BSc Thesis Industrial Engineering and Management

OPTIMIZING EMERGENCY MEDICAL INVENTORY CONTROL USING AUTOMATED MACHINE LEARNING

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Preface

Dear reader,
I am delighted to present this bachelor thesis, titled "*Optimizing Emergency Medical Inventory Control Using Automated Machine Learning"* which represents the thesis assignment of my bachelor's program in Industrial Engineering and Management at the University of Twente.

First and foremost, I would like to express my gratitude to my university supervisors, Dr. Amin Asadi and Dr. Patricia Rogetzer. Their expertise and support have been significant throughout this journey. Their suggestions and encouragement greatly improved the quality of this thesis. I am very grateful for their assistance in completing my bachelor's degree.

In addition, I would like to extend my sincere gratitude to L2R for providing me with the opportunity to collaborate with them, particularly to my company supervisors, Jan Stock and Nele Großfeld. Their belief in my capabilities and consistent motivation during my time at L2R have been exceptionally valuable. Their support in every aspect was crucial to the successful completion of this study.

I hope you enjoy reading my thesis!

Sincerely,

Beril Cosar

Management Summary

This research is conducted at Department of Medical Logistics (DML), an emergency service department responsible for distributing medical equipment and consumables in Germany. DML has observed frequent stockouts in their inventory which led to low customer satisfaction. These stockouts are primarily caused by inefficient inventory control strategies. The goal of this research is to increase the cycle service level (CSL) of products used in treating tracer diagnosis diseases, such as sepsis, brain injuries, and polytrauma, thereby reducing stockouts. Therefore, the research question which is aimed to be answered within this research is formulated as follows:

"How can the Department of Medical Logistics (DML), L2R's customer, optimize the inventory of medical products used in tracer diagnosis, particularly in emergency services, to ensure that their desired service levels are met?"

Thus, the research aims to develop new inventory control policies which increase the service levels of the selected products. The Managerial Problem-Solving Method (MPSM) by Heerkens and Van Winden (2021) is used to systematically address the problem. The research was conducted in several phases, including problem identification, current situation analysis, literature review, solution design, and recommendations.

Initially, the current situation in DML is analyzed. DML handles 455 different products, including medications, consumables, sets, accessories, and test equipment. Consumables make up 50% of the demand, while sets contribute to the smallest demand, at 1.69%. DML uses a Laboratory Information System (LIS) to manage inventory levels. Currently, orders are placed based on manual counts and gut feelings, leading to inefficiencies. To address this, DML plans to implement a Kanban card system to track stock levels and reorder points more accurately.

By means of a literature review, we explored various concepts which are beneficial when determining the optimal stock levels and reorder points while developing new inventory control policies. The literature suggest that the product classification methods are widely used when dealing with large number of items in the inventory. ABC analysis was identified as a suitable method for classifying products based on their importance. Beside this, various demand forecasting methods are reviewed to identify the most appropriate techniques for predicting demand.

Based on the insights gained from the literature review, an AutoGluon forecasting model was developed to predict future demand for products. The tool applied the time series methods such as ARIMA, Exponential Smoothing, and Croston's method which produced the values of demand for the upcoming year. Using the outcome of the tool, the products with their corresponding demands for the following year were categorized using the ABC analysis and new inventory policies were formulated. The Continuous Review Policy (r, Q) and the Periodic Review Policy (T, S) were applied to determine the optimal ordering quantities and reorder points. The costs associated with each policy were also analyzed to compare the performance of the policies. The results indicated that 90.83% of the products have a lower cost using the continuous policy, while the remaining 9.17% of the products have a lower cost using the periodic review policy. DML can choose to apply the recommendations provided within this research to further ensure that the desired service levels are met.

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List of Abbreviations

AIL: Average Inventory Levels

ARIMA: Autoregressive Integrated Moving Average

AutoML: Automated Machine Learning

CSL: Cycle Service Level

DML: Department of Medical Logistics

EOQ: Economic Order Quantity

ERP: Enterprise Resource Planning

ETS: Error, Trend, Seasonality

L2R: Learn to Rescue

LIS: Laboratory Information System

MAPE: Mean Absolute Percentage Error

MPSM: Management Problem-Solving Method

MSE: Mean Squared Error

OUL: Order-Up-to-Level

ROP: Reorder Point

SES: Simple Exponential Smoothing

SS: Safety Stock

1. INTRODUCTION

This chapter introduces the thesis assignment. Section 1.1 starts by introducing the company which this research is done for. Then, Section 1.2 identifies the problem within the company. Following that, Section 1.3 identifies the knowledge problems and the problem-solving approach. Finally, Section 1.4 discusses the research design which this thesis follows.

1.1 Company Information

L2R is a company based in Germany that was founded in 2012 and is the first online learning platform for emergency services. Their core business is to offer digital training and further education in emergency response. They also specialize in working with various customers to manage their supply chain through offering advice and support for increasing the effectiveness of emergency chain processes.

This thesis focusses on one of L2R's customers, the Department of Medical Logistics, who is referred to as DML due to confidentiality reasons. DML is an ambulance service operator which facilitates approximately [redacted] emergency medical service missions in a year. Apart from this, they also handle the procurement and distribution of medical devices and consumables for ambulances. To ensure a smooth flow of the supplies, a total of 12 employees are working in the supply chain team and coordinating the distribution to ten different stations throughout the city of [redacted].

1.2 Problem Identification

This section identifies the core problem tackled within this research. The context of problem is described first, followed by the identification of the action problem. After the action problem is identified, a problem cluster is made, which identifies the core problem.

1.2.1 Problem context

Within the healthcare industry, meeting customer demand is crucial. It could be the difference between life and death for a patient. The problem with meeting demand is that DML do not know what their demand is. There are two types of demand, dependent and independent demand (Slack & Brandon-Jones, 2019). Dependent demand is known, since it is demand that depends on certain products to be finished or on certain factors. For example, during the COVID-19 pandemic, once the vaccine was developed, pharmaceutical companies knew that they need as many injections as they have planned vaccines for.

Conversely, independent demand is unpredictable, since it is not dependent on a certain factor. For example, before the COVID-19 pandemic, demand for emergency beds at hospitals was independent, as there was no virus that led people to the hospital. DML's demand for their products also follows independent demand, since it is unknown how many people need a certain type of medicine, and when they need it.

DML is currently distributing 455 different products used in the ambulances for the treatment paths. Of these 455 products, 120 are for tracer diagnosis. Products for tracer diagnosis are more crucial compared to to those used for diagnosing less severe diseases since tracer diagnosis diseases have high mortality rates. The examples of the diseases are traumatic brain injury, stroke, polytrauma, sepsis, myocardial infarction, and cardiac arrest. Moreover, DML indicated that they are not meeting demand for tracer diagnosis products, which is why they want these products to be the focus of this assignment. The different product types are discussed in Section 2.1.

For DML to ensure that the demand of the tracer diagnosis products is met, they should aim to always have the products available. However, to know how many products to have in stock, the demand should be known. But as mentioned, with independent demand, it is difficult to know the exact number of products to keep on hand. For this reason, a proper service level point should be met. Service level is the expected probability of not hitting a stock-out during the next replenishment cycle or the probability of not losing sales (Rădăsanu, 2016). Suppliers in the healthcare sector should manage their inventory effectively to ensure that the service levels are maximized. However, from a business perspective, achieving high service levels may require high inventory holding costs, hence, there should be a balance between the two. Due to the nature of this sector, there is an inability to predict the future demand which complicates suppliers' tasks. Therefore, it is vital for suppliers to have accurate demand forecasting and optimal inventory policies to ensure a timely response to customer demands.

DML's current strategies for inventory management are not working effectively and they experience frequent stockouts, resulting in failure to meet the demand of the stations. They recently recognized this problem after blankets and aspirin were not in stock during the last winter period when they were urgently needed. The essence of the problem is that DML do not know the optimal ordering quantities and do not have strategies to forecast the future demand. Besides, DML do not use an automated system which can keep track of the inventory levels. The calculations on the current inventory levels are handled by an employee manually. The employee simply checks the amount of products on hand and makes decisions on the quantities to order for the next replenishment based on estimations. This approach clearly fails to fulfill the demand of the supplies and decreases the customer satisfaction. They aim to be able to estimate the future demand and determine the optimal ordering quantities based on that. In the face of the current problem, this research focuses specifically on optimizing the inventory management of products used in tracer diagnoses through the application of developing new inventory policies for DML.

1.2.2 Action Problem

Since the current supply levels of the tracer diagnosis products do not meet the demand, an interview was held with the DML management team to identify some measurements which led to this conclusion. As a result of the interview, DML indicated that they currently meet a 75% service level for their tracer diagnosis products. This means that there is a 25% probability that demand is not met per replenishment cycle.

DML also stated that they have a target service level which they would like to reach for the tracer diagnosis products. After explaining to them the trade-off of having high service levels with the inventory holding costs, DML decided that they want to classify their products based on the criticality of the product, the demand of the product, and the revenue made from the product. They want the products with the least demand, criticality, and revenue to have a service level of 90%, 95% for moderate, and 98% for the highest respectively.

Therefore, the **action problem,** which outlines the discrepancy between the norm and reality of DML's service levels, is formulated as follows:

The service levels of the tracer diagnosis products which DML provides to the ambulances should be increased from 75% to 90%, 95%, and 98%, depending on the criticality, demand, and revenue of the products.

Table A.1. in Appendix A expresses both the norm and reality in terms of variables with the components of the action problem.

1.2.3 Problem cluster

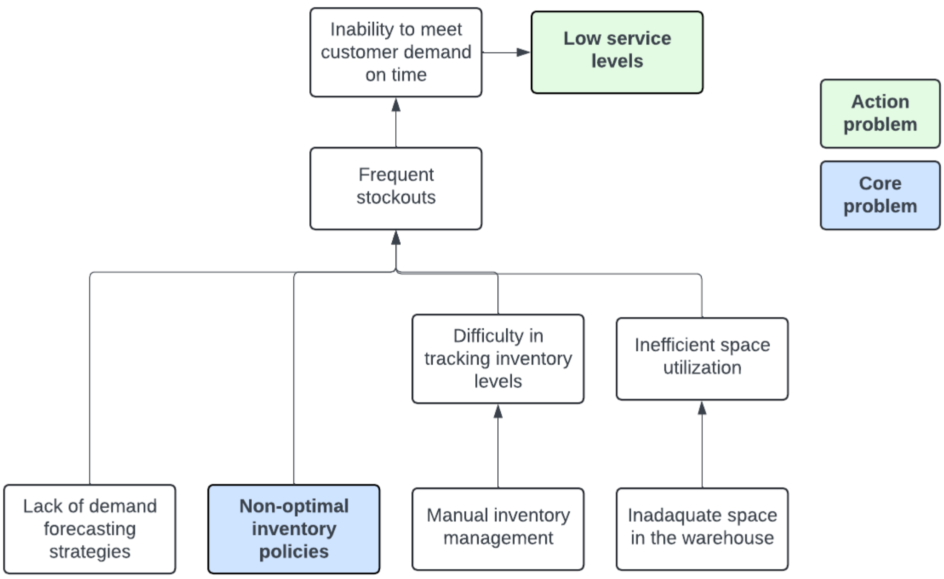

Figure 1: Problem Cluster

After identifying the action problem, the next step is to find out the core problem, which is leading to the action problem of DML. As an initial step, more interviews were conducted to gain insights into the problems leading to the action problem. Following these interviews, cause-and-effect relationships between the problems are identified by mapping them into a problem cluster (See Figure 1). The problems that do not have a direct cause can be defined as the potential core problems (Heerkens & Van Winden, 2021). As can be seen in Figure 1, the potential core problems are:

1. **Lack of demand forecasting strategies**

DML is struggling to forecast the future demand due to the stochastic demand in the medical products. Currently, they do not have a systematic approach to predict the future demand of the supplies and they cannot make estimations on the optimal product quantities to be ordered in the next replenishment cycle. Therefore, this results in ordering the wrong quantities and suffering with frequent stockouts. This problem is not selected as the core problem, but this research aims to address this problem within the solution for "non-optimal inventory policies" since developing optimal policies requires an application of demand forecasting methods.

2. **Non-optimal inventory policies**

Currently, DML does not have an optimal inventory policy since their employee who is responsible for ordering decisions does not follow a certain protocol. The amount of items ordered is based on a gut feeling, and so is the re-ordering point. Throughout the previous years, there have been many instances where the employee makes a purchase order to replenish the stock levels, and during the lead time for the items, they ran out of stock. Moreover, this problem directly impacts the action problem, since making their inventory policy more optimal, reduces the probability of a stockout which increases the service levels. This potential core problem is chosen as the **core problem** for this assignment since it has the biggest impact on the action problem, and it is also implementable within the given time frame.

3. **Manual inventory management**

As aforementioned, the current inventory is managed manually by an employee. This leads to the inability of monitoring the current inventory. Since there are many different types of products which need to be kept in stock, it is easy for the employee to make a mistake with managing the inventory. For these reasons, using an automated Enterprise Resource Planning (ERP) system would be beneficial for DML's inventory management. This problem is not selected as a core problem since obtaining an ERP system is very expensive which is a decision that must be taken by DML's financial and management teams, therefore it is out of scope for this research.

4. **Inadequate space in the warehouse**

There is only one warehouse which is used for storing all the supplies, and its space is very limited. DML need to store a large number of products, considering that they supply products to 12 stations across the city. The management team is currently considering the possibility of opening a second warehouse; however, the final decision has not been reached yet.

According to Heerkens & Van Winden (2021), if the problem cannot be influenced, it cannot be selected as the core problem. Therefore, this problem is not selected as the core problem as it cannot be influenced within the time frame of this research.

1.3 Knowledge Problems & Problem-Solving Approach

This section identifies the main research question, followed by breaking that question down into sub-research questions. Then, the problem-solving approach is discussed.

1.3.1 Research question

The research question is formulated based on the problem definition, action problem, and the chosen core problem, which are derived from the problem cluster.

The main **research question** is:

"How can the Department of Medical Logistics (DML), L2R's customer, optimize the inventory of medical products used in tracer diagnosis, particularly in emergency services, to ensure that their desired service levels are met?"

1.3.2 Sub-questions

With the research question defined, sub-questions are formulated to provide more detailed answers. Table 1 outlines these sub-research questions and indicates the corresponding chapters where they are addressed.

Table 1: Sub-research Questions

Current situation analysis	Chapter 2
1. What are the current strategies to store and manage the medical devices and consumables?	
Literature Review	Chapter 3
2. What are the recommended product classification methods in the literature? 3. Which demand forecasting techniques exist in the literature? 4. What are the recommended inventory policies in the literature?	
Solution Design	Chapter 4
5. How can the recommended inventory policies be applied to DML's inventory management? 6. How can DML formulate effective inventory management strategies to optimize the inventory of tracer diagnosis supplies based on the findings from the literature and the application of the policies?	

1.3.3 Problem Solving Approach

As a research methodology, the Management Problem-Solving Method (MPSM), developed by Heerkens & Van Winden (2021) is used to systemically solve the action problem. As illustrated in Figure 2, the MPSM is a cycle that consists of seven steps.

Figure 2: MPSM Cycle

Initially, all the problems that are present in the company are identified, and the action problem is determined to address the discrepancy between norm and reality (See Section 1.2.2). Following that, the first phase of the MPSM, which is "problem identification" is presented in **Chapter 1** by developing a problem cluster based on cause-and-effect relationships between the problems, which enabled the identification of the core problem. **Chapter 1** also illustrates the second phase, "problem approach", by defining the research design. To answer the main research question and provide more specific direction to the research, sub-questions are defined with respect to the remaining phases of the MPSM.

Chapter 2 deals with the third phase of the MPSM, the problem analysis, since it focuses on analyzing the problem in more detail. The current way that DML manages their inventory is explained. This explanation is compiled after gaining insight through interviews with employees in the department.

Chapter 3 is related to fourth phase of the MPSM, which explores the recommended inventory methods for inventory optimization. This exploration is conducted through a systematic literature review to identify the relevant optimization approaches for the inventory management. Since all the products do not equally contribute to the revenue gained by DML, they are classified based on the usage value. Therefore, classifying the items provide more accurate forecasts of the future demand within each category of the product and benefit the decision making of optimal inventory levels. Finally, the forecasting methods which exist in the literature are executed through a systematic literature review in order to forecast the future demand.

Chapter 4 relates to the fifth and sixth phases of the MPSM**;** the most suitable methods for DML's inventory is chosen based on the findings of the third chapter. Firstly, a forecasting tool is made to forecast the future demand based on past data. Since the historical data includes all the 455 medical products used in emergency services, the data is filtered to extract the relevant information about tracer diagnosis supplies. Following that, the filtered historical data is analyzed to identify the distributions in demand and serve as the basis for demand forecasting when developing inventory policies. This is done to ensure that the inventory policies are tailored to DML's future expected demand.

After forecasting the demand, the results help in classifying the products based on the results of the literature review. Finally, inventory management policies are made using the product classification results and the forecasting tool. These policies are then also be evaluated based on total inventory costs for each tracer diagnosis product.

Finally, the seventh phase of the MPSM is explained in **Chapter 5**. The results from chapter 3 and chapter 4 are evaluated to provide advice for setting up inventory policies. The results of this evaluation aid in providing recommendations to DML. Then, a conclusion is made from this research, connecting the main research question with the findings.

1.4 Research design

After defining the research aim, the research design is addressed which provides a systematic direction for the research. The design includes the data collection and research methods used to answer the research question. Appropriate data collection methods are used for the operationalization of the key variables.

This research encompasses a mixed methods approach by collecting both qualitative and quantitative data. Sub-question 1 includes collecting qualitative data by conducting interviews with the employees to gain insights on current inventory management. Additionally, it analyzes the historical data to identify the demand distribution regarding the product types, which produces quantitative data. Moreover, chapter 3 collects qualitative data by conducting a systematic literature review to find out the existing inventory methods, demand forecasting techniques, and product classification methods. Next, the outcomes of the fourth chapter provide quantitative data through applying the methods and making calculations using Excel. Finally, the chapter also produces quantitative data when providing future recommendations, since the results of the costs are analyzed in order to come up with a recommendation. Table A.2 in the appendix gives an overview of the research design for each sub-question.

1.4.1 Research Scope & Limitations

To stay within the time frame of ten-weeks, the scope of this research is to increase the service levels solely for medical products which are required for tracer diagnosis diseases. There are many other products which are related to other types of diseases which are out of scope of this assignment. Moreover, since the term “inventory management” is very broad, this thesis only focuses on the replenishment strategies for DML’s inventory.

The first limitation for this assignment is the 10-week constraint for the time. This limitation is due to the requirements from the University guidelines. Furthermore, another limitation to this assignment is not being able to test whether the recommendation to DML works in real life or not. For future research, a model can be developed to monitor the stock levels with an implementation of the inventory policies that are formulated, and this model can be implemented in real life.

1.4.2 Reliability and validity

Research cannot be valid without being reliable, which means that reliability is a result of validity in research (Golafshani, 2015). Noble and Smith (2015) state that validity is the integrity and application of the methods undertaken and the precision with which the findings accurately reflect the data, while reliability is concerned with the consistency of the analytical procedures.

This research takes into consideration the threats to both validity and reliability. Triangulation and member validation are two techniques used to ensure the validity of research. Triangulation is used by conducting both quantitative and qualitative research, in other words, a mixed-methods approach, which certifies the validity of the results. The members' validation technique is applied by sending the results of the interview to the participants for correction to validate them (Thornhill, 2019). On the other hand, to ensure reliable results from the interviews, participant error and participant bias are prevented by conducting the interviews online. This gives participants time to complete the interview and to avoid interaction with the interviewer. Besides interviews, reviewing literature also raises concerns in terms of validity and reliability. This time, validity and reliability are ensured by conducting a comprehensive systematic literature review using multiple search strings, databases, sources, and finding the articles that are appropriate to the research question. This is how precautions are taken against situations that threaten validity and reliability in the research, increasing the quality of the research.

