plots for a few selected products.

Visualizing the data revealed that various events significantly impacted the consumption of different products, but these were not reflected in the available data. Expert insights were crucial for understanding the nature and timing of these events, filling gaps in the system, and incorporating qualitative factors that EPSS logistics system miss. Therefore, we conducted interviews with domain experts to collect information on external factors that influence consumption. These interviews allowed us to account for unusual patterns and customize our forecasting models to more accurately reflect the unique consumption behaviors of each product.

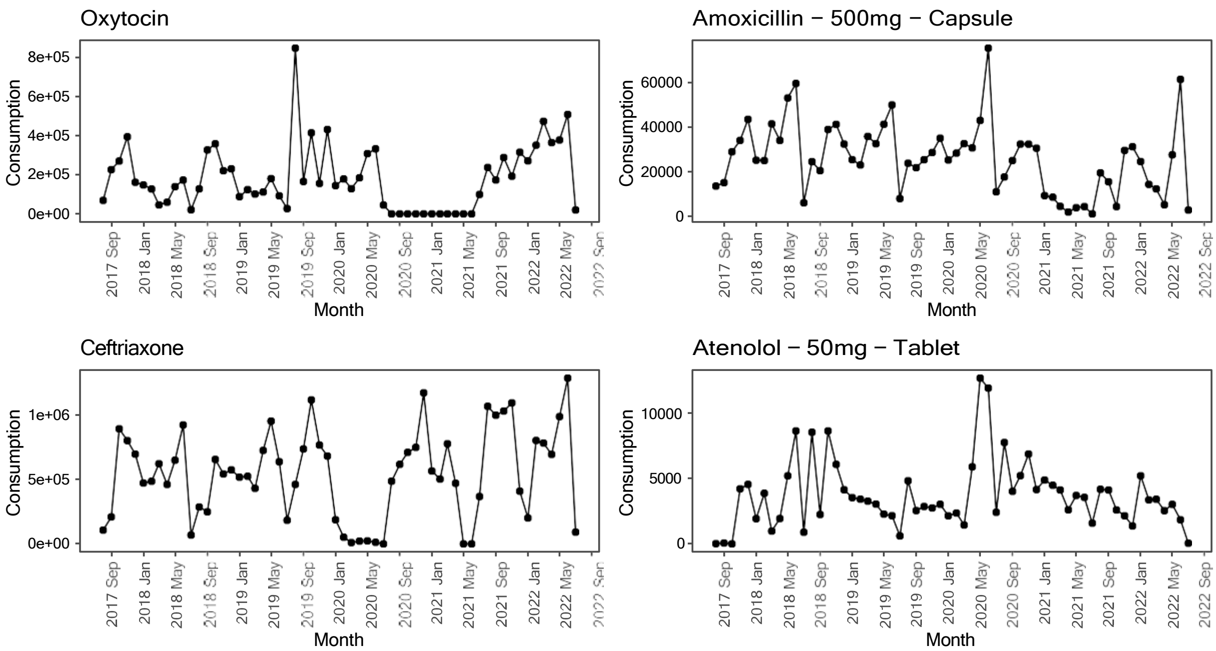


Figure 2: Monthly time plot of consumption. X-axis shows the month, consisting of 60 data points (months) and y-axis shows the comsumption. The panels display data from four products to give a glimpse of the consumption patterns.

Table 2: Summary statistics of the pharmaceutical product time series

item	Mean	Median	Standard deviation	Miinum	Maximum	ACF lag 1	zero_run_mean	nonzero_squared_cv
Adrenaline (Epinephrine) - 0.1% in 1ml Ampoule - Injection	83077.42	69800.00	55257.59	0	204800	0.68	1.0	0.42
Amlodipine - 5mg - Tablet	330051.67	84350.00	473283.80	0	1495700	0.82	2.0	1.75
Amoxicillin - 500mg - Capsule	25880.97	25291.00	15751.99	1137	75305	0.30	0.0	0.37
Anti-Rho (D)	1911.10	1983.00	1475.71	30	8477	0.11	0.0	0.60
Artemether + Lumefanthrine	7364.28	953.00	17714.45	0	88469	0.64	6.5	4.33
Atenolol - 50mg - Tablet	3695.75	3312.50	2587.84	4	12661	0.27	0.0	0.49
Atrovastatin - 20mg - Tablet	3618.97	1302.50	5506.25	0	27973	0.44	1.0	2.26
Ceftriaxone	542999.03	553782.50	346067.19	0	1285708	0.47	2.0	0.36
Dextrose	312489.42	296130.00	255750.02	0	1004850	0.53	5.0	0.39
Frusemide - 10mg/ml in 2ml Ampoule - Injection	176436.17	175360.00	137620.74	17880	940930	0.34	0.0	0.61
Gentamicin	201360.50	182040.00	181410.03	0	654000	0.64	2.0	0.75
Hydralazine - 20mg/ml in 1ml Ampoule - Injection	2952.17	2456.00	2741.23	6	15713	0.57	0.0	0.86
Insulin Isophane Human(Suspension)	66717.83	73816.00	46364.04	0	155631	0.60	11.0	0.21
Insulin Soluble Human	8973.33	8890.50	7140.69	0	28443	0.53	11.0	0.33
Insuline Isophane Biphasic	12795.87	11402.50	8475.27	860	38586	0.45	0.0	0.44
Lamivudine + Efavirenz +Tenofovir	145178.95	167890.50	133576.98	0	550780	0.61	11.0	0.51
Lamivudine + Zidovudine	26784.80	22579.00	22565.25	0	89910	0.55	11.0	0.39
Lidocaine HCL	80100.70	62702.00	105600.48	1000	791050	0.12	0.0	1.74
Magnesium Sulphate	3573.83	1832.50	4465.78	0	22649	0.49	11.0	1.09
Medroxyprogesterone	501663.00	560692.00	328276.14	0	984774	0.65	11.0	0.16
Metformin - 500mg - Tablet	26505.25	20294.75	21695.60	654	86705	0.42	0.0	0.67
Omeperazole - 20 mg - Capsule (Enclosing Enteric Coated Granules)	46368.55	40012.00	38379.32	0	176219	0.62	6.0	0.52
Omeperazole - 4mg/ml in 10ml - Injection	11438.88	3345.50	17643.52	0	81355	0.55	5.0	1.82
Oral Rehydration Salt	507220.42	558426.00	394581.24	0	1384257	0.70	6.0	0.28
Oxytocin	180155.23	151480.00	164309.63	0	846060	0.32	11.0	0.49
Pentavalent	422071.73	474297.50	238940.77	0	944819	0.78	11.0	0.08
Propylthiouracil - 100mg - Tablet	7044.46	6426.50	6112.89	0	28473	0.44	2.0	0.69
RHZ (Rifampicin + Isoniazid + Pyrazinamide)	2260.05	1759.00	2233.00	0	7095	0.70	8.0	0.45
Rapid Diagnostic Test	377843.65	360187.50	264551.71	0	1004325	0.63	11.0	0.21
Ringer's Injection	88896.27	95227.00	54255.34	390	251283	0.53	0.0	0.37
Sodium Chloride (Normal Saline)	300706.82	289171.50	136772.04	60759	702526	0.36	0.0	0.21
Sulphamethoxazole + Trimethoprim - (200mg + 40mg)/5ml - Suspension	84216.90	65917.50	72963.22	20	259512	0.59	0.0	0.75
Tetracycline - 1% - Eye Ointment	199370.65	172721.50	139041.86	7556	585987	0.02	0.0	0.49

Table 2 also provides the summary statistics computed for each pharmaceutical product time series include traditional distributional measures—mean, median, standard deviation, minimum, and maximum—alongside time series–specific and structural characteristics. These include the first-order autocorrelation (ACF at lag 1), the mean length of consecutive zero runs (zero_run_mean), and the squared coefficient of variation computed only on non-zero values (nonzero_squared_cv). Together, these metrics capture not only central tendency and dispersion, but also temporal dependence, sparsity patterns, and relative variability in periods with non-zero consumption.

3.2. Collaborative expert review to identify factors affecting consumption

To incorporate expert knowledge into time series forecasting in a structured and replicable manner, we developed a multi-step process involving expert engagement, collaborative data review, and operational validation. In partnership with the Forecasting and Market Shaping Directorate at EPSS, we identified six experienced professionals from the Warehouse and Inventory Management Directorate with deep operational knowledge of pharmaceutical logistics.

Figure 3 presents a visual overview of the end-to-end approach, highlighting each major stage of the process from expert engagement to model integration.

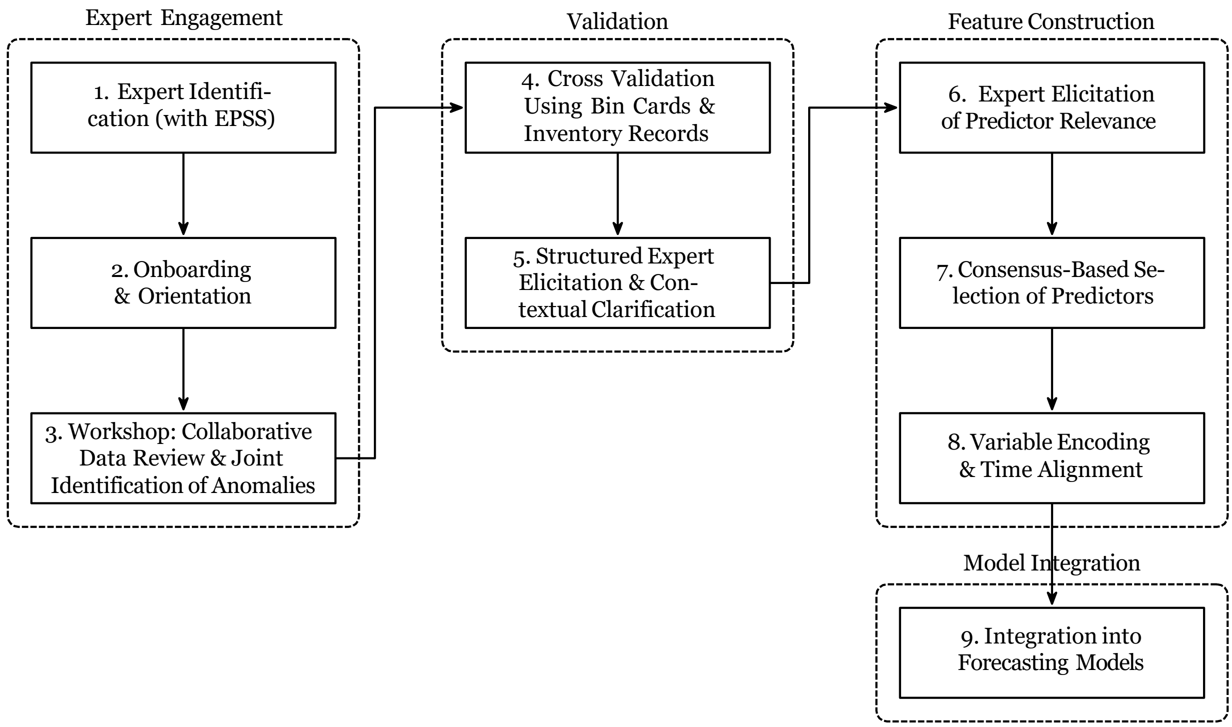


Figure 3: Diagram illustrating the sequential steps involved in collecting, structuring, and utilizing domain knowledge for modeling.

Through a facilitated half-day workshop, these experts reviewed five years of monthly consumption data for 33 pharmaceutical products. Anomalous patterns—such as consumption spikes, prolonged lows, and erratic fluctuations—were jointly identified and interpreted in light of operational events (e.g., emergency distributions, inventory cycles). These insights were cross-validated against bin cards and warehouse records, and internal transfers were excluded to isolate externally relevant events. Dates were standardized to the Gregorian calendar.

Predictor variables were defined through expert consensus, with inclusion contingent on agreement among all six core participants regarding the operational relevance and causal validity of each factor. The final predictors included binary indicators for stock replenishment events, categorical variables for fiscal year inventory counts, and dummy variables for malaria seasonality. A further description of these variables are summarized as followings:

- Stock replenishment: refers to the process of restocking or refilling inventory to ensure that there are sufficient quantities of products or materials available to meet demand. Whenever there was stock replenishment at the central EPSS, consumption and distribution to hubs and health facilities increased. This increase was attributed to the need to restock depleted inventories and the push from central EPSS to manage space constraints.
- Physical fiscal year inventory counting: refers to the process of manually counting and verifying the actual quantities of pharmaceutical products available in stock at a specific location. The process is critical for maintaining the accuracy of inventory records, ensuring that medicines are available when needed, and preventing stockouts or overstocking. Physical inventory counting periods also influenced consumption. Stores closed during these periods, halting transactions. We observed increased consumption before inventory counting periods, as hubs and facilities stocked up. July and August were identified as physical counting periods each year.
- Malaria seasonality: Refers to the predictable patterns and fluctuations in malaria incidence throughout the year, typically influenced by climate and environmental conditions. In many regions, malaria transmission peaks during and shortly after the rainy season, when conditions such as stagnant water pools create ideal breeding sites for the Anopheles mosquitoes that transmit the disease. Conversely, malaria cases often decline during the dry season when mosquito breeding sites are reduced. During peak malaria seasons, there is a significant surge in the demand for antimalarial drugs and other related treatments. Malaria seasonality was another significant predictor. Certain pharmaceuticals, like Artemether + Lumefanthrine and Rapid Diagnostic Test kits, were affected by malaria outbreaks. We identified epidemic periods affecting consumption: September to December 2017, March to May 2018, September to December 2018, March to May 2019, September to December 2019, March to May 2020, September to December 2020, March to May 2021, September to December 2021, and March to May 2022.

These predictors, encoded with known historical and future values, were added to the modeling dataset. This approach ensured consistent integration of expert-informed contextual variables across both point and probabilistic forecasting models.

