ADDIS ABABA UNIVERSITY

SCHOOL OF COMMERCE

The Effect of Demand Forecasting Models on Supply Chain Planning, Inventory Planning & Performance: The Case of Unilever Ethiopia

A thesis submitted to Addis Ababa University School of Commerce department of logistics and supply chain management in the partial fulfillment of the requirements for master's degree in logistics and supply chain management

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This is to certify that the thesis carried out by Esrom Aschalew, The Effect of Demand Forecasting Models in Supply Chain Planning – Inventory Planning & Performance: The Case of Unilever Ethiopia submitted in partial fulfillment of the requirement for the Master of Arts in Logistics and Supply Chain Management complies with the regulation of the University and meets the accepted standards with request to originality and quality.

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June 2024

Addis Ababa, Ethiopia

Declaration

I, the undersigned, declare that this thesis entitled The Effect of Demand Forecasting Models in Supply Chain Planning – Inventory Planning & Performance: The Case of Unilever Ethiopia is my original work and to the best of my knowledge has not been presented for the degree by any other person, and all sources of materials used for the thesis have been duly acknowledged.

Declared by:

Esrom Aschalew

Abstract

This study aimed to understand and evaluate the effect of demand forecasting models on supply chain planning – inventory planning & performance: The Case of Unilever Ethiopia. The researcher employed a mixed-methods research approach integrating quantitative analyses of historical data from Unilever Ethiopia and qualitative insights from research questionnaires and interviews, the researcher used an explanatory and descriptive research design. Major four products from case company's product portfolio and 14 employees who are directly involved in demand forecasting were the target data and population. The study's findings showed that there is a positive correlation between the independent variable and dependent variables except inventory turnover which was not statistically significant. The organization's inventory planning and performance is impacted by the accuracy of the forecast which heavily depends on the forecast model selected. The inventory performance matrices inventory level, inventory cost and safety stock were found to be impacted by the accuracy of demand forecasting. The most common observation from secondary data and from what the respondents mentioned are inadequate and inaccurate demand forecasting led to higher inventory levels and costs significantly affecting the performance of the business. Being a global corporate company operating in different countries with various available resources and technologies, Unilever Ethiopia needs to check and adapt the forecasting model with less error to effectively manage inventory and improve the whole operational performance.

***Keywords**: Fast moving consumer goods (FMCG), Demand forecasting, Supply Chain Planning, Inventory Planning, Inventory Performance*

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List of Abbreviations and Acronyms

SCM - Supply Chain Management

SAP - Systems, Applications, and Products

COR - Supply Chain Operating Reference Model

KPIs - Key Performance Indicators

FMCG - Fast-Moving Consumer Goods

ML – Machine Learning

FEU – Forecasting Engine Utility

DP – Demand Planners

SARIMA - Seasonal Autoregressive Integrated Moving Average

ETS – Exponential Smoothing

LSTM - Long short-term memory

SKU – Stock Keeping Unit

HW – Holt - Winters

F&B – Food and Beverage

FA – Forecast Accuracy

FB – Forecast Bias

ARIMAX - Autoregressive Integrated Moving Average with exogenous variables

SSP - Systematic Strategic Planning

APO - Advanced Planning and Optimization

SC – Supply Chain

CD – Customer Development

CG – Cap Gemini

JIT – Just in Time

GDP – Gross Domestic Product

RBV – Resource Based View

TCE – Transaction Cost Economics

PDCA – Plan Do Check Act

HBMS – Hierarchical Based Measurement System

IBMS – Interface Based Measurement System

PBMS – Perspective Based Measurement System

S & OP – Sales and Operation Planning

ERP – Enterprise Resource Planning

MAD – Mean Absolute Deviation

MAPE – Mean Absolute Percentage Error

RMSE – Root Mean Square Error

FMCG – Fast Moving Consumer Goods

Chapter One

Introduction

Effective supply chain planning is essential for meeting customer needs in the massive global fast-moving consumer goods (FMCG) industry. This thesis examines the critical effect that demand forecasting models have in supply chain planning inventory planning and performance, a critical part of the supply chain, with a particular focus on Unilever Ethiopia.

1.1 Background of the Study

The fast-moving consumer goods (FMCG) sector functions at the intersection of consumer demand and complex supply chain networks. The industry is constantly battling to survive in the highly competitive business environment. The supply chain disruptions are manifested in the mantle of any business resonates with its magnitude of agility and resilience capabilities. Neboh et al. (2022) mentioned on their study although resilience cushions disruptions and allows a cost-effective recovery into a better optimal state, the FMCG industry is epitomized by speedily demand responsiveness as a distinct resilience strategy.

FMCG companies face a dual problem of preserving operational effectiveness and adapting quickly to the ever-changing demands of their customers. With time being a valuable resource and short product life cycles, the supply chain serves as both a strategic enabler and a logistical backbone in today's corporate environment.

Effective supply chain management is essential for success in the fast-moving consumer goods market, given its dynamic and competitive nature. Recent researches have underscored the critical role of supply chain management in enhancing organizational competitiveness and performance. Mishra (2023) and Bocanegra (2023) both highlight the positive impact of supply chain management on competitiveness and performance, with Mishra emphasizing the need for organizations to optimize their supply chain processes and Bocanegra providing empirical evidence of this influence in the context of Mexican manufacturing companies. The modern corporate environment emphasizes how crucial supply chains and supply chain planning are key to success.

Organizations rely on well-designed and efficiently managed supply chains to connect complex networks of production, distribution, and delivery. Supply chains function as strategic tools that impact competitiveness, customer satisfaction, and overall business resilience, extending beyond the conventional domains of logistics. Supply chain planning becomes the compass that leads businesses through the intricacies of customer dynamics, market changes, and global economic upheavals. The capacity to efficiently manage and coordinate the supply chain becomes not simply a function but a foundation for long-term growth and organizational success in a time when flexibility and responsiveness are critical.

Demand forecasting is a critical aspect of supply chain management, enabling organizations to prepare for future demand and make informed decisions. Demand forecasting is a critical component of supply chain management, influencing inventory management, production planning, and distribution network design (Deepika, 2021). The choice of demand forecasting models significantly impacts supply chain planning decisions and overall performance. Recent advances in data analytics and machine learning have led to the development of increasingly sophisticated forecasting techniques, offering organizations a wide array of options to choose from (Rožanec et al., 2021).

Accurate and timely forecasting is the cornerstone of operational efficiency, enabling businesses to navigate the challenges of short product life cycles, minimize stockouts or excess inventory, and ultimately deliver unparalleled customer satisfaction. In an industry where timing is critical and adaptability is key, demand forecasting is the catalyst that empowers FMCG supply chains to stay ahead of the curve, seize opportunities, and deliver products with precision and speed to meet the dynamic needs of the modern consumer.

Unilever, a global consumer goods giant, stands as a beacon of innovation and sustainability in the competitive landscape of the fast-moving consumer goods (FMCG) industry. Founded in 1929 through the merger of British soap maker Lever Brothers and Dutch margarine producer Margarine Unie, Unilever has grown into one of the world's largest and most diversified multinational corporations.

Renowned for its extensive portfolio of household and personal care products, Unilever's presence spans over 190 countries, reaching billions of consumers daily. The company's commitment to sustainable business practices, exemplified by its ambitious Sustainable Living Plan, underscores its dedication to creating positive social and environmental impacts. Unilever's enduring legacy is not only characterized by its iconic brands but also by its ongoing pursuit of corporate responsibility and excellence in meeting the evolving needs of a dynamic global market.

The massive multinational consumer products company Unilever understands the importance of demand forecasting and how it affects supply chain effectiveness. With a particular focus on Unilever Ethiopia, this study explores how current demand forecasting process works and assess the impact of demand forecasting accuracy on Unilever Ethiopia's supply chain planning dimensions specifically the inventory planning & performance.

1.2 Research Problem

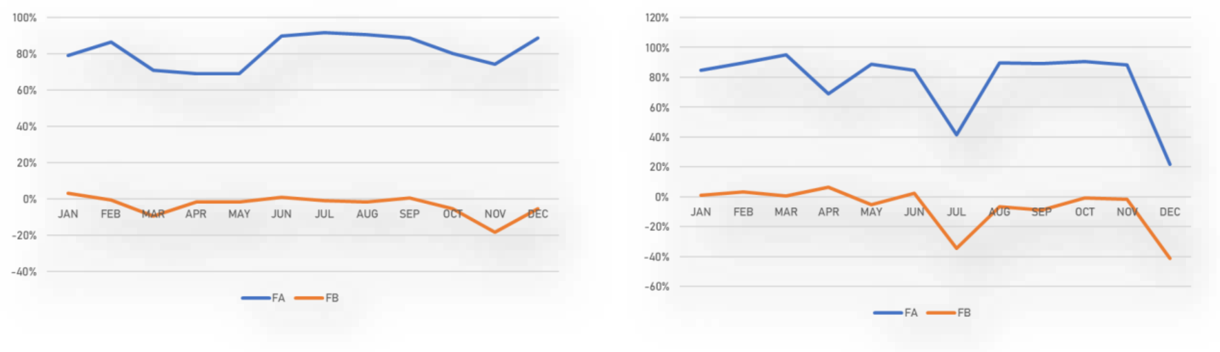
Even though demand forecasting is widely accepted as being important in today's supply chain management literature, Unilever Ethiopia still has difficulties in making precise projections about future demand. Recent academic studies have indicated that enhancing supply chain performance, lowering operational disturbances, and increasing customer satisfaction all depend on effective demand forecasting (Chopra & Meindl, 2019). Prior studies (Ivanov, 2020; Chen et al., 2018) have indicated that Unilever Ethiopia's reliance on subjective evaluation and historical sales data results in irregularities and raises the risk of prediction errors and indicated that these mistakes lead to stockouts, overstocks, and inefficient resource use, all of which have a detrimental effect on supply chain efficiency.

The body of existing research highlights the importance and effects of advanced forecasting models and technology for enterprises, as well as the direct relationship between supply chain effectiveness and demand forecasting accuracy (Tang & Xie, 2015; Chopra & Sodhi, 2004). Demand forecasting plays a crucial role in various supply chain dimensions, including inventory levels, production planning, distribution & logistics, lead time management, and procurement & sourcing (Babai, 2011).

In the domain of supply chain management, while existing research explores the relationship between demand forecasting and planning effectiveness, a thorough examination specific to Unilever Ethiopia is lacking. This knowledge gap hinders the understanding of how current forecasting methods impact the supply chain planning, particularly in the crucial areas of inventory planning and performance. To address this, this research delved into Unilever Ethiopia's current demand forecasting practices and analyze how these practices influence the inventory planning and performance. This investigation will not only contribute to a deeper understanding of this specific case but also offer valuable insights for optimizing inventory planning and performance through improved demand forecasting practices as per points highlighted by Chopra & Meindl.

As observed by the researcher, specifically, within the context of Unilever Ethiopia, there is a lack of comprehensive research addressing the specific effects of demand forecasting model choice such as moving average, exponential smoothing, FEU, etc. on key aspects of operational performance indicators including cost efficiency, inventory management, customer satisfaction, and resource optimization. Additionally, as depicted in the figure below there is a need to understand the inconsistencies on forecast accuracy and bias and related consequences on organizational performance.

Figure 1.1: Demand forecasting performance – Unilever Ethiopia



Source: Unilever Ethiopia – 2022;2023

1.3 Objectives of the study

1.3.1 General Objective of the study

The main objective of the study is to assess the effect of current demand forecasting model on inventory planning and performance for the case of Unilever Ethiopia.

1.3.2 Specific Objective of the study

The specific objectives for this study are as follows:

- To analyze Unilever Ethiopia's current demand forecasting process

- To assess the impact of current demand forecasting accuracy on inventory planning & performance on the specific areas of inventory level, inventory cost, inventory turnover, and safety stock.

1.4 Research Questions

The research questions listed below guides the investigation and focus on addressing the objectives outlined in the study. Each question is designed to explore a specific aspect related to analyzing the effect of demand forecasting models in inventory planning and performance with overview of existing demand forecasting process for Unilever Ethiopia.

- How is demand forecasting currently conducted at Unilever Ethiopia, and what are the key inputs and processes for forecasting?

- What is the direct impact of demand forecasting accuracy on inventory planning and performance?

1.5 Significance of study

The study on Unilever Ethiopia delves into the critical role of accurate demand forecasting within robust and efficient supply chain practices, a cornerstone principle for organizations worldwide. By examining the far-reaching consequences of forecasting errors – stock disruptions, inflated inventory costs, operational inefficiencies, and potential customer dissatisfaction – this study aims to illuminate these challenges and propose advancements specifically for Unilever Ethiopia's operations.

However, the significance of this research extends beyond a single organization. By aligning with the broader goals of the supply chain community – the pursuit of accuracy, flexibility, and a customer-centric approach – this investigation has the potential to yield valuable best practices, strategies, and insights that can contribute to the overall development of supply chain management in Ethiopia. In essence, this study transcends the confines of a single company's challenge, offering the potential to propel the entire field forward.

1.6 Scope of Study

This research investigates the effect of current demand forecasting models on inventory planning and performance within the context of Unilever Ethiopia, a leading Fast-Moving Consumer Goods (FMCG) company operating in the Ethiopian market.

To ensure a comprehensive and focused analysis, the study has a clearly defined scope. Firstly, the research examined the operations of Unilever Ethiopia within the Ethiopian market. This targeted geographical focus allows for a deeper understanding of demand forecasting practices specific to the Ethiopian FMCG landscape.

Secondly, to ensure a robust analysis and capture current trends, the research focused on a three - year timeframe (January 2021 - December 2023). This period provides access to historical data on key SKUs (Stock Keeping Units) from Unilever Ethiopia's product portfolio, including Lifebuoy Total, Lifebuoy Lemon, Knorr All In One, and Knorr Chicken. Three-year period was selected as the data available was consistent and free of external factor like the covid pandemic to avoid wrong results.

Thirdly, the research primarily targets the FMCG industry. By focusing on a single industry, the study can provide more granular insights into demand forecasting within this context, highlighting the specific challenges and opportunities faced by Unilever Ethiopia in this dynamic market.

Finally, to ensure the research considered the practical application of forecasting models within the company, key stakeholders directly involved in Unilever Ethiopia's demand forecasting processes were actively engaged throughout the study. This includes supply chain managers, demand planners, and other relevant personnel in the S&OP process and inventory management.

1.7 Limitations of Study

This research strives to deliver valuable insights, but it's important to acknowledge some limitations to be transparent and manage expectations.

One limitation is the generalizability of the findings. The conclusions may primarily apply to Unilever Ethiopia and the FMCG sector. While the study offers valuable insights, it's important to remember that the effectiveness of demand forecasting models can vary depending on the specific context of a business or industry.

Another limitation is data constraints. The research relies on the accessibility and availability of historical data from Unilever Ethiopia. If there are limitations in obtaining complete data sets, it could affect the breadth and precision of the analysis. The quality of the data directly impacts the accuracy of the research findings.

The study's effectiveness also hinges on the availability and cooperation of key Unilever Ethiopia personnel, particularly those involved in demand forecasting processes. Any challenges in securing their support could potentially influence the findings. Active participation from stakeholders is essential for gathering accurate information and real-world perspectives.

The study period may also be impacted by unforeseen external factors beyond its control. These could include changes in industry dynamics, governmental policies, or economic situations. The research acknowledges these potential influences and discuss their possible impact on the results.

Finally, the study's viability depends on having access to cutting-edge tools or technology for data analysis. By acknowledging these limitations, the study ensures a realistic understanding of its scope and potential impact.

1.8 Organization of the Study

There are five chapters in the study. The statement of the problem, the research questions, and the study's objectives are all included in Chapter One's introduction. Chapter Two reviews the literature pertinent to the issue of the investigation while Chapter Three provides a detailed overview of the design and methodological components used. Chapter 4 contains the study data analysis, the results presentation, and the corresponding remarks. The conclusion of the thesis is presented in Chapter 5, which also contains recommendations based on the study's findings.

1.9 Definition of Terms

1.9.1 Conceptual definition

- **Supply Chain Management**: deals with a system of procurement (purchasing raw materials/components), operations management, logistics and marketing channels, through which raw materials can be developed into finished products and delivered to their end customers (Gartner).