2. CURRENT SITUATION ANALYSIS

The second chapter of this research aims to analyze and explain the current situation regarding inventory management at DML. The goal of this chapter is to answer the following sub-research question: *"What are the current strategies to store and manage the medical devices and consumables?"* **Section 2.1** starts by discussing the product portfolio at DML, concerning the tracer diagnosis products. Then, **Section 2.2** discusses the distribution of the product demand while **Section 2.3** explains the way in which the inventory is currently managed at DML. Finally, **Section 2.4** concludes the second chapter.

2.1 Products

The products offered by DML include medications, accessories, and consumables used in the ambulances. There are total of 455 different products which DML is responsible to supply to the stations in the city of [redacted]. As aforementioned, due to the broad range of the products, the scope of this research is limited to the supplies used in tracer diagnosis diseases. Therefore, there are total of 120 products which are required in tracer diagnosis and the focus of the research is developing policies for the selected products. These 120 tracer diagnosis products also include medications, consumables, sets, accessories, and test equipment. Medications are the medicines which come in a form of capsules or syrup like aspirin. Consumables are items which are consumed once and must be thrown away, such as masks or medical patches. Sets are the medications which come in sets, such as Urine Catheter Set. Then, accessories are items needed for check-ups, like stethoscopes. Finally, test equipment is equipment used for testing whether a patient has a disease or not, such as the I-STAT CG4, which measures sodium, potassium, chloride, etc. levels in a human. A pie chart depicted as Figure 3 below shows the product distribution with regard to the demand. Consumables have the highest contribution to the distribution with 50% while sets have the lowest with 1.69%. Besides gaining insights into the products categories, understanding the demand distributions for different product categories is crucial for accurately forecasting future demand. A detailed analysis of these distributions can help in selecting the most appropriate inventory management strategy. Section 2.2 discusses the demand distributions of the products.

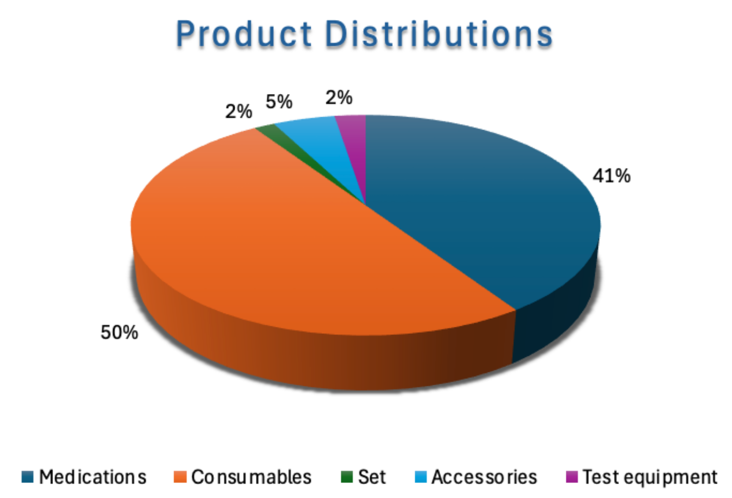

Figure 3: Distribution of Products

2.2 Distribution of demands

Understanding the distribution of product demand is critical for improving inventory management and ensuring smooth supply chain operations. Demand distribution shows how a product's demand fluctuates over time which impacts the inventory decisions. Shapiro-Wilk and Kolmogorov-Smirnov tests are commonly used to test the normality of data. Therefore, both tests are conducted to evaluate the normality of the data using SPSS Statistics.

The Shapiro-Wilk test determines how well the ordered and standardised sample quantiles fit the standard normal quantiles (King & Eckersley, 2019). Similarly, Kolmogorov-Smirnov test is used to determine whether a sample belongs to a specific distribution (Rehal, 2024). The null hypothesis for both tests states that the data are drawn from a normally distributed population. If the p-value is smaller than or equal to 0.05, the null hypothesis is rejected which means that the data does not follow normal distribution at a 95% confidence interval. Conversely, if the p-value is greater than 0.05, it indicates that data shows normality (Mishra et al., 2019).

According to the results from SPSS, 5.83% of the products do not follow normal distribution while the remaining 94.16% are normally distributed. It was observed that all products in the accessory, test equipment and set categories have p-values greater than 0.05 which indicates normal distribution. In contrast, five products in the consumable category namely Cor Patch, Hansaplast, Mini Spike, Larynxtubus and Magilltubus do not follow normal distribution as their p-values are less than 0.05.

Although the p-value of the Shapiro-Wilk test for Cor Patch is above 0.05, the p-value for the Kolmogorov-Smirnov test is below 0.05. Therefore, Corpatch is not normally distributed as both tests needed to indicate normality for a product to be considered normally distributed. Additonally, Ebrantil and NaCl 0.9 which are products in the medication category also do not follow normal distribution.

The outcomes of the tests for the products which are not normally distributed are shown in Table 2:

Table 2: SPSS Statistics Results

Products	Kolmogorov-Smirnov (p-values)	Shapiro-Wilk (p-values)
Cor Patch easy pre-connected	.043	.444
Hansaplast	.008	.004
Mini Spike	.001	.001
Larynxtubus	.009	.001
Magilltubus	.001	.001
Ebrantil	.018	.006
NaCl 0.9	.007	.005

Based on the results, it can be stated that the aforementioned products are not normally distributed as the p-values for both tests are smaller than 0.05. Additionally, histogram and Q-Q plots are created using the SPPS software to visually evalute the normality of the products. The Figure 4 is an example of the histogram for Hansaplast while Figure 5 illustrates the Q-Q plot of the product.

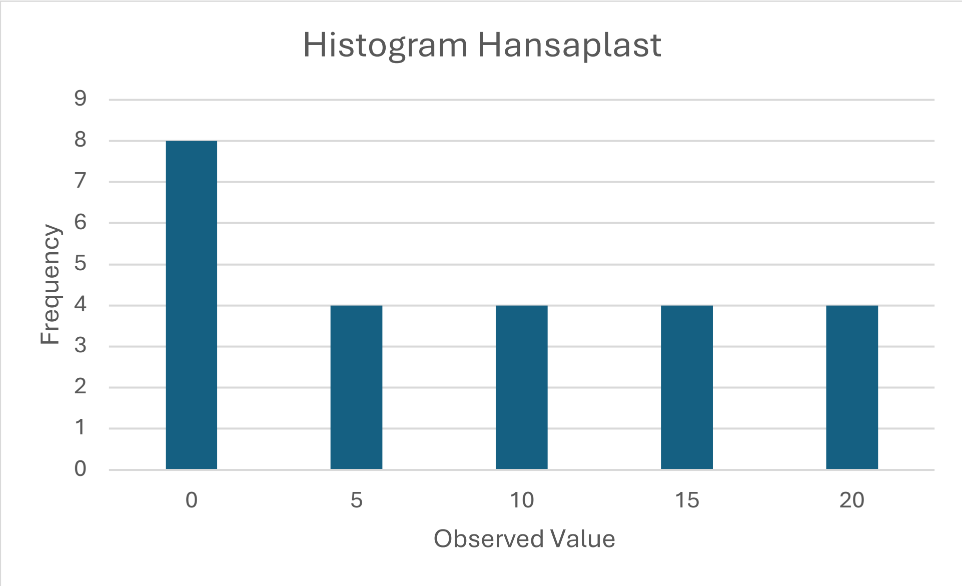

Figure 4: Histogram of Hansaplast

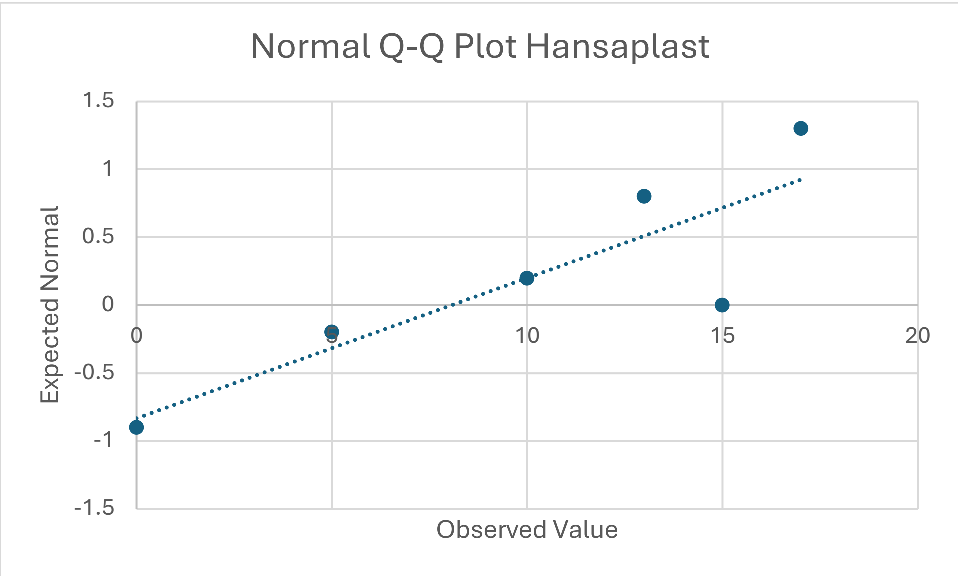

Figure 5: Q-Q Plot of Hansaplast

The histogram of Hansaplast does not show a symmetric distribution while the Q-Q plot has significant deviations at the tails. Both graphs implies that normality assumptions are not met which confirms the results of the Shapiro-Wilk and Kolmogorov-Smirnov tests. The graphs for the remaning products can be found in Appendix B.

We have conducted both tests for all the products offered by DML. It was observed all the products follow normal distribution except seven of them. However, for simplicity reasons, it is assumed that all the products show normality for this research.

2.3 Current Inventory Management in DML

This section describes the current inventory management process at DML by discussing the suppliers (Section 2.3.1), the inventory control methods (Section 2.3.2), and the delivery method at DML (Section 2.3.3).

2.3.1 Suppliers

There are two different paths for the supplies at DML, one for the medical equipment (sets, accessories, test equipment) and consumables, and the other for the medications:

- **Medical Equipment and Consumables:** Manufacturer → Retailer → DML.
- **Medications:** Manufacturer → Regional Retailer → Local Pharmacy → DML.

The consumables are initially produced at the manufacturer then the produced goods are being sent to the retailer, and DML receives the supplies from the retailer. For the medications, retailers receive the products from the manufacturer, distribute them to the local pharmacies and then DML receives the supplies from the pharmacies (See Figure 6). Some products have framework agreements with the suppliers while some do not. The orders for products that have agreements are placed using a digital store system. Conversely, products without framework agreements are ordered via email or telephone. They indicated that each product takes approximately five working days to arrive at DML.

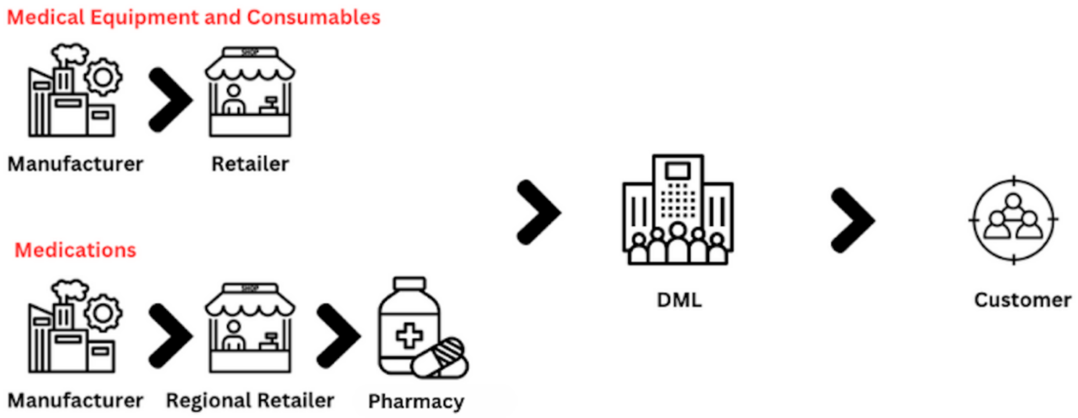

Figure 6: Visualization Map Supply Chain

2.3.2 Inventory control

DML uses a Laboratory Information System (LIS) software which is a healthcare software solution that is used to update and maintain the inventory levels. They are currently using this software to enter the new orders. As they do not have any ordering strategies, they decide on the reorder amounts based on a gut feeling. An employee simply counts the number of the products on hand and determines the order quantities that make sense to her.

However, they are aware that this system is not working well, and they are planning to implement a Kanban card system. These cards will be placed at the warehouse where the orders are stored. A prototype of the card can be seen in Figure 7.

Figure 7: Kanban Card System

The Kanban card will include the barcode number, the current stock levels and the minimum stock levels. The idea is that every time an employee takes an item, they update the current stock value on the card. When they realize that the minimum stock levels are reached, they place the new order. Therefore, a new ordering policy to determine the reorder points and ordering quantities are required.

2.3.3 Delivery

DML is responsible for distributing products to ten different stations, which are the customers of DML, throughout the city of [redacted]. The orders from the stations are received following the milk run every day. Milk run is a delivery method which uses one vehicle to conduct several deliveries in roundtrips (Minh et al., 2020).

The red boxes in Figure 8 represent the stations in the city while the number ten marks the DML's location and, the remaining numbers present the locations that DML is responsible for supplying the emergency supplies to. DML does not use a digital system to receive the orders instead an employee goes through the milk run every day and collects the orders from the stations as paper-based order slips. At the end of the milk run, employee returns to DML and delivers the paper-based slips to the responsible person in the team.

Therefore, the products are picked from DML based on the orders of the previous day and documented in the LIS software using a hand scanner and barcode. The next day employee goes through the milk run again and distributes the orders to the relevant stations and collects the new orders if there are.

[redacted]

CONFIDENTIAL

Figure 8: Milk Run Distribution Map

2.4 Conclusion

This chapter provides a detailed analysis of the current inventory management strategies at DML, aiming to answer the sub-research question: *"What are the current strategies to store and manage the medical devices and consumables?"*

Firstly, the diverse product portfolio managed by DML is outlined, focusing on the 120 tracer diagnosis products. These products include medications, consumables, sets, accessories, and test equipment with consumables comprising the largest demand segment.

Then, the current inventory management practices are analyzed by highlighting the supplier pathways, delivery methods, and inventory control processes. The inefficiencies in the current system are identified such as the reliance on manual counts and gut feelings for reorder decisions, and the planned implementation of a Kanban card system to improve inventory accuracy is discussed.

3. LITERATURE REVIEW

Effective management of inventory in the healthcare industry for the healthcare products is essential to ensure that the patients receive the product at the right time. This chapter introduces relevant concepts which can increase the effectiveness of the inventory management. The aim of this chapter is to address the three following sub-research questions:

1. *What are the recommended product classification methods in literature?*
2. *Which demand forecasting techniques exist in the literature?*
3. *What are the recommended inventory policies in the literature?*

Section 3.1 discusses a product classification method that is commonly used to classify inventory items. Effective classification is crucial because it allows for better management of the diverse range of the products. Healthcare organizations can ensure that the different products are handled appropriately with their varying storage requirements by applying classification methods. Then, **Section 3.2** introduces the different methods of demand forecasting that are essential to predict the future needs of healthcare products. Forecasting allows healthcare providers to determine the quantities of the products that are needed based on historical data and seasonal factors. Besides, accurate demand forecasting prevents both overstocking and understocking situations where overstocking can lead to wastage while in understocking it can result in life threatening shortages. Following that, **Section 3.3** describes the usage of safety stock in inventory management. Safety stock ensures that essential products are always available when needed and acts as a buffer to handle unexpected demand or supply chain distributions. **Section 3.4** focuses on inventory policies that helps determining the amount of stock should be kept on hand, the frequency of the order placement and the management of the inventory flow. Finally, **Section 3.5** concludes the third chapter.

3.1 Product Classification

Product classification is widely used when dealing with a large number of items in the inventory as it is not feasible to set optimal stock levels for each item individually (Cohen et al., 1988). Therefore, the items are classified based on different factors and inventory control policies are applied to each item in a group. The literature suggests many classification methods such as ABC analysis which is used for better management of products in the inventory.

ABC Analysis

ABC analysis was developed by nineteenth-century Italian economist Vilfredo Pareto based on the Pareto Law. Initially, Pareto observed that “In many projects 20% of the total effort produces 80% of the total result” (Rusănescu, 2014). Later on, Pareto discovered that the economy has the same distribution, and this approach can be applied to many areas of life. Many studies confirmed that this principle is the most popular method to classify the inventory items. Figure 9 illustrates the visual representation of the ABC analysis results using Lorenz curve (Keskin & Ozkan, 2013).

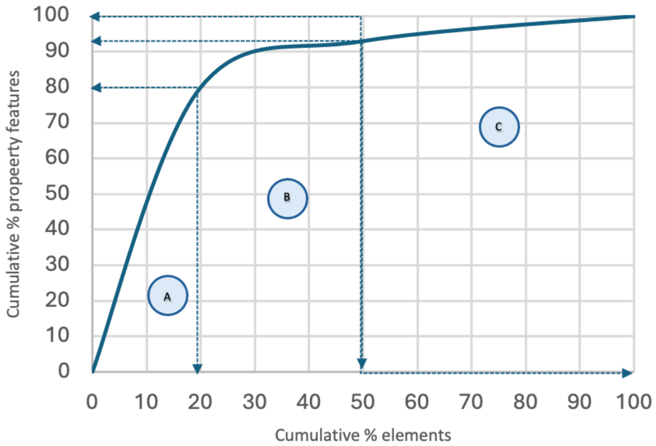

Figure 9: ABC Analysis Diagram

ABC analysis, or in other words "the 80/20 rule" ranks the items that have different levels of significance, since they should be handled differently (Rusănescu,2014). The products are categorized based on the annual consumption value which is calculated according to frequency of the use and their value. The formula for annual consumption value (C_i) is follows (Pandya & Thakkar, 2016):

$$C_i = D_i * p_i \quad (1)$$

where

D_i = annual demand

p_i = item cost per unit

Based on the annual consumption values items are categorized into three groups: **A-class** items, **B-class** items and **C-class** items. A-class items have the highest annual consumption value which usually represent 80% of the value of an inventory and usually account for only 20% of the total inventory. B-class items are the inter class items with a medium annual consumption value. They represent 15% of total usage value of inventory with 30% of the total inventory. C-class items represent the lowest annual consumption value which accounts for 5% of the total usage value of the inventory, and usually account for around 50% of inventory items (Rusănescu, 2014).

By paying close attention to A class items in inventory, firms can minimize the inventory management costs. Even though B class items does not contribute as much as A-class items to the revenue, these items should be managed with formal inventory system through periodic inventory (Pandya & Thakkar, 2016). On the other hand, C class items have the lowest priority compared to other items and it is typically handled by minimal monitoring and control (Ali, 2023).

3.2 Demand Forecasting

Demand forecasting refers to predicting or estimating the need for a product or a component in a future time period (Bandeira et al., 2020). Businesses must be able to effectively analyze the historical data and make predictions on future demand based on that data. The information about the forecasted demand can be used to determine optimal inventory levels and managerial decisions (Bandeira et al., 2020). For example, in Guo et al. (2017), forecasting is used to support the ordering decisions of airplane spare parts while Yu et al. (2011) employs forecasting models to estimate demand of fashion products (Bandeira et al., 2020). In fact, accurate forecasting enables companies to meet customer demands on time, which increases customer satisfaction and service levels. Many companies are facing challenges when managing demand as it is difficult the estimate future consumer needs accurately (Fattah et al., 2018). The literature reveals that the survey conducted found over 74% of respondents reported poor forecasting accuracy as there are increasing major challenges to supply chain flexibility. The best companies tend to improve supply chain flexibility and responsiveness through improving forecasting accuracy. (Fattah et al., 2018).

Demand forecasting methods can be divided into quantitative and qualitative methods. Qualitative methods are applied when little data exists while quantitative methods are used when historical data exists. Quantitative methods can be applied when two conditions are satisfied: a) numerical information about the past is available, b) it is reasonable to assume that some aspects of the past patterns will continue into the future (Hyndman & Athanasopoulos, 2021). Figure 10 illustrates examples of both quantitative and qualitative forecasting methods (Deckert et al., 2022; Vagale et al., 2021).