3.3. Forecasting models

We evaluate a range of univariate models and their counterparts that include predictors, spanning from simpler methods like regression, exponential smoothing, and ARIMA to more complex models such as long short-term memory (LSTM) networks and advanced foundational time series forecasting models. Below, we provide a brief overview of these approaches. Detailed implementation codes in R and Python are available in a GitHub repository and accessible for public.

Exponential Smoothing State Space model (ETS): ETS models, as described by Hyndman and Athanasopoulos (2021), combine trend, seasonality, and error components in time series using different configurations that can be additive, multiplicative, or mixed. The trend component can be specified as none (—N‖), additive (—A‖), or damped additive (—Ad‖); the seasonality can be none (—N‖), additive (—A‖), or multiplicative (—M‖); and the error term can be additive (—A‖) or multiplicative (—M‖). To forecast consumption, we use the ETS() function from the fable package in R, which automatically selects the optimal model for each time series based on the corrected Akaike's Information Criterion (AICc). In our study, an automated algorithm determines the best configuration for trend, seasonality, and error components across each time series, leveraging the ets() function's use of AIC to identify the optimal model. Given the high volume of time series (1530), manual selection of components is impractical, so the algorithm customizes model forms for each series based on its unique characteristics. This results in a tailored combination of additive or multiplicative components, adapting to the specific patterns of each time series.

Multiple Linear Regression (MLR): We use Multiple linear regression to model the relationship between a consumption and potential variables influencing its variation. In our first model, we use multiple linear regression with a trend component to capture the underlying progression over time, i.e., regression. We also incorporate dummy variables for each month to account for seasonal fluctuations, without including any additional predictors, i.e., regression_reg. This approach helps us establish a baseline model focused solely on temporal trends and seasonal patterns. We then extend this model by introducing additional predictors that include variables such as replenishment cycles, fiscal year indicators, and periods with malaria prevalence. These additional predictors allow the model to see if capturing external factors can provide a better understanding of the factors influencing the consumption and result at enhanced accuracy. We produce forecasts using TLSM() function from the fable package in R.

ARIMA and ARIMA with regressors: ARIMA (AutoRegressive Integrated Moving Average) is a powerful statistical model designed to forecast time series by capturing temporal dynamics and are widely used in time series forecasting due to their ability to model complex trends and patterns over time without relying on external predictors. ARIMAX (AutoRegressive Integrated Moving Average with eXogenous variables) extends ARIMA by incorporating external variables, or exogenous predictors, into the model. This modification allows to include relevant information from external factors such as malaria season, and fiscal year period, and stock replenishement period that may explain variations in the series beyond its internal time dynamics, we refer to this in the result as arima_reg. By adding these predictors, ARIMAX combines the strengths of ARIMA's time-series structure with the flexibility of regression models. In our study, we use an automated algorithm to determine the optimal configuration for ARIMA components, following the approach outlined by Hyndman and Athanasopoulos (2021) and We use the ARIMA() function from the fable package in R.

Long Short-Term Memory neural network (LSTM): The LSTM model is a specialised form of recurrent neural network (RNN) used to model sequential data by capturing long-term dependencies (Graves and Graves, 2012). Unlike traditional RNNs, LSTMs can learn to retain information for longer time periods due to their unique architecture, which consists of several gates that control the flow of information. This makes LSTMs particularly effective for time series forecasting. In our implementation, we used a sequential model architecture, comprising one LSTM layer with 50 units, followed by dense layers, with the final output being a single linear unit. The Adam optimizer was employed to minimize the mean squared error, and the model was trained for 100 epochs using the keras_model_sequential() function from the Keras package in R. We use LSTM models both with and without predictors, referring to the LSTM model with predictors as lstm_reg.

To improve the robustness of the LSTM models and address overfitting issues, we introduced dropout regularization layers after the LSTM units and employed early stopping based on validation loss during model training. Each LSTM model was trained independently for each product series. Hyperparameter tuning was performed in a preliminary phase using a subset of products. Various configurations of LSTM units (30–100), dense units (50–200), dropout rates (0.1–0.5), and batch sizes (16–64) were evaluated based on validation set performance. The final model structure — 50 LSTM units, 100 dense units, a 0.2 dropout rate, and a batch size of 32 — was selected as a trade-off between forecast accuracy and model stability across different demand patterns.

TimeGPT: TimeGPT is the first pre-trained foundational model designed specifically for time series forecasting, developed by Nixtla (Garza et al., 2023). It uses a transformer-based architecture with an encoder-decoder configuration but differs from other models in that it is not based on large language models. Instead, it is built from the ground up to handle time series data. TimeGPT was trained on more than 100 billion data points, drawing from publicly available time series across various sectors, such as retail, healthcare, transportation, demographics, energy, banking, and web traffic. This wide range of data sources, each with unique temporal patterns, enables the model to manage diverse time series characteristics effectively. Furthermore, TimeGPT supports the inclusion of external regressors in its forecasts and can generate quantile forecasts, providing reliable uncertainty estimation. We use TimeGpt models both with and without predictors, referring to the model with predictors as timegpt_reg.

3.4. Generating probabilistic forecasts

In addition to point forecasts, we generated probabilistic forecasts to capture the uncertainty surrounding future pharmaceutical consumption. Several approaches are available for generating probabilistic forecasts, including analytical prediction intervals, quantile regression, Bayesian modeling through Markov Chain Monte Carlo (MCMC) methods, bootstrapping, and conformal prediction (Wang et al., 2023).

In this study, we employed a bootstrapping approach to construct predictive intervals. Bootstrapping was chosen primarily for its flexibility and model-agnostic nature, allowing it to be applied uniformly across the diverse range of forecasting methods implemented without requiring strong distributional assumptions. Moreover, pharmaceutical consumption data often exhibit irregular and volatile patterns, making non-parametric approaches like bootstrapping particularly suitable.

Specifically, we assume that future forecast errors will be similar to past forecast errors. The forecast error at time t is defined as: $e_t = y_t - \hat{y}_t$where represents the observed consumption, and denotes the corresponding forecast estimate. To simulate future consumption paths, we randomly sample errors with replacement from the historical error distribution and add them to the point forecast estimates. This process is repeated multiple times (1,000 iterations in our study) to generate a distribution of possible outcomes for each forecast horizon.

Prediction intervals at the desired confidence level (e.g., 95%) are then constructed by taking appropriate quantiles from the empirical distribution of the simulated forecasts (Hyndman and Athanasopoulos, 2021).

The bootstrapping method thus provides a robust and flexible framework to quantify forecast uncertainty across a heterogeneous set of pharmaceutical products without imposing restrictive parametric assumptions.

3.5. Performance evaluation

To evaluate the performance of our forecasting models, we split the data into a series of training and test sets and employed a time series cross-validation approach, following best practices for forecasting evaluation (Hyndman and Athanasopoulos, 2021). Rather than using a fixed training and test split, we used a rolling-origin cross-validation framework, which allows for a more comprehensive assessment across different demand patterns and periods. In our setup, the initial training set consisted of all available historical data from December 2017 up to June 2021. The evaluation period covered the subsequent 12 months, reflecting the operational needs of the EPSS, which plans consumption over a one-year horizon. At each iteration, models were trained on an expanding training window and evaluated over a fixed 6-month forecast horizon, aligned with typical EPSS planning cycles. After each forecast generation, the training set was expanded by one additional month, and the process was repeated, allowing for rolling assessment across the final 12 months of data. This structure ensured that forecasts reflected realistic operational scenarios, where forecasts are continuously updated as new data becomes available. This cross-validation design allowed us to evaluate each model's ability to perform across multiple different forecast origins and a variety of demand conditions, providing a more reliable and generalizable understanding of model performance. Furthermore, all model development steps, including hyperparameter tuning for the LSTM models, were conducted exclusively using the training data available at each iteration. No test set information was used during model selection or tuning.

The error metrics presented here consider a forecasting horizon denoted by by h, which represents the number of time periods ahead we are predicting, with h ranging from 1 to 6 months in our study. Point forecast accuracy is measured using the Mean Squared Scaled Error (MSSE) and the Mean Absolute Scaled Error (MASE). The Mean Absolute Scaled Error (MASE) (Hyndman and Koehler, 2006; Hyndman and Athanasopoulos, 2021) is calculated as follows:

$$\text{MASE} = \text{mean}(|q_j|),$$

where

$$q_j = \frac{e_j}{\frac{1}{T-m}\sum_{t=m+1}^{T}|y_t - y_{t-m}|},$$

,

and e_j is the point forecast error for forecast horizon j, $m = 12$ (as we have monthly seasonal series), y_t is the observation for period t, and T is the sample size (the number of observations used for training the forecasting model). The denominator is the mean absolute error of the seasonal naive method in the fitting sample of Tobservations and is used to scale the error. Smaller MASE values suggest more accurate forecasts. Note that the measure is scale-independent, thus allowing us to average the results across series.

Here, e_j represents the point forecast error for forecast horizon j, with m= 12 (since we are dealing with monthly seasonal data). The term$y_t$denotes the observation at time t, and T is the sample size, or the number of observations used for training the forecasting model. The denominator in the MASE formula is the mean absolute error of the seasonal naive method over the training sample of$T$ observations, providing a basis for scaling the forecast error. Lower MASE values indicate more accurate forecasts. Notably, this measure is scale-independent, allowing us to average results across different series for broader performance comparison.

A related measure is MSSE (Hyndman and Athanasopoulos, 2021; Makridakis et al., 2022), which uses squared errors rather than absolute errors:

$$\text{MSSE} = \text{mean}(q_j^2),$$

where,

$$q_j^2 = \frac{e_j^2}{\frac{1}{T-m}\sum_{t=m+1}^{T}(y_t - y_{t-m})^2},$$

Again, this is scale-independent, and smaller MSSE values suggest more accurate forecasts.

To measure the forecast distribution accuracy, we calculate the Continuous Rank Probability Score (Hyndman and Athanasopoulos, 2021). It rewards sharpness and penalizes miscalibration, so it measures overall performance of the forecast distribution. For probabilistic evaluation, 1,000 future paths were simulated per series, enabling robust estimation of forecast uncertainty

$$\text{CRPS} = \text{mean}(p_j),$$

where

$$p_j = \int_{-\infty}^{\infty} \left(G_j(x) - F_j(x)\right)^2 dx,$$

where *Gj (x)* is the forecasted probability distribution function for forecast horizon j, and *Fj (x)*, and is the true probability distribution function for the same period.

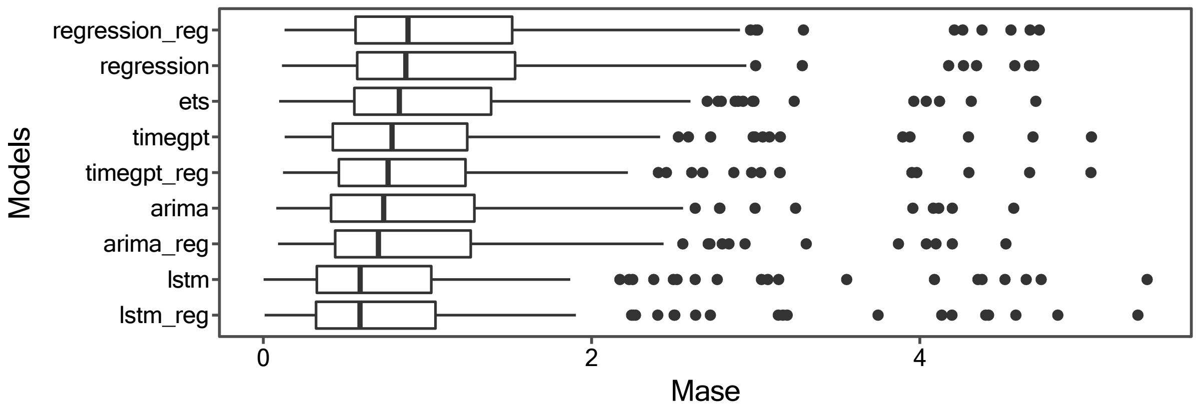
Calibration refers to the statistical consistency between the distributional forecasts and the observations. It measures how well the predicted probabilities match the observations. On the other hand, sharpness refers to the concentration of the forecast distributions — a sharp forecast distribution results in narrow prediction intervals, indicating high confidence in the forecast. A model is well-calibrated if the predicted probabilities match the distribution of the observations, and it is sharp if it is confident in its predictions. The CRPS rewards sharpness and calibration by assigning lower scores to forecasts with sharper distributions, and to forecasts that are well-calibrated. Thus, it is a metric that combines both sharpness and miscalibration into a single score, making it a useful tool for evaluating the performance of probabilistic forecasts.

CRPS can be considered an average of all possible quantiles (Hyndman and Athanasopoulos, 2021, Section 5.9), and thus provides an evaluation of all possible prediction intervals or quantiles. A specific prediction interval could be evaluated using a Winkler score, if required.

4. Results and discussion

In this section, we compare the forecasting performance of various approaches, examining models that incorporate expert-identified business context predictors versus those that rely solely on historical consumption data. Point forecast performance is reported using MASE and RMSSE, while probabilistic forecast accuracy is reported using CRPS.

The forecasting performance is reported in Figure 4, in which the average forecast accuracy over forecast horizon and across all products is calculated for each origin. We report the distribution of accuracy metrics across all rolling origins. This shows how models varies in providing accuracy across different origins. The y-axis displays models sorted by their MASE and RMSSE values, with the model exhibiting the lowest error positioned at the bottom. This model is the LSTM model, followed by ARIMA, which incorporate exogenous variables. Additionally, Figure 4 indicates that predictors obtained through interactions with domain experts enhance point forecast accuracy across most models. This underscores the critical importance of systematically collecting such expert-informed data alongside transactional consumption data.