- **Supply Chain planning**: is the process of optimizing the delivery of goods, services, and information from supplier to customer, which balances supply and demand (Gartner).
- **Fast moving consumer** goods (FMCG): are nondurable products that sell quickly at relatively low costs (Investopedia).
- **Demand forecasting:** is the prediction of the quantity of goods and services that will be demanded by consumers at a future point in time (Gartner).
- **Forecast accuracy:** is the means of measuring how well a demand forecast has predicted actual outcomes or values of sales (Intuendi).
- **Inventory Management**: refers to the process of ordering, storing, using, and selling a company's inventory (Investopedia).
- **Efficiency**: refers to the peak level of performance that uses the least amount of inputs to achieve the highest amount of output (Investopedia).
- **Safety Stock**: is an extra quantity of a product which is stored in the warehouse to prevent an out-of-stock situation (Zoho).

1.9.2 Operational Definition

- **Root mean square error**: is either one of two closely related and frequently used measures of the differences between true or predicted values on the one hand and observed values or an estimator on the other (Gartner).
- **Mean Absolute Percentage error (MAPE)**: is a measure of prediction accuracy of a forecasting method in statistics. It usually expresses the accuracy as a ratio of the absolute of the difference of actual demand and forecasted demand divided by actual demand (Gartner).
- **Inventory Cost**: includes the costs to order and hold inventory, as well as to administer the related paperwork (Deskera).
- **Inventory Level**: is the number of goods a company has across its entire logistics or distribution network (Mecalux).
- **Inventory Turnover**: refers to the amount of time that passes from the day an item is purchased by a company until it is sold (Netsuite).

Chapter Two

Literature Review

2.1 Introduction

Supply Chain Management (SCM) represents the strategic coordination and integration of all activities pertaining to the sourcing, procurement, conversion, and logistics management of goods and services. It encompasses the planning and execution of these activities to deliver value to customers while optimizing costs and efficiency throughout the supply chain. SCM is pivotal for businesses and organizations as it streamlines processes, reduces redundancies, and optimizes operations, thereby improving efficiency and productivity. Additionally, SCM helps in minimizing costs associated with procurement, production, and distribution by optimizing inventory levels, minimizing lead times, and enhancing coordination with suppliers.

Moreover, effective SCM ensures timely delivery of products, better product availability, and responsiveness to customer demands, leading to enhanced customer satisfaction and loyalty. It also aids in identifying and mitigating risks such as supply chain disruptions, quality issues, and demand fluctuations, thereby enhancing supply chain resilience and continuity. A well-managed supply chain can provide a competitive edge by enabling faster responses to market changes, better product quality, and lower costs, thereby increasing market share and profitability. SCM fosters innovation through collaboration with suppliers, customers, and other partners in the supply chain, enabling the development of new products, processes, and business models. Furthermore, it plays a crucial role in promoting sustainable practices such as reducing carbon footprint, minimizing waste, and ensuring ethical sourcing, contributing to environmental and social responsibility goals.

In summary, SCM is indispensable for organizations to effectively manage their supply chain activities, optimize operations, reduce costs, enhance customer satisfaction, mitigate risks, and gain a competitive advantage in today's dynamic business environment.

Supply Chain Management comprises several key components, including procurement, production, distribution, and logistics. Effective procurement ensures that the organization obtains quality materials at the right price and in a timely manner, thereby supporting production and distribution activities. Efficient production processes are essential for meeting customer demand, maintaining product quality, and optimizing resource utilization. Effective distribution ensures that products reach customers in a timely and cost-effective manner, contributing to customer satisfaction and loyalty. Logistics plays a crucial role in optimizing transportation, warehousing, and inventory management processes to ensure the efficient movement of goods through the supply chain. By effectively managing these components, organizations can enhance operational efficiency, reduce costs, improve customer service, and gain a competitive advantage in the marketplace.

Supply chain planning is significant for optimizing operations by ensuring alignment between supply chain activities and organizational goals. It helps in optimizing resource utilization, streamlining processes, reducing lead times, identifying cost-saving opportunities, ensuring product availability, and facilitating continuous improvement. Supply chain planning involves strategic, tactical, and operational processes, which ensure effective coordination of activities across the supply chain. Strategic planning focuses on long-term goals and supply chain design, tactical planning translates strategic objectives into actionable plans, and operational planning ensures day-to-day execution. By integrating these planning processes, organizations can align their supply chain activities with business objectives, optimize resource utilization, improve customer service levels, and enhance overall supply chain performance.

Assessing supply chain performance is crucial for identifying areas of improvement, optimizing operations, and achieving strategic objectives. Key performance metrics include on-time delivery, order fulfillment cycle time, inventory turnover, perfect order rate, supply chain cost, supplier performance, inventory accuracy, cash-to-cash cycle time, return rate, and transportation cost per unit. By tracking and analyzing these metrics, organizations can gain insights into their supply chain performance, identify areas for improvement, and make data-driven decisions to enhance operational efficiency, customer satisfaction, and overall competitiveness.

Technology and analytics play a crucial role in improving supply chain planning and performance by providing real-time visibility, data-driven insights, and automation capabilities. They contribute to enhancing demand forecasting, inventory optimization, supply chain visibility, transportation management, warehouse management, supplier relationship management, and performance monitoring. By leveraging advanced technologies and analytics capabilities, organizations can achieve greater efficiency, agility, and competitiveness in today's complex and dynamic supply chain environment.

Accurate demand forecasting is essential for effective supply chain planning as it serves as the foundation for aligning production, procurement, and distribution activities with customer demand. It helps in optimizing inventory management, production planning, procurement, distribution, resource utilization, and customer service. By leveraging accurate demand forecasts, organizations can enhance operational efficiency, reduce costs, improve customer satisfaction, and gain a competitive edge in today's dynamic business environment.

Ethiopia's fast-moving consumer goods (FMCG) business is at a crossroads where opportunities and difficulties coexist. Urbanization trends, a growing middle class, and population expansion are driving the industry's current solid growth. But there are many obstacles in the way of this growing trajectory, particularly in the areas of demand forecasting models and supply chain planning.

Some of the key challenges identified and highlighted by business entities are Geographical Diversity, Traditional Retail Dominance, Regulatory Considerations, Limited Technology Adoption, Fluctuating Consumer Behavior, Supply Chain Resilience, Limited Historical Data, Talent, and Skill Gaps.

As Ethiopia's FMCG industry develops, the combination of advanced demand forecasting models and smart supply chain planning becomes essential for long-term success. The industry's capacity to adopt agility, leverage technology, and cultivate partnerships that tackle the distinct dynamics of Ethiopia's market landscape will determine its prospects.

Even though the literature on modern supply chain management recognizes the value of demand forecasting, Unilever Ethiopia still has difficulty producing precise demand estimates. The company's current reliance on subjective assessment and historical sales data has been found to be a source of inconsistencies and to raise the possibility of prediction errors. As earlier research (Tang, 2006; Mentzer et al., 2001) has shown, this problem has far-reaching effects that negatively impact Unilever Ethiopia's supply chain's overall efficiency by causing stockouts, overstocks, and poor resource utilization.

This research delves into the critical role of accurate demand forecasting within robust and efficient supply chain practices, a cornerstone principle for organizations worldwide. By examining the far-reaching consequences of forecasting errors – stock disruptions, inflated inventory costs, operational inefficiencies, and potential customer dissatisfaction – this study aims to illuminate these challenges and propose advancements specifically for Unilever Ethiopia's operations.

However, the significance of this research extends beyond a single organization. By aligning with the broader goals of the supply chain community – the pursuit of accuracy, flexibility, and a customer-centric approach – this investigation has the potential to yield valuable best practices, strategies, and insights that can contribute to the overall development of supply chain management in Ethiopia. In essence, this study transcends the confines of a single company's challenge, offering the potential to propel the entire field forward.

2.2 Theoretical Literature Review

2.2.1 Demand Forecasting Models

2.2.1.1 Historical Perspective

Demand forecasting is a systematic process of predicting future demand for products or services based on historical data, market trends, and other relevant factors. It involves analyzing past sales data, market conditions, customer preferences, and external influences to estimate the quantity of goods or services that customers are likely to purchase over a specific time horizon.

In the early days of commerce, demand forecasting was predominantly rooted in intuition and personal experience. Business owners and managers relied on their instincts and anecdotal evidence to anticipate future demand. While this approach might have sufficed for smaller enterprises with relatively straightforward operations, it lacked the precision required for navigating the intricacies of modern business environments.

As markets expanded and complexities grew, the introduction of quantitative techniques marked a turning point. Methods such as moving averages, exponential smoothing, and linear regression began to gain prominence, ushering in a more data-driven approach to forecasting. Historical sales data, though limited in scope, became an asset for making predictions. These techniques laid the foundation for a more systematic and evidence-based approach to forecasting.

At present the contemporary landscape of demand forecasting is marked by an explosion of data and unprecedented technological advancements. In the era of digital transactions, online interactions, and interconnected systems, businesses are presented with an abundance of information that holds the potential to unlock deeper insights. The convergence of advanced data science analytics techniques, including machine learning and artificial intelligence, has ushered in a new era of forecast accuracy.

Modern demand forecasting transcends reliance solely on historical sales data. It integrates an array of factors, ranging from market trends and social sentiment to economic indicators and beyond. This comprehensive approach enables businesses to model intricate relationships and capture nuances that were previously overlooked. Consequently, businesses are now able to make predictions with heightened precision, optimizing vital aspects such as inventory management, resource allocation, and marketing strategies.

As businesses continue to evolve, the evolution of demand forecasting methods marches forward. The future of demand forecasting promises to be characterized by greater accuracy, anticipatory insights, and real-time adaptability. Advanced predictive analytics will empower businesses to anticipate trends before they fully emerge, enabling them to proactively shape strategies in response to emerging consumer behaviors.

Koussalia Hamiche's (2018) work underscores the critical role of forecasting models in supply chain decision-making, stressing the limitations of traditional time series forecasting approaches. While regression, smoothing, statistical, and neural techniques have been commonplace, challenges in creating precise mathematical models and the risk of overfitting have prompted a search for alternatives.

Moreover, demand forecasting will evolve to become more adaptable and responsive to real-time changes. With the integration of real-time data streams and predictive models, businesses can pivot their strategies dynamically in response to unforeseen disruptions or sudden surges in demand. This heightened level of adaptability will be instrumental in navigating the increasingly volatile and unpredictable nature of the business landscape.

The below table summarizes the different methods of forecasting demand under qualitative and quantitative classification being used by businesses:

Table 2.1: Types of Demand Forecasting

<table>
<tr><th>Classification</th><th colspan="2">Method</th></tr>
<tr><td rowspan="7">QUALITATIVE
(rely on predominantly on human judgment)</td><td colspan="2">Jury of execution opinion</td></tr>
<tr><td colspan="2">Delphi Method</td></tr>
<tr><td colspan="2">Sales force composite</td></tr>
<tr><td colspan="2">Historical Analog</td></tr>
<tr><td colspan="2">Market research testing</td></tr>
<tr><td colspan="2">Cross-impact analysis</td></tr>
<tr><td colspan="2">Assumption based</td></tr>
<tr><td>Classification</td><td>Method</td><td>Family</td></tr>
<tr><td rowspan="15">QUANTITATIVE
(methods are predominantly described by numbers and formulas)</td><td>Time Series</td><td rowspan="2">Explanatory Data Analysis</td></tr>
<tr><td>Moving Averages</td></tr>
<tr><td>Exponential Smoothing</td><td rowspan="2">Time Series Modeling</td></tr>
<tr><td>ARIMA</td></tr>
<tr><td>Linear regression</td><td rowspan="4">Linear Regression</td></tr>
<tr><td>Correlation analysis</td></tr>
<tr><td>Linear trend</td></tr>
<tr><td>Elasticities</td></tr>
<tr><td>Logistics regression</td><td>Non-linear Regression</td></tr>
<tr><td>Diffusion models</td><td rowspan="6"></td></tr>
<tr><td>Decision trees</td></tr>
<tr><td>Scenario analysis</td></tr>
<tr><td>Simulation (Monte Carlo)</td></tr>
<tr><td>Expert Systems (role based)</td></tr>
<tr><td>Artificial Neural Networks (ANN)</td></tr>
</table>

Source: Unilever (2023); Demand Forecasting

Organizations assess the accuracy of forecasting models by comparing forecasted values with actual demand data using metrics such as Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), or Forecast Bias. Models with lower forecasting errors are considered more accurate.

The Mean Absolute Percentage Error (MAPE) is a commonly used metric for evaluating the accuracy of forecasting models, particularly in the context of demand forecasting. MAPE measures the average percentage difference between forecasted values and actual values, providing insights into the overall forecasting performance. The formula for calculating MAPE is as follows:

$$\text{MAPE}= \frac{1}{n} \sum_{t=1}^{n} \frac{|A_t - F_t|}{|A_t|} \text{ x } 100$$

Where:

- MAPE = Mean Absolute Percentage Error
- n = Number of data points
- At = Actual value at time t
- Ft = Forecasted value at time t

MAPE is expressed as a percentage, representing the average magnitude of errors in percentage terms. A lower MAPE indicates higher forecasting accuracy, as it signifies that the forecasted values are closer to the actual values.

The Root Mean Squared Error (RMSE) is another commonly used metric for evaluating the accuracy of forecasting models, including demand forecasting. RMSE measures the average of the squared differences between forecasted values and actual values, providing a quantitative assessment of forecasting errors. The formula for calculating RMSE is as follows:

$$\text{RMSE}= \sqrt{\frac{1}{n} \sum_{t=1}^{n} (A_t - F_t)^2}$$

Where:

- RMSE = Root Mean Squared Error
- n = Number of data points
- At = Actual value at time t
- Ft = Forecasted value at time t

Forecast bias (FB) refers to the tendency of a forecasting model to consistently overestimate or underestimate actual demand. It measures the systematic error present in the forecasting process, which can lead to skewed predictions over time. Forecast bias is assessed by examining the direction and magnitude of errors across multiple forecast periods.

- Positive Bias: Indicates a consistent tendency to overestimate actual demand, resulting in forecasts that are higher than observed values.
- Negative Bias: Signifies a consistent tendency to underestimate actual demand, leading to forecasts that are lower than observed values.
- Zero Bias: Occurs when the average forecast error is balanced, with an equal likelihood of overestimation and underestimation.

Table 2.2:Formulas for measuring demand forecasting model accuracy

KPI	**Calculation**
MAPE	$\frac{1}{n}\sum_{t=1}^{n}\frac{\lvert A_t - F_t\rvert}{\lvert A_t\rvert}$ x 100
RMSE	$\sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2}$
FB	$\Sigma Sales - \Sigma\ Forecast / \Sigma\ Forecast$

Source: Unilever (2018); Demand Planning Handbook

2.2.1.2 Contemporary Models

Supply chain management frequently relies on various demand forecasting models to anticipate future demand accurately. These models encompass a range of approaches tailored to different data types and predictive requirements. The book by M. Christopher (2005) tries to give highlight over the different models as follows. Time series models such as Moving Average, Exponential Smoothing, and ARIMA analyze historical data patterns to forecast future demand trends. Causal models like Linear Regression and Multiple Regression establish relationships between demand and influencing factors, while Econometric Models utilize economic indicators for forecasting. Machine Learning Models such as Random Forest, Gradient Boosting, and Neural Networks employ advanced algorithms to capture complex demand patterns. Judgmental Models like Market Research, Delphi Method, and Scenario Planning involve expert opinions and scenario analysis. Collaborative Forecasting Models like Vendor-Managed Inventory (VMI) and CPFR enable supply chain partners to share data and align forecasts for improved coordination. By integrating these diverse models, organizations can optimize their supply chain operations, minimize costs, prevent stockouts, and enhance customer satisfaction through synchronized production and inventory management.

Demand forecasting relies on various models, each offering unique strengths and weaknesses. Time Series Models are prized for their simplicity and effectiveness in capturing stable patterns, making them ideal for quick forecasts. However, they can falter when faced with sudden shifts or irregularities in demand due to their reliance on historical data and their inability to account for external influences.

Causal Models, on the other hand, excel in integrating external factors like price and promotions, enhancing forecast accuracy and providing insights into the drivers of demand. Yet, their reliance on extensive data and the assumption of linearity can pose challenges in data-intensive environments and overlook complex non-linear relationships.

Machine Learning Models stand out for their predictive accuracy and adaptability to changing demand dynamics. Nonetheless, their black-box nature and high data requirements may hinder interpretability and scalability in certain contexts.

Judgmental Models leverage human expertise and flexibility, incorporating qualitative insights that quantitative models may miss. However, they are susceptible to subjectivity and scalability issues, limiting their applicability in large-scale forecasting scenarios.

Collaborative Forecasting Models thrive on information sharing and improved coordination across supply chain partners, enhancing accuracy and alignment of inventory levels. Yet, they rely heavily on partner collaboration and can face complexity and integration challenges.