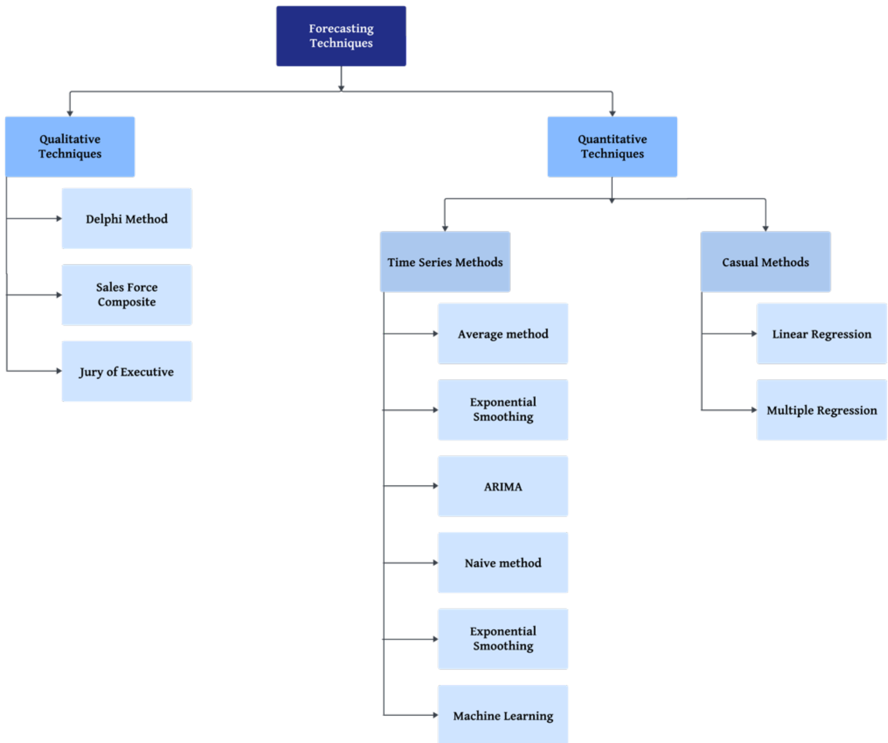

Figure 10: Forecasting tecniques

As can be seen from Figure 10, time series methods are an example of quantitative methods which forecasts the demand based on the historical data and assumes that the factors influencing the past will continue to influence in the future (Ivanov et al., 2021). This research focuses on time series analysis as it is the most appropriate according to the literature when future demand is related to the historical demand (Chopra et al., 2016).

3.2.1 Times Series Forecasting Using Automated Machine Learning (AutoML)

The massive amount of available data makes it difficult for businesses to develop accurate demand forecasting models. This complexity often requires machine learning background and expertise to effectively analyze the data and generate reliable predictions. As can be seen in Figure 10, time series forecasting methods can be integrated with machine learning approaches. Automated Machine Learning (AutoML) tools are transforming the field of machine learning by enabling users to build high-performing models for demand forecasting without extensive knowledge (Westergaard et al., 2024). In recent years, many features have emerged to AutoML tools which led to automate the model selection, hyperparameter optimization, and feature election processes (Alsharef et al., 2022). This approach has become an interesting topic for researchers and industries as it minimizes the human involvement (Westergaard et al., 2024). Consequently, the risk of human bias is reduced which leads to more accurate results.

Some automated forecasting models do not consider uncertainty in demand behavior which is a crucial factor in many practical applications. AutoGluon Time Series is an open source AutoML written in Python which closes this gap and generates times series forecasting in a few lines of code. (Shchur et al., 2023). Figure 11 illustrates the overall process of AutoGluon model development.

The first step is to create the data frame by loading the data set into Python, then clean the data to prepare it for forecasting. AutoGluon enables users to define the forecasting task such as prediction length, quantile levels to be predicted and evaluation metrics. Following that, it integrates a method that automates data preprocessing, fitting, and evaluating various models using cross-validation which is referred as fitting the predictor. During the evaluation of the models, it selects the one which results as the lowest forecasting error and produces a leaderboard showing the ranking between the applied methods (Shchur et al., 2023). While the overall development with AutoGluon automates most of the process, human involvement is necessary for data cleaning and defining the forecasting tasks. The remainder of the development is fully automated.

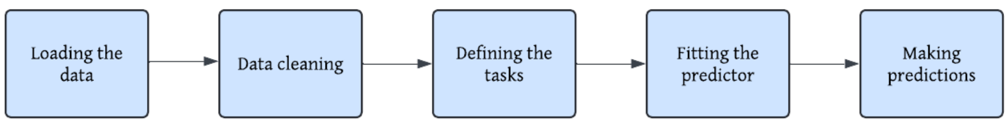

Figure 11: Steps For AutoGluon Model

AutoGluon uses several times series forecasting models which can be divided into two categories:

i) Baseline models (Section 3.2.2)

ii) Statistical models (Section 3.2.3)

Since all categories have a variety of models, the most used ones are explained in the upcoming sections.

3.2.2 Baseline models

A baseline model uses minimal historical data to make predictions in the future demand and serves as a benchmark to evaluate more complex forecasting methods (Erickson et al., 2020). **Average model** is a baseline model that computes the forecast by taking the mean (or "average") of the historical data. If we assume that the historical data can be denoted by $y_1, \ldots, y_T$, then we can compute the forecasts as:

$$\hat{y}_{T+h|T} = \bar{y} = (y_1 + \cdots + y_T)/T \quad (2)$$

where

h = forecast horizon

y = time series

The **naïve model** is another example of a baseline model which sets all the forecasts value to be the value of the last observation. This model only considers the *trend* component while disregarding the *seasonal* factor. As an extension to this model, the **naïve seasonal model** sets each forecast to be equal to the last observed value from the same season of the year which is useful for highly seasonal data. The following Equations (3) and (4) illustrate the computation of both the naïve model (3) and the naïve seasonal model (4):

$$\hat{y}_{T+h|T} = y_T \quad (3)$$

$$\hat{y}_{T+h|T} = y_{T+h-m(k+1)} \quad (4)$$

where

$\hat{y}_{T+h|T}$ y_T = the future values of the time series at time $T + h$

y_T = observed value at time T

m = the seasonal period

k = number of seasonal cycles

3.2.3 Statistical models

A statistical model is used to capture the trend and seasonal components. The examples of the statistical models include **Exponential Smoothing** and **ARIMA** models.

In the late 1950s, exponential smoothing was proposed by Brown (1959), Holt (1957) and Winters (1960). This model forecasts the values with the weighted average of the past observations while the assigned weight decreases as the observation gets older. The simplest form of the model is **Simple Exponential Smoothing (SES).** SES is appropriate to use when the demand has no *trend* or *seasonality.* It works with smoothing parameter α and the parameter α is determined based on the value with the smallest forecasting error (Ivanov et al., 2021). The idea of SES is to assign higher weights for current demand and lower weights to the previous demand:

$$\hat{y}_{t+1} = \hat{\alpha} y_T + (1 - \hat{\alpha})\hat{y}_t \ (5)$$

As SES does not capture trends, Holt (1957) extended SES to allow forecasting of data with a trend (Hyndman & Athanasopoulos, 2021). When experiencing level and trend in demand but no seasonality, **Trend-corrected exponential Smoothing (Holt's Linear Model)** is suitable to use. In this case, we use two smoothing parameters α and β for level (l_t) and trend (b_t) respectively.

$$\hat{y}_{t+h|t} = l_t + hb_t \ (6)$$

$$l_t = \alpha y_t + (1 - \alpha)(l_{t-1} + b_{t-1}) \ (7)$$

$$b_t = \beta(l_t - l_{t-1}) + (1 - \beta)b_{t-1} \ (8)$$

As Holt's Linear model does not consider the seasonality factor, **Trend and Seasonality corrected exponential smoothing (Holt-Winter's model)** is used when the demand has all three characteristics: level, trend and seasonality. Since, a new factor (seasonality) is included, a new smoothing parameter γ is included. The trend formula is same as Holt's Linear Model which is shown in Equation 8. The Equation 9, 10 and 11 illustrates the formulas for Holt's Linear Model.

$$\hat{y}_{t+h|t} = l_t + hb_t + s_{t+h-m(k+1)} \ (9)$$

$$l_t = \alpha(y_t - s_{t-m}) + (1 - \alpha)(l_{t-1} + b_{t-1}) \ (10)$$

$$s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1 - \gamma)s_{t-m} \ (11)$$

AutoGluon combines all the aforementioned exponential smoothing models into a framework known as ETS (Error, Trend, Seasonality) models.

In addition to ETS models, **ARIMA** (Autoregressive Integrated Moving Average) is a widely used statistical model which combines autoregressive process AR (p), integration I (d), and the moving average process MA (q). However, ARIMA does not use the original data series y_t but instead it uses the differenced series $y_t{}'$. Differencing is defined as the change between consecutive observations in the original series and it is needed to transform the non-stationary data into stationary. The formula for differencing is follows:

$$y'_t = y_t - y_{t-1} \quad (12)$$

In general, the model is expressed as ARIMA (p, d, q) where the p is the order of the autoregressive part, d is the degree of first differencing involved and q is the order of the moving average part (Hyndman & Athanasopoulos, 2021). The general formula for ARIMA as follows:

$$\hat{y}_t = \mu + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} \quad (13)$$

As can be seen from the Equation 13, the forecasted demand is equal to sum of constant C, past values of the differenced series $\phi_p y_{t-p}$, the mean of the differenced series μ, past error terms $\theta_q e_{t-q}$ and current error terms (Castellon, 2023).

AutoGluon uses autoARIMA which automatically selects the optimal ARIMA model parameters through statistical techniques such as Akaike Information Criterion (AIC). AIC is commonly used as a measure to determine the parameters of ARIMA model by trying to maximize the log likelihood (Hyndman & Athanasopoulos, 2021). The Equation 14 illustrates the formula for AIC.

$$AIC = -2\log(L) + 2(+p + q + k + 1) \quad (14)$$

where

L = likelihood of the data

$k = 1 \; if \; c \neq 0$

$k = 0 \; if \; c = 0$

AutoARIMA aims to select the parameters that minimizes the AIC which means finding a model that provides a good fit. Since the selection of the parameters can be difficult to determine, it provides fast and effective solution for time series modelling (Castellon, 2023).

Statistical models for sparse data

In addition to baseline and statistical models, there are specific models which are used for intermittent demand data where the data has some periods with zero demand. The Croston's model is an example of statistical models which is applied when dealing with intermittent demand. This method was proposed by J.D.Croston in 1972 and later improved by Syntetos and Boylan (Castellon, 2023). The improved version is called Croston-SBA (Syntetos and Boylan Approximation). In particular, the model applies simple exponential smoothing to both non-zero demand size Z_t' and the inter-arrival times. Therefore, the estimation of demand per period Y_t' can be derived by taking the ratio of those estimates (size/intervals). The idea is that the method updates forecast only after positive demand occurs. Thus, if there is a period where demand is zero, the method only counts the periods since the last positive demand (Xu et al., 2012). The formula for Croston-SBA is follows:

$$Z_t' = \begin{cases} Z_{t-1}' \ (15) & if\ Z_t = 0 \\ Z_t' = \alpha Z_t + (1-\alpha) Z_{t-1}' \ (16) & otherwise \end{cases}$$

$$P_t' = \begin{cases} P_{t-1}' \ (17) & if\ Z_t = 0 \\ \alpha P_t + (1-\alpha) P_{t-1}' \ (18) & \text{where } 0 < \alpha < 1 \end{cases}$$

$$Y_t' = (1 - \frac{\alpha}{2}) \frac{Z_t'}{P_t'} \ (19)$$

where

Y_t' = Average demand per period
Z_t = Actual demand at period
Z_t' = Time between two positive demand
P = Demand size forecast for next period
P_t' = Forecast of demand interval
α = Smoothing constant

3.2.5 Measures of Forecast Error

Before the application of the forecasting methods, validation is required as almost all the forecasting methods have errors in the predicted results (Khair et al., 2017). There are many measures of forecast error which are used to test the accuracy of the methods. One of the measures of forecast error is **Mean Squared Error (MSE)**, which measures the quadratic deviation of forecast and actual data using the following Equation (Ivanov et al., 2021):

$$MSE_n = \frac{1}{n} \sum_{t=1}^{n} E_t^2 \quad (20)$$

This method can be related to the variance of the forecast error, and it is estimated that the random component of demand has a mean of zero and a variance of MSE (Chopra et al., 2016). Beside this method, **Mean Absolute Percentage Error (MAPE)** is also used as a measure of forecast error which can be seen from Equation 21:

$$MAPE_n = \frac{\sum_{t=1}^{n} \left| \frac{E_T}{D_t} \right| 100}{n} \quad (21)$$

MAPE calculates the average absolute error as a percentage of demand (Chopra et al., 2016). It indicates the number of prediction errors compared to the real value (Khair et al., 2017). One problem which might occur using MAPE is that it divides the absolute error by the actual value. Thus, if the demand includes zero values, the MAPE is mathematically undefined.

3.3 Safety Inventory

Safety inventory (stock) is carried to satisfy demand that exceeds the amount forecasts (Winston & Goldberg, 2004). This approach is frequently used in inventory control in order to achieve desired product availability. Determining safety stocks is required to protect against many deviations such as delivery date variances, requirement variances, delivery quantity variances and inventory variances (Radasanu, 2016). Figure 12 summarizes the relationship among these deviations (Radasanu, 2016).

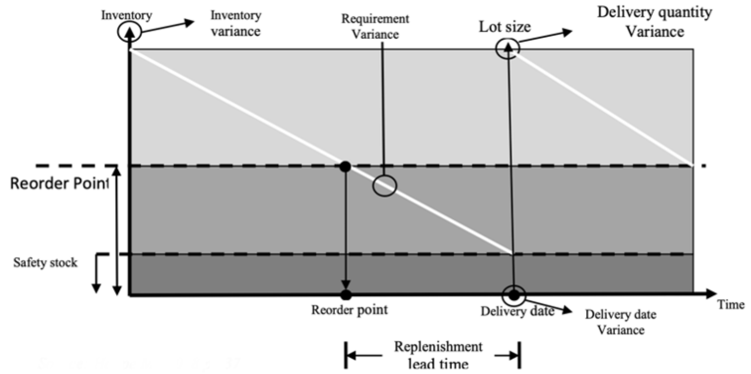

Figure 12: Safety Invetory Deviations (Radasanu, 2016).

According to Radasanu (2016), statistical functions can be used to calculate the safety stock levels with the target of achieving a specified service level. The relation between both terms is non-linear and the required safety stock level increases, as the level of service increases. This means that the cost of inventory increases along with the service level. The companies should consider this trade-off and set desired service levels accordingly. Rather than using fixed service factor for all products, the firm can assign different levels of service levels based on the product characteristic.
Furthermore, the safety inventories are also influenced by the implemented inventory policies which are explained in the upcoming section.

3.4 Continuous & Periodic Policies

A continuous review policy involves constantly monitoring inventory levels and placing orders when they fall below a predetermined reorder point (ROP). This approach uses the EOQ model to determine the optimal order size, ensuring that inventory is replenished efficiently and cost-effectively. This policy is referred as (r,Q) model where r represents the reorder point and Q signifies the fixed order quantity. Additionally, the demand is assumed to be normally distributed with mean D and standard deviation σ_D (Chopra et al., 2016).
The formulas for EOQ , mean, standard deviation and ROP are follows:

$$EOQ = q = \left(\frac{2KE(D)}{h}\right)^{\frac{1}{2}} \quad (22)$$

$$Mean\ during\ lead\ time\ D_L = D * L \quad (23)$$

$$Standard\ deviation\ during\ lead\ time = \sigma_L = \sqrt{L}\sigma_D \quad (24)$$

$$Safety\ stock = F_s^{-1}(CSL) * \sigma_L \ (25)$$

$$Reorder\ point = D_L + ss \ (26)$$

On the other hand, a periodic review policy involves checking inventory levels at regular, predetermined intervals. Orders are placed to replenish stock up to a specific order-up-to level (OUL) regardless of the current inventory position. This policy follows the (T,S) model which refers to fixed period T and order-up-to level S (Goltsos et al., 2022). Therefore, Equation (27), (28), (29) and (30) illustrates the formulas for periodic review policy parameters.

$$Mean\ during\ T + L\ periods = D_{T+L} = (T + L)D \ (27)$$

$$Standard\ deviation\ during\ T + L\ periods = \sigma_{T+L} = \sqrt{T + L} * \sigma_D \ (28)$$

$$Safety\ stock = F_s^{-1}(CSL) * \sigma_{T+L} \ (29)$$

$$Order\ up\ to\ level = D_{T+L} + ss \ (30)$$

3.5 Conclusion

This chapter reviews literature in a systematic way, such that the literature can be applied into practice. The chapter starts by introducing the ABC analysis for product classification, then safety inventory, demand forecasting, and finally inventory policies. Within Chapter 4, products are categorized into A, B and C classes and service levels are assigned accordingly. Highest service levels are assigned to A class items while C class items have the lowest one. We ensured that most critical (A class) items receive higher safety stock levels by assigning different service levels to each item category. Chapter 4 applies the theory of demand forecasting from Section 3.2 to predict the future demand by using methods like time series analysis and AutoML tools such as AutoGluon. The time series methods integrated in AutoGluon which are AutoARIMA, Seasonal Naïve, Naïve, ETS and Croston are applied in Chapter 4 for accurate forecasting of the future demand. Following that, next chapter utilizes inventory policies which are mentioned in Section 3.4. The continuous and periodic review methods are applied based on EOQ models. These policies aim to optimize inventory levels and ensure product availability while minimizing costs. Thus, the policies provide parameters for making inventory management decisions such as safety stock, reorder point, etc.

4. SOLUTION DESIGN

The fourth chapter applies the theory reviewed in Chapter 3. In this chapter, the following two research questions are answered:

1. How can the recommended inventory policies be applied to DML's inventory management?
2. How can DML formulate effective inventory management strategies to optimize the inventory of tracer diagnosis supplies based on the findings from the literature and the application of the policies?

Firstly, **Section 4.1** uses past demand data to create a forecasting tool which can forecast the data of the following year. Then, using the results of the forecasting tool, **Section 4.2** categorizes the products using the ABC analysis. Following that, in **Section 4.3,** we come up with inventory policies for the products, based on the results of Sections 4.1 and 4.2. Then, **Section 4.4** evaluates the inventory policies based on costs. Finally, **Section 4.5** summarizes the fourth chapter.

4.1 Application of AutoGluon Forecasting model

To apply new inventory policies for the upcoming year, the demand for that period should be forecasted based on the past data. The demand cannot be forecasted manually since there are over 100 products. As previously mentioned in Section 3.2.1, an automated forecasting tool are applied using AutoGluon which can predict the future values of demand for the next year. This section details the development of this tool.

4.1.1 Input Data

The historical data is retrieved from the ISE software which is an ERP software DML uses to keep track of the inventory records. The data set included the daily and hourly demand of the products between the years of 2019 and 2022, the type of the product, and the name of the product. Since the results would be more accurate with more data points when forecasting the future demand, we wanted to generate data for 2023. Based on the results from Section 2.2 , it is assumed that the demand follows normal distribution. The daily demand data between 2019-2022 for each product is added. Accordingly, the means and standard deviations of the products are calculated to generate random data from normal distribution (See Appendix C.1). The complete data set is then loaded into Python. After importing the file, the next step is to transform the data into a format suitable for a time series analysis. The first column of the historical data includes both the date and time of the order placement and named "timestamp".

The imported file reads the Date time objects as a string rather than a Date time object. In order to convert the string into Python Date time object, pd.to_datetime syntax is used (Pankaj, 2022). Next, considering that the management team stated a different ordering policy for medical devices which are ordered less frequently compared to the other products, they indicated that medical devices should be excluded from the data set.