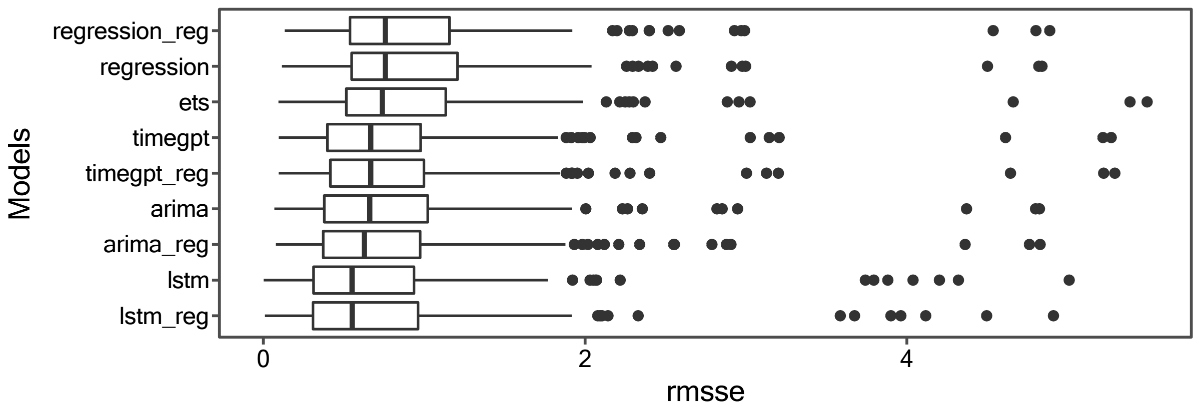


Figure 4: Distribution of point forecast accuracy across different origins, averaged across the forecat horizon and all products. The total number of months used to calculate the accuracy in the test set is 12 months for each product. MASE and MSSE are relative to the corresponding values for the training set.

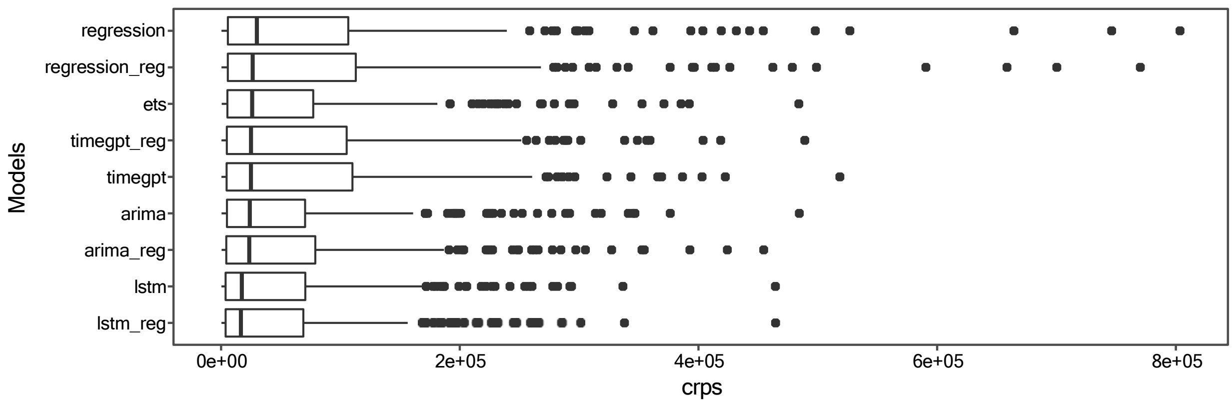


Figure 5: Distribution of probabilistic forecast accuracy across different origins, averaged across the forecat horizon and all products. The total number of months used to calculate the accuracy in the test set is 12 months for each product.

Figure 5 illustrates the forecast distribution accuracy measured by CRPS, which evaluates both forecasting calibration and interval sharpness. A smaller CRPS value indicates better overall performance. We observed that incorporating domain knowledge improved forecast accuracy for most models, enhancing not only point forecasts but also probabilistic forecasts. Notably, LSTM and ARIMA yielded the most accurate probabilistic forecasts when identified predictors were incorporated. This aligns with the findings related to point forecast accuracy, reinforcing the earlier explanations for these results.

While LSTM models achieved the best overall forecast accuracy across products, their performance exhibited notable variability depending on the characteristics of individual demand patterns. For example, the product $Amlodipine - 5mg - Tablet$demonstrates periods of extreme variability, with spikes in demand followed by periods of very low or zero consumption. Such patterns align well with the strengths of univariate LSTM models, which are adept at capturing long-term dependencies and managing complex temporal fluctuations. In contrast, the demand for [illegible] is erratic and sparse, with frequent random fluctuations and little structural consistency. This lack of clear temporal patterns can make it challenging for LSTM models to learn generalizable signals, particularly given the limited data length available for training. Although LSTM can manage irregular data to some extent, it performs best when patterns are consistent or cyclic. These variations across product types contributed to the observed distribution of forecast errors across the product portfolio. Moreover, although we expect that multivariate LSTM models benefit from expert-informed predictors, our results show that the univariate LSTM consistently achieved better forecast performance. This outcome may be attributed to the nature of the predictors—binary, static, or weakly aligned with short-term temporal dynamics—which can disrupt rather than enhance learning when added to a neural network sensitive to input configuration. Moreover, with relatively short historical series and limited training samples, the inclusion of additional variables may have led to overfitting or reduced generalization. These findings suggest that while LSTM models can effectively learn temporal patterns from consumption data alone, incorporating structured external knowledge requires careful feature engineering and alignment to be beneficial.

The findings emphasize the importance of incorporating relevant domain knowledge into forecasting models. In pharmaceutical supply logistics administration systems, data often consists solely of transactional records on consumption and distribution. Including exogenous variables such as administrative procedures, seasonal patterns, or conflicts, or any other relevant factor that could be identified by those with domain knowledge proved essential for reducing forecast errors. This approach improved both point and probabilistic forecast accuracy, enabling a more confident assessment of uncertainty. Therefore, the systematic collection of information about significant events and their impact on consumption is vital. Recording details of events such as policy changes, administration procedures, conflicts, and incorporating this information into forecasting models creates a comprehensive understanding of consumption. This practice enhances modeling reliability and allows institutions in developing countries and humanitarian organizations to better forecast demand, allocate resources effectively, and respond proactively. Establishing robust data collection systems is thus a critical step for strengthening forecasting capabilities and operational resilience.

4.1. Computational efficiency and resource considerations

In addition to forecast accuracy, it is also important to consider the computational efficiency of each model, particularly in settings where computational resources and technical expertise are limited.

Table 3 shows the total runtime required to train and generate forecasts across all 33 pharmaceutical product time series for each method for all origins. All models were implemented using R, except TimeGPT, which was run via Google Colab using a T4 GPU backend. All other models were executed on a local machine with 7 CPU cores (11th Gen Intel(R) Core(TM) i5-1135G7 @ 2.40 GHz and 8 GB RAM)

Table 3: Computation time required for training and generating forecasts for each model across all products.

Model	Runtime (Seconds)	Runtime type	category
LSTM	6892.30	CPU with 7 cores	high
LSTM with regressors	7234.00	CPU with 7 cores	high
Regression	27.48	CPU with 7 cores	low
Regression with regressors	47.38	CPU with 7 cores	low
ARIMA	96.27	CPU with 7 cores	low
ARIMA with regressors	138.08	CPU with 7 cores	medium
TimeGPT	2.57	Colab T4 GPU	low
TimeGPT with regressors	3.72	Colab T4 GPU	low
ETS	75.71	CPU with 7 cores	low

As shown in Figure 4 and 5, models that incorporated expert-informed regressors generally achieved better forecast accuracy compared to their univariate versions. This trend was most evident in classical models such as ARIMA and regression, where the inclusion of regressors led to a noticeable shift toward lower and more concentrated error distributions. However, this improvement came with an increase in computational cost. In all cases, the addition of regressors increased runtime—by 72% in the regression model (from 27.48 to 47.38 seconds) and by 43% in ARIMA (from 96.27 to 138.08 seconds). TimeGPT also showed a slight increase in runtime (from 2.57 to 3.72 seconds), although the total processing time remained extremely low overall. Moreover, LSTM exhibited the largest increase in runtime when regressors were added, rising from 6,892 to 7,234 seconds. This sharp increase reflects the sensitivity of neural networks to input configuration, especially in contexts with limited data, irregular demand, and noisy signals.

These results underscore the importance of balancing model performance with implementation cost. While deep learning models such as LSTM offer strong potential when well-tuned, they demand significantly more computational resources and may be less robust when integrating static or weakly aligned contextual features. By contrast, TimeGPT, a foundational model pretrained on large-scale time series data, provides a compelling alternative. It required less than 4 seconds to forecast all products, offered competitive accuracy, and required no tuning or retraining—making it well-suited for practical use in low-resource environments.

4.2. An illustration of probabilistic forecast for Pharmacuitical product consumption

In this section, we present an illustrative example of a probabilistic forecast for future consumption of Sodium Chloride (Normal Saline) product. Due to the complexity of including such visualizations for all products, only one example is shown here. However, it is feasible to generate these plots for all products if needed.

In practice, point forecasts are commonly used despite their limitations, but they do not account for the inherent uncertainty associated with forecasts. The future is inherently uncertain, and effective planning requires considering alternative scenarios. Probabilistic forecasts offer a comprehensive approach by assigning likelihoods to a range of possible outcomes, recognizing that different consumption levels may occur with varying probabilities. The goal is to maximize the sharpness of these predictive distributions—i.e., how concentrated the forecasts are—while maintaining calibration, meaning that the predicted probabilities align well with actual outcomes (Gneiting and Katzfuss, 2014). This approach allows decision-makers to fully leverage available information, incorporating uncertainty in a structured and measurable way. The primary purpose, as illustrated in Figure 6, is to quantify and communicate uncertainty. This figure displays the forecast distribution of consumption over a 6-month horizon using a density plot. For each month within the forecast period, a separate distribution is generated. The plot also includes the point forecast alongside 80% and 90% prediction intervals to illustrate potential variability.

Probabilistic forecasts enhance planning and decision-making by offering a comprehensive view of potential future outcomes and their likelihood, rather than relying on a single point estimate. A probabilistic forecast takes the form of a predictive probability distribution over future quantities or events of interest.

It is important to note that while point forecasts and prediction intervals can be derived from probabilistic forecasts, the reverse is not true. A single-point forecast cannot inherently provide the probabilistic context needed to capture the range of possible outcomes. Although prediction intervals can indicate a range of potential values, they do not convey the detailed probabilities of low or high consumption. This distinction highlights the value of probabilistic forecasting in supporting informed decision-making by offering a clearer view of future uncertainties.

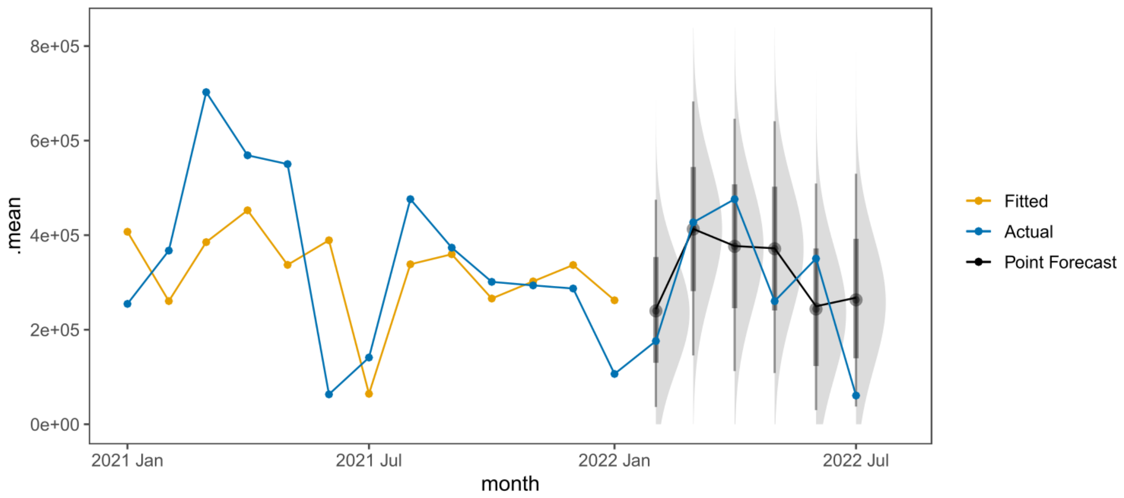


Figure 6: A graphical illustration of the forecast distribution of a pharmacutical product (i.e. total incidence attended) for the SB health board for a horizon of six month. For each month, we display the point forecast (black point), the histogram, and 80% (thick line) and 90% (thin line) prediction intervals. It also shows a portion of a historical time series as well as its fitted values.

To further illustrate the practical relevance, we consider an illustrative case where the mean forecasted consumption for the next month is 1,000 units, with a 90% prediction interval ranging from 850 to 1,150 units. Table 4 summarizes the decision outcomes under each approach.

Under a traditional approach, inventory decisions would rely solely on the point forecast. Based on the mean prediction of 1,000 units, the store manager would order precisely that quantity, assuming it would meet the expected demand. However, this approach does not incorporate any adjustment for uncertainty, potentially leading to stockouts if actual demand exceeds 1,000 units, or excess inventory if consumption is lower.

In contrast, utilizing the full probabilistic forecast allows the decision-maker to take variability into account. If a higher service level is required, for example 95%, the inventory policy may be adjusted by stocking closer to the upper bound of the 90% prediction interval (e.g., 1,150 units). If inventory holding costs are a major concern and the organization can tolerate a modest risk of shortage, the order quantity could remain closer to the median forecast of 1,000 units.

Table 4: Comparison of ordering decisions under point and probabilistic forecasts - an illustrative example.