Understanding the nuances of each model is crucial for selecting the most suitable approach based on specific requirements and data characteristics. Often, organizations employ a combination or hybrid approach to leverage the strengths of different models while mitigating their weaknesses, ultimately improving the accuracy and robustness of demand forecasting in supply chain management.

Different studies were also done by different scholars to evaluate the strength and weakness of different forecasting models.

The study by Yvonne Badulescua et al. (2021) identified weakness for the different demand forecasting models in their study. They identified for Autoregressive Time-Series Models found out that they have limited adaptability a struggle to adapt to sudden changes or irregular patterns in the data, leading to potential inaccuracies in forecasting and additionally found out to be sensitive to outliers which may impact the accuracy of the forecast.

For Exponential Smoothing Models it was identified that they lack complexity to capture intricate patterns or trends in the data, potentially leading to oversimplified forecasts. Hybrid Models were found to be subjective to judgmental adjustments which introduces bias into the forecasting process, potentially affecting the accuracy of the forecasts. Also, integrating quantitative and qualitative information in hybrid models can be complex and may require careful calibration to ensure optimal performance.

On a similar note the study by Halima Bousqaoui et al. (2021) also evaluates various demand forecasting models, highlighting their distinct strengths and weaknesses. On their study Autoregressive Integrated Moving Average (ARIMA) emerges as a well-established statistical model adept at capturing linear dependencies in time series data, particularly suited for stationary data. However, it struggles with complex nonlinear patterns, necessitates manual hyperparameter selection, and may underperform with non-stationary or irregular data.

Multi-Layer Perceptron (MLP) offers flexibility in capturing complex nonlinear relationships and handling large datasets, excelling in pattern recognition. Yet, it is susceptible to overfitting, especially with smaller datasets, and requires meticulous tuning of hyperparameters, potentially hindering performance with time series data featuring long-term dependencies.

Long Short-Term Memory (LSTM) models, tailored for sequence prediction tasks like time series forecasting, stand out for their ability to capture long-term dependencies and handle sequential data with varying time lags. However, their complex architecture may lead to extended training times, necessitating careful hyperparameter tuning to mitigate overfitting risks, particularly with noisy or sparse data.

Convolutional Neural Networks (CNNs) excel in capturing spatial and temporal patterns, making them suitable for processing image and sequence data. While adept at automatically learning relevant features, they may require substantial data for training to prevent overfitting and exhibit limited capability in capturing long-term dependencies in sequential data. Additionally, their intricate architecture may pose challenges in model interpretability.

Additionally, Halima Bousqaoui et al. (2021) have identified ARIMA models are well-suited for capturing linear dependencies and simple seasonal patterns, while deep learning models like MLPs, LSTMs, and CNNs are more adept at handling complex nonlinear relationships, long-term dependencies, and irregular patterns in demand data. The choice of model should be based on the specific characteristics of the demand patterns present in the data and the desired level of forecasting accuracy.

By selecting the right forecasting model tailored to the characteristics of a specific product category, organizations can enhance operational efficiency, improve customer satisfaction, mitigate risks, make informed strategic decisions, gain a competitive edge, and foster innovation and growth within their supply chain operations.

The forecasting results in the study by Anna Borucka (2018) were based on sales data provided by the considered enterprise, specifically concerning the sale of the company's flagship product. The analysis utilized this sales data to construct and compare two forecasting models: the regression function and the ARIMA model. The study compared the forecasted values generated by both the regression model and the ARIMA model with empirical test observations that were not used in constructing the models. The comparison aimed to evaluate the accuracy and reliability of the forecasts produced by each model and determine their effectiveness in predicting demand for the company's flagship product. By comparing the forecasted values with empirical data, the study assessed the performance and reliability of each model in predicting demand, ultimately highlighting the importance of selecting the right forecasting model for effective demand forecasting in the analyzed context.

Zenah Yaser Alzubaidi (2020) conducted a study that examines demand forecasting models in the FMCG industry. Because of the large number of transactions and intricate demand planning involved in the FMCG sector, the study highlights the crucial role that forecasting models play in this sector. To estimate the 3-month demand for FMCG products in Gulf countries, the study analyzes time series forecasting models using statistical and machine learning techniques. The analysis's result is that statistical approaches—more especially, SARIMA and ETS models—perform better than machine learning strategies in most cases. SARIMA is advised for 3-month demand forecasting that is short-term.

On the other hand, the machine learning technique LSTM demonstrated potential and was recommended for usage in longer-term forecasting, like for the upcoming year.

The article also addresses how product portfolios and supply chain complexity can be reduced by using clustering techniques, such as K-means, to classify SKUs according to demand. However, it points out that more research on clustering techniques is required before deciding on a final product segmentation plan.

Delving into the dynamic realm of forecasting models within the Fast-Moving Consumer Goods (FMCG) industry, Güzin Tirkeş (2017) paints a vivid narrative. This insightful piece illuminates the pivotal role of demand forecasting in the Food and Beverage (F&B) sector, weaving a story of intricate production planning and scheduling designed to harmonize with the heartbeat of customer needs.

In the quest for precision, Tirkeş conducts a captivating symphony of forecasting models: Trend Analysis, Decomposition, and the enchanting Holt-Winters (HW) model. As the curtain rises on their performance, the HW and Decomposition models emerge as shining stars, their brilliance outshining others on the stage of efficacy. The HW model, an unassuming virtuoso, captivates with its simplicity, delivering forecasts that dance on the edge of precision. Its secret lies in a delicate balance, leaning less on the echoes of history and more on the resonance of recent values.

Yet, the Decomposition model unveils its own mesmerizing allure, dissecting data into components like a masterful storyteller revealing the layers of a plot—trend, seasonality, cyclic, and the whims of randomness. A demanding maestro, it craves a rich historical tapestry for its performance, demanding the stage be set with ample data for its successful rendition.

In this study, the Trend Analysis model takes a supporting role, its simplicity and accessibility adding a harmonious note to the ensemble. However, it whispers its limitations in the ears of the audience—suited for simplicity, yet hesitant when confronting the complexities of long-term, seasonal, and cyclical data patterns.

Tirkeş' exploration becomes a theatrical spectacle, where forecasting models emerge as characters, each with its unique traits and melodies. The stage is set, the models take their places, and the drama unfolds, offering a captivating portrayal of the intricate dance between demand forecasting and the demanding cadence of the FMCG industry.

Embarking on a journey into the realm of forecasting, Bakytbek B. (2021) orchestrates a narrative that resonates with the symphony of machine learning (ML) models—a tale of innovation to elevate forecast accuracy (FA) while gently nudging human errors to the wings.

The study sheds light on the intricate complexities surrounding demand planning, navigating through uncertainties influenced by promotional activities, competitive strategies, and weather fluctuations. Amidst this complexity, a guiding principle emerges—restraint in feature selection for modeling systems. This deliberate choice aims to avoid excess, conserve resources, and achieve a harmonious balance in the forecasting process.

The anticipation unfolds as machine learning models take center stage, promising not only accuracy but also reduced reliance on human intervention. Envisioning a future where algorithms, fueled by data and informed by research insights, lead the performance towards financial prosperity.

In this narrative, the document remains mysterious, withholding the identity of the superior model. A suspenseful promise reveals a lineup of contenders: Moving Average, ARIMAX, SARIMAX, LSTM, linear regression, and ordinary least squares regression. Each poised for comparison, each with its unique approach, competing for the title of the finest performer in the spectacle of forecasting excellence.

In the realm of supply chain dynamics, Andrii Galkin (2021) emerges as a master storyteller, illuminating the world of demand forecasting models within urban transport systems. A symphony of econometric models—OLS, PA, ReADLM, VAR, TVP, and structural time series models—takes the spotlight as Galkin unveils their strengths, limitations, and applications against the backdrop of evolving consumer behaviors and urbanization trends.

With precision, Galkin weaves together the narrative, highlighting identified strengths as guiding lights. These models possess the unique ability to integrate economic activity, employment, and consumer behavior seamlessly into supply chains, attuned to consumer demand for precision and efficiency.

Beyond numbers and equations, the study delves into consumer behavior and the geographical landscape that shapes it. Services are targeted with precision, resources maximized strategically. Galkin's methodology considers purchasing costs, consumer movements, and retail network characteristics, influencing sales volume and unlocking new opportunities through dynamic inventory management.

However, amidst strengths, limitations loom. Galkin's narrative navigates challenges posed by traditional methods in managing cargo distribution for Fast-Moving Consumer Goods (FMCG), advocating for new frameworks in response to evolving consumer landscapes.

The study progresses to explore the impact of end-consumer behavior on logistics decisions. Supply Chain Management (SCM) systems emerge as orchestrators of automation in demand forecasting and planning—a crucial melody for the development of demand-driven supply chains in the world of FMCG.

As the narrative unfolds, Galkin's story resonates with the pursuit of optimization. The frequency and size of purchases become pivotal elements in a symphony where logistics infrastructure sets the stage, and stock placement and order strategies dictate the choreography—a saga of precision and efficiency leaving a lasting imprint on supply chain innovation and demand forecasting.

2.2.2 Dimensions of Supply Chain Planning

The smooth progression of goods and services from their raw state to the final consumer is fundamental to effective supply chain management. To facilitate this seamless flow, companies must address various crucial aspects during the planning phase.

Strategic sourcing and procurement stand out as a pivotal dimension. It involves the meticulous selection of dependable suppliers offering competitive pricing for materials. Building strong supplier relationships and negotiating contracts are integral components of this dimension.

Accurate demand forecasting emerges as another pivotal factor. By adeptly predicting customer requirements, companies can align production, inventory levels, and transportation needs accordingly. Diverse forecasting techniques are employed based on product specifics, industry nuances, and available data.

Inventory management assumes a critical role in balancing customer demand with storage expenses. The objective is to ascertain the optimal inventory level, ensuring sufficient stock availability while minimizing storage costs. Strategies encompass managing safety stock, lead times, and averting stockouts.

Production planning concentrates on scheduling and refining the production process to meet customer demand efficiently while maximizing resource utilization. This involves considering capacity constraints, lead times, and material availability.

Logistics and transportation entail intricately orchestrating the movement of goods across the supply chain. This dimension encompasses optimizing transportation routes, selecting suitable transport modes, and efficiently managing warehouse operations for a seamless material and product flow.

Effective communication and information exchange are imperative for successful supply chain planning. This dimension underscores the significance of data sharing among all chain partners, including demand forecasts, inventory levels, production schedules, and transportation plans, fostering enhanced collaboration and coordination.

Supply chains are inherently vulnerable to diverse risks such as natural calamities, political instability, or supplier failures. Proactive risk management strategies are essential to mitigate these risks and ensure uninterrupted supply chain continuity.

Lastly, sustainability is emerging as a pivotal dimension in supply chain planning. Companies are integrating eco-friendly practices by sourcing materials responsibly, reducing transportation emissions, and adopting recyclable packaging materials, thereby minimizing the environmental footprint of the supply chain.

By meticulously considering these dimensions, companies can craft robust supply chain plans that optimize efficiency, minimize costs, and effectively cater to customer demand.

2.2.3 Demand Forecasting Models and Inventory Planning & Performance

Inventory management plays a crucial role in enhancing supply chain efficiency through the following key aspects of Optimizing Inventory Levels, Reducing Lead Times, Enhancing Forecast Accuracy, Minimizing Costs, Improving Customer Service, Streamlining Operations, and Mitigating Risks. Key metrics used to measure inventory performance include:

- Inventory Turnover: Inventory turnover ratio calculates how many times a company's inventory is sold and replaced over a specific period. It is calculated as the cost of goods sold divided by the average inventory level. A high inventory turnover ratio indicates efficient inventory management and a lower risk of excess stock.
- Inventory Level: Inventory level refers to the quantity of goods or materials held in stock at a specific point in time. Monitoring inventory levels helps in maintaining optimal stock levels to meet customer demand while minimizing holding costs and stockouts.
- Inventory Cost: Inventory cost includes expenses associated with holding, storing, and managing inventory. It comprises costs such as storage costs, insurance, obsolescence, and capital tied up in inventory. Managing inventory costs efficiently is essential for maximizing profitability and operational efficiency.
- Safety Stock: Safety stock is the extra inventory held to mitigate the risk of stockouts due to variability in demand or supply lead times. Maintaining an appropriate level of safety stock helps in ensuring product availability, reducing the impact of demand fluctuations, and enhancing customer satisfaction.

The study conducted by Abdul Talib Bon and Chong Yi Leng (2009) identified a significant relationship between demand forecasting and inventory management in the context of the CCTV distributor Company. The study highlighted that the accuracy of demand forecasting significantly affects safety stock levels, inventory holding costs, and customer service levels. By improving the accuracy of demand forecasts, companies can optimize their inventory levels to meet customer demand efficiently.

Through the study it was also identified high forecast errors can lead to unnecessary high stocks or stockouts, resulting in suboptimal inventory management decisions. Therefore, reducing forecast errors through accurate forecasting techniques is crucial for effective inventory management.

Accurate demand forecasting enables companies to make informed decisions about inventory levels, production planning, and supply chain management. By aligning inventory levels with forecasted demand, companies can improve operational efficiency and customer satisfaction.

Demand forecasting serves as the foundation for supply chain planning, providing a continuous link to manage inventory positions and product demand. Effective forecasting helps in optimizing supply chain operations and improving overall inventory management practices.

In summary, the study identified a strong and interdependent relationship between demand forecasting and inventory management, emphasizing the critical role of accurate forecasting in optimizing inventory levels, reducing costs, and enhancing customer service in supply chain operations.

The study also points out that the relationship between demand forecasting and inventory management is not strictly direct, linear, or proportional. Instead, it is a complex and dynamic relationship that involves various factors and interactions. Here are some key points regarding the nature of this relationship:

- The relationship between demand forecasting and inventory management is often non-linear due to the dynamic nature of demand patterns, market fluctuations, and supply chain complexities. Changes in demand may not always result in proportional changes in inventory levels, as other factors such as lead times, order quantities, and supply chain disruptions can influence inventory decisions.
- Demand forecasting and inventory management are interconnected processes that influence each other. Accurate demand forecasting can lead to optimized inventory levels, but inventory management practices also impact the quality of demand forecasts. This mutual influence highlights the interdependence of these two functions in supply chain operations.
- The relationship between demand forecasting and inventory management often involves feedback loops, where inventory levels impact future demand forecasts and vice versa. Adjustments in inventory levels based on forecasted demand can affect future forecasting accuracy, leading to a continuous feedback loop that requires ongoing adjustments and improvements.
- The relationship between demand forecasting and inventory management is characterized by complex dynamics, including lead time variability, demand uncertainty, seasonality, and market trends. These factors contribute to the non-linear and dynamic nature of the relationship, requiring sophisticated forecasting techniques and inventory management strategies to effectively manage inventory levels.

In conclusion, the relationship between demand forecasting and inventory management is multifaceted, involving non-linear interactions, interconnected processes, feedback loops, and complex dynamics. While the relationship is not strictly direct, linear, or proportional, it underscores the importance of accurate forecasting and effective inventory management practices in optimizing supply chain operations and meeting customer demand efficiently.

Inventory control is an important part of the supply chain management that deals with optimal balancing service levels against investment over a very large assortment of the stock keeping units (SKUs) and uncertainties. According to Kot S. et. al (2011), Demand forecasting plays a crucial role in inventory management, influencing various aspects of supply chain operations and inventory performance. Here are some key effects of demand forecasting on inventory management identified through their studies.

One key advantage is finding the optimal inventory level. By accurately predicting demand, businesses can avoid the twin pitfalls of overstocking and understocking. Holding excess inventory ties up cash and incurs storage costs, while stockouts lead to lost sales and frustrated customers. Demand forecasts guide companies to the sweet spot, where they have just the right amount of inventory to meet demand without unnecessary costs.

Demand forecasting also empowers businesses to effectively manage safety stock. This buffer protects against unexpected fluctuations in demand. By anticipating these variations, companies can maintain the right amount of safety stock to prevent stockouts and ensure high customer service levels. It's about striking the perfect balance – having enough inventory on hand to meet customer needs while keeping costs under control.

Forecasting also injects intelligence into ordering and replenishment strategies. Companies can set reorder points and quantities based on anticipated demand, ensuring they order products at the right time. This optimizes inventory turnover, reduces lead times, and keeps inventory levels aligned with customer needs. It's a smarter approach that prevents stockouts and lost sales opportunities.