Moreover, the demand values were aggregated by summing the sales of each product for each day as the data set was created daily and hourly. We then transposed the results of the summation by taking each product from columns and putting them as rows of one column. In order to prepare the data set for training and evaluation with times series analysis, the prediction length which specifies how far the future prediction is defined. We defined the prediction length as ten periods and the interval as six weeks so that we can retrieve the future values from July 2024 to July 2025. Now that the data is prepared, a tool is designed to forecast the future demand with AutoGluon time series analysis.

4.1.2 Creating the Model

To begin, time series models (Naïve, Seasonal Naïve, ETS, ARIMA and Croston) which are mentioned in the literature review are defined in the tool with importing Times Series Data Frame. These models were selected based on their ability to capture the different patterns in the demand values, taking into account different variations such as trend and seasonality. Beside these individual methods, AutoGluon can combine several methods by assigning weights to each of them. This combination of methods is referred to as Weighted Ensemble method. Using the Weighted Ensembling method ensures that the strength of the methods is weighted to predict more reliable results.

After defining the time series methods, the data is then split into train and test sets. The training sets consist of around 75% of the data while the remaining 25% is the testing data (Galarnyk, 2022). It is important not to train and test on the entire data set as it leads to "overfitting". This procedure is required for validation of the trained model since it allows to see how well the method performs for the unseen data (Galarnyk, 2022). AutoML does this procedure automatically as it has the ability to try the time series models on both train and test sets and selects the one with the lowest forecasting error.

Additionally, it was observed that some products do not have orders for some periods and for those periods, the cells are empty. Therefore, the missing values are filled with zero values to get more accurate results as the model predicts better with a complete data set. We then converted the daily demand values to weekly values as the goal is to forecast in weekly periods. After all the adjustments, the model is trained and is capable of selecting the best method out of five of them. (See Appendix B)

4.1.3 Results

An automated tool is developed in AutoGluon which applies time series models to predict demand for the following year. The purpose of these models depends on the characteristics of the demand which means that not every method is optimal for forecasting. Therefore, the model with the lowest forecasting error rate should be selected to achieve accurate results. The most used forecasting errors which are integrated in AutoGluon are MSE and MAPE. MSE is more sensitive for the outliers, whereas MAPE becomes undefined when the historical data contains zero values (Shchur et al., 2023). MAPE includes division with the actual values which can lead to undefined values with a division with zero values. MSE does not have this issue since it takes the squared difference of the values.

It was observed that some products have periods with no orders which leads to zero values in the historical data. Therefore, the correctness of the models is tested using MSE. In total, the model trained five different time series models and evaluated the results with MSE. The forecast error rates for each model that AutoGluon printed are illustrated in Table 3 as follows:

Table 3: MSE Validation Scores of the products

Ranking	Method	MSE
1	Weighted Ensemble	706,83
2	AutoARIMA	715,85
3	Seasonal Naive	1189,15
4	Naive	1189,15
5	ETS	1189,84
6	CrostonSBA	1622,34

As can be seen from Table 3, Weighted Ensemble has the lowest MSE score in comparison to other methods. The results indicated that none of the methods can predict accurately on its own, but a combination of them which is known as "Weighted Ensemble" produced better predictions. The model suggests that combination of ARIMA with 0.91 weight and Croston with 0.09 weight produce the best results compared to other models (See Appendix C.2). For example, the forecasted demand for a certain product using ARIMA is multiplied by 0.91 while the forecasted demand with Croston is multiplied by 0.09. The final predicted value is the summation of both values. Furthermore, AutoGluon Time Series predictor generates two types of forecasts, namely mean and the quantile levels. Quantiles are usually set to be between 0.1 and 0.9. The predicted value of 0.1 indicates that the demand is below the predicted value 10% of the time while the value of 0.5 is known as "median" and indicates that the value is below or above that point with 50% probability. Therefore, predicted results are imported to Excel, and it shows the predicted mean and quantiles for all the products in the next periods.

During the prediction, the mean takes the value of median as it is less sensitive to the outliers. When the median is not considered as the mean, the accuracy of the results would be affected since large deviations can skew the mean. Thus, the predicted results include both the mean and the quantile and used when formulating the inventory policies.

4.1.4 Validity of the Model

Section 4.1.3 presented the validation scores for various time series methods. Section 4.1.4 illustrates the calculation of the MSE for the predicted demand values. Due to the large variety of the products in inventory, we selected a representative product (NaCI) to demonstrate this calculation. The MSE score for NaCI is presented in Table 4.

Table 4: Validity Analysis of NaCl

	Period	Actual values	Predicted values	Error	Square root of the error
NaCI	1	502	525.1281	-23.1281	534.9090096
	2	602	525.5973	76.4027	5837.372567
	3	535	523.602	11.398	129.914404
	4	535	540.4312	-5.4312	29.49793344
Weekly Average		90.5833	88.1149		
MSE Score					1632.923479

To start, four periods were chosen, with each period representing six weeks. The actual values were provided by DML for the year of 2023 for the months of January till June, however, since the tool only forecasts for the year of 2025, the predicted values of 2025 were compared to the actual values of 2023.

For each period, the error is calculated as the difference between actual and the predicted values. Accordingly, these errors are squared and averaged over the four period to compute the MSE score. The calculated MSE score for NaCI is 1632.92. Taking into account the four periods, **the weekly average predicted is only 2.80% lower than the actual value, showing the accuracy of the forecasting method.** Although this validation analysis is only limited to one product, it serves as an example to show model's accuracy.

4.2 ABC- Classification Results

To come up with inventory policies for DML, calculating the safety stock per product is essential, and as the results of the literature review show, the z-score is required to calculate the safety stock. Obtaining this z-score requires specifying a certain service level. These service levels were provided by DML during the initial interviews held with the management teams. As stated in the first chapter, tracer diagnosis products with the highest demand, criticality, and revenue should have a 98% service level. Since there are 120 products, it is not possible to identify the criticality of each product. For this reason, the usage value is calculated as used to classify the products.

The annual consumption value is computed for each product using Equation 1. Accordingly, products which accounts for 80% of the total inventory value are classified as “A” group items, those that account for the next 15% are classified as “B” group items and the remaining 5% are classified as “C” group items.

The results show that 78,97% of the items can be classified as A products while 15,41% for B group and 5,62% of them for C group items. The distributions per product type is illustrated in Table 5. Higher service levels are assigned to A class items to ensure that the most critical items are reliably available as those items have a significant contribution to the total inventory value. This desired service levels play a crucial role when determining the safety stocks and reorder points in the later stages of this research.

Table 5: ABC Results

Class	Medications	Consumables	Sets	Accessories	Test Equipment
A	4	10	1	0	0
B	13	22	0	1	0
C	32	27	0	2	3

Moreover, in the case of medications, they are more commonly categorized as C items with 32 products followed by 13 for B class items and with the rest falling into A class items. Similarly, consumables show the highest contribution to C class items with 27 products while A class items have the lowest contribution with 10 products. These findings highlight the importance of inventory classification when setting optimal inventory levels considering the characteristics of different items in the inventory.

Now that the products are classified, each product class has a different desired service level. The class A products, which are the critical products that account for around 80% of the sales of DML should have the highest service level, such that they are almost always available. For this reason, class A products are assigned a service level of 98%. Then, class B, the interclass products, are assigned a service level of 95%. Finally, class C products are assigned a desired service level of 90%. Because class C products have a lower contribution to the sales of DML, it would not make sense for them to always be as available as class A products, because they contribute less to the total usage value of DML.

4.3 Development of inventory control policies

Since we classify products of DML into three categories with different assigned service levels, the inventory policies per product can be determined. As previously mentioned (Section 3.3.2), both continuous and periodic review policies need the service level values in order to calculate the safety stocks and reorder points. As the service levels are assigned for each group, we formulate the inventory policies. To come up with these policies, we need to make some assumptions:

- The demand remains steady over time and is normally distributed.
- Demand and lead times are presented as weeks.
- The lead time of all the products is five working days. However, for simplicity we assume that it is one week, considering that it takes a week for a product to arrive including the weekends.
- The holding costs of the products are 20% of the unit price with fixed ordering costs of €25 per order.
- For both policies, desired service level for A class items is 98%, 95% for B class items and 90% for the C class items.

It is not feasible to display the results of the policies for all products since there are over 100 items. Therefore, some examples are illustrated to show the methodology and the process behind coming up with the policies. The top two products which have the highest consumption rate per classification group are selected and the calculations are shown in Section 4.3.1.

4.3.1 Average Demand & Standard Deviation

The developed forecasting tool in AutoGluon provided the results for the average demand of the products for the time between July 2024 and July 2025 with using both ARIMA and Croston's method. The forecasting was completed in six weeks of intervals with ten time periods, totaling a forecast of 60 weeks. Therefore, the average of the demand between July 2024 and July 2025 was calculated and divided by six to obtain the weekly averages. We then used the same values from the model to calculate the standard deviations using Equation 24 and 28. Depending on the policy, the mean demand of the product is calculated.

For the continuous review policy, the annual demand which is used while calculating the EOQ represents the weekly demand of the products. The weekly demand for products were calculated by using the forecasting tool. Thus, this amount is used as the annual demand for EOQ. Additionally, continuous review policy requires the value of mean lead time. Since the lead time for all the products is defined as one week, the weekly demand already results as the mean lead time. Even though both values are needed for different purposes, the formula returns the same values.

Within the periodic review policy, mean during T+L periods is needed. T (2 weeks) represents the fixed period when the stock levels are checked while L is the lead time. Therefore, Table 6 shows the calculations for mean demand and standard deviation of both inventory control policies.

Table 6: Demand & Standard Deviation Both Policies

Product	Class	Policy Type	Mean demand	Standard deviation
Sterofundin	A	*Continuous Review Policy*	$D_L = D * L = 500.34 * 1 = 500.34$	$\sigma_L = \sqrt{L}\sigma_D = \sqrt{1} * 196.81 = 196.81$
		Periodic Review Policy	$D_{T+L} = (T + L)D = (2 + 1) * 500.34 = 1501.03$	$\sigma_{T+L} = \sqrt{T + L} * \sigma_D = \sqrt{3} * 196.81 = 340.89$
Buccolam	A	*Continuous Review Policy*	10.25	56.87
		Periodic Review Policy	30.77	98.50
Aspirin	B	*Continuous Review Policy*	47.01	29.57
		Periodic Review Policy	141.05	51.23
Heparin	B	*Continuous Review Policy*	43.39	28.84
		Periodic Review Policy	130.17	49.95
NaCl 0,9 %	C	*Continuous Review Policy*	87.98	43.82
		Periodic Review Policy	263.95	75.90
Salbutamol	C	*Continuous Review Policy*	90.77	69.03
		Periodic Review Policy	272.32	119.57

4.3.2 Continuous Review Policy: (r,Q)

Economic Order Quantity

As previously mentioned in Section 3.3.2 the number of items (the order quantity (Q)) is ordered when the inventory level reaches the reorder point (r) within the continuous review policy. In this case, the order quantity for all the products is calculated using the EOQ formula with Equation (22). In order to calculate the EOQ, the holding cost (K), annual demand (D) and ordering cost (h) are required. The calculations for annual demand were already done in Section 4.3.1. As a next step, the EOQ levels can be determined for each product. Table 7 displays the chosen products and the EOQ levels.

Table 7: EOQ Levels

Products	Unit Price	Holding costs	EOQ
Sterofundin	€0.52	€0.104	$q = \sqrt{\frac{2KD}{h}} = \sqrt{\frac{2(25)(500.34)}{(0.104)}} =$ 490.45 ≈491
Buccolam	€23.72	€4.74	10.39 ≈11
Aspirin	€0.32	€0.064	155.429 ≈156
Heparin	€0.72	€0.144	122.74≈123
NaCl 0,9 %	€0.12	€0.024	428.14 ≈429
Salbutamol	€0.12	€0.024	434.87 ≈435

Safety Stock (ss) & Re-order Point (ROP)

To develop continuous review policies, the last step is to calculate the reorder points and safety stock levels. We need the parameters of CSL and σ_L for the safety stock levels while D_L and ss are required for determining the ROP. All the parameters were derived in the previous sections. Now, we can plug them into the formulas and find our ss and ROP levels.

Table 8: SS & ROP Continuous Policy

Class	Products	Safety Stock	Reorder Point
A	Sterofundin	$F_s^{-1}(CSL) * \sigma_L = F_s^{-1}(0.98) *$ 196.81 = 404.21≈405	$ROP = D_{T+L} +$ ss =500.34+402.21=904.55≈905
	Buccolam	116.79≈117	127.05≈128
B	Aspirin	$F_s^{-1}(0.95) * 29{,}5 = 48.65$≈49	95.67≈96
	Heparin	47.43≈48	90.82≈91
C	NaCl 0,9 %	$F_s^{-1}(0.90) *$ 43.82=56.16≈57	144.14≈145
	Salbutamol	88.47≈89	179.25≈180

The results suggest that for Sterofundin, a new order should be placed when the inventory level reaches 905 units. The optimal order quantity is 491 units, and it is expected that approximately every week ($\frac{q}{E(D)} = \frac{491}{500.34} = 0.98\ weeks \approx 1$ week) the inventory reaches the reorder point. By following this policy, the company can ensure that they can achieve a 98% service level.

Similarly, one unit of Aspirin should be ordered with the reorder point of 96 units. The idea is the same for all the products and following these numbers ensures 98% ,95% and 90% of service level respectively for the A, B and C class items. Figure C.3 shows the values for all the products in Appendix C.

4.3.3 Periodic Review Policy: (T,S)

Safety Stock (ss) & Order-Up-to-Level (OUL)

The periodic review policy uses the (T,S) system. In contrast to continuous review policy, this policy focuses on the timing of the orders rather than calculating specific order quantities. This time, the inventory levels are checked after a fixed period of time $T$and the order is placed such that the current stock levels plus the replenishment lot size equals to order-up-to level (OUL) (Chopra et al., 2016). T is determined as 2 weeks and Equations (29) and (30) are used to compute safety stock and order-up-to levels for the chosen products as follows:

Table 9: SS & OUL Periodic Review

Class	Products	Safety Stock	OUL
A	Sterofundin	$F_S^{-1}(CSL) * \sigma_L =$ $F_S^{-1}(0.98) *$ 340,89 =700,11≈701	$ROP = D_{T+L} + ss$ $= 700{,}11 + 150103$ $= 2201{,}14≈2202$
	Buccolam	202,29≈203	233,06≈234
B	Aspirin	84,26≈85	225,32≈226
	Heparin	82,16≈83	212,33≈213
C	NaCl 0,9 %	56,16≈57	144,14≈145
	Salbutamol	153,24≈154	425,56≈426

Based on the results, Heparin should be ordered every 2 weeks and the current inventory levels should reach to 213 units. For example, if the current inventory level is 100 units, 113 orders should be placed for the new replenishment cycle. This policy ensures that with 95% probability, they do not experience stockouts.
Likewise, the new order for Salbutamol should be placed every 2 weeks to ensure that the current inventory level reaches the order up to level of 426 products. Appendix C shows the calculations for all the products.

4.4 Cost Evaluation

We have formulated both continuous and periodic review policies in Section 4.3. Now, we want to evaluate the costs of the formulated policies and analyze the results. To begin, average inventory levels (AIL) per policy are derived. AIL represent an estimation of the expected annual stock levels. Thus, the total holding costs are calculated by multiplying the average inventory levels with the holding cost (h) of the products. Accordingly, total ordering costs are calculated by multiplying the number of orders per period and the unit ordering costs (S). The total inventory cost is then the summation of both holding and ordering costs. The formulas necessary to calculate are illustrated in Table 10.

In general, the periodic review policy requires to purchase in fixed intervals, which were selected as two weeks, and for the continuous review policy, for some products, the calculations suggest that the products should be ordered in intervals shorter than two weeks.

This resulted in higher ordering costs and overall higher total inventory costs for the continuous review policy, since the ordering cost has a higher weight than the holding cost.

As can be seen from Table 9 and 10, some products resulted in a lower total cost within the continuous review policy while some of them were lower for the periodic review policy. Sterofundin and Buccolam have higher unit prices which also means that they have higher holding costs. However, their ordering costs are also quite high, especially for the continuous review policy. Within the continuous review policy for both of these products, the average inventory levels are much lower than in the periodic review policy, resulting in many more orders during the year. This means that the ordering costs are much higher. In this case and with the assumptions taken previously, the ordering costs outweigh the holding costs, so the periodic review policy is cheaper.

Conversely, Aspirin, Heparin, NaCI and Salbutamol have higher overall costs with the periodic review policy. These items are lower in demand and demand variability compared to Sterofundin and Buccolam which results as higher ordering costs for the periodic review policy. When both demand and standard deviation are low, it is not optimal to order very frequently. Therefore, placing an order every ordering period (T) might be unnecessary for these items. Since the ordering cost have much more weight in the total cost, these items are relatively cheaper within the continuous review policy. Table 9 shows the formulas for both inventory costs and AIL. Tables 11 and 12 illustrate the overall costs for both policies with the chosen products.

Table 10: Average Inventory Level and Cost Formulas

Policy	**AIL**	**Total Holding Costs**	**Total Ordering Costs**	**Total Costs**
Continuous Review	$\frac{Q}{2} + ss$	$AIL * h$	$\frac{D}{Q} * S$	Total Holding Costs+ Total Ordering Costs
Periodic Review	$\frac{DT}{2} + ss$	$AIL * h$	$\frac{1}{T} + \left(\frac{DT}{2} + ss\right) * h$	Total Holding Costs+ Total Ordering Costs

Table 11: Continuous Policy Costs

Products	AIL (C)	Ordering Cost	Holding cost	Total cost
Sterofundin	649,44	25,50	1,29	26,80
Buccolam	121,99	24,66	11,12	35,79
Aspirin	144,48	6,13	0,17	6,31
Heparin	108,80	8,83	0,30	9,13
NaCl 0,9 %	270,23	5,13	0,12	5,26
Salbutamol	18,77	3,17	0,16	3,33

Table 12: Periodic Policy Costs

Products	AIL (P)	Ordering Cost	Holding cost	Total cost
Sterofundin	2201,14	12,50	4,40	16,90
Buccolam	233,06	12,50	21,26	33,76
Aspirin	225,32	12,50	0,27	12,77
Heparin	212,33	12,50	0,58	13,08
NaCl 0,9 %	361,23	12,50	0,16	12,66
Salbutamol	25,58	12,50	0,21	12,71

We only showed a couple of examples from the product list. When we look at the general distribution of the selected policies, we observed that 90.83% of the products have lower costs using the continuous policy while the rest (9.16%) is more cost-efficient for the periodic review policy. Specifically, 10 out of the 15 products that belong to A class items are more cost-efficient with the periodic review policy. In contrast, all the products of B class and C class items consistently resulted in lower costs with the continuous review policy. Even though the continuous review policy is more cost-efficient compared to periodic review policy, it requires more human work which means higher monitoring costs. Because the inventory levels should be reviewed every day, and the order should be placed when the inventory reaches to the reorder point. This is not the case for the periodic review policy as there is a fixed review period for checking the inventory. This situation is a trade-off that company should decide on.

4.5 Conclusion

The fourth chapter applied the theory, which was reviewed in the third chapter, with the goal of answering the following two sub-research questions:

1. *How can the inventory methods be applied to DML's inventory management?*
2. *How can DML formulate effective inventory policies to optimize the inventory of tracer diagnosis supplies based on the findings from the literature and the application of the methods?*

Coming up with inventory policies for DML to follow included analyzing their past demand data. Through this analysis, a forecasting tool was made. Since the demand data was incomplete, the data had to first be completed using the mean and the standard deviation of the provided data. After that, the demand was forecasted for the following year using AutoML. Using the outcome of the tool, the products with their corresponding demands for the following year were categorized using the ABC analysis. Then, using two different inventory management strategies, continuous and periodic review policies, inventory management policies were made for each product of the 120 tracer diagnosis products with the specified service levels. Since the tables with the results are made on Excel and are too large to show, examples of each product type (ABC) were provided to show how the calculations were made. Following the development of the inventory policies, a cost analysis was made to evaluate the total costs per product for both the inventory policies. The results show that 90,83% of the products have a lower cost using the continuous policy. A flowchart of the whole process which explains how the forecasting method and inventory management techniques are merged are illustrated in Figure D.1 (Appendix D).