Forecast Type	Ordering Quantity	Risk Consideration
Point Forecast Only	1,000 units	No explicit consideration of uncertainty
Probabilistic Forecast (95% service level)	1,150 units	Adjusts inventory to account for demand variability

This illustrative comparison indicates that point forecasts provide a single estimate without adjusting for forecast uncertainty, while probabilistic forecasts allow decision-makers to explicitly align inventory decisions with risk tolerance and service level requirements. This is particularly important for pharmaceutical products, where the consequences of stockouts or overstocking can be significant both operationally and clinically.

4.3. Managerial Implications

This study offers actionable lessons for supply chain managers, public health planners, and policymakers navigating the uncertainty of pharmaceutical demand—particularly in systems like Ethiopia, where operational constraints and demand volatility are the norm, not the exception.

At present, national forecasting at the Ethiopian Pharmaceutical Supply Service (EPSS) still relies heavily on basic extrapolation tools—usually Excel sheets or donor-developed software such as the Quantification Analysis Tool (QAT). These tools are easy to use but limited: they assume stable demand, ignore uncertainty, and often miss the operational signals embedded in local experience. In practice, forecasts are sometimes adjusted based on gut feeling or anecdotal program insights—not because planners want to—but because the tools don't offer a better alternative.

The models developed here—freely available, open-source, and designed to integrate directly with routine EPSS data—allow planners to make decisions using full probabilistic forecasts, not just single-point estimates. Forecasts are delivered with prediction intervals (e.g., 80% or 90%) that help teams decide not only how much to order, but how much risk they're willing to tolerate. For products with known seasonality—like antimalarials or diagnostic kits—this matters. The system doesn't just forecast a number; it gives planners a buffer strategy.

Beyond accuracy, the models also reflect how medicines actually move through the system. Predictors based on warehouse replenishments, fiscal year inventory routines, and known disease cycles are embedded into the forecasts—not hard-coded, but learned from the data in ways that are transparent and reproducible. These inputs are drawn from expert operational knowledge and can be updated or modified as the system evolves.

Importantly, the entire modeling pipeline is built in R and Python, and is already shared alongside code and data. This makes it immediately usable by EPSS analysts and regional logistics teams, even in settings without access to proprietary tools or high-end infrastructure. It's not a black box; it's something the system can own, modify, and grow with.

To support real uptake, we recommend five practical steps:

- Embed these probabilistic models into EPSS quantification rounds to replace rigid extrapolation methods and bring scenario-based planning into monthly and quarterly cycles.
- Use prediction intervals to define risk-informed buffer policies, especially for high-volatility products. Not every item needs the same margin of error.
- Automate the collection of domain knowledge (e.g., replenishment events, stock counts, seasonal triggers) into the logistics data stream to reduce reliance on manual elicitation while preserving contextual intelligence.
- Train regional and central teams using the open-source tools and shared codebase, turning forecasting into a hands-on, in-country competency rather than a dependency on external tools or consultants.
- Establish routine forecast review sessions, supported by visual dashboards that reflect not just what the model says, but how uncertain that estimate is—and what that means for stock levels, procurement plans, and emergency readiness.

Taken together, these steps push forecasting beyond formulas and into real decision-making.

5. Conclusion and future reserach

In this study, we conducted an extensive analysis of pharmaceutical demand forecasting within the EPSS. Using five years of consumption data for 33 key pharmaceutical products, along with additional information gathered through collaboration with domain experts at EPSS, our goal is to contribute to enhancing the demand forecasting process and emphasize the importance of integrating domain knowledge into model building. This step is critical, as the phase of understanding the data and incorporating valuable contextual information is often overlooked. Too frequently, forecasting efforts rely solely on consumption data, leading to building models with little relevance to reality. Our approach highlights the necessity of including domain insights to construct more accurate and effective forecasting models.

Our findings highlight the importance of collecting and incorporating domain knowledge when building forecasting models. We evaluated both point and probabilistic forecasts using a range of models, from simple univariate approaches like ARIMA to complex models such as LSTM. We demonstrated that while the use of complex models may improve forecast accuracy in the pharmaceutical supply context, this comes at the cost of significantly increased computational time—an important consideration for resource-constrained settings in low- and middle-income countries (LMICs). Additionally, our research indicates that newly developed foundational time series forecasting models hold promise, particularly in settings with limited computational infrastructure and constrained access to advanced analytical expertise, as often seen in pharmaceutical supply chains in developing countries.

To advance forecasting practices further, exploring additional predictor variables—such as public health campaigns, disease outbreaks, and economic indicators—could provide valuable insights into demand dynamics. Improving the granularity of historical consumption data, through finer temporal intervals and geographic differentiation, also holds potential for more precise predictions. Additionally, hybrid forecasting models that combine judgmental point forecasts with probabilistic machine learning models could enhance predictive performance. Empowering EPSS staff through training in foundational time series models, data interpretation, and collection will enable informed decision-making and strengthen workforce capabilities. Replicating this study across diverse healthcare settings and conducting comparative analyses would help validate the adaptability and applicability of the findings. Additionally, it is recommended that pharmaceutical supply services systematically collect and maintain detailed records of events that may influence consumption, alongside consumption data. This practice is essential for refining demand models and enhancing forecast accuracy.

5.1. Practical challenges and limitations

Despite dedicated efforts to engage with domain experts to better understand the data—and spending significant time over two weeks collaborating with them—we found that the process of interpreting data through domain knowledge is complex and presents unique challenges. These challenges include defining what constitutes domain knowledge and determining how best to incorporate it to enhance model reliability and accuracy. Below, we summarize some of these key challenges. One issue involved capturing accurate information from bin cards and expert review, particularly during periods of disruption like COVID-19 and conflicts. For instance, during the COVID-19 pandemic, experts noted a decrease in demand due to travel restrictions. However, despite the reduced demand, there were still significant distributions of pharmaceuticals from the EPSS central to various hubs and health facilities. This was because, in response to anticipated shortages, a political decision was made to push products to these facilities before the travel restrictions took full effect. The rationale was that if the facilities remained closed, patients would have no access to medications, necessitating the preemptive stockpiling of essential pharmaceuticals. This scenario illustrates how policy decisions can significantly impact supply chain data, making it challenging to model distribution patterns accurately. Similarly, experts indicated that conflicts would disrupt the distribution of pharmaceuticals. While conflict zones did indeed hinder transportation, distribution still occurred whenever roads were temporarily opened, even amidst on-going conflict. This created inconsistencies in the data, as periods of halted distribution were followed by rapid replenishment once access was restored. Such fluctuations add complexity to modelling the supply chain from the central EPSS to hubs and health facilities. Other challenges involved seasonal or periodic activities, such as the fiscal year-end stock counting. During this time, EPSS temporarily halts transactions to conduct a full inventory count, which can take anywhere from one to two months, depending on the circumstances. This inconsistency in the duration of inventory counts adds a layer of unpredictability to supply chain modelling.

5.2. Future reserach

Following the current research, several promising areas could further advance knowledge and practical applications in this area:

- Future research could focus on developing intelligent systems that incorporate domain-specific knowledge into model building. This would involve creating algorithms capable of identifying relevant domain insights and integrating them effectively into model training processes. Such tools would bridge the gap between purely data-driven approaches and expert-knowledge-enhanced modeling, leading to more robust and contextually informed forecasts.
- Large Language Models (LLMs) for time series forecasting, like the one included in this study, offer transformative opportunities for developing countries by making advanced forecasting methods accessible, even in contexts with limited expertise or infrastructure. However, future research should explore their applicability, advantages, limitations, and performance relative to traditional and hybrid forecasting methods.
- Disruptions such as the COVID-19 pandemic and armed conflicts may alter consumption patterns in time series data, introducing irregularities that challenge the assumptions of traditional forecasting methods. In such contexts, it becomes important not only to model observed consumption but also to account for censored demand—i.e., the unmet need that would have been fulfilled under normal conditions and is essential for effective replenishment planning. Future research could focus on developing and evaluating forecasting strategies that are specifically designed to handle disrupted time series and estimate censored demand. In particular, methods that enhance the robustness of probabilistic forecasts in the presence of structural breaks or exogenous shocks are especially relevant. One promising direction is also the development of causal forecasting models that incorporate policy changes, epidemic dynamics, and socio-economic factors—an approach that may be particularly well suited to the realities of pharmaceutical supply chains in low- and middle-income countries (LMICs).
- Future research should explore the integration of probabilistic forecasting into inventory management policies, with a focus on evaluating the operational impact of forecast uncertainty. In addition,

there is substantial potential in leveraging more granular data—such as daily or weekly consumption patterns—and examining forecasts at hierarchical levels, including individual sites or health facilities. Investigating how fine-grained temporal and spatial forecasts influence decision-making in inventory control could provide valuable insights into reducing stockouts, minimizing holding costs, and decreasing pharmaceutical waste.

Reproducibility

To enhance transparency and reproducibility, we not only provide data and the code, but also the entire paper that is written in R & Python. All materials to reproduce this paper is available at Insert Github link once paper accepted.

The repository contains the raw data, all R and Python scripts used in experiments, the results used in the paper, as well as the quarto files for producing this paper.

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Paper IV

pharmacy

Article

Effective Supply Chain Strategies in Addressing Demand and Supply Uncertainty: A Case Study of Ethiopian Pharmaceutical Supply Services

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Abstract: Background: Ensuring the consistent availability of essential medicines is crucial for effective healthcare systems. However, Ethiopian public health facilities have faced frequent stockouts of crucial medications, highlighting systemic challenges such as inadequate forecasting, prolonged procurement processes, a disjointed distribution system, suboptimal data quality, and a shortage of trained professionals. This study focuses on the Ethiopian Pharmaceutical Supply Services (EPSS), known for its highly unstable and volatile supply chain, aiming to identify risks and mitigation strategies. Methods: Using a mixed-method approach involving surveys and interviews, the research investigates successful and less successful strategies, key success factors, and barriers related to pharmaceutical shortages. Results: Proactive measures such as communication, stock assessment, supervision, and streamlined procurement are emphasized as vital in mitigating disruptions, while reactive strategies like safety stock may lack long-term efficacy. The study highlights the importance of aligning supply chain strategies with product uncertainties, fostering collaboration, and employing flexible designs for resilience. Managerial implications stress the need for responsive structures that integrate data quality, technology, and visibility. Conclusions: This study contributes by exploring proactive and reactive strategies, elucidating key success factors for overcoming shortages in countries with unstable supply chains, and offering actionable steps for enhancing supply chain resilience. Embracing uncertainty and implementing proactive measures can help navigate volatile environments, thereby enhancing competitiveness and sustainability.

Keywords: demand; pharmaceutical supply chain; proactive; reactive; strategies; supply

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1. Introduction

Universal access to essential medicines is crucial for effective healthcare systems, yet equitable availability remains a global challenge [1,2]. Many nations, particularly in Africa and Asia, struggle with access due to unaffordability and supply chain inefficiencies [3,4]. Drug shortages also impact developed countries like the U.S. and Europe, affecting healthcare quality and patient care [5,6]. These shortages, caused by supply chain disruptions, have financial and patient care consequences [5,7,8].

Factors such as globalization, manufacturing issues, natural disasters, pandemics, and regulatory requirements contribute to medicine shortages [8,9]. Supply chain complexities introduce additional challenges like demand variations and resource limitations [10]. Recent disruptions, including material cost increases [11], demand variations due to the COVID-19 pandemic [12], and supply chain interruptions, have exposed the vulnerability of supply chains [13–16]. These challenges necessitate a reevaluation of supply chain strategies to enhance resilience and adaptability [17,18].

Inaccurate demand forecasting increases healthcare costs and inefficiencies, affecting drug therapy and patient safety [19–24]. A robust supply chain strategy integrates suppliers, manufacturers, and distribution mechanisms to optimize resources and service levels [24]. Addressing shortages, especially in low-income countries, involves managing stock use restrictions, efficient redistribution, and enhancing stakeholder communication [25]. Persistent research gaps in low- and middle-income countries highlight the need for collaborative efforts to tackle this challenge.

An efficient supply chain is integral to organizational success, particularly in healthcare, consumer goods, and agriculture, where shortages can have costly consequences [26,27]. Managing supply and demand uncertainty remains a persistent challenge [28]. Fisher (1997) categorized supply chains into efficient and responsive types based on demand predictability, while Lee (2002) extended this framework to include supply uncertainties. Effective management of these uncertainties involves mechanisms to cope with them and meet customer demands efficiently [29,30].

As supply chain management becomes increasingly complex due to changing customer demands, disruptions, and natural disasters, recent global economic turbulence emphasizes the urgency for resilient and sustainable strategies. Demand uncertainty, arising from factors like seasonal fluctuations and economic conditions, necessitates a flexible supply chain. Supply uncertainty poses challenges such as supplier unreliability, communication issues, and quality concerns. Effective management requires robust supplier relationships, rapid onboarding, and harmonized communication. Operational uncertainties, including transportation delays and production disruptions, impact the supply chain, requiring real-time tracking and effective inventory management. The COVID-19 pandemic and geopolitical events, such as Brexit and conflicts in Ukraine, Gaza, and Yemen, have amplified global supply chain disruptions. Issues like chip shortages and shipping delays underscore the need for strategic supply chain planning and resilience. Geopolitical events disrupt international supply chains, highlighting their vulnerability. The disruption emphasizes the challenges of internal supply chain volatility, necessitating strategies to transform volatility into opportunities.

In Ethiopia, the pharmaceutical supply chain has evolved with EPSS and the Pharmaceutical Logistics Master Plan but still faces issues like stock-outs and wastage [31–33]. Comprehensive research is needed to develop effective mitigation strategies, especially in resource-limited settings. This paper aims to identify risks in the EPSS supply chain and strategies to mitigate drug shortages, using literature reviews, surveys, and interviews to guide effective supply chain strategies.

2. Literature Review

Our work relates to several streams of literature, including relevant studies that focus on pharmaceutical drug shortages, supply chain risks, factors that contribute to drug product shortages, challenges in the Ethiopian Pharmaceutical Supply Services, and supply chain strategies during demand uncertainties in the pharmaceutical industry.