The impact of demand forecasting extends beyond inventory management. It acts as a cost optimization powerhouse. By minimizing carrying costs associated with excess inventory and stockouts, companies can significantly improve their bottom line. Accurate forecasts allow them to align inventory levels with anticipated demand, leading to optimized costs, improved cash flow, and enhanced profitability.

Furthermore, demand forecasting is a key ingredient in boosting supply chain efficiency. When integrated with inventory management practices, it allows companies to align production, distribution, and inventory levels with expected demand. This smoother operation translates to reduced lead times, improved responsiveness to market changes, and an overall boost to supply chain performance.

Ultimately, happy customers are loyal customers. Demand forecasting plays a vital role in achieving this by positively impacting customer service levels. Businesses can meet customer expectations, reduce stockouts, improve order fulfillment rates, and enhance customer satisfaction by ensuring the right products are available at the right time and place. This focus on customer needs leads to increased loyalty and repeat business. In short, demand forecasting is a win-win for businesses and their customers.

According to Yue Zhou et. al (2023), the relationship identified through the study between demand forecasting and inventory control is not explicitly categorized as linear or non-linear. However, based on the insights provided in the study, we can infer that the relationship between demand forecasting and inventory control is likely to exhibit characteristics of both linear and non-linear dynamics.

The study has identified in traditional inventory control models, there is often a linear relationship between demand forecasts and inventory levels. For example, in basic reorder point models, inventory replenishment is triggered when stock levels reach a certain threshold based on forecasted demand. Linear relationships may be observed in certain aspects of inventory control, such as calculating safety stock levels or determining order quantities based on forecasted demand and lead times.

But according to the study demand forecasting errors can introduce non-linear effects on inventory performance. Small deviations in demand forecasts can lead to disproportionate impacts on inventory decisions and system profitability. Non-linear relationships may arise when considering the effects of forecasting errors on optimal inventory levels, reorder points, and supply chain dynamics. For instance, the impact of a large forecasting error on order quantities may not be directly proportional to the magnitude of the error.

The study's findings regarding the differential impact of mean and variance errors on system profit suggest non-linear effects of forecasting inaccuracies on inventory control decisions. While the study does not explicitly classify the relationship between demand forecasting and inventory control as linear or non-linear, the complexities of demand variability, forecasting errors, and inventory optimization likely involve a combination of linear and non-linear dynamics. The interplay between demand forecasting accuracy and inventory management decisions may exhibit both linear relationships in certain aspects of inventory control models and non-linear effects when considering the broader implications of forecasting errors on system performance and profitability.

The study by Leo W.G.Strijbosch et. al (2011), also support the idea of the previous study. The relationship between demand forecasting and stock control often exhibits non-linear dynamics, where changes in forecasting accuracy or inventory levels may not have a linear impact on stock control performance. The effects of forecasting errors or inventory decisions can be non-linear and may vary based on different scenarios or demand patterns.

Additionally, it was identified that demand forecasting and stock control are interconnected processes with feedback loops. Changes in demand forecasts can influence inventory decisions, which in turn affect future demand forecasting. This feedback loop can lead to dynamic and non-linear relationships between forecasting and stock control.

The study A. Syntetosa (2010) highlighted that the efficiency of inventory systems is not directly correlated with demand forecasting performance, as measured by traditional forecasting accuracy metrics. This finding underscores the importance of considering accuracy-implication metrics in addition to standard forecast accuracy measures when evaluating forecasting methods for inventory management.

Traditional forecasting accuracy metrics, such as Mean Absolute Percentage Error (MAPE) and symmetric Mean Absolute Percentage Error (sMAPE), focus on the precision of demand forecasts but may not fully capture the impact of forecast accuracy on stock control performance. The study suggests that while a forecasting method may perform well in terms of traditional accuracy measures, it does not guarantee optimal stock control outcomes.

By emphasizing the need to evaluate forecasting methods based on their implications for stock control through accuracy-implication metrics, the study highlights the complexity of the relationship between demand forecasting and inventory management. It suggests that factors beyond forecast accuracy, such as service levels, inventory costs, and the practical implications of forecasting decisions, play a crucial role in determining the overall efficiency of inventory systems.

Therefore, the study's finding underscores the importance of a holistic approach to evaluating forecasting methods, considering not only forecast accuracy but also the practical implications for stock control and inventory management efficiency.

2.3 Empirical Literature Review

The empirical findings by A.P. Arnaiz et. al (2023) supported a positive correlation between the choice of forecasting method and inventory performance. Organizations that selected appropriate forecasting methods, such as time series algorithms, experienced improved forecasting accuracy, optimized inventory levels, reduced holding costs, minimized stockouts, enhanced operational efficiency, made informed decisions, and demonstrated adaptability to market changes, ultimately leading to enhanced inventory performance.

The study utilized data related to inventory management and demand forecasting practices. The researchers collected data on inventory levels, sales data, historical demand patterns, market trends, and other relevant factors to analyze and improve the inventory management system. Additionally, the study incorporated real-time inventory monitoring data to predict future demand for products using automatic inventory forecasting models. The researchers also considered user feedback and responses gathered through survey interviews to evaluate the inventory management system and its impact on inventory performance.

The study by Liao et.al (2010) found that there is either negligible or minimal correlation between forecasting errors and inventory costs in the context of supply chain management. The numerical study in the research was conducted on a 3-echelon 30-product serial supply chain. This means that the study focused on a supply chain consisting of three echelons (levels) and involving 30 different products.

While forecasting errors can influence inventory planning decisions and potentially lead to suboptimal inventory levels, the study suggests that the relationship between forecasting errors and inventory costs is not strong or consistent. This finding underscores the complexity of supply chain dynamics and the multitude of factors that can affect inventory performance beyond just the accuracy of demand forecasts.

The study emphasized that the best forecasting method for minimizing inventory costs was dependent on the specific inventory policy and lead time in use. This suggests that the effectiveness of forecasting methods in improving inventory performance varied based on the context of inventory management strategies.

Empirical findings by Solis et al. (2012) revealed that the choice of forecasting method, particularly the selection of Syntetos-Boylan approximation (SBA), had a significant impact on inventory performance. SBA method was identified as the best performing method overall in terms of statistical accuracy when tested over multiple time periods, indicating its effectiveness in improving inventory control performance. The study reported that the Syntetos-Boylan approximation (SBA) method consistently resulted in the lowest average levels of inventory on hand for a 95% target fill rate across all evaluated stock-keeping units (SKUs) compared to other forecasting methods like Simple Moving Average (SMA) and Single Exponential Smoothing (SES).

Based on the findings of the study, we can conclude that the choice of forecasting method has a positive correlation with inventory performance. The selection of an effective forecasting method, such as the Syntetos-Boylan approximation (SBA) in this study, can lead to improved inventory control efficiency, lower inventory levels, and better management of backorder frequency. However, to achieve optimal inventory performance, several other factors like demand variability, lead time, service level objective, inventory control policies, and supply chain collaboration need to be considered in conjunction with the forecasting method.

There were other studies done by the scholars like Kourentzes et. al (2020), which emphasized the importance of establishing a direct link between forecasting models and inventory decisions. By integrating inventory metrics and cost functions into the parameterization process, the study aimed to align forecasting outcomes with inventory objectives, leading to more informed decision-making in inventory management.

The parameterization process involved developing a cost function that was inferred directly from inventory decisions, minimizing the fitting error on past historical demand, simulating inventory scenarios and tracking appropriate performance indicators. The cost function quantified the difference between target and realized service levels, providing a basis for evaluating the performance of forecasting models in the context of inventory planning. The parameterization approach was tested using real data from a UK manufacturing firm, allowing for a practical assessment of its effectiveness in a real-world inventory management setting.

The parameterization process resulted in a reduction in forecast accuracy decreased by up to 9%, improvement of up to 62% in forecast bias reduction, approach achieved minimal differences between target and realized service levels in inventory performance, process resulted in dominating trade-off curves over other estimators in terms of inventory performance. By considering the balance between inventory on hand and out-of-stock volume, the optimized forecasting model showcased superior trade-off decisions, highlighting the effectiveness of the parameterization approach in optimizing inventory performance.

The study M.Z. Babai et. al (2013) conducted an empirical investigation based on sales data related to 329 Stock Keeping Units (SKUs) from a major European superstore. The study identified several key relationships between forecasting and inventory performance in a two-stage supply chain with ARIMA (0,1,1) demand processes: Higher levels of forecasting accuracy were associated with improved inventory performance, as evidenced by reductions in Mean Squared Error (MSE) and inventory costs. Effective forecasting accuracy contributed to better demand prediction, leading to optimized inventory levels and reduced holding costs in the supply chain. Utilizing the Forecast Information Sharing strategy between the retailer and manufacturer resulted in significant benefits for inventory performance. The study demonstrated that sharing forecast information led to substantial reductions in forecasting errors, inventory holdings, and inventory costs, highlighting the positive impact of collaborative forecasting on supply chain efficiency. The smoothing constant "a" in the ARIMA (0,1,1) demand process played a crucial role in influencing inventory performance metrics. Higher values of parameter "a" were associated with greater reductions in MSE and inventory costs, indicating the importance of parameter selection in optimizing inventory management strategies. the smoothing constant "a" is used to adjust the weight given to the most recent observation relative to the previous forecast. A higher value of "a" places more emphasis on recent demand data, leading to a more responsive forecast that quickly adapts to changes in demand patterns.

The study by Rego et. al (2015) on spare parts demand forecasting and inventory control within the context of an automaker operating in Brazil covering a 10,032 Stock Keeping Units (SKUs) of spare parts over a period of six years of demand data. identified a strong correlation between demand forecasting models and inventory performance in the context of automotive spare parts management. By evaluating different forecasting models, such as Simple Moving Average (SMA), Syntetos–Boylan Approximation (SBA), and Bootstrapping, the research aimed to understand how the choice of forecasting method impacts inventory control strategies and overall performance.

The study assessed the accuracy of forecasts generated by each model and how well they aligned with actual demand patterns. Models that provided more accurate forecasts were associated with improved inventory performance, as they enabled better inventory planning and control.

Certain forecasting models, such as the Syntetos–Boylan Approximation (SBA) and Bootstrapping, may be better suited to handle lead time variability and demand uncertainty. These models can help in setting appropriate reorder points and order quantities, leading to optimized inventory levels and service levels. The choice of forecasting model can impact inventory costs, including holding costs, stockouts, and ordering costs. Models that generate more precise forecasts can help in reducing excess inventory levels and minimizing stockouts, thereby improving cost-effectiveness.

Effective demand forecasting models contribute to achieving desired service levels by ensuring that the right amount of inventory is available at the right time. Models that accurately predict demand fluctuations can enhance service levels and customer satisfaction.

Overall, the correlation between demand forecasting models and inventory performance underscores the importance of selecting the most suitable forecasting approach to drive efficient spare parts inventory management and study concluded by leveraging advanced forecasting techniques tailored to the specific characteristics of spare parts, organizations can enhance inventory performance, reduce costs, and optimize customer service levels.

2.4 Research Gap

The extant literature on demand forecasting within supply chain management (SCM) has extensively explored various methods across diverse industries. However, a notable gap remains regarding the optimal integration of emerging technologies, specifically blockchain and the Internet of Things (IoT), into forecasting processes tailored for the fast-moving consumer goods (FMCG) sector. While prior research has delved into advanced analytics techniques like machine learning (ML) and artificial intelligence (AI), there is a paucity of investigation into how blockchain and IoT can enhance demand forecasting accuracy, particularly in complex supply chain networks and volatile market environments. Furthermore, the potential synergies between these technologies and traditional forecasting methods, along with their implications for supply chain resilience and adaptability, have not been thoroughly examined.

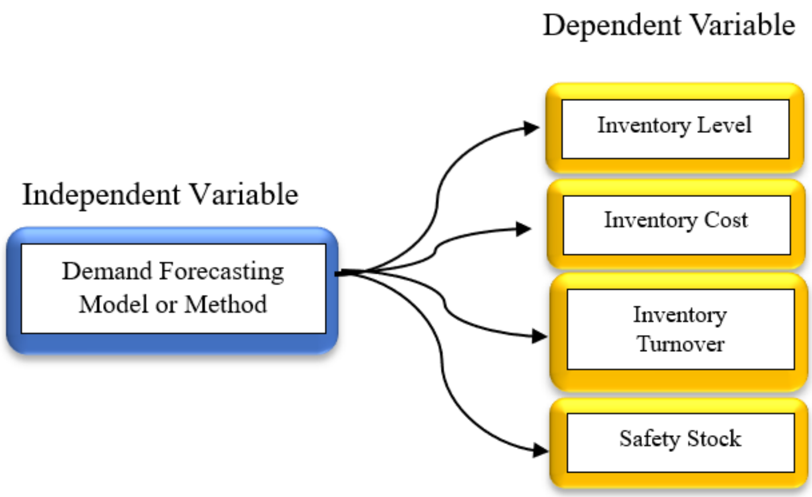
Within the FMCG domain, a compelling need exists for a comprehensive comparative analysis that integrates both statistical and ML techniques, while simultaneously considering the unique characteristics and challenges inherent to FMCG supply chains. Existing studies have documented the effectiveness of individual forecasting methods, such as exponential smoothing, ARIMA models, and judgmental adjustments. However, a critical gap exists in research that systematically evaluates the performance of these methods in inventory performance. Such an evaluation should consider factors like forecast accuracy, computational efficiency, and scalability to diverse product categories and market conditions within the FMCG sector.

Furthermore, the synergistic effects of combining forecasts from multiple models within the FMCG sector require a deeper understanding, as evidenced by previous studies demonstrating the promise of such combination strategies for improving accuracy. However, the applicability of these strategies across diverse FMCG product portfolios and supply chain structures remains largely unexplored.

2.5 Conceptual Framework of Study

The strategic plan to adapt best demand forecast model for Unilever Ethiopia and the literature reviews (data-driven theoretical framework) are used to build the conceptual framework below. The accuracy in choice of demand forecasting models in demand forecasting are viewed as independent variables in this paradigm, whilst inventory planning and performance metrics such as inventory level, inventory cost, inventory turnover and safety stock are seen as dependent variables. The conceptual model for this investigation is displayed in Figure 2.1 below.

Figure 2.1: Conceptual framework of Study



Source: This framework is the author's own elaboration

Chapter Three

Methods of the Study

3.1 Introduction

The study is focused to show how demand forecasting model choice plays a big role on inventory planning and performance show casing Unilever Ethiopia and suggest new model based on different studies and condition of the business.

The main objective of this chapter is to provide the study design, population and sample, data source and type, data collection procedure, validity and reliability tests of the instrument, ethical considerations, and data analysis method.

3.2 Research Approach

This study employed a mixed-methods research approach to comprehensively understand the effect of demand forecasting models in supply chain planning dimension specifically inventory planning & performance. This approach integrates both quantitative and qualitative methodologies to gain a richer and more nuanced understanding of the phenomenon under investigation. The **quantitative analysis of the secondary data source was the major and primary focus of this study** and the research questionnaire tried to support the findings from the secondary source by gauging the perspective of stakeholders involved in demand forecasting and inventory management.

3.3 Research Design

The study employed explanatory and descriptive research design. The purpose of this research design is to highlight the effect of demand forecasting model on inventory planning and performance.

3.4 Population of the study

The study focused on employees who directly involved in the demand forecasting process and inventory management at Unilever Ethiopia. These employees are the Planning Manager, Demand Planner, Supply Planner, Material Planner for the different business Categories (Beauty & Wellbeing, Foods), Marketing Managers for the different business categories (Life Buoy, Knorr), Customer Development Excellence Manager, Category & Channel Development Manager, Sales Managers, Finance Manager, Warehouse Managers and Manufacturing Manager, which in total would be **14 people.**

3.5 Sampling Design and Sampling Procedure

The sampling frame and focus area for this research is Unilever Ethiopia at central head office, which is located in the capital of Ethiopia, Addis Ababa and manufacturing site at Dukem, Oromia. A census sampling method was employed, targeting individuals with expertise in demand forecasting within the organization. Employees directly involved in the S&OP process (Demand Forecasting Core Members) and inventory management are selected for the survey. Specifically, **14 people** were involved in the survey.

Inclusion/Exclusion Criteria: Participants must be involved demand forecasting and inventory management at Unilever Ethiopia.

Sampling Rationale: This approach ensures that the sample consists of individuals with the necessary expertise and experience related to the research objectives.

3.6 Data Collection Procedure

Data was collected through a combination of qualitative and quantitative methods:

Qualitative: Questionnaire and Semi-structured interviews.

Quantitative: Historical demand and performance data collected for statistical analysis from company database.