5. RECOMMENDATIONS & CONCLUSION

Within the fifth chapter, the recommendations and conclusions are given. **Section 5.1** gives the recommendations to DML following the cost evaluation of the policies. Then, **Section 5.2** concludes this thesis. Finally, **Section 5.3** discusses the future research opportunities which arise as an outcome to this research.

5.1 Recommendations

The first recommendation for DML is to replace the holding costs and ordering costs for each product in the Excel sheet which contains the calculations for the reorder points and order-up-to levels with the real-life cost values (See Appendix C , Fig. C.3). By doing so, and dragging down the columns, Excel automatically recalculates the total costs using the updated values which results in more accurate and cost-effective inventory policies.

Following that, DML should also consider the trade-offs of using a continuous and periodic review policy regarding checking the inventories daily for the continuous review policy. If DML decides to use continuous review policies for any products, they should purchase an automated system which can interact with their ERP system and update them with the inventory levels of each product.

In general, DML should make use of the forecasting tool to input the more recent past demand data to forecast the future demand more accurately. Then, they can use the forecasted demand to come up with inventory policies for the following year. This should be done at the end of each year to ensure that they are ready to meet the desired service levels in the following years.

5.2 Conclusion

DML is faced with the problem of meeting desired service levels for their tracer diagnosis products. Currently, the service levels are at 75%, meaning that there is a 25% probability of losing sales when replenishing the orders. DML would like the desired service levels to reach 90%, 95%, and 98%, depending on the importance of the product with respect to the revenue demand, and criticality. With these requirements from DML, a research question was made to guide this research. The goal of this research was to answer the following research question:

"How can the Department of Medical Logistics (DML), L2R's customer, optimize the inventory of medical products used in tracer diagnosis, particularly in emergency services, to ensure that their desired service levels are met?"

To answer the research question in more detail, sub-research questions are formulated which breaks down the research question into smaller parts and shape the format of this research. Using these sub-research questions, a conclusion is made.

Firstly, by categorizing inventory items into A, B, and C classes based on their consumption value, the research uses the ABC Analysis to prioritize products within the product portfolio. Class A items, representing the highest usage value receive more attention by having a higher service level assigned to them while Class B and C items receive a lower service level. This method allows DML to ensure that critical items are always available while minimizing holding costs for less critical items.

Secondly, the research used several quantitative forecasting methods, which were all included in the AutoGluon forecasting tool. The methods include time series analysis such as ARIMA, Exponential Smoothing, and Croston's method. These methods provide a reliable way for predicting DML's future demand considering the trend and seasonal factors.

Finally, the study applied the Economic Order Quantity (EOQ) model to determine optimal order quantities and inventory levels. Continuous review policies (r,Q) and periodic review policies (T,S) were used to determine the reorder points and safety stock levels with the desired service levels. The results show that 90,83% of the products have a lower cost using the continuous policy, while the remaining 9,17% of the products have a lower cost using the periodic review policy. These policies ensure that stock levels are sufficient to meet demand without experiencing stockouts. DML can choose to apply the recommendations provided within this research to further ensure that the desired service levels are met.

5.3 Future Research

This research highlights several key areas where further investigation and research could help DML with gaining valuable insights.

The first future research opportunity is about enhancing the forecasting tool which was made using AutoGluon. While AutoGluon provides effective demand forecasting, future research could explore more advanced forecasting tools and techniques to achieve even better and more accurate forecasts. This is particularly important when growing the solution to support other customers that handle a larger number of inventory items. In such cases, deep machine learning methods are capable of capturing more complex patterns in demand and might provide more reliable results.

Furthermore, the forecasting tool can be updated, such that it always provides real-time data based on the current demand and orders. This was not possible to do with the provided data since the data was from 2019-2022 and it was not up to date.

A future study could explore the right value of desired service level based on total costs. An analysis on the total inventory costs can be made by comparing the total cost and service levels and choosing the optimal service levels based on the costs. Then, new inventory policies can be made based on the new chosen desired service levels.

Another future research opportunity would include implementing the recommendations at DML. The implementation of these methods is quite complex and should be done in the future. For the implementation, the organizational structure needs to change. Furthermore, the technology currently used at DML needs to be integrated with the new policies. The LIS and Kanban Card Systems must be integrated together such that the system is always up to date. By addressing these future research opportunities, DML can continue to improve their inventory management control, ensuring that they meet their demand with a minimized cost.

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Appendix

Appendix A

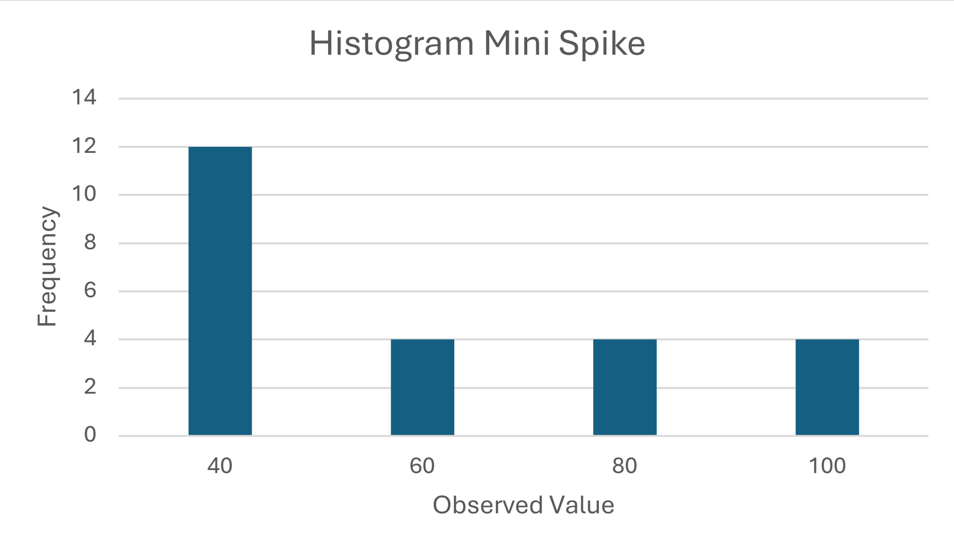
Variable	Norm	Reality	Problem owner
Service level of medical devices and consumables required in tracer diagnosis	98%, 95%, 90% service level	75% service level	Department of Medical Logistics (DML)

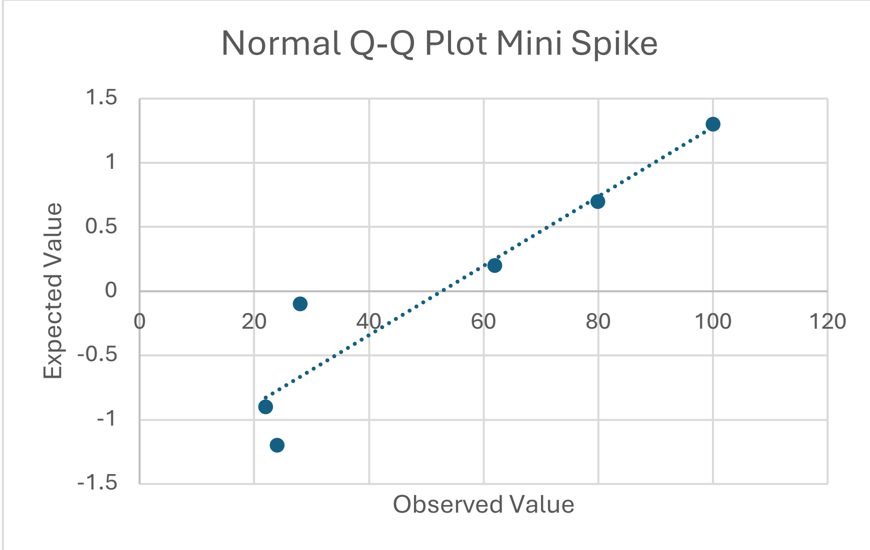
Table A.1

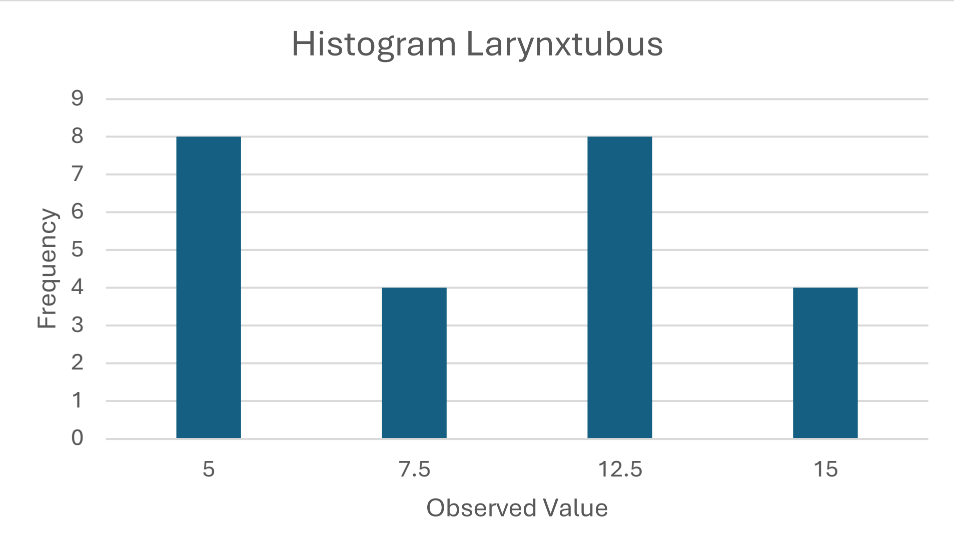
Knowledge questions	Data source	Data type	Research type	Research population	Data gathering methods	Activities
1. ***What are the current strategies to store and manage the medical devices and consumables?***	Qualitative	Primary data	Descriptive	Company	Interviews with employees	▪ Observation of the current process. ▪ Process flow of supply chain
2. ***What are the recommended product classification methods in the literature?***	Qualitative	Secondary data	Descriptive	Literature	Literature Review	▪ Identifying product classification methods
3. ***Which demand forecasting techniques exist in the literature?***	Qualitative	Secondary data	Descriptive	Literature	Literature Review	▪ Identifying demand forecasting techniques
4. ***What are the recommended inventory policies in the literature?***	Qualitative	Secondary data	Descriptive	Literature	Systematic Literature Review	▪ Defining the existing inventory methods
7. ***How can the recommended inventory policies be applied to DML's inventory management?***	Qualitative, Quantitative	Primary data, Secondary data	Descriptive	Company, Literature	Mathematical models and Excel	▪ Calculations for the inventory parameters ▪ Application of demand forecasting and product classification methods ▪ Development of decision-making model
5. ***How can DML formulate effective inventory management strategies to optimize the inventory of tracer diagnosis supplies based on the findings from the literature and the application of the policies?***	Qualitative	Secondary data	Descriptive	Company	Data analysis and Literature review	▪ Recommendations for developing inventory policy(s)

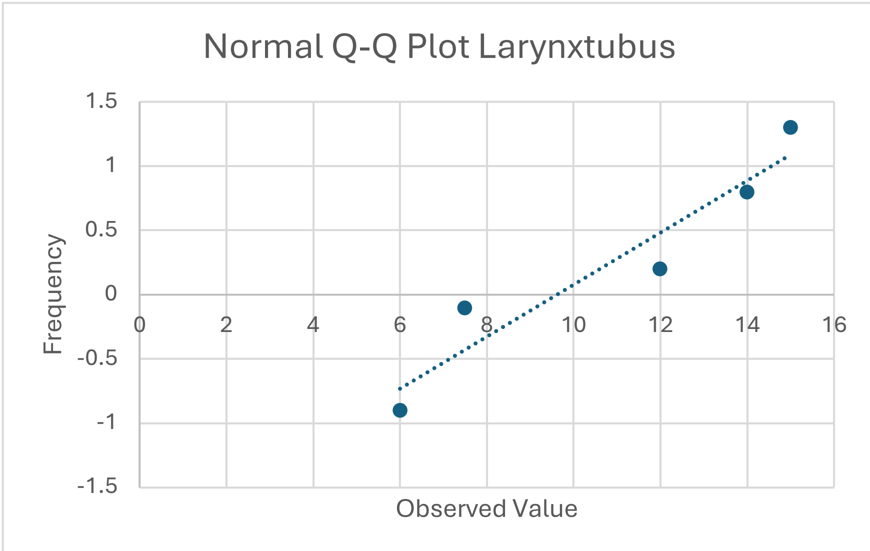
Table A.2

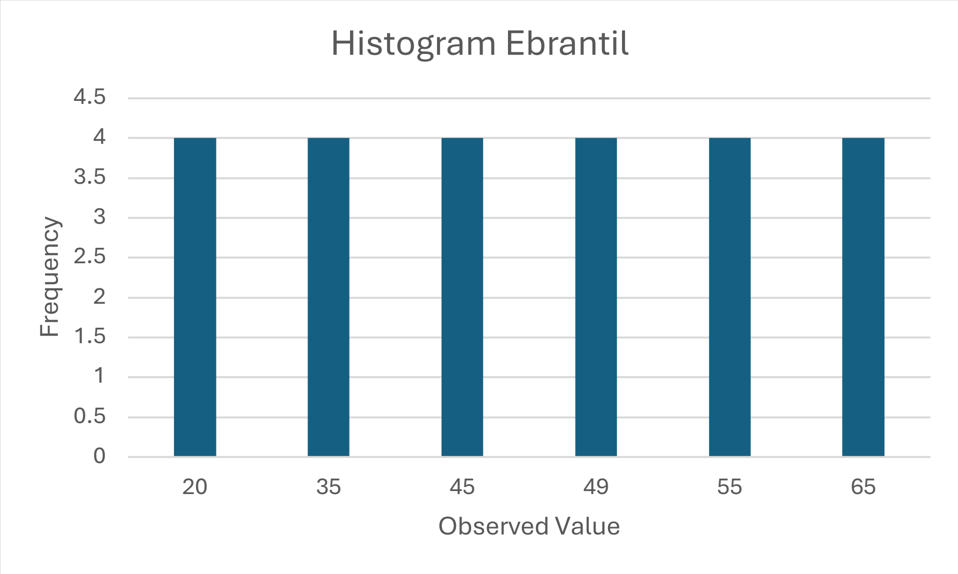
Appendix B

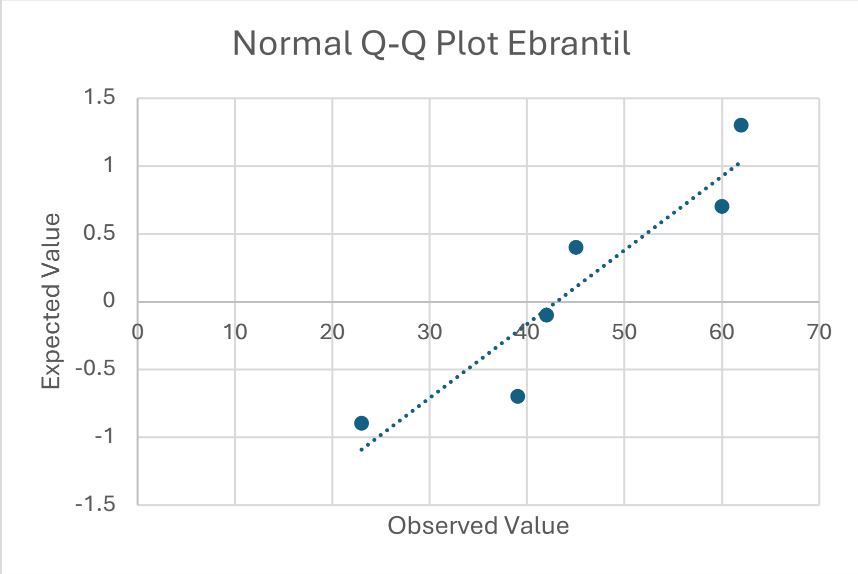

Histogram Mini Spike
Frequency
14
12
10
8
6
4
2
0
40
60
80
100
Observed Value

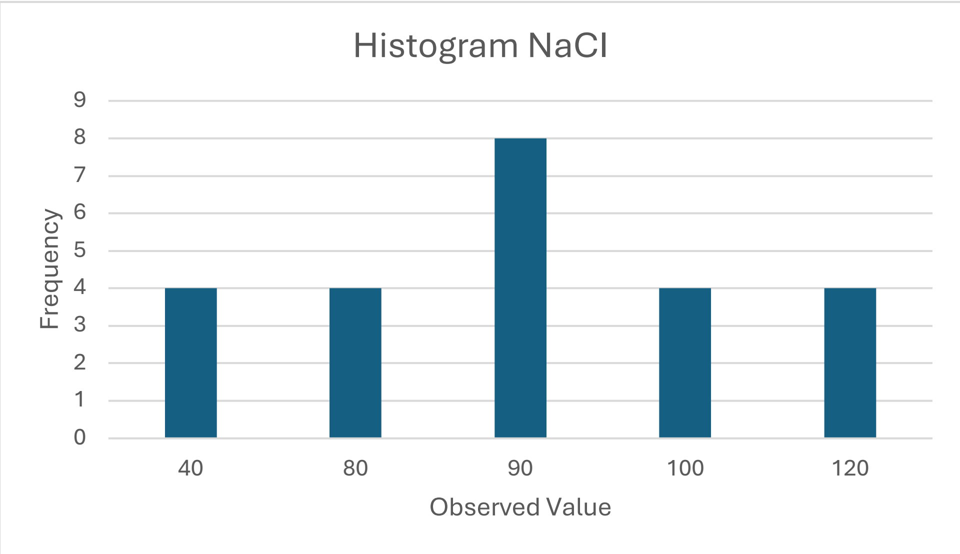

Normal Q-Q Plot Mini Spike
Expected Value
1.5
1
0.5
0
-0.5
-1
-1.5
0
20
40
60
80
100
120
Observed Value

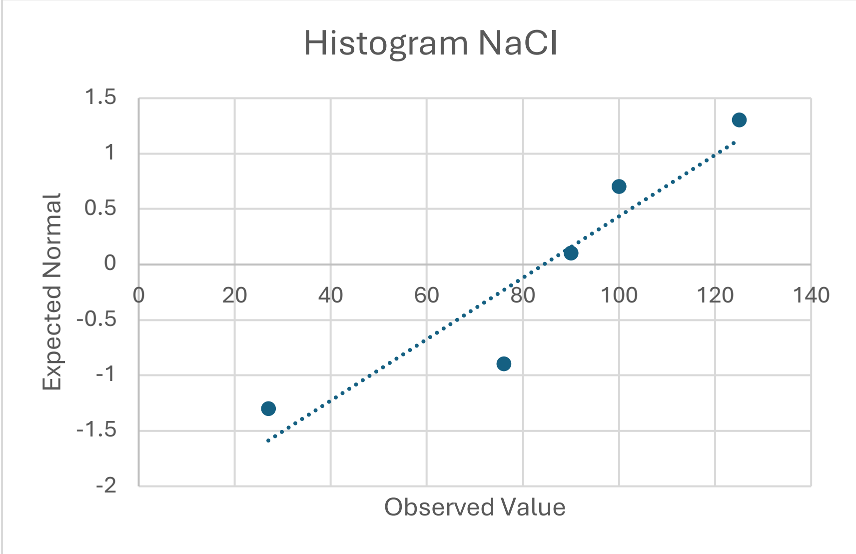

Histogram Larynxtubus
Frequency
9
8
7
6
5
4
3
2
1
0
5
7.5
12.5
15
Observed Value

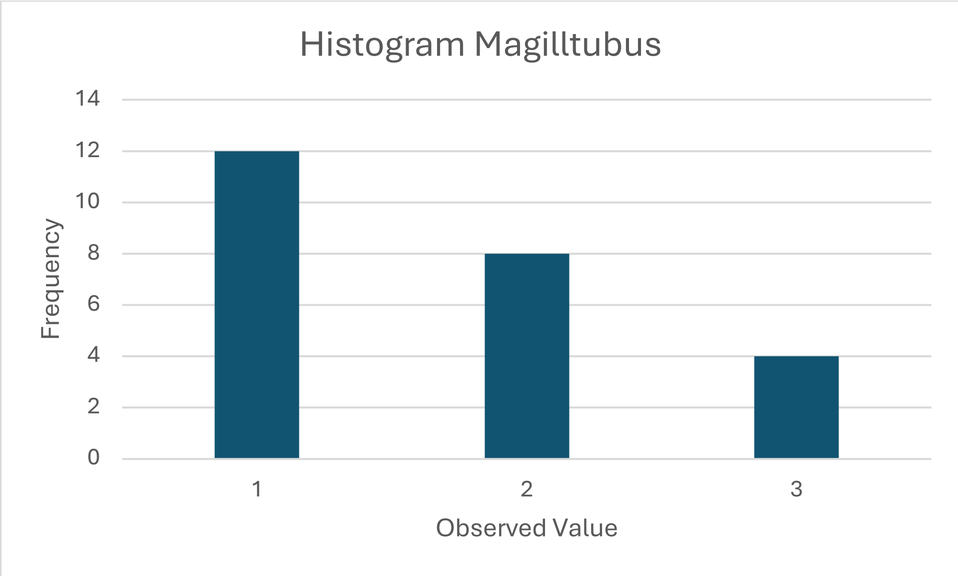

Normal Q-Q Plot Larynxtubus
Frequency
1.5
1
0.5
0
-0.5
-1
-1.5
0
2
4
6
8
10
12
14
16
Observed Value