2.1. Drug Shortages Factors That Contribute to Drug Shortages

Drug shortages occur when the total supply of all clinically interchangeable versions of a regulated drug falls short of demand [34]. Despite increased research, reliable data to assess and combat medicine shortages globally remain insufficient [35,36]. In the U.S., medicine shortages have been tracked since the early 2000s but still persist [35,37]. The global rise in essential medicine shortages poses a significant challenge [35,38,39]. Unpredictable demand, limited planning resources, and organizational constraints exacerbate this issue [40]. Drug shortages significantly impact global healthcare, driven by multifaceted factors. These include non-traditional economics where patients lack control over prescriptions and limited transparency in manufacturing [41,42]. Medical supply chains face access, security, and traceability issues [40]. Manufacturing delays, capacity limits, and business decisions disrupt supply, alongside shortages in active pharmaceutical ingredients (APIs) and raw materials. Inefficient inventory practices and restricted distribution exacerbate the issue [39,43,44]. Additional challenges like single sourcing, global sourcing risks, minimal buffer stocks, and a focus on cost reduction increase vulnerabilities [45,46]. Supply chain risks from environmental, organizational, or network sources lead to chaos, inertia, and a lack of confidence [47–49]. Regulatory demands and market entry barriers further complicate the situation [35,44]. Understanding these factors is crucial for developing strategies to mitigate the impact of drug shortages on healthcare.

In Ethiopia, frequent stockouts of essential medicines worsen healthcare challenges [31,50]. Effective solutions are urgently needed to address these shortages. Understanding the definition, prevalence, and consequences of drug shortages is crucial for mitigating their impact on healthcare systems and patient well-being.

2.2. Supply Chain Risks

Organizations form interconnected networks, increasing interdependence and associated risks [51]. These complex supply chains span globally, with risks multiplying across components and processes [52,53]. Modern technology helps mitigate these risks through digitalization and data analytics [54]. Supply chain risks are categorized into demand risks, such as seasonal fluctuations, and supply risks, like manufacturing challenges [55]. Risks include delays, disruptions, forecast inaccuracies, and intellectual property breaches [56]. External risks stem from events like natural disasters, while internal risks arise from supply chain management [46]. Supply disruptions can lead to customer dissatisfaction, revenue loss, and safety concerns [45]. Understanding and mitigating these risks is crucial for maintaining a robust supply chain.

2.3. Challenges in the Ethiopian Pharmaceutical Supply Services

The Ethiopian Pharmaceutical Supply Services (EPSS) plays a vital role in providing affordable and reliable pharmaceuticals to public health facilities in Ethiopia. However, several challenges have hampered its ability to effectively manage drug shortages and ensure the availability of essential medications. One significant challenge faced by the EPSS is inaccurate drug forecasting. A study conducted within the EPSS [57] revealed that the mean percentage forecast error for program commodities stood at 27.8%. This error rate exceeds the acceptable threshold, which is 25% or less [58], and there are variations in forecast accuracy among individual items. For instance, forecast errors for HIV/AIDS and malaria commodities reached 31.71% and 37.25%, respectively, deviating from the expected range [57,59]. The EPSS encounters lengthy procurement lead times, with an average of 137.3 days and orders sometimes experiencing delays of up to 294 days. Such delays significantly impact drug availability. In addition, poor data quality and inaccurate and incomplete consumption reports from service delivery points have led to unacceptable forecasting errors. Coupled with communication and coordination challenges within the EPSS, these further exacerbate supply chain problems [60]. A study involving 40 health facilities in Ethiopia identified human resources, financial resources, infrastructure, and information technology challenges as key issues in pharmaceutical supply chain management [40].

The EPSS grapples with systemic weaknesses, including the absence of a robust system to manage its operations, weak demand planning, extended procurement lead times, inadequate medical equipment management, and a lack of emphasis on market shaping [19,61]. A SWOT analysis conducted in the EPSS unveiled several areas of concern, such as inadequate customer and stakeholder satisfaction, unsatisfactory supplier relationship management, inventory management challenges, weak distribution planning, and a deficient track and trace system. Furthermore, issues like the absence of a robust information system, inadequate financial sustainability planning, cash shortages, untrained staff, inefficient workforce utilization, and organizational culture problems have been identified [61].

In conclusion, the Ethiopian Pharmaceutical Supply Services faces multifaceted challenges that hinder its ability to effectively manage drug shortages and ensure drug availability. Addressing these challenges requires a comprehensive and coordinated effort to improve forecasting, streamline procurement processes, enhance data quality, and bolster the overall pharmaceutical supply chain management system.

2.4. Supply Chain Strategies

The pharmaceutical industry involves a range of entities including research-based multinationals, generic manufacturers, biotech startups, and specialized logistics providers [62]. Managing this complex supply chain is challenging due to factors like product diversity, short life cycles, outsourcing, technological advancements, and globalization [30]. Additionally, high costs, prolonged clinical trials, and uncertainties in demand and capacity planning further complicate the industry [63]. In low-income countries, ensuring the availability and affordability of essential medicines is crucial. Strategies such as limiting stock use, transparent redistribution, and proactive shortage management are employed [25]. Effective communication among regulatory bodies, harmonization, and robust reporting systems are essential for mitigating drug shortages [37,64]. Investments in research, policies, guidelines, education, and training are also necessary [25,38]

Supply chain strategies must account for demand and supply uncertainties. Fisher's framework categorizes products as functional or innovative based on demand predictability and supply processes as stable or evolving [29]. For stable products, efficient supply chains focus on productivity and logistics optimization [30]. Innovative products require responsive strategies to adapt to changing demands [65]. Companies dealing with both innovative products and unstable supply processes must use a combination of risk-hedging and responsive strategies to manage uncertainties [30]. Global collaboration, particularly among low-income countries, is essential for developing effective mitigation strategies for drug shortages. International regulatory bodies should work together on a unified definition and global mitigation plan. Nationally, countries should establish proactive systems for drug shortage notification, reporting, and tracking. Policies should promote robust supply chains, encourage quality manufacturing systems, and prioritize the production of high-risk medicines. Training healthcare professionals and educating the public is also critical to minimize health-related consequences [25].

In conclusion, addressing demand uncertainties in the pharmaceutical industry requires a nuanced understanding of product characteristics, supply processes, and effective supply chain strategies. Also, it is clear that collaboration at both national and international levels is critical to mitigating the global issue of drug shortages across all economic levels (Table 1).

Table 1. Supply chain strategies for managing uncertainties.

Supply Chain Strategies for Management of Drug Shortages	References
Using different forecasting methods	[66]
Market monitoring enhancement	[67]
Selecting drug suppliers with short lead times	[68]
Strengthen demand forecasting	[69,70]
Improve inventory management along supply chains	[71]
Implement buffer stock and emergency procurement mechanisms	[37]
Increasing the quantity of the safety stock	[72]
Establishing feedback loops among stakeholders involved in the forecasting process	[42]

Shortage reporting and tracking system	[25,67,73–77]
Maintain end-to-end public health supply chain visibility	[67]
Engage in systematic de-bottlenecking	[78]
Minimizing wastage of products	[25,76,79]
Strengthening access to medicines through public-private partnerships	[80]
Increase communication among stakeholders	[34,41,67,64,70,71,74,80–81]
Advance notification system when there is shortage	[67,74,82]
Improving the procurement lead time	[74]
Restriction and quota for those pharmaceuticals with unstable demand	[25]
Education and training for the staff on how to handle shortages	[25,70,74]
Establishing robust supply chain management systems	[83]
Fast decision-making	[42]
Collaborative planning, forecasting and replenishment (CPFR)	[84,85]
Developing guidelines on procurement strategies under a crisis	[86,87]
The Reorder Level Strategy, also known as a two-bin system	[88]
Communicating with the purchasing officer and provide what you have in the stock	[25,89]
Time Postponement	[90]
Buy to Order (BTO) *(*also known as Purchase-to-Order*)*	[91]
Redistribution of the stock	[25]

The aim of this study is to understand the risks in the EPSS supply chains and identify strategies that could be engaged to mitigate the risk of drug shortages. Thus, the specific research questions of this paper are:

1. Which supply chain strategies, individually or in combination, provide an effective means for minimizing the drug shortages in Ethiopian Pharmaceutical Supply Services?
2. What strategies have been the least effective in reducing or eliminating supply chain disruptions?
3. What are the barriers that prohibit supply chain management strategies from becoming successful?

3. Research Method

3.1. Context

The Ethiopian Pharmaceutical Supply Services (EPSS) falls under the Ministry of Health, which is responsible for the forecasting, procurement, warehousing, and distribution of pharmaceuticals throughout the country. It has 19 branches, which are found in all regions of Ethiopia. The EPSS operates as a government agency under the Ministry of Health, tasked with centralizing the procurement and distribution of pharmaceuticals and medical supplies for the public health sector. It plays a crucial role in ensuring the availability and accessibility of essential medicines and medical products across the country.

The EPSS is entrusted with procuring pharmaceutical products and medical supplies through competitive bidding processes, aiming to secure high-quality products at reasonable prices. It maintains central medical stores strategically positioned throughout the country, acting as warehouses that manage and distribute the procured pharmaceuticals to regional and district health facilities. The EPSS places significant emphasis on improving supply chain management practices to reduce stock outs and minimize the wastage of pharmaceuticals. Through the use of information systems and logistics management tools, the agency strives to optimize inventory and enhance the efficiency of the distribution process.

Furthermore, the EPSS collaborates with the Ethiopian Food and Drug Authority (EFDA) to ensure that all procured medicines and medical supplies meet the required quality standards. The agency actively works towards enhancing access to essential medicines, particularly in underserved and remote areas, through its distribution networks and partnerships with health authorities and stakeholders. Additionally, the EPSS engages in collaboration with international organizations, donors, and development partners to strengthen its capacity and continually improve pharmaceutical supply chain practices.

3.2. Research Design

This study utilized a cross-sectional case study research design to assess the effectiveness of supply chain strategies employed to deal with drug shortages within the EPSS. The research was structured into two sequential parts, a survey and semi-structured interviews.

3.2.1. Part 1—Survey

The first part of the study comprised a survey that included socio demographic questions (such as years of experience in the sector, education level, and professions), as well as questions about supply chain strategies and their effectiveness. In this section, the respondents were presented with different supply chain strategies and asked to rate their effectiveness using a 5-point Likert scale, ranging from "highly effective" to "never effective". The questionnaire, which is provided in Appendix 1, was completed by 50 respondents with the demographic profile, as summarized in Table 2.

Table 2. Socio demographic profile of respondents in EPSS in 2023.

Socio Demographic Variables	Frequency	Percent
Gender		
Female	16	32
Male	34	68
Age in years		
25–30	16	32
30–35	19	38
Year of experience		
1–5	16	32
Greater than 5	34	68
Profession		
Pharmacist	37	74
Laboratory	8	16
Biomedical engineer	5	10
Level of education		
Degree	31	62
MSc	19	38
Current working department		
Contract management	6	12
Quantification market shaping	13	26
Tender management	12	24
Warehouse inventory management	19	38

After the data collection phase, the questionnaires were coded, and the completeness of the data was thoroughly checked to ensure accuracy and consistency. Subsequently, the Likert-scale responses were converted into numerical values for analysis using multipliers commonly used in quality function deployment [92–94]. The use of 9 for highly effective, 3 for effective, 1 for limited effectiveness, and 0 for do not know ensures significant distances between highly effective and less effective strategies. The scores were then summed to prioritize the strategies based on their overall effectiveness (Table 3).

Table 3. Summary of findings from the survey of supply chain practitioners.

Supply Chain Strategies for Management of Drug Shortages	Highly Effective (x9)	Effective (x3)	Don't Know (x0)	Less Effective (x-3)	It Will Never Be Effective (x-9)	Weighted Score	Rank
Using different forecasting methods	28 (56%)	15 (30%)	5 (10%)	2 (4%)	0	291	1
Market monitoring enhancement	27 (54%)	17 (34%)	5 (10%)	1 (2%)	0	291	1
Selecting drug suppliers with short lead times	19 (38%)	21 (42%)	7 (14%)	3 (6%)	0	225	2
Strengthen demand forecasting	20 (40%)	17 (34%)	8 (16%)	5 (10%)	0	216	3
Improve inventory management along supply chains	19 (38%)	20 (40%)	6 (12%)	5 (10%)	0	216	3
Implement buffer stock and emergency procurement mechanisms	15 (30%)	26 (52%)	9 (18%)	0	0	213	4
Increasing the quantity of the safety stock	15 (30%)	26 (52%)	6 (12%)	3 (6%)	0	204	5
Establishing feedback loops among stakeholders involved in the forecasting process.	16 (32%)	23 (46%)	6 (12%)	4 (8%)	0	201	6
Shortage reporting and tracking system	15 (30%)	24 (48%)	8 (16%)	3 (6%)	0	198	7
Maintain end-to-end public health supply chain visibility	16 (32%)	21 (42%)	10 (20%)	3 (6%)	0	198	7
Engage in systematic de-bottlenecking	10 (20%)	36 (72%)	4 (8%)	0	0	198	7
Minimizing wastage of products	14 (28%)	26 (52%)	7 (14%)	3 (6%)	0	195	8
Strengthening access to medicines through public-private partnerships	15 (30%)	24 (48%)	4 (8%)	4 (8%)	0	195	8
Increase communication among stakeholders	17 (34%)	18 (36%)	9 (18%)	6 (12%)	0	189	9
Advance notification system when there is shortage	16 (32%)	21 (42%)	6 (12%)	6 (12%)	0	189	9
Improving the procurement lead time	18 (36%)	16 (32%)	12 (24%)	2 (4%)	2 (4%)	186	10
Restriction and quota for those pharmaceuticals with unstable demand	15 (30%)	19 (38%)	13 (26%)	3 (6%)		183	11
Education and training for the staff on how to handle when there is shortage	12 (24%)	29 (58%)	4 (8%)	4 (8%)	0	183	11
Establishing robust supply chain management systems	13 (26%)	23 (46%)	9 (18%)	3 (6%)	0	177	12
Fast decision-making	12 (24%)	26 (52%)	6 (12%)	4 (8%)	0	174	13
Collaborative planning, forecasting and replenishment (CPFR)	12 (24%)	26 (52%)	6 (12%)	6 (12%)	0	168	14
Developing detailed guidelines on procurement strategies under a crisis	11 (22%)	29 (58%)	2 (4%)	8 (16%)		162	15
The Reorder Level Strategy, also known as a two-bin system	13 (26%)	22 (44%)	5 (10%)	6 (12%)	1 (2%)	156	16
Communicating with the purchasing officer and provide what you have in the store	16 (32%)	15 (30%)	5 (10%)	9 (18%)	2 (4%)	144	17
Time Postponement	7 (14%)	28 (56%)	11 (22%)	4 (8%)	0	135	18

Buy to Order (BTO) (also known as Purchase-to-Order)	11 (22%)	16 (32%)	15 (30%)	5 (10%)	0	132	19
Redistribution of the stock	13 (26%)	28 (56%)	6 (12%)	3 (6%)	9	111	20

3.2.2. Part 2—Interviews

In the second part of the study, we further narrowed down the participants to 34 and conducted semi-structured interviews with the selected participants. During this stage, in-depth discussions were held to explore the strategies further. The participants were asked about the critical factors they consider when implementing strategies to mitigate or eliminate supply chain disruptions. Additionally, insights were gathered regarding which strategies were perceived as the least effective in addressing supply chain and distribution channel disruptions.