3.7 Data Collection Instrument

Instruments/Tools: Interview guides for qualitative data; data collection templates for quantitative data from company SAP system.

1. Participant Recruitment: Participants were recruited through official channels, with the HR department facilitating contact.
2. Informed Consent: Participants were provided with detailed information about the study.
3. Data Gathering: Qualitative data was gathered through questionnaire and interviews and quantitative data was extracted from internal databases.
4. Interventions: No interventions or experimental manipulations were planned.

3.8 Data Analysis Methods

Both quantitative and qualitative data were gathered for this investigation. Descriptive and inferential statistical techniques were used to analyze the quantitative data that was gathered. The statistical package for social sciences (SPSS) program was utilized in this investigation to examine quantitative data. This type of software is primarily applicable for this kind of research or study. Measures of central tendencies, including means, and standard deviation, were obtained using closed-ended questions. Both correlation and regression analysis were used to ascertain how the independent and dependent variables related to one another. Discussions that add more insight to the findings come after the tables that show the results.

***Quantitative Approach*:**

The quantitative design utilized statistical analyses, including:

Regression analysis: To explore the relationships between demand forecasting accuracy metrics (RMSE; MAPE) and inventory planning & performance metrics.

Correlation analysis: To assess the strength and direction of the relationships between variables.

***Qualitative Approach*:**

The qualitative design employed thematic analysis to identify recurring patterns and themes within the questionnaire and interview data.

Variables:

Independent Variable: Demand forecasting models (different models used by Unilever Ethiopia) measured through RMSE and MAPE

Dependent Variables:

- ✓ Inventory Levels
- ✓ Inventory Cost
- ✓ Inventory Turnover
- ✓ Safety Stock

Control Variables: While not applicable in this study due to its exploratory nature, potential control variables for future research could include factors like lead time, product category, seasonality, and marketing campaigns.

3.9 Validity and Reliability Test

According to Creswell (2009), a test's validity refers to the extent to which it captures the intended outcomes. It is the extent to which findings from data analysis accurately reflect the phenomenon being investigated.

A Cronbach's alpha estimates the proportion of variance in the best scores that can be attributes to the true score of variances (Brown, 2019). The researcher used the Cronbach's alpha to estimate internal consistency & reliability for the scales. The Reliability test is a tool to measure a questionnaires internal consistency (Brown, 2019). For our questionnaire we made sure the Cronbach's alpha exceeds 0.600. Therefore, a pre-determined questionnaire by P. Danese et.al (2011) and Jeong-A Kim (2018) was used.

Secondary data taken from the business's SAP system is used in this study which is secure and integrated throughout the business. But to guarantee the accuracy and consistency of the data utilized in this investigation, the following factors were considered: the information came from the company's Sales, Finance, and warehouse departments. Qualified staff with knowledge of SAP quality control and data management work in this department. Also, the information was examined internally to look for errors and missing values to handle any inconsistency.

To ensure a robust analysis and capture current trends, the research focused on a three - year timeframe (January 2021 - December 2023). This period provides access to historical data on key SKUs (Stock Keeping Units) from Unilever Ethiopia's product portfolio, including Lifebuoy Total, Lifebuoy Lemon, Knorr All In One, and Knorr Chicken. Three-year period was selected as the data available was consistent and free of external factor like the covid pandemic to avoid wrong results.

3.10 Ethical Considerations

Ethical considerations include ensuring participant confidentiality, obtaining informed consent, and minimizing any potential risks associated with participation. Anonymity has been maintained during data analysis and reporting.

Chapter Four

Results and Discussion

4.1 Introduction

The objective of this section is to present, examine, and interpret the information gathered via secondary data (primary focus) and self-administered surveys (supportive study). Secondary data source needed for the study was extracted from Unilever Ethiopia data base up on approval and employees who directly are involved in the demand forecasting completed a self-administered questionnaire to gather the effect of demand forecasting accuracy on inventory planning and performance. Each variable required was extracted and each responder received a questionnaire in person, and both quantitative and qualitative data were gathered. Considering this, the results were presented, examined, and evaluated as shown below.

The findings and discussion are organized in two sections. The first section focused on the results and discussion of the secondary data source which is our primary source of analysis and discussion. The second section focused on analysis of survey.

4.2 Findings and Discussions

4.2.1 Secondary Data Source

As highlighted in the conceptual framework and method of study, the study focused on understanding the effect and relationship of demand forecasting model accuracy on inventory metrics inventory level, inventory cost, inventory turnover and safety stock. The study collected data from the Unilever data base for the year 2021-2023 for the major SKU Life Buoy Total, Life Buoy Lemon, Knorr All in One and Knorr Chicken. Below explanatory and descriptive statistics findings are presented.

Table 4.1: Descriptive statistics of secondary data variables under study

Variable	N	Minimum	Maximum	Mean	Std. Deviation
RMSE (€)	134	.14	2916.67	162.2451	367.91934
MAPE (%)	134	.20	52000.51	509.9619	4610.13303
Inventory Level '000 (€)	144	10.92	3470.00	625.3971	819.62700
Inventory Cost (€)	144	.00	7856.96	588.7500	1325.57433
Inventory Turnover (%)	135	.00	6029.63	313.3820	876.58724

Safety Stock '000 (€)	144	1.09	1388.00	231.2464	338.09622
Valid N (listwise)	134				

Source: Own analysis, 2024

4.2.1.1 Pearson Correlation Analysis

Correlations estimate the strength of the linear relationship between two (and only two) variables. Correlation coefficients range from -1.0, a perfect negative correlation, to +1.0, a perfect positive correlation. The closer correlation coefficients get to -1.0 or 1.0, the stronger the correlation. The closer a correlation coefficient gets to zero, the weaker the correlation is between the two variables. Furthermore, according to Field (2005) general guidelines correlations of 0.1 – 0.29 are considered small, correlations of 0.30 – 0.49 are considered moderate and correlations above or equal to 0.5 are considered large.

Correlation for the relationship between inventory metrics and independent variables (RMSE; MAPE), the Pearson correlation was computed. As it can be seen from the results in table below, there is positive and significant relationship between the accuracy of demand forecasting and three dependent variables, and non-significance with inventory turnover. RMSE & Inventory level ($r = 0.671$, $p < 0.01$), inventory cost ($r = 0.560$, $p < 0.01$), inventory turnover ($r = -0.131$, $p = 0.13$), and safety stock ($r = 0.664$, $p < 0.01$). The relationship between these independent variables and dependent variable is positive relation for inventory level, cost and safety stock, and negative relation for inventory turnover.

Table 4.2: Correlation results for secondary data source analysis

Independent variables	**Dependent variable**	
dependent variable	Pearson Correlation	1
Sig. (2-tailed)		
N	144	
Inventory Level (€)	Pearson Correlation	.671**
Sig. (2-tailed)	<.001	
N	134	
Inventory Cost (€)	Pearson Correlation	.560**
Sig. (2-tailed)	<.001	
N	134	
Inventory turnover (%)	Pearson Correlation	-.131**
Sig. (2-tailed)	.013	
N	134	
Safety Stock (€)	Pearson Correlation	.664**

Sig. (2-tailed)	<.001
N	134

Source: Own analysis from Unilever Ethiopia Data, 2024

4.2.1.2 Normality Test

One way of measuring the normality of physical distribution is checking skewness and kurtosis. The range for normality of distribution is between 1 up to -1 (Matt et al, 2018).

Table 4.3: Normality Test for secondary data variables

Normality Test

	N	Kurtosis	
	Statistic	Statistic	Std. Error
RMSE (€)	134	29.375	.416
MAPE (%)	134	119.699	.416
Inventory Level '000 (€)	144	2.256	.401
Inventory Cost (€)	144	16.689	.401
Inventory Turnover (%)	135	26.185	.414
Safety Stock '000 (€)	144	2.057	.401
Valid N (listwise)	134		

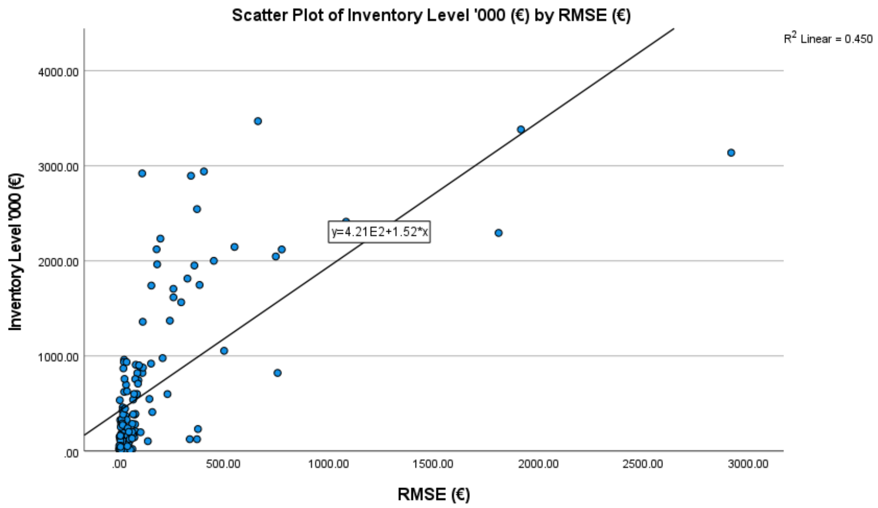
Source: Own analysis from Unilever Ethiopia Data, 2024

The low kurtosis value suggests that the distribution of inventory levels, inventory costs, inventory turnover and safety stock is approximately normal distribution.

4.2.1.3 Linearity Test

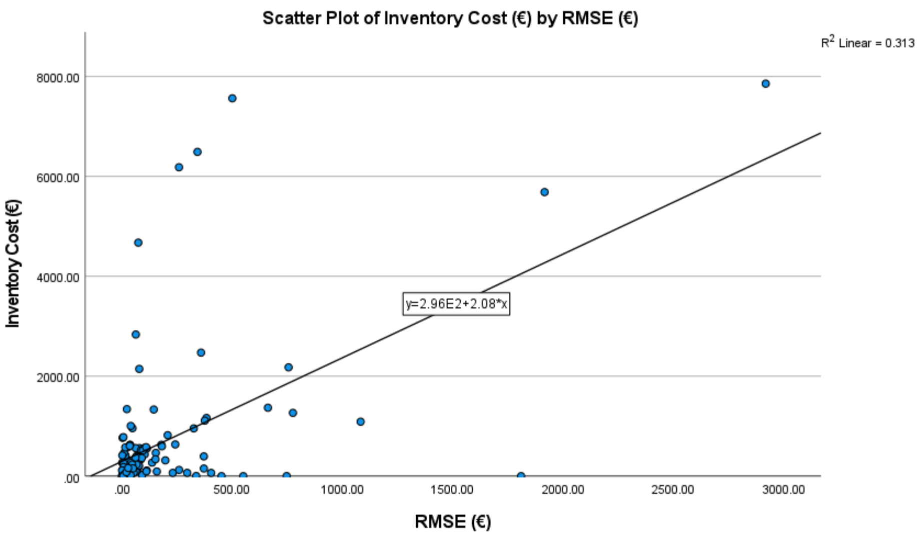
Linearity of the relationships between dependent and the independent variables. As showed in the below graph most of the variables are linear with the line showing that there is linear relationship between accuracy of demand forecasting model and inventory metrics.

Figure 4.1: Scatter plot showing relationship between inventory level and RMSE.



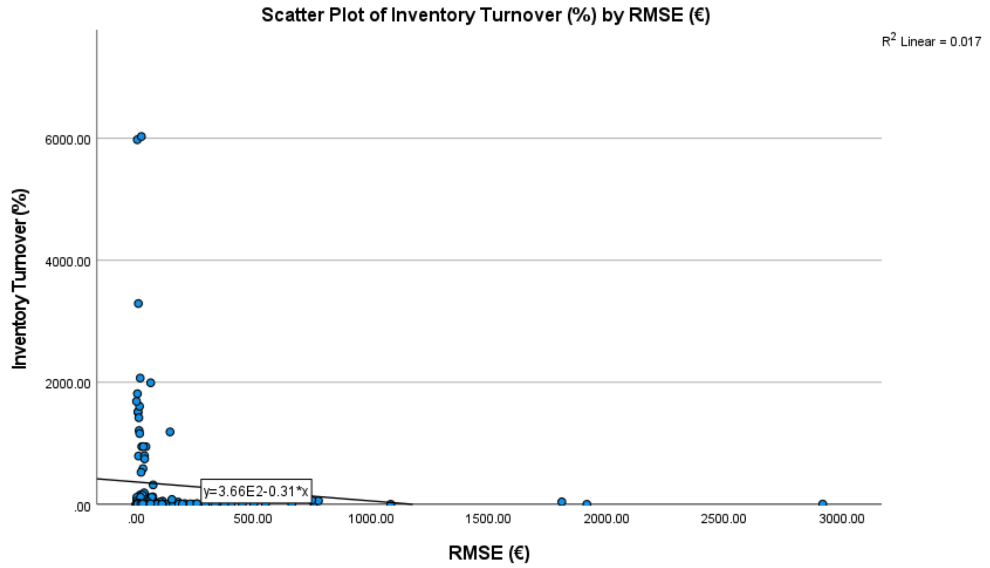
Source: Own analysis from Unilever Ethiopia Data, 2024

Figure 4.2: Scatter plot showing relationship between inventory cost and RMSE



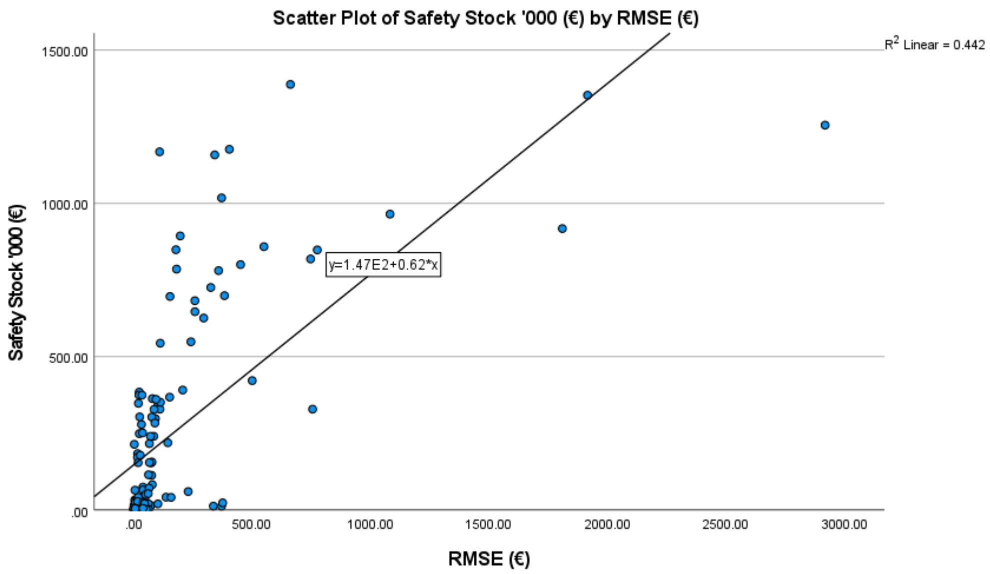
Source: Own analysis from Unilever Ethiopia Data, 2024

Figure 4.3: Scatter plot showing relationship between inventory cost and RMSE



Source: Own analysis from Unilever Ethiopia Data, 2024

Figure 4.4: Scatter plot showing relationship between inventory cost and RMSE



Source: Own analysis from Unilever Ethiopia Data, 2024

From the figures above, we can see there is a linear relationship of factors 0.45, 0.442 and 0.313 for Inventory Level, Safety stock and Inventory cost.

4.2.1.4 Regression analysis

The model for the different variables were analyzed as follows:

- **Inventory Level**

Table 4.4: Model Summary Table for Inventory Level

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.671[a]	.450	.446	621.38142
a. Predictors: (Constant), RMSE (€)				

Source: Own analysis from Unilever Ethiopia Data, 2024

The correlation coefficient, R indicates existence of moderate (nearly strong) correlation 0.671 between the demand forecast accuracy and the dependent variable inventory level. Adjusted R^2 amounted to 0.450 revealed that 45.0% of the relationship or the variation on inventory level is explained by the variation independent variables forecast accuracy **(RMSE; MAPE)**. The remaining 55% is explained by different other factor not studied in this research.