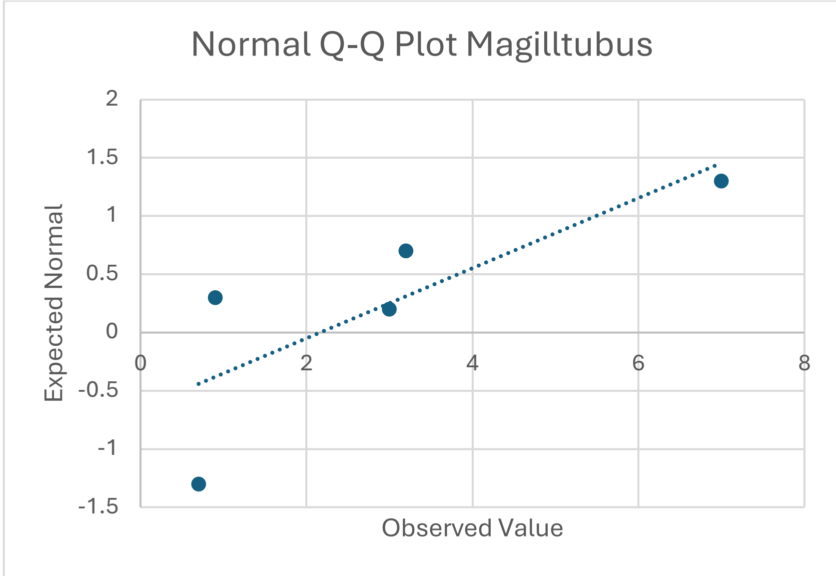

Histogram Ebrantil
Frequency
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
20
35
45
49
55
65
Observed Value


Normal Q-Q Plot Ebrantil
Expected Value
1.5
1
0.5
0
-0.5
-1
-1.5
0
10
20
30
40
50
60
70
Observed Value


Histogram NaCl
Frequency
9
8
7
6
5
4
3
2
1
0
40
80
90
100
120
Observed Value


Histogram NaCl
Expected Normal
1.5
1
0.5
0
-0.5
-1
-1.5
-2
0
20
40
60
80
100
120
140
Observed Value


Histogram Magilltubus
Frequency
0
2
4
6
8
10
12
14
1
2
3
Observed Value


Normal Q-Q Plot Magilltubus
Expected Normal
2
1.5
1
0.5
0
-0.5
-1
-1.5
0
2
4
6
8
Observed Value

Appendix C

```
import pandas as pd

data = pd.read_excel(path)
# Convert timestamp column to datetime
data["timestamp"] = pd.to_datetime(data["timestamp"])

data.head()

# Calculate daily sales for each Product and put 0 for missing weeks
daily_sales_sums = (
    data.groupby(["articleName", pd.Grouper(key="timestamp", freq="D")])["quantity"]
    .sum()
    .unstack()
    .fillna(0)
)

# Transpose the data to have products as rows and dates as columns
timeseries = daily_sales_sums.T
# Sort the data by date
timeseries.sort_index(inplace=True)

# Take each product from columns and put as rows of one column
timeseries = pd.melt(timeseries.reset_index(), id_vars="timestamp", var_name="articleName", value_name="demand")
```

```
# For every product in the data calculate mean and std of the demand
# Then generate random values from a normal distribution with the calculated mean and std until 2024
import numpy as np

# Calculate mean and std of the demand for each product
mean_demand = timeseries.groupby("articleName")["demand"].mean()
std_demand = timeseries.groupby("articleName")["demand"].std()
```

```
# Write mean and std for every product to a csv file
mean_std = pd.DataFrame({"mean": mean_demand, "std": std_demand})
mean_std.to_csv("mean_std.csv")
```

```python
# Generate random values from a normal distribution with the calculated mean and std until 2024
# Create a dataframe to store the generated values
generated_data = pd.DataFrame(columns=["timestamp", "articleName", "demand"])

# Set the seed for reproducibility
np.random.seed(0)

# Calculate how many days are there till 2024 from the last date in the data
days_till_2024 = (
    pd.Timestamp("2024-01-01") - timeseries["timestamp"].max()
).days

# Generate dates until 2024
generated_dates = pd.date_range(
    start=timeseries["timestamp"].max() + pd.Timedelta(days=1),
    periods=days_till_2024,
    freq="D",
)

# For each product generate random values from a normal distribution with the calculated mean and std
for item_id in timeseries["articleName"].unique():
    mean = mean_demand[item_id]
    std = std_demand[item_id]
    type = data[data['articleName'] == item_id]['type'].iloc[0]
    # Generate random values from a normal distribution with the calculated mean and std
    generated_values = np.random.normal(mean, std, days_till_2024)
    # Round up the generated values
    generated_values = np.round(generated_values, 0)
    # Make negative values 0
    generated_values[generated_values < 0] = 0
    # Generate dates until 2024

    generated_data = pd.concat(
        [
            generated_data,
            pd.DataFrame(
                {
                    "timestamp": generated_dates,
                    "articleName": item_id,
                    "demand": generated_values,
                    "type": type,
```

Figure C.1

```
QUALITY_CHOISES = ["fast_training", "medium_quality, high_quality, best_quality"]
EVAL_METRIC_CHOISES = ["MAPE", "MSE"]
HYPER_PARAMETERS = {
      "AutoARIMAModel": {},
      "ETS": {},
      "Naive": {},
      "SeasonalNaive": {},
      "CrostonSBAModel": {},
}
```

```
prediction_length = 10
freq = "6W"
quality_of_model = "fast_training"
eval_metric = "MSE"
```

```
if quality_of_model not in QUALITY_CHOISES:
    print("Quality of model is not in the choises please choose one of the following: fast_training, medium_quality, high_quality, best_quality")
```

```
from pathlib import Path
# Get the path to the data file and if data name is wrong or file is not found
# print an error message
path = Path('data') / 'data.xlsx'
if not path.exists():
    print("Data file not found please make sure the data file is in the data folder and named as data.xlsx")
```

```
import pandas as pd

data = pd.read_excel(path)
# Convert timestamp column to datetime
data["timestamp"] = pd.to_datetime(data["timestamp"])
# Remove products which types are contains with "medical device"
data.loc[:, "type"] = data["type"].fillna("unknown")
data = data[~data["type"].str.contains("medical device")]
# Show the unique types of the products
data["type"].unique()
```

```python
# Find the type for every product
static_features = data.groupby("articleName")
static_features = static_features[["articleName", "type"]].first()
static_features.reset_index(drop=True, inplace=True)

# Calculate weekly sales for each Product and put 0 for missing weeks
daily_sales_sums = (
    data.groupby(["articleName", pd.Grouper(key="timestamp", freq="D")])["demand"]
    .sum()
    .unstack()
    .fillna(0)
)

# Transpose the data to have products as rows and dates as columns
timeseries = daily_sales_sums.T
# Sort the data by date
timeseries.sort_index(inplace=True)

# Take each product from columns and put as rows of one column
timeseries = pd.melt(timeseries.reset_index(), id_vars="timestamp", var_name="articleName", value_name="demand")
```

```python
from autogluon.timeseries import TimeSeriesDataFrame
# Define the prediction length
# Create a TimeSeriesDataFrame
timeseries = TimeSeriesDataFrame(
    timeseries, timestamp_column="timestamp", id_column="articleName", static_features=static_features
)
# Convert the frequency of the data to weekly
timeseries = timeseries.convert_frequency(freq=freq)
# Seperate the data into train and test sets
train_data, test_data = timeseries.train_test_split(prediction_length=prediction_length)
# Fill missing values with 0
train_data.fillna(0, inplace=True)
test_data.fillna(0, inplace=True)
# Instead of averages, we will use the sum of sales for the prediction
number_of_days_in_freq = pd.date_range(start=train_data.index[0][1], end=train_data.index[1][1], freq='D').shape[0] - 1
train_data.loc[:, "demand"] = train_data["demand"] * number_of_days_in_freq
test_data.loc[:, "demand"] = test_data["demand"] * number_of_days_in_freq
```

```python
from autogluon.timeseries import TimeSeriesPredictor, TimeSeriesDataFrame
model_path = Path("AutogluonModels") / (quality_of_model + "_" + freq + "_" + eval_metric + "_Predict" + str(prediction_length))
# Create a TimeSeriesPredictor
predictor = TimeSeriesPredictor(
    path=model_path,
    prediction_length=prediction_length,
    eval_metric=eval_metric,
    target="demand",
    freq=freq
)
# Train the model
predictor.fit(train_data=train_data, presets=quality_of_model, hyperparameters=HYPER_PARAMETERS)
```

	model	score_val	pred_time_val	fit_time_marginal	fit_order
0	WeightedEnsemble	-7.068334e+05	174.297411	2.199725	6
1	AutoARIMA	-7.158580e+05	166.847806	0.055479	5
2	SeasonalNaive	-1.189157e+06	1.686496	0.050505	2
3	Naive	-1.189157e+06	2.206358	0.073348	1
4	ETS	-1.189845e+06	36.917669	0.053210	3
5	CrostonSBA	-1.622344e+06	7.449605	0.051796	4

```python
# Make predictions using train_data
train_predictions = predictor.predict(train_data)
# Create predictions directory if it does not exist
Path("predictions").mkdir(exist_ok=True)
train_predictions_path = Path("predictions") / ("train_predictions_" + (quality_of_model + "_" + freq + "_" + eval_metric + "_Predict" +
                                                                       str(prediction_length)) +".xlsx")
# Get types for every row from static features
train_predictions["timestamp"] = train_predictions.index.get_level_values("timestamp")
train_predictions = train_predictions.merge(static_features, left_on="item_id", right_on="item_id")
train_predictions = TimeSeriesDataFrame(train_predictions)
train_predictions.to_excel(train_predictions_path)
```

```python
# Make predictions using test_data
test_predictions = predictor.predict(test_data)
test_predictions_path = Path("predictions") / ("test_predictions_" + (quality_of_model + "_" + freq + "_" + eval_metric + "_Predict" +
                                                                      str(prediction_length)) +".xlsx")
# Get types for every row from static features
test_predictions["timestamp"] = test_predictions.index.get_level_values("timestamp")
test_predictions = test_predictions.merge(static_features, left_on="item_id", right_on="item_id")
test_predictions = TimeSeriesDataFrame(test_predictions)
test_predictions.to_excel(test_predictions_path)
```