3.3. Reflexivity

None of the authors of this study were affiliated with the EPSS. Three team members (A.B., T.G., and U.S.) possess extensive experience and expertise in qualitative research methodology. The interviews were conducted by one of the local authors, A.B. All authors had prior training and a thorough understanding of the study context and values, enabling them to perform transcription and crosscheck the contents during translation. The authors discussed an initial analysis of potential informants and created schedules to conduct the interviews at the participants' offices.

3.4. Selection of Participants for the Interview

Participants were chosen based on their roles, ensuring a comprehensive representation across all departments within EPSS. Their involvement was contingent on obtaining consent, with efforts made to guarantee their full understanding of the study's objectives and the confidentiality of their privacy. Emphasis was placed on the voluntary nature of participation, and oral consent was obtained from each participant.

Informed by the findings of the survey (Table 3), the interviews focused on surfacing the types of strategies employed to manage supply disruptions in the pharmaceutical supply chain and distribution channels. Additionally, participants were asked about the most crucial factors considered during the implementation of strategies to reduce or eliminate supply chain disruptions, the identification of strategies that have been least effective in addressing disruptions, the specifics of supply chain management strategies used to tackle disruptions, and an exploration of barriers hindering the success of supply chain management strategies.

After obtaining participants' consent, in-depth interviews were conducted. Both tape recordings and notes were employed for comprehensive documentation. The researchers facilitated the interviews by posing questions naturally, attentively listening to participants' responses, and incorporating follow-up questions and probes based on those responses. These interviews took place either face-to-face or online, involving one interviewer and one participant. The choice of interview location was convenient for participants, occurring in their offices or the researcher's office. Online interviews were conducted in participants' homes based on their preferences and residences. The demographics of interview participants are summarized in Table 4.

Table 4. Interview participant profile.

Socio Demographic Variables	Frequency	Percent
Gender		
Female	14	41.17%
Male	20	58.82%
Age in years		
25–30	12	35.29%
30–35	14	41.17%
Greater than 35	8	23.52%
Year of experience		
1–5	16	32%
Greater than 5	34	68%
Profession		
Pharmacist	26	76.47%
Laboratory	4	11.76%
Biomedical engineer	4	11.76%
Level of education		
Degree	22	64.70%
MSc	12	35.30%
Current working department		
Contract management	4	11.76%
Quantification market shaping	10	29.41%
Tender management	8	23.52%
Warehouse inventory management	10	29.41%

3.5. Ethical Approval

Ethical approval was obtained from Addis Ababa University's Institutional Review Board and the School of Pharmacy's Ethics Review Committee (Protocol 010/22/SoP). The EPSS Directors also granted permission. The participants were assured of their right to withdraw and gave written consent. Privacy was maintained, using pseudonyms for interviewees. Records were securely stored.

3.6. Analysis

Data collection and analysis were conducted simultaneously. Interviews were recorded, transcribed, and translated. A line-by-line coding approach yielded 70 codes, which were merged into 9 family codes and then into 4 main themes. Thematic analysis was included to identify and organize central themes. An inductive approach guided further data collection and analysis until theoretical saturation was reached.

4. Results

The survey findings are summarized in Table 2. In part 2, semi-structured interviews informed by the survey provided deeper insights into drug shortages and pharmaceutical supply chain management, identifying four themes detailed below (Figure 1).

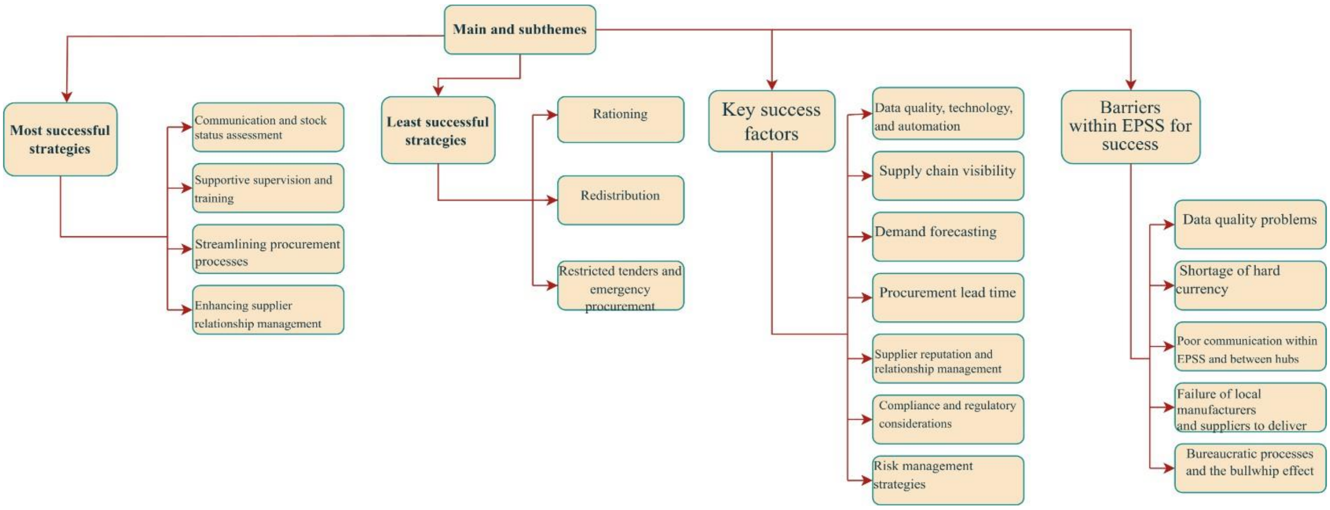

Figure 1. The main themes and sub-themes of the thematic analysis.

Themes 1—Most Successful Strategies

a. Communication and Stock Status Assessment:
Regular central-level stock assessments and hub updates optimize planning and prevent stockouts or overstocking. A participant noted, "*Good communication and sharing stock status information with hubs is crucial.*" (Participant 8)

b. Supportive Supervision and Training:
Providing guidance and training to staff minimizes drug shortages and motivates them. A participant stated, "*Supportive supervision and training are very helpful for mitigating drug shortages.*" (Participant 23)

c. Streamlining Procurement Processes:
Early tender notifications expedite supply acquisition, reduce lead times, and enhance supply chain responsiveness, despite potential challenges. A respondent remarked, "*Early tendering and procurement notification is crucial.*" (Participant 17)

d. Enhancing Supplier Relationship Management:
Collaboration with suppliers and stakeholders improves communication and response coordination during disruptions. A participant emphasized, "*Effective supplier relationship management ensures a seamless supply chain.*" (Participant 10)
These interconnected strategies—Communication and Stock Status Assessment, Supportive Supervision and Training, Streamlining Procurement Processes, and Enhancing Supplier Relationship Management—demonstrate a holistic and collaborative approach to optimizing pharmaceutical supply chain management.

Theme 2—Least Successful Strategies Used by EPSS

a. Rationing:
Rationing controls pharmaceutical supply allocation to ensure fair distribution during scarcity. Though not as proactive as other strategies, it can help balance supply and demand. However, some participants question its effectiveness, with one stating, "*Rationing will not solve the problem; it is just taken as a painkiller.*" (Participant 15)

b. Redistribution:
Redistributing products between hubs can incur high costs and time. Efficient redistribution requires strong communication and coordination. A respondent

noted, "*Redistribution is costly and time-taking, creating a burden on professionals.*" (Participant 29)

c. Restricted Tenders and Emergency Procurement:
Restricted tenders and emergency procurement can meet immediate needs but disrupt routine practices. This may cause future shortages. One participant highlighted, "*Emergency situations make us neglect routine practice, creating another shortage.*" (Participant 34)
In summary, while rationing, redistribution, and restricted tenders with emergency procurement are less effective strategies, they can still mitigate shortages temporarily until more proactive methods are implemented. These methods underscore the need for balancing reactive and proactive approaches in pharmaceutical supply chain management.

Theme 3—Key Success Factors

a. Data Quality, Technology, and Automation, Supply Chain Visibility, Demand Forecasting:
Accurate data are crucial for effective supply chain management. Real-time, high-quality data enable informed decisions and prompt responses to disruptions. A participant noted, "*Data quality plays a significant role in the whole cycle of supply chain management*" (Participant 28). Technology and automation reduce manual errors and enhance efficiency. Transparent supply chain visibility aids in better planning and risk management. Proper demand forecasting minimizes overstocking and stockouts, ensuring a smooth flow of products.
b. Procurement Lead Time and Supplier Reputation and Relationship Management:
Shortening procurement lead time is critical. Delays can affect the entire supply chain. A respondent said, "*Reducing the procurement lead time will have a great impact on the whole supply chain process*" (Participant 26). Reliable suppliers are vital for timely deliveries and quality products. Effective supplier management fosters strong relationships. As one participant highlighted, "*Managing suppliers is quite important*" (Participant 33).
c. Compliance and Regulatory Considerations, Risk Management Strategies:
Adhering to industry regulations avoids delays and disruptions. Developing risk management strategies specific to the pharmaceutical supply chain is essential. Identifying risks, assessing their impact, and establishing contingency plans enhance resilience. Considering these factors helps organizations proactively address disruptions, leading to a more robust and reliable pharmaceutical supply chain.

Theme 4—Barriers within EPSS for Success

Several barriers impede effective supply chain management at EPSS, highlighting logistical and organizational challenges.

a. Data Quality Problems: Poor data quality due to inaccurate demand reports from health professionals compromises reliability. A respondent noted, "*Professionals from health facilities often submit inaccurate demand reports, assuming EPSS won't fulfill their requested amounts, compromising data quality.*" (Participant 22)
b. Shortage of Hard Currency: Currency shortages delay procurement and disrupt the supply chain. "Even with effective forecasting and tender processes, currency shortages in the country delay EPSS's ability to procure products on time." (Participant 19)
c. Poor Communication within EPSS and Between Hubs: Internal communication gaps worsen shortages. "*Poor communication within departments and between central EPSS and hubs exacerbates shortages.*" (Participant 11)
d. Failure of Local Manufacturers and Suppliers to Deliver: Local manufacturers, reliant on imported raw materials, often fail to meet commitments. "*Local*

manufacturers, reliant on global supply chains for raw materials, coupled with low capacity, impact product availability." (Participant 9)

e. Bureaucratic Processes and the Bullwhip Effect: Bureaucratic delays and intensified demand fluctuations add complexity.
Addressing these challenges requires improving data quality, streamlining procurement, enhancing communication, investing in human resources, and tailoring procurement laws to the pharmaceutical sector. These measures can lead to a more successful and resilient supply chain system, benefiting both the EPSS and the broader pharmaceutical industry.

5. Discussion

The primary aim of this research was to comprehend the risks within EPSS supply chains and identify strategies for mitigating the risk of drug shortages. Building on the literature review, the study explored various shortage-mitigating strategies through a survey and participant interviews. The findings highlighted successful and less successful strategies, key success factors, and barriers within the EPSS concerning drug shortages. This study's contributions are twofold. First, it advances our theoretical understanding by exploring proactive and reactive supply chain strategies for mitigating drug shortages within the pharmaceutical supply chain. Second, it sheds light on key success factors crucial for overcoming drug shortages in resource-limited countries, providing practical insights.

The literature review emphasized the dichotomy of proactive and reactive strategies in supply chain risk management. Proactive strategies involve anticipatory and preventive actions to address potential challenges before they occur, while reactive strategies respond to challenges after they have manifested [95]. These strategies include supplier development, supply chain contracts, contingency planning, and disaster management [96]. Studies from various contexts have identified specific strategies such as establishing information systems, imposing public service obligations, influencing trade rules, and forming committees to collaboratively tackle shortages [97]. The EPSS study aligns with these findings, offering insights into the effectiveness of such strategies within a developing country's pharmaceutical supply chain (Figure 2).