Table 4.5: ANOVA Table for Inventory Level

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	41681574.918	1	41681574.918	107.951	.000[b]
	Residual	50967163.339	132	386114.874		
	Total	92648738.257	133			
a. Dependent Variable: Inventory Level '000 (€)						
b. Predictors: (Constant), RMSE (€)						

Source: Own analysis from Unilever Ethiopia Data, 2024

The study used ANOVA to establish the significance of the regression model. In testing the significance level, the statistical significance was considered significant if the p-value was less or equal to 0.05. The significance of the regression model in the above table is with P-value of 0.00 which is less than 0.05. This indicates that the regression model is statistically significant in predicting the relationship between inventory level and demand forecast accuracy. The overall ANOVA results indicates that the model was significant at F = 107.951, p = 0.000.

Table 4.6: Coefficients Table for Inventory Level

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	420.501	58.703		7.163	.000
	RMSE (€)	1.522	.146	.671	10.390	.000
a. Dependent Variable: Inventory Level '000 (€)						

Source: Own analysis from Unilever Ethiopia Data, 2024

As can be seen in above table, the p value of the t statics for the independent variables' RMSE for inventory level (t=10.390, p=0.00) which implies the coefficient of the independent variable is significant.

- **Inventory Cost**

Table 4.7: Model Summary Table for Inventory Cost

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.560[a]	.313	.308	1134.67209
a. Predictors: (Constant), RMSE (€)				

Source: Own analysis from Unilever Ethiopia Data, 2024

The correlation coefficient, R indicates existence of moderate (nearly strong) correlation 0.560 between the demand forecast accuracy and the dependent variable inventory level. Adjusted R^2 amounted to 0.308 revealed that 30.8% of the relationship or the variation on inventory cost is explained by the variation independent variables forecast accuracy **(RMSE; MAPE)**. The remaining 69.2% is explained by different other factor not studied in this research.

Table 4.8: ANOVA Table for Inventory Cost

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	77599665.439	1	77599665.439	60.272	.000[b]
	Residual	169947458.423	132	1287480.746		
	Total	247547123.862	133			
a. Dependent Variable: Inventory Cost (€)						
b. Predictors: (Constant), RMSE (€)						

Source: Own analysis from Unilever Ethiopia Data, 2024

The study used ANOVA to establish the significance of the regression model. In testing the significance level, the statistical significance was considered significant if the p-value was less or equal to 0.05. The significance of the regression model in the above table is with P-value of 0.00 which is less than 0.05. This indicates that the regression model is statistically significant in predicting the relationship between inventory level and demand forecast accuracy. The overall ANOVA results indicates that the model was significant at F = 60.272, p = 0.000.

Table 4.9: Coefficients Table for Inventory Cost

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	295.847	107.194		2.760	.007
	RMSE (€)	2.076	.267	.560	7.764	.000
a. Dependent Variable: Inventory Cost (€)						

Source: Own analysis from Unilever Ethiopia Data, 2024

As can be seen in above table, the p value of the t statics for the independent variables' RMSE for inventory level (t=7.764, p=0.00) which implies the coefficient of the independent variable is significant.

- **Inventory turnover**

Table 4.10: Model Summary Table for Inventory Turnover

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.131[a]	.017	.010	875.228809042552000
a. Predictors: (Constant), RMSE (€)				

Source: Own analysis from Unilever Ethiopia Data, 2024

The correlation coefficient, R indicates existence of very weak correlation 0.131 between the demand forecast accuracy and the dependent variable inventory turnover. Adjusted R^2 amounted to 0.017 revealed that 1.7% of the relationship or the variation on inventory turnover is explained by the variation independent variables forecast accuracy **(RMSE; MAPE)** which is significantly very low. Totally, this tell us demand forecast accuracy had very little to do with inventory turnover.

Table 4.11: ANOVA Table for Inventory Turnover

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	1751993.459	1	1751993.459	2.287	.133[b]
	Residual	101115361.800	132	766025.468		
	Total	102867355.259	133			

a. Dependent Variable: Inventory Turnover (%)

b. Predictors: (Constant), RMSE (€)

Source: Own analysis from Unilever Ethiopia Data, 2024

The study used ANOVA to establish the significance of the regression model. In testing the significance level, the statistical significance was considered significant if the p-value was less or equal to 0.05. The significance of the regression model in the above table is with P-value of 0.133 which is greater than 0.05. This indicates that the regression model is statistically non - significant in predicting the relationship between inventory turnover and demand forecast accuracy. The overall ANOVA results indicates that the model was significant at F = 2.287, p = 0.133.

Table 4.12: Coefficients Table for Inventory Turnover

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	366.333	82.684		4.431	.000
	RMSE (€)	-.312	.206	-.131	-1.512	.133

a. Dependent Variable: Inventory Turnover (%)

Source: Own analysis from Unilever Ethiopia Data, 2024

As can be seen in above table, the p value of the t statics for the independent variables' RMSE for inventory turnover (t=-1.512, p=0.133) which implies the coefficient of the independent variable is non - significant.

- **Safety Stock**

Table 4.13: Model Summary Table for Safety Stock

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.664[a]	.442	.437	258.56874

a. Predictors: (Constant), RMSE (€)

Source: Own analysis from Unilever Ethiopia Data, 2024

The correlation coefficient, R indicates existence of moderate (nearly strong) correlation 0.664 between the demand forecast accuracy and the dependent variable safety stck. Adjusted R^2 amounted to 0.442 revealed that 44.2% of the relationship or the variation on safety stock is explained by the variation independent variables forecast accuracy **(RMSE; MAPE)**. The remaining 55.8% is explained by different other factor not studied in this research.

Table 4.14: ANOVA Table for Safety Stock

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6977003.760	1	6977003.760	104.356	.000[b]
	Residual	8825228.948	132	66857.795		
	Total	15802232.709	133			
a. Dependent Variable: Safety Stock '000 (€)						
b. Predictors: (Constant), RMSE (€)						

Source: Own analysis from Unilever Ethiopia Data, 2024

The study used ANOVA to establish the significance of the regression model. In testing the significance level, the statistical significance was considered significant if the p-value was less or equal to 0.05. The significance of the regression model in the above table is with P-value of 0.00 which is less than 0.05. This indicates that the regression model is statistically significant in predicting the relationship between inventory level and demand forecast accuracy. The overall ANOVA results indicates that the model was significant at F = 104.356, p = 0.000.

Table 4.15: Coefficient Table for Safety Stock

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	147.032	24.427		6.019	.000
	RMSE (€)	.623	.061	.664	10.215	.000
a. Dependent Variable: Safety Stock '000 (€)						

Source: Own analysis from Unilever Ethiopia Data, 2024

As can be seen in above table, the p value of the t statics for the independent variables' RMSE for inventory level (t=10.215, p=0.00) which implies the coefficient of the independent variable is significant.

The standardized coefficients are the coefficients that can explain the relative importance of factors in terms of how they affect the dependent variable. As a result, after standardizing each explanatory variable, the regression analysis' coefficients were determined. The standardized coefficient of RMSE is the largest on inventory level and then safety stock, and inventory cost as shown in the tables above. The larger the standard coefficient, the higher is the relative effect.

The significance tests of the four variables indicate that three of the dependent variables (inventory level, inventory cost and safety stock) are significant with p-value ($p<0.05$) for being impacted by accuracy of demand forecasting.

4.2.2 Research Survey or Questionnaire

The survey findings were used to support the finding from the secondary data source and compare findings. The summaries in this section are high level and mostly supported with figures and tables.

4.2.2.1 Response Rate

For this research 14 questionnaires were distributed, and 14 of them were correctly completed and returned, yielding a 100% response rate. The responses provided served as the basis for the analysis that followed on the second section. The frequency, percentage, mean, and standard deviation of the data were used to create the following summary and presentation.

4.2.2.2 Demographic Characteristics of Respondents

Based on their features, the demographic data of the respondents who took part in the collection of both quantitative and qualitative data were shown in table form. In order to conduct the research, it was necessary to collect data on respondents' personal and professional characteristics, including gender, education level, organizational position, and years of experience.

Table 4.16: Questionnaire respondent socio-demographic characteristics

No.	Variable	Frequency	Percent
1	**Gender**		
	Female	5	35.7
	Male	9	64.3
2	**Age Group**		
	25-30 years	6	42.9
	31-45 years	7	50.0

	46-50 years	1	7.1
3	**Education Level**		
	First Degree	13	92.9
	Second Degree and Above	1	7.1
4	**Department**		
	Customer Development	2	14.3
	Customer Service Excellence	1	7.1
	Finance	1	7.1
	Manufacturing	1	7.1
	Marketing	2	14.3
	Planning	5	35.7
	Warehouse	2	14.3
5	**Experience**		
	5-7 years	13	92.9
	7 years and above	1	7.1

Source: Own Survey, 2024

4.2.2.3 Descriptive Statistics

- **Inventory Level**

Table 4.17: Mean and Standard Deviation of effect of accuracy on Inventory Level

Variables	Mean	SD
The accuracy of demand forecasting significantly influences our organization's inventory management decisions.	4.71	.469
Inaccurate demand forecasting leads to higher inventory levels in our organization.	4.79	.426
Forecast accuracy is a key factor in minimizing excess inventory levels in our organization.	4.57	.514
Our organization experiences improved inventory management outcomes when demand forecasts are accurate.	4.07	.475
Inadequate inventory levels can result in frequent stock outs, affecting customer satisfaction and supply chain reliability.	4.64	.497
Maintaining optimal inventory levels is a critical aspect of supply chain performance and responsiveness to demand variability.	4.29	.469

Our organization faces challenges in meeting customer demand when forecast accuracy is low.	4.29	.726
Valid N (listwise)		

Source: Own Survey, 2024

From the findings of the assessment, it shows that 100% of the respondents agree that demand forecasting accuracy affects the inventory levels and inaccurate demand forecasting leads to high inventory levels. Similarly, they agree due to inadequate demand forecasting the organization faces stock out.

- **Inventory Cost**

Table 4.18: Mean and Standard Deviation of effect of accuracy on Inventory Cost

Variables	Mean	SD
Poor forecast accuracy is associated with increased inventory costs in our organization.	5.00	.000
Inaccurate demand forecasting results in higher inventory holding costs for our organization.	4.64	.497
Inaccurate demand forecasting leads to increased obsolescence costs for our inventory.	4.64	.497
Forecast accuracy influences the effectiveness of inventory replenishment processes in our organization.	4.43	.514
Forecast accuracy is crucial in reducing costs related to stockouts in our supply chain.	4.93	.267
Forecasting errors contribute to increased inventory carrying costs, highlighting the importance of accurate demand projections.	4.64	.633
Valid N (listwise)		

Source: Own Survey, 2024

From the findings of the assessment, it shows that 100% of the respondents agree that demand forecasting accuracy affects the inventory costs and high forecast errors leads to increased inventory carrying cost and obsolescence cost.

- **Inventory Turnover**

Table 4.19: Mean and Standard Deviation of effect of accuracy on Inventory turnover

Variable	Mean	SD

Forecast accuracy directly impacts the efficiency of inventory turnover in our supply chain.	4.21	.426
Inaccurate demand forecasting leads to delays in inventory turnover in our organization.	4.43	.514
Enhancing demand forecasting accuracy is expected to positively influence inventory turnover rates. Poor forecast accuracy is associated with increased inventory costs in our organization.	4.21	.426
Valid N (listwise)		

Source: Own Survey, 2024

From the findings of the assessment, it shows that 100% of the respondents agree that demand forecasting accuracy affects the efficiency of inventory turnover causing delays and overstock of inventory.

- **Inventory Safety Stock**

Table 4.20: Mean and Standard Deviation of effect of accuracy on safety stock

Variable	Mean	SD
Maintaining optimal safety stock levels becomes more challenging when demand forecasting accuracy is low.	4.71	.469
The level of safety stock required is closely tied to the accuracy of demand forecasts in our supply chain.	4.71	.469
Inaccurate demand forecasting leads to increased risks of stockouts and disruptions in our supply chain.	4.93	.267
Our organization faces challenges in adjusting safety stock levels based on inaccurate demand forecasts.	3.57	.852
Forecast accuracy is essential for ensuring the adequacy of safety stock levels in our organization.	4.71	.469
Valid N (listwise)		

Source: Own Survey, 2024

From the findings of the assessment, it shows that nearly 100% of the respondents agree that demand forecasting accuracy affects the organizations safety stock level and inaccuracies lead to stock outs and disruptions in supply chain.

4.2.2.4 Pearson correlation analysis

Table 4.21: Correlation coefficient from Survey results

Independent Variable		Dependent variable
Dependent variable	Pearson Correlation	1
	Sig. (2-tailed)	
	N	14
Inventory Level	Pearson Correlation	0.639
	Sig. (2-tailed)	0.014
	N	14
Inventory Cost	Pearson Correlation	0.784
	Sig. (2-tailed)	0.015
	N	14
Inventory Turnover	Pearson Correlation	0.806
	Sig. (2-tailed)	0.003
	N	14
Safety Stock	Pearson Correlation	0.6906
	Sig. (2-tailed)	0.031
	N	14

Source: Own Survey, 2024

Correlation for the relationship between demand forecasting accuracy and dependent variables (Inventory Level; Inventory Cost; Inventory Turnover; Safety Stock), the Pearson correlation was computed from the survey. As it can be seen from the results in table below, there is positive and significant relationship between the accuracy of demand forecasting and four dependent variables, which is different from the case of the secondary source.

4.2.2.5 Normality testing

Table 4.22: Normality test from Survey results

	N	Kurtosis	
	Statistic	**Statistic**	**Std. error**
Inventory Level	14	1.387	1.154
Inventory Cost	14	0.027	1.154

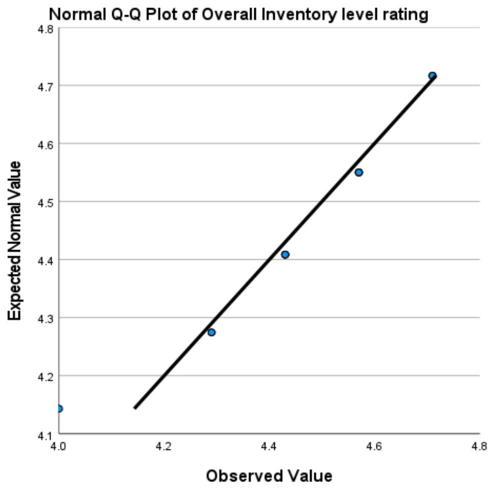
Inventory Turnover	14	0.162	1.154
Safety Stock	14	0.408	1.154

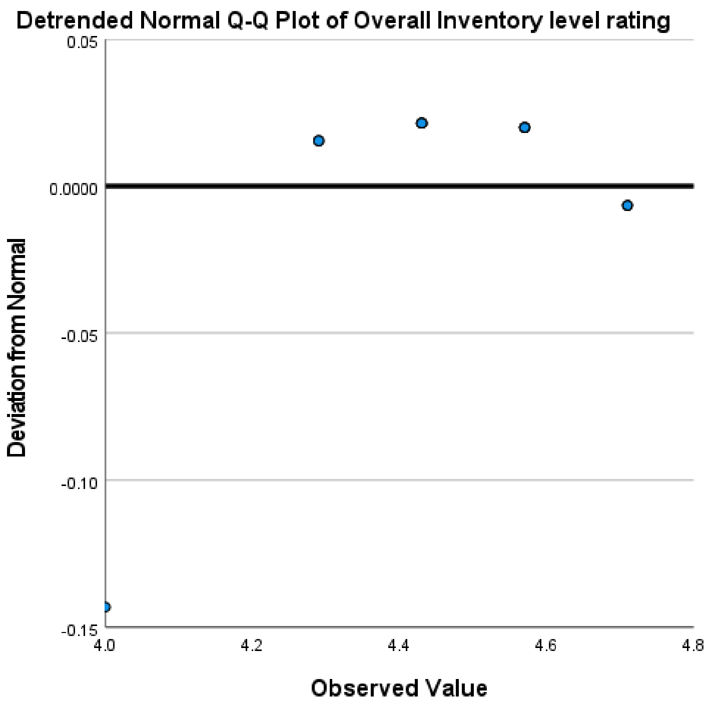
Source: Own Survey, 2024

4.2.2.6 Linearity testing

Linearity of the relationships between dependent and the independent variables. As showed in the below graph most of the variables are linear with the line showing that there is linear relationship between observed values of each variable.