Figure C.2

Product Name	Type	Forecasted demand (weeks)	Standard deviation(week	Unit price	Holding cost	Ordering cost	Lead time(week)	Class	CSL	Continuous Review Policy	EOQ	Frequency of the orders (week	Safety Stock	Reorder Poin	Periodic Review Policy	Review Period(T	Mean during T+L period	Standard deviation during T+L perio	Safety Stock2	Order up-to level(OUL	AIL	Ordering Co	Holding Co	Total cost	AIL2	Ordering Cost3	Holding c	Total cost2	Selected Policy
Adrekar	medication	6,092884064	11,50065874	5,36	1,072	25	1	B	0,95		16,85773	2,766789713	18,91690025	25,00978431		2	18,27865219	19,91972526	32,76503235	51,04368454	27,345765	9,03574272	0,5637435	9,599486	51,04368	12,5	1,052285	13,5522852	Continuous Review Policy
Adrenalin jenapharm	medication	30,92246424	82,16774233	0,32	0,064	25	1	C	0,90		155,429	5,026410653	105,3021988	136,2246631		2	92,76739273	142,3187045	182,3887585	275,1561512	183,0167	4,97372812	0,2252513	5,198979	275,1562	12,5	0,338654	12,8386537	Continuous Review Policy
Alpred forte	medication	0,668038118	1,356801051	1,3	0,26	25	1	C	0,90		11,33441	16,96671271	1,738810511	2,406848628		2	2,004114354	2,350048355	3,011708149	5,015822503	7,4060159	1,47347341	0,0370301	1,510503	5,015823	12,5	0,025079	12,5250791	Continuous Review Policy
Ampuwa 20 ml	medication	6,439452616	15,38200444	0,15	0,03	25	1	C	0,90		103,5974	16,08792003	19,71283187	26,15228449		2	19,31835785	26,64241321	34,14362636	53,46198421	71,511531	1,55396098	0,0412567	1,595218	53,46198	12,5	0,030843	12,5308435	Continuous Review Policy
Anexate	medication	1,704583995	3,629633924	6,48	1,296	25	1	C	0,90		8,109456	4,757439765	4,651563038	6,356147033		2	5,113751984	6,28671037	8,056743516	13,1704955	8,7062909	5,25492728	0,2169876	5,471915	13,1705	12,5	0,328249	12,8282493	Continuous Review Policy
Anticholium	medication	0,339654521	2,786873995	6,55	1,31	25	1	C	0,90		3,600543	10,60060506	3,571522732	3,911177253		2	1,018963563	4,827007354	6,186058832	7,205022395	5,3717944	2,35835595	0,1353279	2,493684	7,205022	12,5	0,181511	12,6815111	Continuous Review Policy
Arterenol 1 ml	medication	11,41642316	32,74650109	0,41	0,082	25	1	C	0,90		83,43401	7,308244139	41,96632973	53,38275289		2	34,24926949	56,71860365	72,6878153	106,9370848	83,683334	3,42079431	0,1319622	3,552756	106,9371	12,5	0,168632	12,6686316	Continuous Review Policy
Aspirin i.V.	medication	47,01931508	29,57886223	0,32	0,064	25	1	B	0,95		191,6607	4,076212964	48,65289882	95,67221391		2	141,0579453	51,23209222	84,2692927	225,3272379	144,48327	6,13314373	0,1778256	6,310969	225,3272	12,5	0,277326	12,7773258	Continuous Review Policy
BACTEC Plus Anaerobic (orange)	medication	5,584423129	10,87393325	5,1	1,02	25	1	B	0,95		16,54528	2,962755123	17,88602854	23,47045167		2	16,75326939	18,83420486	30,97951018	47,73277956	26,158668	8,4380919	0,5131123	8,951204	47,73278	12,5	0,936297	13,4362968	Continuous Review Policy
Beloc 5 ml	medication	16,88439573	10,04949871	0,51	0,102	25	1	C	0,90		90,97618	5,388180739	12,8789508	29,76334653		2	50,65318718	17,40624235	22,30699713	72,96018431	58,367039	4,63978497	0,1144892	4,754274	72,96018	12,5	0,143114	12,6431142	Continuous Review Policy
Berotec N	medication	0,805139375	6,92820323	3,93	0,786	25	1	C	0,90		7,156641	8,888698924	8,878849696	9,683989071		2	2,415418124	12	15,37861879	17,79403691	12,45717	2,81256011	0,1882949	3,000855	17,79404	12,5	0,268964	12,7689637	Continuous Review Policy
Bronchiospasmin	medication	11,22377828	98,8289002	0,42	0,084	25	1	C	0,90		81,73629	7,282421631	126,6543318	137,8781101		2	33,67133484	171,1766764	219,3717376	253,0430725	167,52247	3,432924	0,2706132	3,703537	253,0431	12,5	0,408762	12,9087619	Continuous Review Policy
Buccolam 5 mg FSP	medication	10,25680319	56,87040025	23,72	4,744	25	1	A	0,98		10,39725	1,013693474	116,7975226	127,0543257		2	30,77040958	98,50242267	202,2992433	233,0696528	121,99615	24,6622876	11,129803	35,79209	233,0697	12,5	21,26312	33,7631237	Periodic Review Policy
Buscopan	medication	9,420366732	9,046596547	0,41	0,082	25	1	C	0,90		75,79001	8,045335714	11,59367997	21,0140467		2	28,2611002	15,66916486	20,08084275	48,34194295	49,488686	3,10739053	0,0780399	3,18543	48,34194	12,5	0,076232	12,5762315	Continuous Review Policy
C3 CorPatch easy Pediatric (10)	consumables md	0,719328237	1,715938357	431	86,2	25	1	A	0,98		0,645944	0,89798238	3,524106531	4,243434768		2	2,15798471	2,972092417	6,103931563	8,261916273	3,8470786	27,8401899	6,3772726	34,21746	8,261916	12,5	13,69572	26,1957151	Periodic Review Policy
C3 CorPatch easy pre-connected (Erw) (10)	consumables md	2,94455115	2,539088359	390	78	25	1	A	0,98		1,373875	0,466582182	5,214649952	8,159201102		2	8,83365345	4,397830043	9,032038661	17,86569211	5,9015875	53,5811289	8,8523813	62,43351	17,86569	12,5	26,79854	39,2985382	Periodic Review Policy
Calcium	medication	5,522023392	25,85390188	0,28	0,056	25	1	C	0,90		70,21665	12,71574669	33,13310843	38,65513182		2	16,56607018	44,78027163	57,38822721	73,95429739	68,241434	1,96606622	0,0734908	2,039557	73,9543	12,5	0,079643	12,5796431	Continuous Review Policy
Cathejell	medication	21,0418176	21,45538006	0,56	0,112	25	1	C	0,90		96,92094	4,606110633	27,4961759	48,5379935		2	63,1254528	37,16180835	47,62477367	110,7502265	75,956646	5,42757263	0,1635989	5,591172	110,7502	12,5	0,238539	12,7385389	Continuous Review Policy
Chir. Best. Susi (Set)	set	2,233527422	4,640892025	36,5	7,3	25	1	A	0,98		3,911283	1,751168464	9,531226941	11,76475436		2	6,700582266	8,03826078	16,50856932	23,20915159	11,486868	14,2761822	1,6125796	15,88876	23,20915	12,5	3,258208	15,7582078	Periodic Review Policy
Cordarex 100 mg	medication	28,99910762	29,27093915	0,79	0,158	25	1	B	0,95		95,79631	3,303422647	48,14641043	77,14551804		2	86,99732285	50,69875379	83,39202906	170,3893519	96,044565	7,5679084	0,2918277	7,859736	170,3894	12,5	0,517721	13,0177215	Continuous Review Policy
Cyklokapron 1000mg 10ml	medication	1,755714782	3,918680978	9,53	1,906	25	1	B	0,95		6,786573	3,865418948	6,445656619	8,201371401		2	5,267144346	6,787354552	11,16420475	16,4313491	9,8389432	6,46760425	0,3606351	6,828239	16,43135	12,5	0,602272	13,1022721	Continuous Review Policy
Dormicum	medication	34,71468175	39,99194995	1,1	0,22	25	1	B	0,95		88,82399	2,558686441	65,78090392	100,4955857		2	104,1440453	69,2680892	113,9358678	218,079913	110,1929	9,7706384	0,4662007	10,23684	218,0799	12,5	0,922646	13,4226458	Continuous Review Policy
Ebrantil	medication	37,78272247	40,89111558	0,54	0,108	25	1	B	0,95		132,2573	3,500471131	67,25989977	105,0426222		2	113,3481674	70,82548976	116,4975637	229,8457311	133,38856	7,14189578	0,2770378	7,418934	229,8457	12,5	0,477372	12,9773719	Continuous Review Policy
Fentanyl	medication	37,42664134	20,00056817	0,56	0,112	25	1	B	0,95		129,2607	3,453707575	32,8980071	70,32464844		2	112,279924	34,64200026	56,98101977	169,2609438	97,528344	7,23859778	0,210061	7,448659	169,2609	12,5	0,364562	12,864562	Continuous Review Policy
FFP 3 Masken	consumables su	2247,221387	7151,340921	0,7	0,14	25	1	A	0,98		895,8678	0,39865577	14687,05863	16934,28001		2	6741,66416	12386,48582	25438,73175	32180,39591	15134,993	62,7107441	40,748057	103,4588	32180,4	12,5	86,63953	99,1395275	Periodic Review Policy
Glucose 10 %	medication	15,08989334	17,9972641	2,13	0,426	25	1	B	0,95		42,08461	2,788926812	29,60286513	44,69275847		2	45,26968002	31,17217582	51,27366646	96,54334648	50,645169	8,96402153	0,4149008	9,378922	96,54335	12,5	0,790913	13,2909128	Continuous Review Policy
Haldol	medication	2,977713871	7,115390915	0,19	0,038	25	1	C	0,90		62,59429	21,02092012	9,118740367	12,09645424		2	8,933141613	12,32421858	15,79412162	24,72726323	40,415883	1,18929142	0,0295347	1,218826	24,72726	12,5	0,01807	12,5180699	Continuous Review Policy
Hamilton Beatmungsschlauch (20)	consumables md	0,568523645	0,527046277	15,75	3,15	25	1	C	0,90		3,004028	5,283910578	0,675436981	1,243960626		2	1,705570936	0,912870929	1,169891168	2,875462105	2,177451	4,73134426	0,1319033	4,863248	2,875462	12,5	0,174187	12,6741866	Continuous Review Policy
Hansaplast 6cm	consumables su	10,72240512	28,83652986	1,9	0,38	25	1	B	0,95		37,56119	3,503056145	47,43187073	58,15427585		2	32,16721535	49,94633484	82,15441001	114,3216254	66,212464	7,13662555	0,4838603	7,620486	114,3216	12,5	0,835427	13,3354273	Continuous Review Policy
Heparin	medication	43,39	28,84	0,72	0,144	25	1	B	0,95		122,7435	2,828843561	47,4375786	90,8275786		2	130,17	49,95234529	82,16429633	212,3342963	108,80934	8,83753359	0,3013182	9,138852	212,3343	12,5	0,588003	13,0880027	Continuous Review Policy
Hyperventilationsmaske	consumables su	15,04280027	24,07878483	0,85	0,17	25	1	B	0,95		66,51581	4,421770489	39,60607656	54,64887682		2	45,1284008	41,70567871	68,59973688	113,7281377	72,863982	5,65384388	0,2382092	5,892053	113,7281	12,5	0,371804	12,8718035	Continuous Review Policy
I-STAT Kartusche-CG4+	consumables md	2,411945438	27,5317998	5,1	1,02	25	1	C	0,90		10,87348	4,50817926	35,28342113	37,69536657		2	7,235836315	47,68647607	61,11267806	68,34851438	40,720162	5,54547602	0,7987416	6,344218	68,34851	12,5	1,340682	13,8406824	Continuous Review Policy
I-STAT Kartusche-CG8+	consumables md	3,17447834	26,98114421	7,06	1,412	25	1	B	0,95		10,60239	3,339884665	44,38003291	47,55451125		2	9,52343502	46,73271262	76,86847185	86,39190687	49,681229	7,48528842	1,3490364	8,834325	86,39191	12,5	2,345873	14,8458725	Continuous Review Policy
I-STAT Kartusche-cTnL	consumables md	2,520254437	48,15357377	9,5	1,9	25	1	B	0,95		8,143862	3,231364933	79,20558046	81,7258349		2	7,560763311	83,40443633	137,1880896	144,7488529	83,277511	7,73666872	3,0428321	10,7795	144,7489	12,5	5,2889	17,7889004	Continuous Review Policy
I-STAT Kontrolllösung CG4 und CG8	testequipment	1,65949839	58,68986284	4,33	0,866	25	1	C	0,90		9,788462	5,898446417	75,2140856	76,87358399		2	4,978495169	101,6538243	130,2746177	135,2531129	80,108317	4,23840419	1,3341116	5,572516	135,2531	12,5	2,252485	14,7524845	Continuous Review Policy
Iprabronch	testequipment	53,47021891	75,8209114	0,21	0,042	25	1	C	0,90		252,2995	4,718504525	97,16840771	150,6386266		2	160,4106567	131,3256708	168,300619	328,7112758	223,31814	5,29828887	0,1803723	5,478661	328,7113	12,5	0,265498	12,7654976	Continuous Review Policy
Isoptin	testequipment	2,475817188	72,56207374	0,32	0,064	25	1	C	0,90		43,97991	17,76379401	92,9920392	95,46785639		2	7,427451563	125,6811984	161,0669366	168,4943882	114,98199	1,40735701	0,1415163	1,548873	168,4944	12,5	0,207378	12,7073777	Continuous Review Policy
Ketamin S 20 mg	medication	17,98713862	20,12687033	3,24	0,648	25	1	A	0,98		37,25448	2,071173393	41,335538	59,32267663		2	53,96141586	34,860762	71,59525198	125,5566678	59,962779	12,0704525	0,7472285	12,81768	125,5567	12,5	1,564629	14,0646292	Continuous Review Policy
Larynxmaske Kind Gr. 1	medication	0,797838481	2,340126167	4,5	0,9	25	1	C	0,90		6,657654	8,344614108	2,998992353	3,796830834		2	2,393515444	4,053217417	5,194407126	7,58792257	6,3278195	2,99594441	0,10952	3,105464	7,587923	12,5	0,131329	12,6313294	Continuous Review Policy
Larynxmaske Kind Gr. 1,5	medication	0,613606652	2,02758751	4,5	0,9	25	1	C	0,90		5,838601	9,515217459	2,598457948	3,212064599		2	1,840819955	3,511884584	4,500661187	6,341481142	5,5177583	2,62737033	0,0954997	2,72287	6,341481	12,5	0,109756	12,6097564	Continuous Review Policy
Larynxmaske Kind Gr. 2	consumables su	0,811016273	2,615202806	4,5	0,9	25	1	C	0,90		6,712411	8,27654276	3,35151725	4,162533523		2	2,43304882	4,529664131	5,804998159	8,238046979	6,7077227	3,02058489	0,1160952	3,13668	8,238047	12,5	0,142582	12,6425816	Continuous Review Policy
Larynxmaske Kind Gr. 2,5	consumables su	0,780810865	2,115700942	4,5	0,9	25	1	C	0,90		6,586227	8,435111419	2,711379855	3,492190719		2	2,342432594	3,664501525	4,696247667	7,038680261	6,0044932	2,96380199	0,1039239	3,067726	7,03868	12,5	0,121823	12,6218233	Continuous Review Policy
Larynxmaske Kind Gr. 3	consumables su	0,68202074	2,598076211	4,5	0,9	25	1	C	0,90		6,155489	9,025368788	3,329568636	4,011589376		2	2,046062219	4,5	5,766982045	7,813044264	6,407313	2,76996991	0,1108958	2,880866	7,813044	12,5	0,135226	12,6352258	Continuous Review Policy
Larynxtubus Gr. 3	consumables su	3,921529833	19,05236007	11,69	2,338	25	1	B	0,95		9,157786	2,335258638	31,33834356	35,2598734		2	11,7645895	32,99965565	54,27960328	66,04419278	35,917277	10,7054523	1,6149442	12,32035	66,04419	12,5	2,969449	15,4694485	Continuous Review Policy
Larynxtubus Gr. 4	consumables su	8,701455116	23,32510677	11,69	2,338	25	1	A	0,98		13,64139	1,567713891	47,90391263	56,60536775		2	26,10436535	40,40027003	82,97201056	109,0763759	54,724609	15,9467873	2,4605026	18,40729	109,0764	12,5	4,904242	17,4042417	Periodic Review Policy
Larynxtubus Gr. 5	consumables su	3,846099091	9,468848447	11,69	2,338	25	1	B	0,95		9,069284	2,35804731	15,57486971	19,4209688		2	11,53829727	16,4005266	26,97646566	38,51476293	20,1095912	10,6019925	0,9041546	11,50615	38,51476	12,5	1,731683	14,231683	Continuous Review Policy
Lasix 40	consumables su	18,10684929	11,36448482	0,28	0,056	25	1	C	0,90		127,1488	7,022140995	14,56417331	32,6710226		2	54,32054787	19,6838651	25,22588814	79,54643601	78,138598	3,56016776	0,0841493	3,644317	79,54644	12,5	0,085665	12,5856654	Continuous Review Policy
Leukoplast 2,5 cm (12)	consumables su	4,359446144	5,212891944	18,6	3,72	25	1	A	0,98		7,654718	1,755892298	10,70597115	15,0654173		2	13,07833843	9,028993702	18,54328598	31,62162441	14,53333	14,2377763	1,0396921	15,27747	31,62162	12,5	2,262162	14,7621624	Periodic Review Policy
Lidocain	medication	9,113708496	17,77873261	0,35	0,07	25	1	C	0,90		80,68328	8,852958236	22,78436261	31,89807111		2	27,34112549	30,79366818	39,46367367	66,80479915	63,126003	2,82391482	0,0849773	2,908892	66,8048	12,5	0,08993	12,5899295	Continuous Review Policy
Lysthenon	consumables su	2,722915618	27,06837582	0,29	0,058	25	1	C	0,90		48,44937	17,793194	34,68951941	37,41243503		2	8,168746853	46,8838022	60,08401011	68,25275697	58,914202	1,40503161	0,065712	1,470744	68,25276	12,5	0,076128	12,5761281	Continuous Review Policy
Lysthenon 500 mg	medication	0,316243609	3,882193783	4,58	0,916	25	1	C	0,90		4,154781	13,13791315	4,975231521	5,29147513		2	0,948730826	6,724156878	8,617353773	9,5660846	7,0526221	1,90288973	0,1242347	2,027124	9,566085	12,5	0,16851	12,6685103	Continuous Review Policy
Magill Zange groß	medication	4,286538188	4,535215741	2,35	0,47	25	1	C	0,90		21,3545	4,981759121	5,812112833	10,09865102		2	12,85961456	7,855224087	10,06687473	22,92648929	16,489363	5,01830767	0,1490385	5,167346	22,92649	12,5	0,20722	12,7072202	Continuous Review Policy
Magill Zange klein	medication	2,487514114	3,604500554	2,35	0,47	25	1	C	0,90		16,26743	6,539631791	4,619353328	7,106867442		2	7,462542343	6,243178095	8,000954662	15,463497	12,753067	3,8228452	0,1152681	3,938113	15,4635	12,5	0,139766	12,6397662	Continuous Review Policy
Magillitubus Gr. 2,5	accessories	2,010722001	8,649312462	0,79	0,158	25	1	C	0,90		25,22508	12,54528245	11,08453993	13,09526193		2	6,032166004	14,98104863	19,19898633	25,23115233	23,697078	1,99278096	0,0720027	2,064784	25,23115	12,5	0,076664	12,5766639	Continuous Review Policy
Magillitubus Gr. 3,0	accessories	1,71674765	4,735424207	0,79	0,158	25	1	C	0,90		23,30825	13,57698155	6,068690307	7,785437956		2	5,150242949	8,201995323	10,51127995	15,66152289	17,722816	1,84135184	0,0538501	1,895202	15,66152	12,5	0,047587	12,5475869	Continuous Review Policy
Magillitubus Gr. 3,5	consumables su	1,912386815	8,162645687	0,79	0,158	25	1	C	0,90		24,60052	12,86377953	10,46085162	12,37323843		2	5,737160444	14,1381174	18,11872649	23,85588693	22,761113	1,94344127	0,0691588	2,0126	23,85589	12,5	0,072485	12,5724852	Continuous Review Policy
Magillitubus Gr. 4,0	consumables su	1,82196517	6,105139415	0,79	0,158	25	1	C	0,90		24,0119	13,17912034	7,824050975	9,646016145		2	5,46589551	10,57441165	13,55165381	19,01754932	19,83	1,89693996	0,0602527	1,957193	19,01755	12,5	0,057784	12,5577841	Continuous Review Policy
Magillitubus Gr. 4,5	consumables su	1,704629564	9,194860224	0,79	0,158	25	1	C	0,90		23,22584	13,62515497	11,78368752	13,48831708		2	5,113888693	15,92596508	20,40994548	25,52383417	23,396609	1,83484152	0,0710897	1,905931	25,52383	12,5	0,077553	12,5775532	Continuous Review Policy
Magillitubus Gr. 5,0	consumables su	1,779071617	5,089353117	0,79	0,158	25	1	C	0,90		23,72757	13,33704889	6,522268455	8,301340072		2	5,337214851	8,815018177	11,29690034	16,6341152	18,386051	1,87447765	0,0558653	1,930343	16,63412	12,5	0,050542	12,5505421	Continuous Review Policy
Magillitubus Gr. 5,0 mit Cuff (10)	consumables su	0,346958148	1,013793755	16,9	3,38	25	1	C	0,90		2,265506	6,529622986	1,299228974	1,646187122		2	1,040874445	1,755942292	2,250330594	3,291205039	2,4319819	3,82870497	0,1580788	3,986784	3,291205	12,5	0,213928	12,7139283	Continuous Review Policy
Magillitubus Gr. 5,5	consumables su	1,69259367	6,287915297	0,79	0,158	25	1	C	0,90		23,1437	13,67351283	8,058287693	9,750881363		2	5,07778101	10,89098877	13,95736371	19,03514472	19,630138	1,8283524	0,0596454	1,887998	19,03514	12,5	0,057838	12,5578376	Continuous Review Policy
Magillitubus Gr. 6,0 mit Cuff (10)	consumables su	0,567913926	1,236033081	16,9	3,38	25	1	C	0,90		2,898464	5,103702994	1,58404013	2,151954056		2	1,703741777	2,140872096	2,743637987	4,447379764	3,0332721	4,89840416	0,1971627	5,095567	4,44738	12,5	0,28908	12,7890797	Continuous Review Policy
Magillitubus Gr. 7,0 mit Cuff (10)	consumables su	1,139030679	3,256694736	16,9	3,38	25	1	B	0,95		4,104822	3,603785563	5,356786149	6,495816828		2	3,417092037	5,640760748	9,278225775	12,69531781	7,4091973	6,93714972	0,4815978	7,418748	12,69532	12,5	0,825196	13,3251957	Continuous Review Policy
Magillitubus Gr. 8,0 mit Cuff (10)	consumables su	1,594384813	2,449489743	16,9	3,38	25	1	B	0,95		4,856498	3,046001252	4,029052088	5,623436901		2	4,78315444	4,242640687	6,978522922	11,76167736	6,4573012	8,20748185	0,4197246	8,627206	11,76168	12,5	0,764509	13,264509	Continuous Review Policy
Magnesium Verla	consumables su	1,44326965	5,310795181	0,59	0,118	25	1	C	0,90		24,72964	17,13445357	6,806057878	8,249327529		2	4,32980895	9,198567082	11,78843804	16,118247	19,170876	1,45904857	0,0435031	1,502552	16,11825	12,5	0,036576	12,536576	Continuous Review Policy
MANV Karten	accessories	3,635222149	27,03824452	3,3	0,66	25	1	C	0,90		16,59505	4,565071211	34,65090459	38,28612674		2	10,90566645	46,83161325	60,01712728	70,92279373	42,948429	5,47636583	0,5451147	6,021481	70,92279	12,5	0,900174	13,4001739	Continuous Review Policy
Medumat/Meduvent Maske Gr. M (grün) (10)	consumables md	1,557163636	109,8605176	18,12	3,624	25	1	B	0,95		4,635089	2,976622643	180,7044709	182,2616345		2	4,671490908	190,2839983	312,9893247	317,6608156	183,02202	8,39878043	12,755227	21,15401	317,6608	12,5	22,13852	34,6385153	Continuous Review Policy
Medumat/Meduvent Maske Gr. S (gelb) (10)	consumables md	1,139049991	96,46415569	18,12	3,624	25	1	B	0,95		3,964262	3,480322708	158,6694164	159,8084664		2	3,417149973	167,0808188	274,8234907	278,2406407	160,65155	7,18324193	11,196177	18,37942	278,2406	12,5	19,39123	31,8912323	Continuous Review Policy
Metalyse 50 mg	medication	0,39568884	2,315952582	867,66	173,532	25	1	A	0,98		0,337654	0,853332557	4,756385093	5,152073933		2	1,187066519	4,011347541	8,238300642	9,425367161	4,9252122	29,2969017	16,436191	45,73309	9,425367	12,5	31,4539	43,9539003	Periodic Review Policy
Mini-Spike	consumables su	52,57064158	53,2102747	0,45	0,09	25	1	B	0,95		170,8974	3,250813906	87,52311333	140,0937549		2	157,7119247	92,16289926	151,5944791	309,3064039	172,9718	7,69038177	0,2993743	7,989756	309,3064	12,5	0,535338	13,035338	Continuous Review Policy
Morphin	medication	43,36216939	23,0486968	0,19	0,038	25	1	C	0,90		238,8629	5,508555165	29,53809347	72,90026286		2	130,0865082	39,92151391	51,16147865	181,2479868	148,96954	4,53839514	0,1088624	4,647258	181,248	12,5	0,13245	12,6324505	Continuous Review Policy
NaCl 0,9 %	medication	87,98635254	43,82368254	0,12	0,024	25	1	C	0,90		428,1412	4,865995737	56,16230897	144,1486615		2	263,9590576	75,90484474	97,27597261	361,2350302	270,23292	5,1376946	0,1247229	5,262417	361,235	12,5	0,166724	12,6667239	Continuous Review Policy
Naloxon	medication	20,18084946	78,61933604	0,75	0,15	25	1	B	0,95		82,01798	4,064149277	129,3173	149,4981495		2	60,54254837	136,1726845	223,984134	284,5266823	170,32629	6,15134885	0,4913258	6,642675	284,5267	12,5	0,82075	13,32075	Continuous Review Policy
Nitrolingual infus.	medication	4,821709029	23,75952759	0,47	0,094	25	1	C	0,90		50,64325	10,50317438	30,44905979	35,27076881		2	14,46512709	41,15270896	52,73931859	67,20444568	55,770685	2,38023278	0,1008162	2,481049	67,20445	12,5	0,121485	12,621485	Continuous Review Policy
Nitrolingual Spray	medication	5,210839144	16,0623784	1,73	0,346	25	1	C	0,90		27,44105	5,266148715	20,58476619	25,79560533		2	15,63251743	27,82085549	35,6538609	51,28637834	34,305293	4,74730232	0,2282621	4,975564	51,28638	12,5	0,341252	12,8412517	Continuous Review Policy
O^2-Brillen (50)	consumables su	2,037617175	4,43385734	28	5,6	25	1	A	0,98		4,265327	2,093291415	9,106029681	11,14364686		2	6,112851524	7,679666186	15,77210606	21,88495759	11,238693	11,9429143	1,2103208	13,15324	21,88496	12,5	2,356842	14,8568416	Continuous Review Policy
O^2-Maske Erwachsene (24)	consumables su	2,395066516	2,906367096	21,12	4,224	25	1	A	0,98		5,324537	2,223126921	5,968948257	8,364014773		2	7,185199547	5,033975476	10,33852165	17,5237212	8,6312167	11,2454218	0,7011204	11,94654	17,52372	12,5	1,423465	13,9234654	Continuous Review Policy
Oxybag (Tasche) 2 l	accessories	0,105060158	0,577350269	70	14	25	1	C	0,90		0,612548	5,83044844	0,739904141	0,8449643		2	0,315180475	1	1,281551566	1,59673204	1,0461781	4,28783485	0,2816633	4,569498	1,596732	12,5	0,429889	12,9298894	Continuous Review Policy
Oxytocin	medication	1,576818053	13,69671493	0,27	0,054	25	1	C	0,90		38,21017	24,23245029	17,55304647	19,12986452		2	4,730454159	23,72340616	30,40276831	35,13322247	36,658129	1,03167446	0,0380681	1,069743	35,13322	12,5	0,036485	12,5364845	Continuous Review Policy
Paracefan	medication	2,656250509	9,288311325	0,51	0,102	25	1	C	0,90		36,0844	13,58471092	11,90344992	14,55970043		2	7,968751526	16,08782713	20,61738005	28,58613157	29,945648	1,84030416	0,0587395	1,899044	28,58613	12,5	0,056073	12,5560728	Continuous Review Policy
Patienteneigentumstasche	accessories	9,224256643	33,13734047	0,2	0,04	25	1	C	0,90		107,3793	11,64097396	42,46721056	51,6914672		2	27,67276993	57,39555732	73,55536634	101,2281363	96,156876	2,14758663	0,0739668	2,221553	101,2281	12,5	0,077868	12,5778678	Continuous Review Policy
PEEP Ventil einweg (10)	consumables su	1,00353303	3,570714214	41	8,2	25	1	B	0,95		2,473682	2,464973419	5,873302226	6,876835256		2	3,010599089	6,184658438	10,17285786	13,18345695	7,1101433	10,1420972	1,1212149	11,26331	13,18346	12,5	2,07893	14,5789298	Continuous Review Policy
Perfusor Spritze	consumables su	8,365695445	21,72747876	0,33	0,066	25	1	C	0,90		79,60935	9,516166004	27,84488442	36,21057987		2	25,09708633	37,63309714	48,22875455	73,32584088	67,649558	2,62710844	0,0858629	2,712971	73,32584	12,5	0,093067	12,5930674	Continuous Review Policy