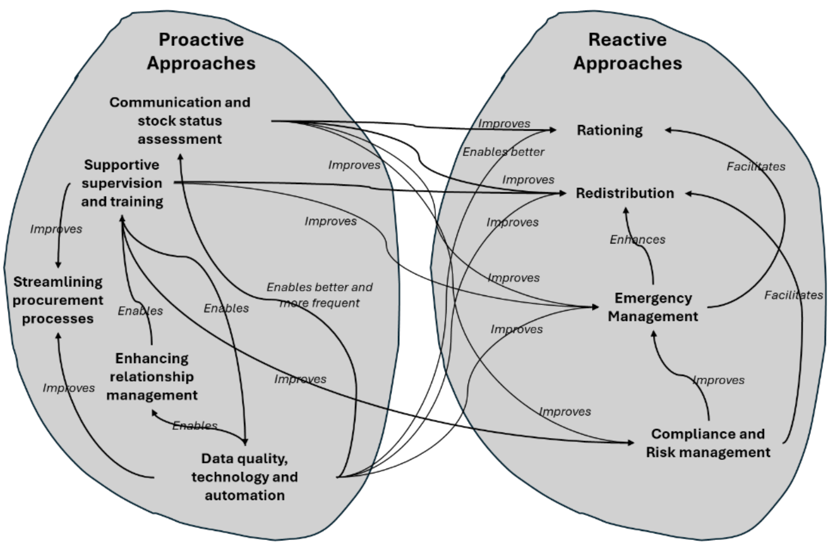

Figure 2. How the different strategies interact to aid improved management of supply chain performance under demand uncertainties.

Additionally, the research provides a unique perspective by delving into specific proactive strategies employed by EPSS, such as communication, stock status assessment, supportive supervision and training, and streamlining procurement processes. Resource sharing through strategic alliances was also identified as a proactive resilience strategy [9]. Reactive strategies discussed in the literature, such as safety stock, capacity buffers, and supplier backups, were found to be used in response to uncertainty in the pharmaceutical supply chain [98]. It is important to understand that both proactive and reactive strategies do not stand alone as single entities; they interact with each other. This interaction is illustrated in Figure 2. For instance, **data quality, technology, and automation** *enable better and more frequent* **communication and stock status assessment,** which in turn *improves* **rationing**, **redistribution**, **emergency management**, **compliance**, and **risk management**. The role of data quality, technology, and automation also helps us to easily communicate and address information.

Furthermore, our findings reveal that supportive supervision and training are crucial when dealing with uncertainty of demand and supply, and this was evident in one of the studies conducted by Bilal et al. [19], which emphasized the pivotal role of training in fostering workforce competence and motivation. While short-term training interventions were deemed crucial for immediate skill enhancement, participants emphasized the long-term imperative of elevating the quality of education programs, including degree-level education, in cultivating a pipeline of skilled professionals.

The study adds depth by examining how the EPSS utilizes these strategies to address medicine shortages. Furthermore, the study acknowledges the scarcity of research on supply chain risk management in developing countries. This gap is critical because of the heightened uncertainty in such regions, emphasizing the study's relevance to a more fragile economic and political structure.

In terms of managerial implications, the study underscores the importance of a responsive supply chain structure for mitigating risks effectively. It highlights the need for a nuanced approach, understanding that certain strategies may not be effective in isolation and that a combination of proactive and reactive strategies may be necessary. Managers are encouraged to focus on key success factors, including data quality, technology, automation, and supply chain visibility while addressing barriers like data quality problems and communication issues. The success of reactive and proactive strategies hinges on their alignment with the company's overall supply chain goals and the particular uncertainties encountered. Combining both strategies in a balanced manner can create a more resilient supply chain that effectively handles uncertainties. In essence, although reactive and proactive strategies have distinct roles, their interaction is vital for optimal supply chain flexibility. Companies that effectively merge these approaches can boost their responsiveness to uncertainty and advance long-term enhancements in their supply chain design and operations.

While interpreting the findings, it is essential to acknowledge the study's limitations, including its focus solely on EPSS. The reliance on self-reported data and a relatively small sample size may limit the generalizability of insights. Future research should adopt broader sampling methods to enhance the study's external validity. In conclusion, despite these limitations, this study provides valuable insights into pharmaceutical supply chain management within EPSS. The identified strategies, success factors, and barriers offer actionable steps for stakeholders to enhance the resilience and efficiency of pharmaceutical supply chains in Ethiopia. The continuous evaluation and adaptation of these strategies are imperative for maintaining a responsive and sustainable pharmaceutical supply chain in the country.

6. Conclusions

This paper has shed light on the proactive and reactive strategies that are important in reducing drug shortages in the Ethiopian pharmaceutical supply chain. By showing how these strategies work together, we emphasize the need to use both for effective mitigation. The distinction between effective and ineffective strategies in this study is a useful guide for supply chain management practitioners. It gives clear insights into areas that need improvement and changes in their current practices. This practical advice is crucial for improving supply chain operations and building resilience against drug shortages.

In conclusion, this paper not only contributes to the existing knowledge by unraveling the dynamics of mitigating drug shortages but also provides a roadmap for future exploration. The intricacies of this study pave the way for further research, encouraging a deeper understanding of how to address and mitigate drug shortages in the complex landscape of resource-limited countries.

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Appendix 1

Part II: Please indicate by ticking in the box in which you think is right strategies to minimize the drug shortages in EPSS

S.no	Supply chain strategies for management of drug shortages	Highly effective	Effective	Don't know	Less effective	It will never be effective
1	To use different forecasting methods depending on the demand characteristics of the pharmaceuticals					
2	Engage in systematic de-bottlenecking (not just focusing on existing bottlenecks, but also identifying future potential bottlenecks (in other words, forecasting them) and addressing them before they materialize or become acute)					
3	Strengthen demand forecasting: (Accurate demand forecasting is essential to prevent stockouts. Analyzing historical consumption data, patient trends, and disease patterns can help forecast future demand for medicines more accurately, enabling proactive procurement and supply management)					
4	Collaborative planning, forecasting and replenishment (CPFR) analysts (CPFR analysts are responsible for analyzing data, coordinating activities, and fostering collaboration among trading partners to improve supply chain performance and achieve common goals)					
5	Market monitoring enhancement" (to identify more rapidly and accurately the market needs and medicine shortages in the country)					
6	Developing detailed guidelines on procurement strategies under a crisis					
7	Improving the procurement lead time					
	Considering multiple suppliers					
8	Selecting drug suppliers with short lead times (The tender process should not only consider the price per unit of drugs from each potential supplier, but also the costs that would be incurred if the supply chain must compensate for longer supplier lead times)					
9	Restriction and quota for those pharmaceuticals with unstable demand					
10	Redistribution of the stock which are excess in some hub and distribute to other hub which have shortage					
11	Minimizing wastage of products					
12	Improve inventory management along supply chains					

13	Time Postponement: This approach involves delaying the delivery or shipping of products until demand patterns become clearer. For example, EPSS may hold off on replenishing inventory at stores until it can assess actual sales data or customer demand.					
14	Implement buffer stock and emergency procurement mechanisms (Having buffer stock or emergency procurement mechanisms in place can help mitigate the risk of stockouts).					
15	Increasing the quantity of the safety stock					
16	Increase communication among stakeholders (Collaboration and coordination among all stakeholders involved in the pharmaceutical supply chain, including government agencies, health facilities, procurement agencies, and suppliers, is crucial to prevent stockouts.)					
17	Establishing feedback loops among stakeholders involved in the forecasting process can facilitate continuous improvement. Regular feedback from health facilities, procurement agencies, and suppliers can help identify areas for improvement and refine forecasting models to prevent stockouts.					
18	Shortage reporting and tracking system (It typically involves a structured approach to reporting and tracking shortages, as well as coordinating efforts to address them in a timely and efficient manner.)					
19	Maintain end-to-end public health supply chain visibility (end-to-end supply chain data access)					
20	Advance notification system when there is shortage					
21	Education and training for the staff on how to handle when there is shortage					
22	Establishing robust supply chain management systems					
23	Fast decision-making **(**Having high quality and timely information does little good if managers running health care systems are unwilling and unable to respond quickly to that information)					
24	Strengthening access to medicines through public-private partnerships (Collaborating with private sector entities, such as pharmaceutical manufacturers, distributors, and retailers, can help improve the availability of medicines and ensure timely replenishment of stock)					

25	Communicating with the officer who came to purchase and provide what you have in the store for example if the person who came from health facilities came to purchase albendazole tablet and if Albendazole is stock out negotiate to change it in to Mebendazole tablet					
26	The Reorder Level Strategy, also known as a two-bin system (which is technique used to determine when to reorder items that have a predictable demand pattern. A specific quantity of stock is set as the reorder level, which serves as a trigger to reorder more inventory. When the stock level in the active bin reaches the reorder level, it signals that it's time to reorder to avoid stockouts).					
27	Buy to Order (BTO) strategy also known as Purchase-to-Order, is approach where products are only purchased from suppliers or manufactured in response to specific customer orders. In other words, inventory is not pre-stocked, but instead, products are procured or produced on demand as orders are received					

Appendices

Appendix 1: Information Sheet and Consent Form

Addis Ababa University School of Graduate Studies

Department of Pharmaceutics and Social Pharmacy Subject Information Sheet and Informed Consent Form I

Informed Consent Form

This informed consent form is for expert from Ethiopian Food and Drug Authority, Ethiopian Pharmaceutical Supply Agency, and National Bank of Ethiopia, Ethiopian Shipping Lines, Non- Governmental Organization who support EPSS and who we are inviting to participate in research titled " FORECASTING ACCURACY FOR PHARMACEUTICALS: THE CASE OF ETHIOPIAN PHARMACEUTICAL SUPPLY Services ".

Investigator's name and address:

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University Email address: U.S.Bititci@hw.ac.uk,

Subject Information Sheet Form I (Key informant Interview)
Introduction

Good Morning/Afternoon,

My name is **Arebu Issa.** Currently, I am enrolled into doctoral study in Social and Administrative Pharmacy, at the Department Pharmaceutics and Social Pharmacy, School of Pharmacy, Addis Ababa University. My research advisors are **Prof. Teferi Gedif** (Professor, Pharmaceutics and Social Pharmacy Department, School of Pharmacy, Addis Ababa University) and **Prof.** Umit S Bititci (Professor, Edinburgh Business School Heriot-Watt University). And Dr. Bahman Rostami-Tabar

I invite you to participate in this study entitled: ***Forecasting accuracy for Pharmaceuticals: The case of Ethiopian Pharmaceutical Supply Services.*** Which is one of the bottlenecks of the pharmaceuticals supply chain in Ethiopia? You are chosen purposefully and because you fulfill our criteria on Forecasting accuracy for Pharmaceuticals in Ethiopian Pharmaceutical Supply Agency

I am going to give you information and invite you to be part of this research. You do not have to decide today whether or not you will participate in the research. Before you decide, you can talk to anyone you feel comfortable with about the research. This consent form may contain words that you do not understand. Please ask me to stop as we go through the information and I will take time to explain. If you have questions later, you can ask them of me or of another researcher.

The purpose of the research

Accurate forecasts are important to the success of supply chain companies. Decisions relating to transportation, purchasing, inventory control, work-force scheduling, production planning and cash-flow planning are all dependent on them. The purpose of this project is to provide an effective and practicable means for achieving better forecasting accuracy in EPSS. Such an integrated approach can enable to identify what are the drivers of forecast inaccuracy. We believe that you can help us by telling us what you know about forecast accuracy in EPSS. We want to learn What are the level of forecasting accuracy in Ethiopia Pharmaceutical Supply Agency. How is the trend in forecasting accuracy in Ethiopian Pharmaceutical Supply Agency? What are the barrier and drivers of forecasting accuracy in Ethiopia Pharmaceutical Supply Agency? What will be the changes in forecast accuracy if different models are applied for quantification.

Type of Research Intervention

This research will involve your participation in a in key informant interview that will take about 30-45 minutes of interview.

Participant Selection

You are chosen purposefully because the research team believed that you have a good knowledge on the issue of barriers and drivers of forecast accuracy in EPSS moreover you fulfill our criteria on Forecasting accuracy for Pharmaceuticals in Ethiopian Pharmaceutical Supply Services so that you can contribute much to our understanding and knowledge forecast accuracy in EPSS.

Voluntary Participation

Your participation in this research is entirely voluntary. It is your choice whether to participate or not. The choice that you make will have no bearing on your job or on any work-related evaluations or reports. You may change your mind later and stop participating even if you agreed earlier.

Procedures

We are asking you to help us learn more about forecast accuracy. We are inviting you to take part in this research project. If you accept, you will be asked to participate in an interview with myself. During the interview, I or another interviewer will sit down with you in a comfortable place at the Centre. If it is better for you, the interview can take place in your home or a friend's home. If you do not wish to answer any of the questions during the interview, you may say so and the interviewer will move on to the next question. No one else but the interviewer will be present unless you would like someone else to be there. The information recorded is confidential, and no one else except me and my supervisors will access to the information documented during your interview. The entire interview will be tape-recorded, but no-one will be identified by name on the tape. The tape will be kept in a secured location in a locked cabinet where no one except the researchers will. The information recorded is confidential, and no one else except the PI will have access to the tapes. The tapes will be destroyed after 180 days.

Duration

The research takes place over 90 days in total. During that time, we will visit you two times for interviewing you at one month interval and each interview will last for about 30-45 minutes each.

Risks

If we are asking you to share with us some very personal and confidential information, and you may feel uncomfortable talking about some of the topics. You do not have to answer any question or take part in the interview if you don't wish to do so, and that is also fine. You do not have to give us any reason for not responding to any question, or for refusing to take part in the interview.

Benefits

There will be no direct benefit to you, but your participation is likely to help us find out more about forecast accuracy.

Confidentiality

The information that we collect from this research project will be kept private. Any information about you will have a number on it instead of your name. Only the researchers will know what your number is and we will lock that information up with a lock and key. It will not be shared with or given to anyone. The knowledge that we get from this research will be shared with you before it is made widely available to the public. Each participant will receive a summary of the results. Following the meetings, we will publish the results so that other interested people may learn from the research.

Right to Refuse or Withdraw

You do not have to take part in this research if you do not wish to do so, and choosing to participate will not affect your job or job-related evaluations in any way. You may stop participating in the interview at any time that you wish without your job being affected. I will give you an opportunity at the end of the interview to review your remarks, and you can ask to modify or remove portions of those, if you do not agree with my notes or if I did not understand you correctly.