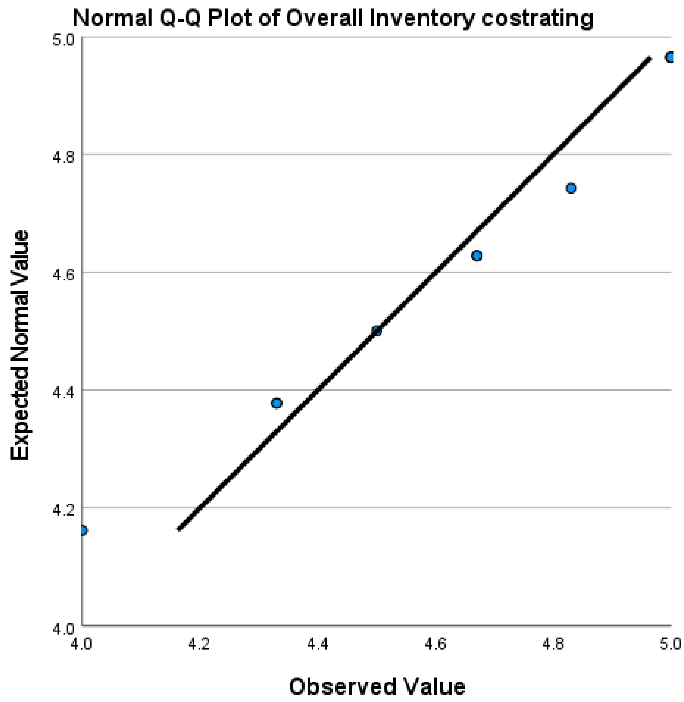
Figure 4.5: Linearity test for Inventory Level

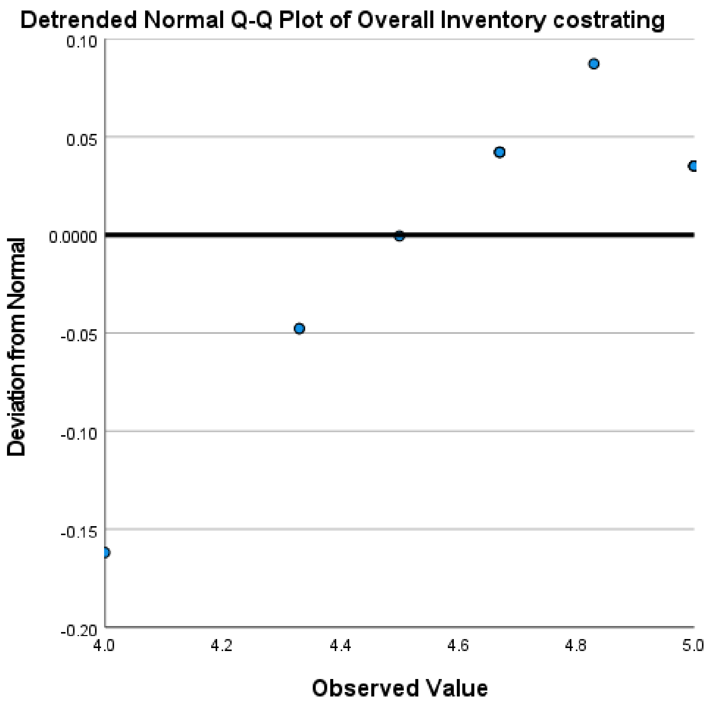




Source: Own Survey, 2024

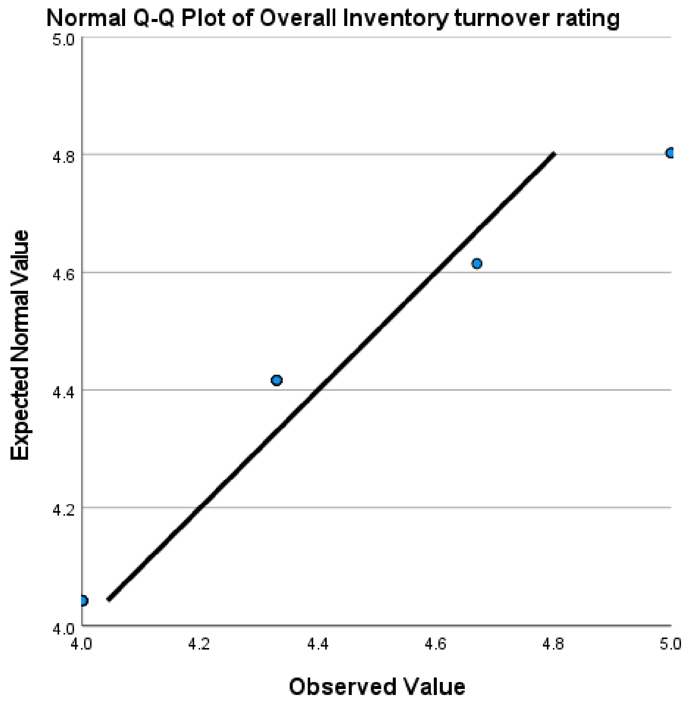
Figure 4.6: Linearity test for Inventory Cost

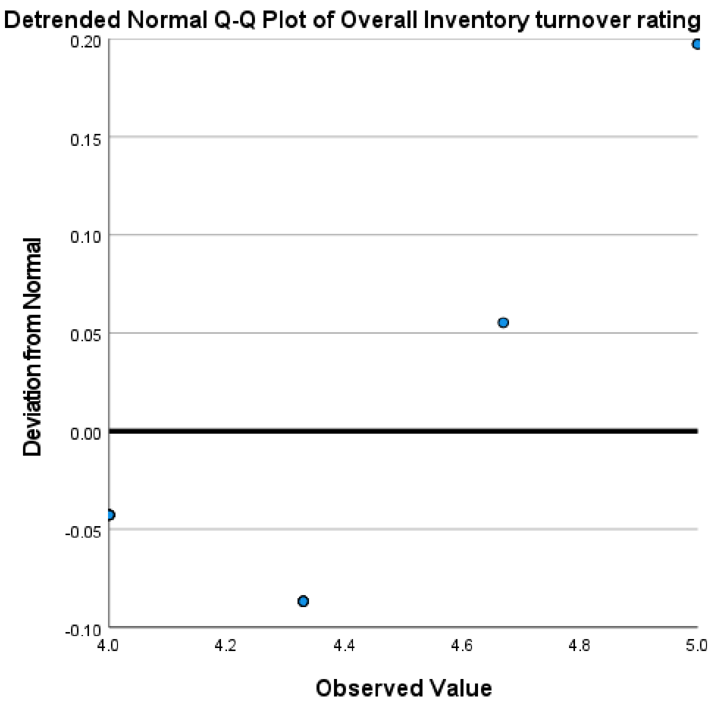




Source: Own Survey, 2024

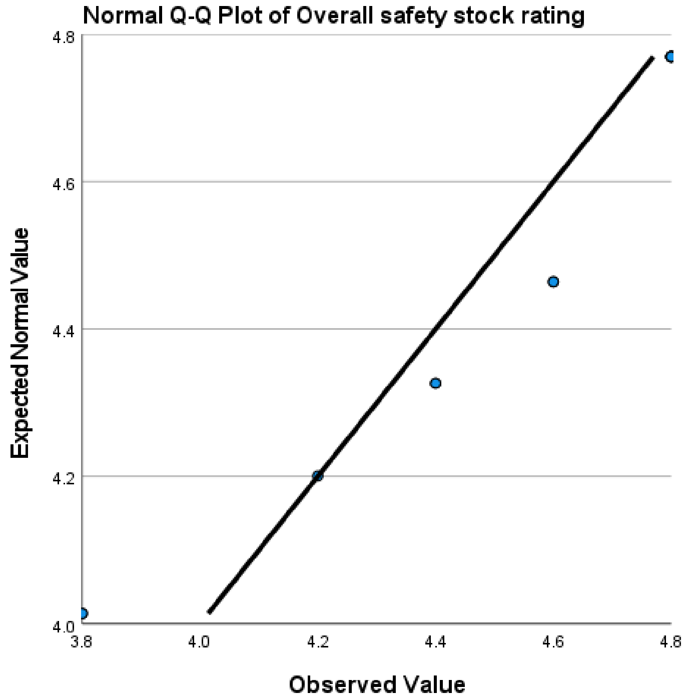
Figure 4.7: Linearity test for Inventory Turnover

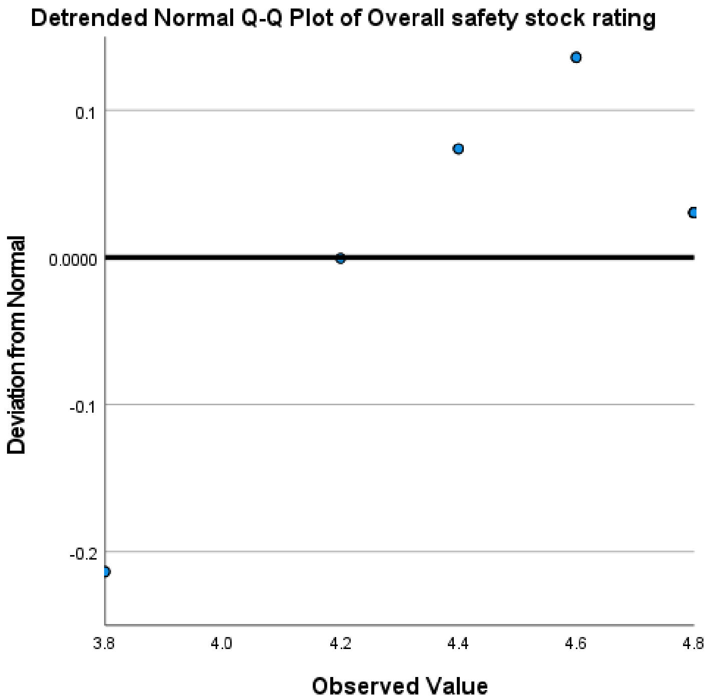




Source: Own Survey, 2024

Figure 4.8: Linearity test for Safety Stock





Source: Own Survey, 2024

4.2.2.7 Regression analysis

From the all the tables below the survey concluded that the variables are significant and had strong relationship. Below is the regression analysis done for each variable.

Table 4.23: Model Summary, ANOVA and Coefficient table for Inventory Level from Survey results

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.639[a]	.409	.360	.375

a. Predictors: (Constant), Demand Forecast Accuracy

ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	1.168	1	1.168	8.302	.014[b]
	Residual	1.689	12	.141		
	Total	2.857	13			

a. Dependent Variable: Inventory Level

b. Predictors: (Constant), Demand Forecast Accuracy

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-2.108	2.370		-.889	.391
	Overall Inventory level rating	1.523	.529	.639	2.881	.014

a. Dependent Variable: Inventory Level

Source: Own Survey, 2024

Table 4.24: Model Summary, ANOVA and Coefficient table for Inventory Cost from Survey results

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.784[a]	.565	.528	.341

a. Predictors: (Constant), Demand Forecast Accuracy

ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	1.815	1	1.815	15.565	.002[b]
	Residual	1.399	12	.117		
	Total	3.214	13			

a. Dependent Variable: Inventory Cost

b. Predictors: (Constant), Demand Forecast Accuracy

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.802	1.383		-.580	.573
	Overall Inventory costrating	1.155	.293	.784	3.945	.0015

a. Dependent Variable: Inventory Cost

Source: Own Survey, 2024

Table 4.25: Model Summary, ANOVA and Coefficient table for Inventory Turnover from Survey results

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.806[a]	.528	.489	.304

a. Predictors: (Constant), Demand Forecast Accuracy

ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	1.245	1	1.245	13.436	.003[b]
	Residual	1.112	12	.093		
	Total	2.357	13			

a. Dependent Variable: Turnover

b. Predictors: (Constant), Demand Forecast Accuracy

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.597	.990		.603	.558
	Overall Inventory turnover rating	.844	.230	.727	3.665	.003

a. Dependent Variable: Turnover1

Source: Own Survey, 2024

Table 4.26: Model Summary, ANOVA and Coefficient table for Safety Stock from Survey results

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.861[a]	.742	.720	.248

a. Predictors: (Constant), Overall safety stock rating

ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	2.120	1	2.120	34.509	.000[b]
	Residual	.737	12	.061		
	Total	2.857	13			

a. Dependent Variable: Safety1

b. Predictors: (Constant), Overall safety stock rating

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.301	.856		-.351	.731
	Overall safety stock rating	1.107	.189	.861	5.874	.000

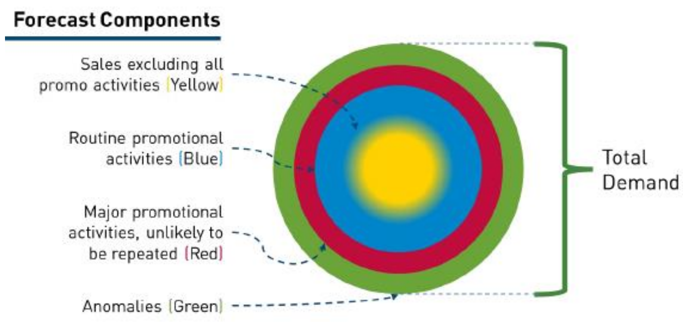
a. Dependent Variable: Safety1

Source: Own Survey, 2024

Additionally, through our questionnaire we identified the demand forecasting model implemented in Unilever Ethiopia. Unilever Ethiopia uses a Moving Average explanatory time series forecasting model which is explained below. The process starts with base line forecasting.

The baseline forecasting is the predicted underlying sales, which is made by taking the sales history, cleansing it to remove demand caused by major/unique promotions and anomalies, and then projecting that cleansed sales history forward to the future.

Figure 4.9: Components of Total Demand for Unilever Ethiopia



Source: Unilever (2018); Demand Planning Handbook

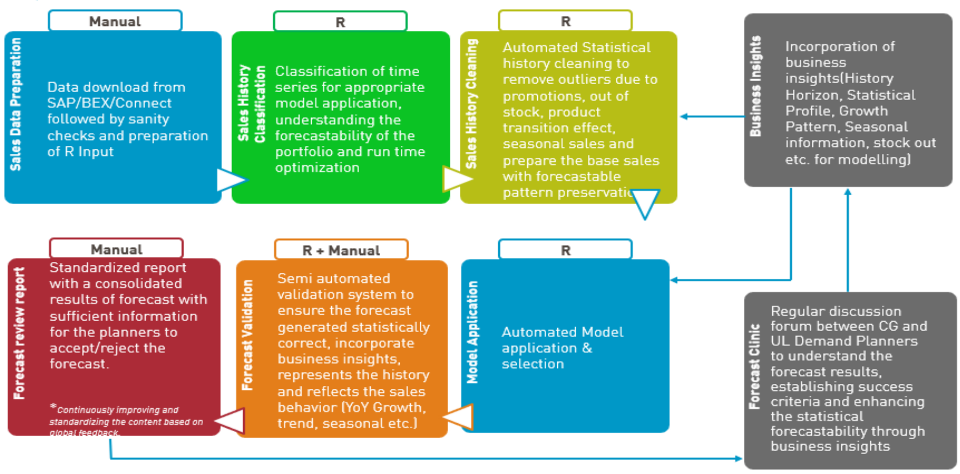
Figure 1. describes the components of a forecast in an onion model, which breaks down total demand into 4 main components, which are "sales excluding all promotional activities" depicted as the yellow layer, "routine promotional activities" depicted as the blue layer, "major promotional activities" depicted as the red layer, and "anomalies" depicted as the green layer. The two components that make up the baseline are the **yellow** and **blue** layer.

$$\boldsymbol{Baseline} = \boldsymbol{Yellow} + \boldsymbol{Blue}$$

$$\boldsymbol{Baseline} = \boldsymbol{Sales\ Excluding\ Promo\ Activities} + \boldsymbol{Routine\ Promo\ Activities}$$

The baseline forecasting for Unilever Ethiopia is provided by Cap Gemini (CG) and is used by Demand Planners to generate forecasts. The overall process done by CG is depicted in the below figure:

Figure 4.10: Baseline Forecasting overview process of Cap Gemini



Source: Capgemini (2016); Statistical Forecasting

The current existing forecasting in addition to the baseline generated from CG will consider demand drivers that gets added or deducted on the baseline. Percentages of this parameters are taken as inputs from sales and marketing function. Below shows the demand forecast done for the year 2024 for one of the SKU's (Knorr All in One) for the months of Jan -Apr.2024.