Product Name	Type	Forecasted demand (weeks)	Standard deviation (week)	Unit pric	Holding cos	Ordering cost	Lead time (week)	Class	CSL
Perfusor Spritze	consumables su	8,365695445	21,72747876	0,33	0,066	25	1	C	0,90
Port Nadel	consumables su	0,918394637	2,182575626	7,45	1,49	25	1	C	0,90
Propofol	medication	6,952984746	10,82785409	0,81	0,162	25	1	C	0,90
Rectodelt 100 mg	medication	4,697306156	14,83520587	1,25	0,25	25	1	C	0,90
Replantatbeutel Arm	consumables su	1,665022628	12,96779227	9,23	1,846	25	1	B	0,95
Replantatbeutel Bein	consumables su	0,909218876	4,57165178	13,98	2,796	25	1	B	0,95
Rettungsdecke Gold/Silber	consumables su	20,50553525	34,82194971	0,5	0,1	25	1	C	0,90
Rocuronium 100mg	medication	6,731702868	32,1963672	4,45	0,89	25	1	B	0,95
Sab simplex Tropfen	medication	0,320691937	3,012096823	1,78	0,356	25	1	C	0,90
Safety Multifly Kanülen	consumables su	8,588203112	212,7885563	0,45	0,09	25	1	C	0,90
Salbutamol	medication	90,77453918	69,03863653	0,12	0,024	25	1	C	0,90
Sam Splint Bein	consumables su	3,150212987	5,517877282	7,59	1,518	25	1	B	0,95
Sam Splint Set	consumables su	8,584566816	12,44624807	16,1	3,22	25	1	A	0,98
Sharpsafe	consumables su	10,67607791	15,20765358	3,17	0,634	25	1	B	0,95
Sharpsafe mini	consumables su	69,52049154	40,56158804	0,83	0,166	25	1	A	0,98
Silberwindeln	consumables su	1,705368344	9,701803956	4,9	0,98	25	1	C	0,90
Sterofundin	medication	500,344043	196,8165389	0,52	0,104	25	1	A	0,98
Tavor 2,5mg Expidet Plättchen	medication	14,83642069	32,75563796	0,16	0,032	25	1	C	0,90
Thoraxdrainage CH 14	consumables su	1,646521282	6,042776805	13,5	2,7	25	1	B	0,95
Thoraxdrainage CH 24	consumables su	1,621457179	6,042776805	13,95	2,79	25	1	B	0,95
Thoraxdrainage CH 30	consumables su	1,442745908	6,042776805	13,95	2,79	25	1	B	0,95
Thoraxdrainage Chir. Schere	consumables su	2,131219244	6,042776805	1,84	0,368	25	1	C	0,90
Thoraxdrainage Heimlichventil	consumables su	1,87117157	6,042776805	13,8	2,76	25	1	B	0,95
Tourniquet	consumables su	7,114907328	11,032665	28	5,6	25	1	A	0,98
Tubusklemme	consumables su	0,334759905	1,303840481	9,9	1,98	25	1	C	0,90
Tubusverlängerung (25)	consumables su	1,324465354	1,12815215	24,75	4,95	25	1	B	0,95
Ultracarbon	medication	0,789866074	1,555050423	11,83	2,366	25	1	C	0,90
Ultraschallgel	consumables md	1,816375462	9,070013865	2,22	0,444	25	1	C	0,90
Universalhalter	accessories	8,111773491	16,50803294	1,62	0,324	25	1	B	0,95
Urinkatheter CH 14	consumables su	0,643650826	1,802775638	6,66	1,332	25	1	C	0,90
Urinkatheter CH 16	consumables su	0,686587389	1,802775638	6,66	1,332	25	1	C	0,90
Urinkatheter Set DKM	set	0,734296823	1,763834207	9,06	1,812	25	1	C	0,90
Vecuronium Inresa	medication	0,489694178	1,632993162	5,24	1,048	25	1	C	0,90
Vomex	medication	34,56701965	28,26645404	0,9	0,18	25	1	B	0,95
ZVK Gr. 1	consumables su	0,281499847	2,149196971	9,9	1,98	25	1	C	0,90
ZVK Gr. 12	consumables su	0,519129177	1,951800146	58,1	11,62	25	1	B	0,95
ZVK Gr. 2	consumables su	0,551004318	2,458545189	16,5	3,3	25	1	C	0,90

Product Name	Continuous Review Policy	EOQ	Frequency of the orders (weeks)	Safety Stock	Reorder Point	Periodic Review Policy	Review Period (T)	Mean during T+L period	Standard deviation during T+L period	Safety Stock2
Perfusor Spritze		79,60935	9,516166004	27,84488442	36,21057987		2	25,09708633	37,63309714	48,22875455
Port Nadel		5,551451	6,044734057	2,797083211	3,715477848		2	2,755183911	3,780331876	4,844690234
Propofol		46,32476	6,662571099	13,87645336	20,82943811		2	20,85895424	18,75439342	24,03472225
Rectodelt 100 mg		30,65063	6,525150971	19,01208131	23,70938747		2	14,09191847	25,69533032	32,92989079
Replantatbeutel Arm		6,715513	4,033286603	21,33012015	22,99514278		2	4,995067883	22,46087507	36,94485183
Replantatbeutel Bein		4,03228	4,434883308	7,519698012	8,428916887		2	2,727656627	7,918333158	13,02449901
Rettungsdecke Gold/Silber		101,256	4,93798137	44,62612417	65,13165942		2	61,51660576	60,31338612	77,29471441
Rocuronium 100mg		19,44699	2,888866879	52,95831136	59,69001422		2	20,1951086	55,7657438	91,72648595
Sab simplex Tropfen		6,711259	20,92743408	3,860157399	4,180849337		2	0,962075812	5,217104735	6,685988741
Safety Multifly Kanülen		69,07405	8,04289861	272,6995075	281,2877106		2	25,76460934	368,5605908	472,3294021
Salbutamol		434,872	4,790682122	88,47657272	179,2511119		2	272,3236176	119,5784261	153,2459192
Sam Splint Bein		10,18636	3,233546849	9,07610046	12,22631345		2	9,450638962	9,557243802	15,72026713
Sam Splint Set		11,54559	1,344924403	25,56146841	34,14603522		2	25,75370045	21,55753401	44,273762
Sharpsafe		29,01658	2,717906461	25,01436414	35,69044205		2	32,02823372	26,34042866	43,32614961
Sharpsafe mini		144,7063	2,081491018	83,30331725	152,8238088		2	208,5614746	70,25473132	144,2855779
Silberwindeln		9,327839	5,469691924	12,43336205	14,13873039		2	5,116105032	16,80401738	21,53521478
Sterofundin		490,459	0,980243488	404,2117524	904,5557954		2	1501,032129	340,8962452	700,1152922
Tavor 2,5mg Expidet Plättchen		152,2561	10,26231741	41,97803911	56,8144598		2	44,50926208	56,73442918	72,70809654
Thoraxdrainage CH 14		5,521878	3,353663203	9,939483345	11,58600463		2	4,939563847	10,46639645	17,21569015
Thoraxdrainage CH 24		5,390582	3,324529252	9,939483345	11,56094052		2	4,864371538	10,46639645	17,21569015
Thoraxdrainage CH 30		5,084846	3,524422579	9,939483345	11,38222925		2	4,328237724	10,46639645	17,21569015
Thoraxdrainage Chir. Schere		17,01669	7,984487188	7,744130075	9,875349319		2	6,393657732	10,46639645	13,41322675
Thoraxdrainage Heimlichventil		5,822202	3,111527588	9,939483345	11,81065491		2	5,613514709	10,46639645	17,21569015
Tourniquet		7,970317	1,120227848	22,65832372	29,77323105		2	21,34472198	19,10913632	39,2453679
Tubusklemme		2,907496	8,6853173	1,67093881	2,005698715		2	1,004279715	2,258317958	2,894150915
Tubusverlängerung (25)		3,657655	2,761608441	1,855645155	3,180110509		2	3,973396063	1,954016842	3,214071689
Ultracarbon		4,085586	5,172504793	1,992877304	2,782743378		2	2,369598222	2,693426341	3,451764744
Ultraschallgel		14,30199	7,873914669	11,62369047	13,44006593		2	5,449126387	15,70972484	20,13282246
Universalhalter		35,38102	4,36168793	27,15329785	35,26507134		2	24,33532047	28,59275178	47,03089148
Urinkatheter CH 14		4,915391	7,636735067	2,310349941	2,954000767		2	1,930952477	3,122498999	4,001643481
Urinkatheter CH 16		5,076692	7,39409419	2,310349941	2,99693733		2	2,059762168	3,122498999	4,001643481
Urinkatheter Set DKM		4,501339	6,130135596	2,26044449	2,994741312		2	2,202890468	3,055050463	3,915204704
Vecuronium Inresa		4,833557	9,87056222	2,092764943	2,582459121		2	1,469082534	2,828427125	3,62477521
Vomex		97,98954	2,834769695	46,49417946	81,06119911		2	103,701059	48,95893455	80,53028107
ZVK Gr. 1		2,666192	9,471381405	2,754306743	3,035806589		2	0,84449954	3,722518349	4,770599218
ZVK Gr. 12		1,494582	2,879016931	3,210425549	3,729554726		2	1,557387531	3,380617019	5,560620165
ZVK Gr. 2		2,889386	5,243853269	3,150752435	3,701756754		2	1,653012955	4,258325179	5,4572633

Product Name	Order up-to level (OUL)	AIL	Ordering C	Holding C	Total cos	AIL2	Ordering Cost3	Holding	Total cost2	Selected Policy
Perfusor Spritze	73,32584088	67,649558	2,62710844	0,0858629	2,712971	73,32584	12,5	0,093067	12,5930674	Continuous Review Policy
Port Nadel	7,599874145	5,5728089	4,13583125	0,1596824	4,295514	7,599874	12,5	0,217766	12,7177656	Continuous Review Policy
Propofol	44,89367649	37,038831	3,75230517	0,1153902	3,867695	44,89368	12,5	0,139861	12,6398611	Continuous Review Policy
Rectodelt 100 mg	47,02180926	34,337397	3,83132898	0,1650836	3,996413	47,02181	12,5	0,226066	12,7260664	Continuous Review Policy
Replantatbeutel Arm	41,93991971	24,687877	6,19841892	0,8764196	7,074839	41,93992	12,5	1,488867	13,9888671	Continuous Review Policy
Replantatbeutel Bein	15,75215564	9,5358378	5,6371269	0,5127347	6,149862	15,75216	12,5	0,846981	13,3469813	Continuous Review Policy
Rettungsdecke Gold/Silber	138,8113202	95,2541	5,06279755	0,183181	5,245979	138,8113	12,5	0,266945	12,7669448	Continuous Review Policy
Rocuronium 100mg	111,9215946	62,681808	8,65391209	1,0728233	9,726735	111,9216	12,5	1,915581	14,4155811	Continuous Review Policy
Sab simplex Tropfen	7,648064553	7,2157871	1,19460417	0,0494004	1,244005	7,648065	12,5	0,05236	12,5523598	Continuous Review Policy
Safety Multifly Kanülen	498,0940115	307,23653	3,10833211	0,5317555	3,640088	498,094	12,5	0,862086	13,3620858	Continuous Review Policy
Salbutamol	425,5695368	305,91255	5,21846354	0,1411904	5,359654	425,5695	12,5	0,196417	12,6964167	Continuous Review Policy
Sam Splint Bein	25,17090609	14,169281	7,73144821	0,413634	8,145082	25,17091	12,5	0,734797	13,2347968	Continuous Review Policy
Sam Splint Set	70,02746244	31,334265	18,5884054	1,9403141	20,52872	70,02746	12,5	4,336316	16,8363159	Periodic Review Policy
Sharpsafe	75,35438333	39,522655	9,19825622	0,4818724	9,680129	75,35438	12,5	0,918744	13,4187438	Continuous Review Policy
Sharpsafe mini	352,8470525	155,65646	12,0106211	0,4969033	12,50752	352,8471	12,5	1,126396	13,6263964	Continuous Review Policy
Silberwindeln	26,65131981	17,097282	4,57064134	0,322218	4,892859	26,65132	12,5	0,502275	13,0022749	Continuous Review Policy
Sterofundin	2201,147421	649,44125	25,5038675	1,2988825	26,80275	2201,147	12,5	4,402295	16,9022948	Periodic Review Policy
Tavor 2,5mg Expidet Plättchen	117,2173586	118,10607	2,43609694	0,0726807	2,508778	117,2174	12,5	0,072134	12,5721338	Continuous Review Policy
Thoraxdrainage CH 14	22,155254	12,700422	7,45453508	0,659445	8,11398	22,15525	12,5	1,150369	13,650369	Continuous Review Policy
Thoraxdrainage CH 24	22,08006169	12,634774	7,51986164	0,6779042	8,197766	22,08006	12,5	1,18468	13,6846802	Continuous Review Policy
Thoraxdrainage CH 30	21,54392788	12,481906	7,09336053	0,6697023	7,763063	21,54393	12,5	1,155915	13,6559146	Continuous Review Policy
Thoraxdrainage Chir. Schere	19,80688448	16,252476	3,13107147	0,1150175	3,246089	19,80688	12,5	0,140172	12,6401718	Continuous Review Policy
Thoraxdrainage Heimlichventil	22,82920486	12,850584	8,03463871	0,6820695	8,716708	22,8292	12,5	1,211704	13,711704	Continuous Review Policy
Tourniquet	60,59008989	26,643482	22,3168885	2,8692981	25,18619	60,59009	12,5	6,525087	19,0250866	Periodic Review Policy
Tubusklemme	3,89843063	3,1246868	2,87842103	0,1189785	2,997399	3,898431	12,5	0,14844	12,6484402	Continuous Review Policy
Tubusverlängerung (25)	7,187467752	3,6844725	9,05269539	0,3507334	9,403429	7,187468	12,5	0,684192	13,1841916	Continuous Review Policy
Ultracarbon	5,821362966	4,0356703	4,8332483	0,183623	5,016871	5,821363	12,5	0,264872	12,764872	Continuous Review Policy
Ultraschallgel	25,58194885	18,774683	3,17504076	0,1603069	3,335348	25,58195	12,5	0,21843	12,7184305	Continuous Review Policy
Universalhalter	71,36621195	44,84381	5,73172597	0,2794114	6,011137	71,36621	12,5	0,444666	12,9446664	Continuous Review Policy
Urinkatheter CH 14	5,932595958	4,7680454	3,27365029	0,1221353	3,395786	5,932596	12,5	0,151966	12,6519657	Continuous Review Policy
Urinkatheter CH 16	6,061405649	4,8486959	3,38107676	0,1242012	3,505278	6,061406	12,5	0,155265	12,6552652	Continuous Review Policy
Urinkatheter Set DKM	6,118095172	4,511114	4,07821322	0,157195	4,235408	6,118095	12,5	0,213192	12,7131921	Continuous Review Policy
Vecuronium Inresa	5,093857744	4,5095434	2,53278379	0,0908846	2,623668	5,093858	12,5	0,102661	12,6026608	Continuous Review Policy
Vomex	184,23134	95,488949	8,81905858	0,3305387	9,149597	184,2313	12,5	0,637724	13,1377239	Continuous Review Policy
ZVK Gr. 1	5,615098758	4,0874029	2,63953049	0,1556357	2,795166	5,615099	12,5	0,213806	12,7138057	Continuous Review Policy
ZVK Gr. 12	7,118007696	3,9577164	8,68351962	0,8843974	9,567917	7,118008	12,5	1,590601	14,090601	Continuous Review Policy
ZVK Gr. 2	7,110276255	4,5954453	4,76748656	0,291634	5,059121	7,110276	12,5	0,451229	12,9512291	Continuous Review Policy

Figure C.3

Appendix D

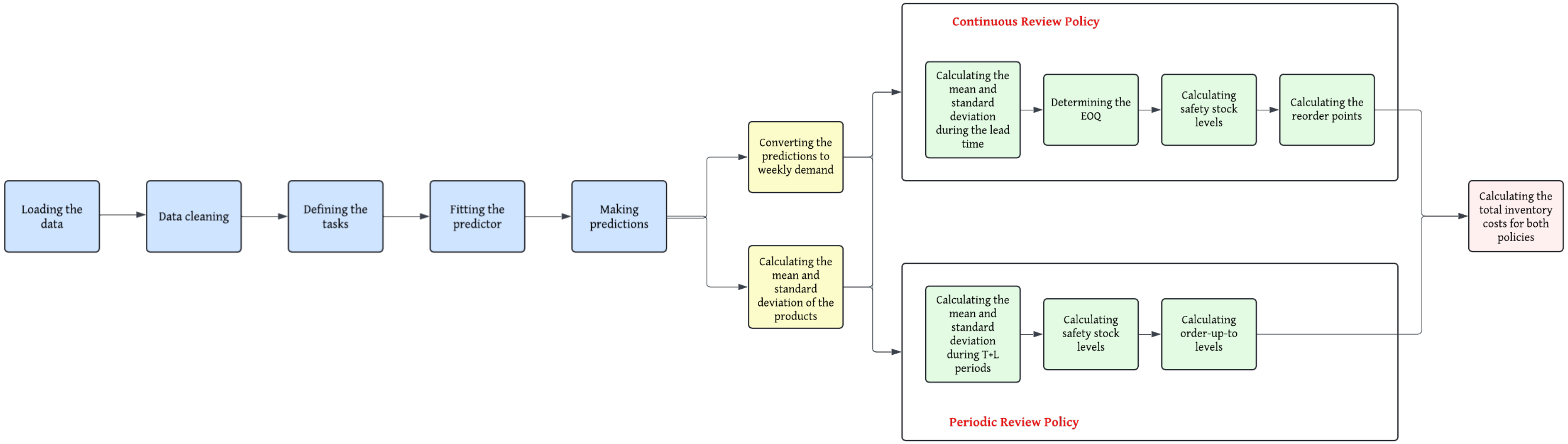


Figure D.1

Generative AI was used to getting ideas for spell check in this assignment.