If you have any questions, you can ask them now or later. If you wish to ask questions later, you may contact any of the following: Betselot , +251913 001278, chs.irb@aau.edu.et, This proposal has been reviewed and approved by College of Health Sciences IRB, which is a committee whose task it is to make sure that research participants are protected from harm.

Certificate of Consent

I have been invited to participate in research about forecasting Accuracy in Ethiopian Pharmaceutical Supply services.

I have read the foregoing information, or it has been read to me. I have had the opportunity to ask questions about it and any questions I have been asked have been answered to my satisfaction. I consent voluntarily to be a participant in this study

Name of Participant__________________________Signature of Participant ___________________Date _ Statement

I have accurately read out the information sheet to the potential participant, and to the best of my ability made sure that the participant understands that the following will be done:

1.

2.

3.

I confirm that the participant was given an opportunity to ask questions about the study, and all the questions asked by the participant have been answered correctly and to the best of my ability. I confirm that the individual has not been coerced into giving consent, and the consent has been given freely and voluntarily.

A copy of this ICF has been provided to the participant.

Name of Researcher/person taking the consent_ Signature of Researcher /person

taking the consent____Date

Appendix 2: Qualitative Interview to with experts in the supply chain and EPSS Staff

To explore the drivers of forecast inaccuracy in Ethiopia Pharmaceutical Supply Agency (What are the barrier and drivers of forecasting accuracy in Ethiopia Pharmaceutical Supply Agency)

Are you willing to participate in this research?

Yes No

Part I: Sociodemographic characteristics

1. Gender

Male Female

2. Age in Years____________________________________

3. Year of experience: ____________________________________

4. Profession:

Pharmacist Laboratory professional Biomedical engineer

5. Level of education

Diploma Degree Masters PhD

6. Department currently working on:____________________________________

Part II: Key Informant interview

Introduction and Context Questions:

1. How do you see the health supply chain in Ethiopia and in particular in EPSS
- Probe on what are the problems
2. What are the factors which affect the availability of pharmaceuticals in Ethiopia and imp articular with EPSS
3. Explain the problems in forecasting and ask why there is huge forecasting problems in EPSS
4. Discuss on the solutions which helps to improve on the availability of pharmaceutical in Ethiopia and in EPSS
- Probe what to be done regarding forecasting problems of pharmaceuticals in EPSS

5. What are the barrier and drivers of forecasting accuracy in Ethiopia Pharmaceutical Supply services
6. Can you provide an overview of your role and experience within the Ethiopian Pharmaceutical Supply Services (EPSS) or the health supply chain in Ethiopia?

7. How long have you been involved in forecasting and supply chain management in the pharmaceutical sector?

8. What are your primary responsibilities related to forecasting and supply chain management within EPSS or other relevant organizations?

Understanding Forecasting Practices:

1. Could you describe the current forecasting practices and methodologies used within EPSS or other relevant organizations in Ethiopia?

2. What types of data sources and information are typically considered when making forecasts for pharmaceutical supply in Ethiopia?

3. How do you assess the accuracy of forecasts, and what key performance indicators (KPIs) are used to measure forecast accuracy?

Identifying Drivers of Forecast Inaccuracy:

1. In your experience, what are the common factors or challenges that contribute to forecast inaccuracy in the pharmaceutical supply chain in Ethiopia?

2. Are there specific external factors or events that have a significant impact on forecast accuracy? (e.g., policy changes, disease outbreaks, economic fluctuations)

3. How do demand variations and seasonality affect forecasting accuracy, and how are these factors managed?

4. What role does data quality and availability play in forecasting accuracy, and how are data- related challenges addressed?

Stakeholder Collaboration:

1. Can you describe the collaborative efforts and partnerships among stakeholders involved in forecasting and supply chain management for pharmaceuticals in Ethiopia?

2. How do you engage with pharmaceutical manufacturers, healthcare facilities, and government agencies to improve forecasting and mitigate supply chain challenges?

Improvement Strategies:

1. Based on your expertise, what strategies or initiatives have been effective in addressing forecast inaccuracy and improving the reliability of pharmaceutical supply in Ethiopia?

2. Are there any innovative technologies or tools that have been adopted to enhance forecasting practices and supply chain management?

3. What recommendations or best practices would you suggest for enhancing forecast accuracy and reducing stockouts within EPSS and the broader health supply chain?

Challenges and Opportunities:

1. In your opinion, what are the key opportunities for enhancing forecast accuracy and pharmaceutical supply chain efficiency in Ethiopia?

2. What major challenges or barriers do you foresee in implementing improvements to forecasting practices and supply chain management?

Conclusion and Future Outlook:

1. How do you envision the future of forecasting and pharmaceutical supply chain management in Ethiopia, and what role should stakeholders play in driving positive changes?

2. Is there anything else you would like to share or emphasize regarding the drivers of forecast inaccuracy in Ethiopia's pharmaceutical supply services?

Appendix 3: Semi structured interview for experts in EPSS

Dear colleagues I am Arebu Issa a PhD student from Addis Ababa University. I am doing my PhD on Forecasting accuracy of Ethiopian Pharmaceutical Supply Services. I have been reviewing the last five-year data of EPSS and I want to triangulate my finding with your thoughts and experiences. The findings of the survey will be used to identify the supply chain strategies that are tailored to EPSS and helps the organization to focus and prioritize on these strategies when shortages occur. You are selected for this study since you are currently working in EPSS and your input and suggestion are paramount for solving the stockout of pharmaceuticals in EPSS as well as in Ethiopia. Therefore, we kindly request you to fill the questionnaire genuinely and responsibly. It takes you only 20-30 minutes to complete the questionnaire. Your response will be kept confidential. If you need further information, you can contact me. Arebu Issa:

+251913 490403 or Professor Umit Bititci at U.S.Bititci@hw.ac.uk and Professor Teferi Gedif Fenta +2519 11684854

Are you willing to participate in this research?

Yes No

Part I: Sociodemographic characteristics

1. Gender

Male Female

2. Age in Years____

3. Year of experience: ____________________________________

4. Profession:

Pharmacist Laboratory professional Biomedical engineer

5. Level of education

Diploma Degree Masters PhD

6. Department currently working on:_______________________________________

Part II: Please indicate by ticking in the box in which you think is right strategies to minimize the drug shortages in EPSS

S.no	Supply chain strategies for management of drug shortages	Highly effective	Effective	Don't know	Less effective	It will never be effective
1	To use different forecasting methods depending on the demand characteristics of the pharmaceuticals					
2	**Engage in systematic de-bottlenecking (***not just focusing on existing bottlenecks, but also identifying future potential bottlenecks (in other words, forecasting them) and addressing them before they materialize or become acute)*					
3	Strengthen demand forecasting: *(Accurate demand forecasting is essential to prevent stockouts. Analyzing historical consumption data, patient trends, and disease patterns can help forecast future demand for medicines more accurately, enabling proactive procurement and supply management)*					
4	***Collaborative planning, forecasting and replenishment (CPFR) analysts (****CPFR analysts are responsible for analyzing data, coordinating activities, and fostering collaboration among trading partners to improve supply chain performance and achieve common goals***)**					
5	Market monitoring enhancement‖ *(to identify more rapidly and accurately the market needs and medicine shortages in the country)*					
6	Developing detailed guidelines on procurement strategies under a crisis					
7	Improving the procurement lead time					

	Considering multiple suppliers					
8	Selecting drug suppliers with short lead times *(The tender process should not only consider the price per unit of drugs from each potential supplier, but also the costs that would be incurred if the supply chain must compensate for longer supplier lead times)*					
9	Restriction and quota for those pharmaceuticals with unstable demand					
10	Redistribution of the stock which are excess in some hub and distribute to other hub which have shortage					
11	Minimizing wastage of products					
12	Improve inventory management along supply chains					
13	Time Postponement: This approach involves delaying the delivery or shipping of products until demand patterns become clearer. For example, EPSS may hold off on replenishing inventory at stores until it can assess actual sales data or customer demand.					
14	Implement buffer stock and emergency procurement mechanisms *(Having buffer stock or emergency procurement mechanisms in place can help mitigate the risk of stockouts).*					
15	Increasing the quantity of the safety stock					
16	Increase communication among stakeholders *(Collaboration and coordination among all stakeholders involved in the pharmaceutical supply chain, including government agencies,*					

	health facilities, procurement agencies, and suppliers, is crucial to prevent stockouts.)					
17	Establishing feedback loops among stakeholders involved in the forecasting process can facilitate continuous improvement. Regular feedback from health facilities, procurement agencies, and suppliers can help identify areas for improvement and refine forecasting models to prevent stockouts.					
18	Shortage reporting and tracking system (It typically involves a structured approach to reporting and tracking shortages, as well as coordinating efforts to address them in a timely and efficient manner.)					
19	Maintain end-to-end public health supply chain visibility (end-to-end supply chain data access)					
20	Advance notification system when there is shortage					
21	Education and training for the staff on how to handle when there is shortage					
22	Establishing robust supply chain management systems					
23	**Fast decision-making (***Having high quality and timely information does little good if managers running health care systems are unwilling and unable to respond quickly to that information)*					
24	Strengthening access to medicines through public-private partnerships (Collaborating with private sector entities, such as pharmaceutical manufacturers, distributors, and retailers, can help improve the availability of medicines and ensure timely replenishment of stock)					

25	Communicating with the officer who came to purchase and provide what you have in the store for example if the person who came from health facilities came to purchase albendazole tablet and if Albendazole is stock out negotiate to change it in to Mebendazole tablet					
26	The Reorder Level Strategy, also known as a two-bin system (which is technique used to determine when to reorder items that have a predictable demand pattern. A specific quantity of stock is set as the reorder level, which serves as a trigger to reorder more inventory. When the stock level in the active bin reaches the reorder level, it signals that it's time to reorder to avoid stockouts).					
27	Buy to Order (BTO) strategy also known as Purchase-to-Order, is approach where products are only purchased from suppliers or manufactured in response to specific customer orders. In other words, inventory is not pre-stocked, but instead, products are procured or produced on demand as orders are received					

Part III: Please share us your experience and thoughts to these questions

1. What types of strategies do you use to manage supply disruptions in the pharmaceutical supply chain and distribution channel?

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2. What are the most important factors you consider when implementing strategies to reduce or eliminate supply chain disruptions?

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3. What strategies have been the least effective in reducing or eliminating supply chain and or distribution channel disruptions?

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4. What specific supply chain management strategies do you use to address disruptions in the supply chain or distribution channel?____

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6. What barriers prohibit supply chain management strategies from becoming successful?

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7. What other information would you like to discuss, which we have not already addressed?

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Thank you so much for your time

Appendix 4: List of key pharmaceuticals selected from (Revolving Drug Fund) RDF and Programme products for assessing forecasting accuracy in EPSS.

List of pharmaceuticals (RDF)	**List of pharmaceuticals (Programme)**
Amoxicillin - 500mg	Artemether + Lumefanthrine - (20mg+120mg)
Anti-Rho (D) Immune Globulin - 300 mcg	Ferrous Sulphate + Folic Acid - 60mg Iron + 400mcg
Atenolol - 50mg	Lamivudine + Efavirenz +Tenofovir - (300mg +600mg+300mg)
Ceftriaxone - 1 g	Medroxyprogesterone Acetate - 150mg/ml in 1ml
Insulin Isophane Human - 100IU/ml in 10ml	Oxytocin - 10 Units/ml in 1ml
Metformin - 500mg	Pentavalent (Diphteria^^ Pertusis^^ Tetanus^^ Hepatistis B^^ and Haemophilus InfluenzaeB)
Propylthiouracil - 100mg	RHZE (Rifampicin + Isoniazid + Pyrazinamide + Ethambutol) + RH (Rifampicin + Isoniazide) - (150mg+75mg+400mg+275mg) of 6x28 tablets + (150mg+75mg)
Ringer's Injection-Solution	Lamuvudine + Zidovudine 150+300mg
Sodium Chloride (Normal Saline)	RHZ (Rifampicin + Isoniazid + Pyrazinamide) - 75mg + 50mg + 150mg
Tetracycline - 0.01	Malaria, Rapid Diagnostic Test (MRDT), Pf-Pan Cassette

Appendix 5 IRB letter

ADDIS ABABA UNIVERSITY, COLLEGE OF HEALTH SCIENCES (IRB)
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Institutional Review Board

ANNEX 3
Form AAUMF 03-008

IRB's Decision

Meeting No: 02/2022 Meeting Date: February 23,2022
Protocol number: 010/22/SoP

Protocol Title: Forecasting accuracy for pharmaceuticals: The case of Ethiopian pharmaceutical supply services	
Principal Investigator:	Arebu Issa
Institute:	College of Health Sciences, AAU
Elements Reviewed (AAUMF 01-008)	☑ Attached ☐ Not attached
Review of Revised Application ☐ Yes ☐ No	Date of Previous review:
Decision of the meeting:	☑Approved ☐ Approved with Recommendation ☐Resubmission ☐ Disapproved

I. Elements approved-
1. Protocol Version No: 2
2. Protocol Version Date:
3. Informed consent Version No. 2
4. Informed Consent Version Date:

II. Obligations of the PI-
1. Should comply with the standard international & national scientific and ethical guidelines
2. All amendments and changes made in protocol and consent form needs IRB approval
3. The PI should report SAE within 10 days of the event
4. End of the study, including manuscripts and thesis works should be reported to the IRB
5. The PI should report non-compliance and unanticipated events

III. TO NERC ☐

Institution Review Board (IRB) Approval: Period from: April 28, 2022 to April 27, 2023
Follow up report expected in 3 Months ___6 months ___ 9 months ✔ one year____

Chairperson, IRB
Dr. Adamu Addissie

Signature
Date: April 28, 2022

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Institutional Review Board Office (IRB) Faculty of Medicine
ADDIS ABABA UNIVERSITY