Figure 4.11: Demand Forecasting Baseline + S&OP Review [Case: Knorr All in One]

YEAR	PRODUCT DESC	RODUCT GI	DESCRIPTION	Jan-24	Feb-24	Mar-24	Apr-24	M
2024	KNORR ALL IN ONE CUBE FORT 12X20X(6X8G)	Knorr AiO 8G	**BASELINE (Tn)**	**844**	**851**	**864**	**877**	
2024	KNORR ALL IN ONE CUBE FORT 12X20X(6X8G)	Knorr AiO 8G	TRADE PROMOTION [DD,QPS,DFF,DE] (%)					
2024	KNORR ALL IN ONE CUBE FORT 12X20X(6X8G)	Knorr AiO 8G	Activation (%)					
2024	KNORR ALL IN ONE CUBE FORT 12X20X(6X8G)	Knorr AiO 8G	SEASONALITY (%)					
2024	KNORR ALL IN ONE CUBE FORT 12X20X(6X8G)	Knorr AiO 8G	OTHERS [Tender etc] (%)			-20%	-12%	
2024	KNORR ALL IN ONE CUBE FORT 12X20X(6X8G)	Knorr AiO 8G	PRICE CHANGE (%)				-20%	
2024	KNORR ALL IN ONE CUBE FORT 12X20X(6X8G)	Knorr AiO 8G	BLG [RTM expansion] (%)	5%	5%	5%	5%	
2024	KNORR ALL IN ONE CUBE FORT 12X20X(6X8G)	Knorr AiO 8G	BLG [HH penetration etc] (%)	10%	10%	10%	10%	
2024	KNORR ALL IN ONE CUBE FORT 12X20X(6X8G)	Knorr AiO 8G	CANNIBALIZATION (%)			0%	-3%	
2024	KNORR ALL IN ONE CUBE FORT 12X20X(6X8G)	Knorr AiO 8G	**UNCONSTRAINED S&OP (Tn)**	**971**	**978**	**828**	**703**	

Source: Unilever (2024); Demand Forecast for Knorr All in One for FY 2024

The results and findings are summarized below:

Table 4.27: Summary table for both secondary data and questionnaire – R Square

Data Source	Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
Secondary Source	Inventory Level	.671a	.450	.446	621.38142
	Inventory Cost	.560a	.313	.308	1134.67209
	Inventory turnover	.131a	.017	.010	875.22880
	Safety Stock	.664a	.442	.437	258.56874
	a. Predictors: (Constant), Demand Forecast Accuracy (RMSE (€))				
Questionnaire	Inventory Level	.639a	.409	.360	.375
	Inventory Cost	.784a	.565	.528	.341
	Inventory turnover	.806a	.528	.489	.304
	Safety Stock	.861a	.742	.720	.248
	a. Predictors: (Constant), Demand Forecast Accuracy				

Source: Own Survey, 2024

Table 4.28: Summary table for both secondary data and questionnaire – Coefficient and p-value

Data Source	Model	F	t	Sig.
Secondary Source	Inventory Level	107.951	10.390	.000[b]
	Inventory Cost	60.272	7.764	.000[b]
	Inventory turnover	2.287	-1.512	.133
	Safety Stock	104.356	10.215	.000[b]
Questionnaire	Inventory Level	8.302	2.881	.014[b]
	Inventory Cost	15.565	3.945	.0015 [b]
	Inventory turnover	13.436	3.665	.003 [b]
	Safety Stock	34.509	5.874	.000 [b]

Source: Own Survey, 2024

Chapter Five

Summary, Conclusion and Recommendation

5.1 Summary of Findings

Demand forecasting accuracy plays a critical role in optimizing inventory management and directly impacts several key metrics such inventory levels, holding cost, inventory turnover, customer satisfaction and so on. The main purpose of the study was to assess the how the current demand forecasting model implemented by Unilever Ethiopia is affecting the main inventory metrics. The study was conducted through an explanatory and descriptive design with analysis of secondary data source as a primary focus of study and additionally using a questionnaire with a census target population of 14 respondents in Unilever Ethiopia who are directly involved in the demand forecasting process to gauge their perspective.

The secondary data source revealed that the inventory matrices are impacted by the accuracy of the forecast demand for inventory level, with a mean and standard deviation of 625.39 and 819.62; inventory cost, with a mean and standard deviation of 588.75 and 1325.57; and safety stock, with a mean and standard deviation of 231.24 and 338.09, respectively. This information was also found to be consistent with the questionnaire, with the exception of inventory turnover, where respondents thought there was a strong correlation between accuracy and turnover, a finding refuted by the secondary data source.

The correlation coefficient, R indicates existence of moderate correlation 0.671 between RMSE and inventory level, moderate correlation 0.56 between RMSE and inventory cost, weak correlation 0.131 between RMSE and inventory turnover, and moderate correlation 0.664 between RMSE and safety stock. Adjusted R^2 amounted to 0.45, 0.313. 0.017 and 0.442 for inventory level, inventory cost, inventory turnover and safety stock respectively revealed that the models accounts for different percentage with the highest being for inventory level and lowest for inventory turnover. The study also used ANOVA to establish the significance of the regression model using the secondary data. In testing the significance level, the statistical significance was considered significant if the p-value was less or equal to 0.05. The significance of the regression model in the above tables were with P-value of 0.00 for the three variables which is less than 0.05 and was 0.13 for inventory turnover which is greater than 0.05. This indicates that the regression model is statistically significant in predicting the effect of demand forecasting accuracy on inventory level, inventory cost and safety stock and the model is not statistically significant for inventory turnover. Coefficients of beta, the significance tests of the four variables indicate that the three of the explanatory variables (inventory level, inventory cost and safety stock) for impacting supply chain practice. The rest one variable (inventory turnover) has a p-value greater than 0.05, thus this factor is not statistically significant to impact supply chain practice.

5.2 Implication of the study

The findings of this study have an impact on the inventory management of Unilever Ethiopia and customer service level of the business. According to the analysis, the company's inventory management matrices (three variables) were influenced by accuracy of demand forecast and model used indirectly. Therefore, managers at various levels engaged in the demand forecast decisions and models must focus on these aspects to lessen their impact and ultimately enhance organizational performance. To address the issues and assist in enhancing the performance, a team effort is needed since the concerns include numerous multidepartment stakeholders.

5.3 Conclusion

The effects of demand forecasting model accuracy on inventory performance in Unilever Ethiopia can be summarized in the following conclusion based on the overall findings of the study.

Both the qualitative and quantitative data showed that accuracy of demand forecasting model has effect on inventory performance specifically on inventory level, inventory cost and safety stock on a moderate level. Additionally, based on the model summary of the regressions it is concluded that the stated independent variable had impact in explaining the variance in the three dependent variable. Inventory Level ($r = 0.671$, $p < 0.01$), Inventory Cost ($r = 0.560$, $p < 0.01$) and Safety stock ($r = 0.664$, $p < 0.01$). The relationship between the independent variable and three dependent variable is positive relation from the secondary data source.

The results from secondary data analysis are mostly consistent with the information gathered from the questionnaire, which was used to assess Inventory Level ($r = 0.639$, $p = 0.014$), Inventory Cost ($r = 0.784$, $p = 0.015$), Inventory Turnover ($r = 0.806$, $p = 0.003$), and Safety Stock ($r = 0.6906$, p = *031). Demand forecasting accuracy has a considerable impact on both inventory level and safety stock, even though the differences between the r- and p-values are not as large. Comparably, the secondary data source and the questionnaire both found positive associations for inventory cost; the only difference was that the value changed from moderate to strong (0.56 to 0.784). Nonetheless, we can draw the conclusion that demand accuracy significantly lowers inventory costs. The variance in results between demand forecast accuracy and turnover is the only significant difference between the secondary data finding and the questionnaire; in the latter case, the dependent variable had a strong and significant relationship with demand accuracy, which is completely at odds with the secondary data finding. The study came to the conclusion that there is a weak association between the variables and that the dependent variable is heavily influenced by other factors since the secondary data source is more trustworthy.

From the findings it can be concluded that Unilever Ethiopia's choice of demand forecasting model affects the inventory planning and performance which had led the business to reduced performance and additional costs.

5.4 Recommendation

The study revealed a robust association between the accuracy of demand forecasting and crucial inventory management indicators, such as inventory cost, level, and safety stock. Considering the demand forecasting model that Unilever Ethiopia currently uses, the following suggestions are meant to improve forecast precision and accomplish the best possible inventory management:

- Put into Practice a Multi-Method Forecasting Strategy: Accuracy may be limited if one just uses the model that is currently chosen. Examine combining the current model with other forecasting techniques like machine learning algorithms, FEU,etc. This makes it possible to produce a more accurate forecast that makes use of the advantages of many strategies.
- Integrate External Data Sources: Incorporate pertinent external data sources for your products to improve the forecasting process. This could include patterns of the weather, competitor behavior, industry trends, or economic data strictly.
- Consistently Review and Improve the Forecasting Model: Demand trends are ever-changing. Plan on reviewing the forecasting model's performance on a regular basis. To maintain ideal accuracy, analyze forecast mistakes, modify model parameters, or even investigate alternative models.
- Divide Demand Information into Product and Sales Channel Segments: Forecasting using a "one-size-fits-all" strategy could miss the distinctive demand trends of various product categories or sales channels. Demand data segmentation enables customized projections that more accurately capture the dynamics of certain products and channels.

- Put Collaborative predictions into Practice: Use information from marketing, sales, and other pertinent areas to inform your predictions. This cooperative strategy makes use of the knowledge of multiple teams to produce a more thorough grasp of future demand.
- Make use of Collaborative Planning, Forecasting, and Replenishment (CPFR): Exchange demand projections and data with important suppliers in collaboration. By promoting transparency across the supply chain, CPFR lowers overall risk and improves inventory planning synchronization.
- Put Safety Stock Optimization Techniques into Practice: Safety stock levels can be optimized with increased forecasting accuracy. The ideal level of safety stock for any product can be determined by using strategies like statistical inventory models or service level agreements, which balance the expenses of carrying inventory with the risk of a stock out.
- Make an Investment in Training and Development: Give your staff the know-how they need to use the forecasting tools and analyze the data they provide with accuracy. Training can be provided on subjects like best practices for inventory management, data analysis, and forecasting techniques.
- Make Use of Advanced Forecasting Technologies: Investigate the possibilities provided by artificial intelligence (AI) and machine learning, two examples of advanced forecasting technologies.

5.5 Suggestion for further research

The findings of this research have contributed to provide the overview of the factors that affect inventory performance. It can be used as reference for all stakeholders to improve the gaps in Unilever Ethiopia as the research provides an insight on which inventory matrices are directly affected by the implemented demand forecasting model.

The research has limitations as it is focused on the effect of demand forecasting on inventory matrices being dependent on demand forecasting only. Thus, the researcher advises other interested parties to conduct thorough research by excluding the limitations of this particular study by adding more factors which can affect the inventory planning and performance to find a broader understanding of the effects and apply sustainable solutions to enhance performance.

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Appendix I

ADDIS ABABA UNIVERSITY

SCHOOL OF COMMERCE

Department of Logistics and Supply Chain Management

Program: Master of Arts in Logistics & Supply Chain Management

Research survey questionnaire.

Dear respondents!

The main objective of this questionnaire is to gather your opinion regarding the ***The Effect of Demand Forecasting Models on Supply Chain Planning – Inventory Planning & Performance: The Case of Unilever Ethiopia***. This questionnaire aims to understand the effect of demand forecasting on inventory planning and performance at Unilever Ethiopia. The data and opinions gathered will be used for partial fulfillment of the requirement for a Master of Logistics and Supply Chain Management. Your honest feedback will be crucial in this research. Thank you for participating in this survey.

Please note that: The information you provide will be kept confidential. there are no right or wrong answers. Please answer to the best of your knowledge and experience.

If you have problems completing this form, please do not hesitate to contact me.

Esrom Aschalew

Mobile No: +251905704840

Thank you in advance!!

Part I: General Information of Respondents

Note: no need to write your name

Tick your answer on the boxes

1. Gender :

   ☐ Male ☐ Female

2. Department

   ☐ Planning ☐ Customer Development ☐ Warehouse ☐ Customer Service Excellence ☐ Finance ☐ Marketing ☐ Manufacturing

3. Age:

   ☐ 20-25 years

   ☐ 25-30 years

   ☐ 31-45 years

   ☐ 46-50 years

☐ 51 and above years

4. Education Qualification:

   ☐ Certificate

   ☐ Diploma

   ☐ First Degree

   ☐ Second Degree and Above

5. Year of experience at Unilever Ethiopia

   ☐ 1 to 3 year ☐ 3 to 5 years ☐ 5 to 7 years ☐ 7 and above

Part II: **Specific Questions to assess effect of demand forecasting on inventory performance**

6. Please select the primary demand forecasting method(s) used in your organization:

   ☐ Moving Average

   ☐ Exponential Smoothing

   ☐ Trend Analysis

   ☐ Seasonal Analysis

   ☐ Machine Learning

   ☐ Other (Specify) ________________________

7. How often do you think demand forecasts is updated?

   ☐ Daily

   ☐ Weekly

   ☐ Monthly

   ☐ Quarterly

   ☐ Other (Specify) __________________________

8. Does Unilever Ethiopia consider factors beyond historical sales data in the forecasting process?

   ☐ Yes

   ☐ No

9. If you answered yes to question 8, which of the following factors do you consider:

   ☐ Promotions

☐ Seasonality

☐ Economic Trends

☐ Marketing Campaigns

☐ Customer Feedback

☐ Other (please specify) ______________________

Please rate your level of agreement for each given statement by tick (√) against corresponding lines.

Note: Strongly disagree (1), Disagree (2), Neutral (3), Agree (4) and strongly agree (5)

A. Demand forecasting accuracy on Inventory Levels

S.No.	Demand Forecasting accuracy on Inventory Levels	Scales				
		1	2	3	4	5
10	The accuracy of demand forecasting significantly influences our organization's inventory management decisions.					
11	Inaccurate demand forecasting leads to higher inventory levels in our organization.					
12	Forecast accuracy is a key factor in minimizing excess inventory levels in our organization.					
13	Our organization experiences improved inventory management outcomes when demand forecasts are accurate.					
14	Inadequate inventory levels can result in frequent stock outs, affecting customer satisfaction and supply chain reliability.					
15	Maintaining optimal inventory levels is a critical aspect of supply chain performance and responsiveness to demand variability.					
16	Our organization faces challenges in meeting customer demand when forecast accuracy is low.					

B. Demand forecasting accuracy on Inventory Cost

S.No.	Demand Forecasting accuracy on Inventory Cost (Holding, Ordering, Stock out Cost)	Scales				
		1	2	3	4	5
17	Poor forecast accuracy is associated with increased inventory costs in our organization.					
18	Inaccurate demand forecasting results in higher inventory holding costs for our organization.					
19	Inaccurate demand forecasting leads to increased obsolescence costs for our inventory.					
20	Forecast accuracy influences the effectiveness of inventory replenishment processes in our organization.					
21	Forecast accuracy is crucial in reducing costs related to stockouts in our supply chain.					
22	Forecasting errors contribute to increased inventory carrying costs, highlighting the importance of accurate demand projections.					

C. Demand forecasting accuracy on Inventory Turnover

S.No.	Demand Forecasting accuracy on Inventory Turnover	Scales				
		1	2	3	4	5
23	Forecast accuracy directly impacts the efficiency of inventory turnover in our supply chain.					
24	Inaccurate demand forecasting leads to delays in inventory turnover in our organization.					
25	Enhancing demand forecasting accuracy is expected to positively influence inventory turnover rates.Poor forecast accuracy is associated with increased inventory costs in our organization.					

D. Demand forecasting accuracy on Safety Stock

S.No.	Demand Forecasting accuracy on Safety Stock	Scales				
		1	2	3	4	5

26	Maintaining optimal safety stock levels becomes more challenging when demand forecasting accuracy is low.					
27	The level of safety stock required is closely tied to the accuracy of demand forecasts in our supply chain.					
28	Inaccurate demand forecasting leads to increased risks of stockouts and disruptions in our supply chain.					
29	Our organization faces challenges in adjusting safety stock levels based on inaccurate demand forecasts.					
30	Forecast accuracy is essential for ensuring the adequacy of safety stock levels in our organization.					

31. Please indicate the range for your typical safety stock levels as a percentage of average demand:

☐ 0-10%

☐ 11-20%

☐ 21-30%

☐ 31-40%

☐ More than 40%

32. Have you noticed any challenges or limitations in implementing demand forecasting for inventory management in Unilever Ethiopia?

☐ Yes, please specify the challenges in the space provided below

☐ No, no significant challenges encountered

____

____

____

33. How likely are you to recommend demand forecasting as a strategy for improving inventory management efficiency in FMCG manufacturing factories?

☐ Highly likely to recommend

☐ Somewhat likely to recommend

☐ Not likely to recommend

☐ Undecided