# Departmental integration of an automated material logistic system

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Case study of integrating an automated material logistics system within the Zaans Medisch Centrum surgical department.

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coppa

zaans medisch centrum

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# Management summary


### Motivation of the research

Given the expanding demand for healthcare services, which is expected to grow in quantity, quality, and complexity, healthcare decision-makers are facing a pressing need to develop more efficient and effective healthcare systems. As part of this growth, healthcare costs also increase [63; 7; 53]. Among the various expenses incurred within healthcare establishments, logistics-related costs emerge as the second-largest cost category [63; 53]. Hence, this research focuses on optimising material logistics processes, specifically enhancing the efficiency of replenishment procedures within healthcare departments. The current material logistics techniques employed in healthcare establishments are burdened by specific limitations [4; 30], like limited data collection, limited data analyses, and demand fluctuation. These limitations lead to imprecise replenishment estimates, inefficiencies that waste valuable time, and a lack of strategic decision-making and data analysis capabilities. This leads to financial waste, fluctuations in stock levels, and disruptions in the continuity of care.

To address the limitations, the primary objective of this research is twofold. First, it aims to develop a technique that significantly enhances the accuracy of replenishment quantity estimations while improving overall operational efficiency. Second, the goal is to automate the decision-making process related to replenishment strategies entirely. A collaborative effort is conducted with Coppa Consultancy BV (Coppa) and Zaans Medisch Centrum (ZMC) to achieve these objectives. The effectiveness and practicality of the proposed automated material logistics technique are assessed through a case study conducted within the surgical department of ZMC. This case study will illustrate how the model addresses the identified limitations and positively changes material logistics processes.

### Methods

We construct a simulation model using replenishment data from ZMC. From this data, we select a subset of 43 items from the department's storage cabinets based on two primary criteria: their annual costs and annual replenishment frequency. This selection accounts for 12% of all cabinet items and represents 53% of the total yearly expenses. Replenishments for the department occur on Mondays and Thursdays; any replenishments on other days are considered emergency orders. This approach divides the week into two periods: Monday to Wednesday and Thursday to Sunday.

Our integration of an automated material logistics system utilises employing Radio-Frequency Identification (RFID) technology, enabling the use of RFID-equipped storage cabinets. These cabinets allow precise item counting. We test the conceptual decision-making strategy through simulation. To create a simulation, a distribution is established for each item during each period, enabling the modelling of cabinet inventory flow and assessment of the decision-making strategy.

The decision-making strategy of the conceptual model involves determining the replenishment quantities based on a predetermined probability threshold. When determining the replenishment quantity, the method assesses the likelihood that the usage will be equal to or less than the in-stock items for the upcoming period. This decision is based on the probability that the current stock in the storage cabinets is sufficient to cover the period until the next scheduled ordering moment. If this probability is less than the selected probability threshold, the stock is replenished to its maximum capacity, considering the order size at which individual items are packaged. Only multiples of this order size are placed as orders. If the likelihood that the usage is equal to or less than the number of items available in the storage cabinet does not exceed the established probability threshold, no order is initiated. Instead, the system waits until the next scheduled ordering moment. The assessment of this likelihood depends on the Normal or Poisson distribution used to characterise the item.

We evaluate and measure the optimisation of the conceptual decision-making strategy through three diverse experiments.

1. The first assesses the Markov chain decision policy implementation on traditional replenishment days (Monday and Thursday).
2. The second evaluates the implementation of the Markov chain decision policy on traditional replenishment days (Monday and Thursday) and its application on additional replenishment days (Tuesday, Wednesday, and Friday).
3. The third experiment aims to optimise the capacity of items stocked in the storage cabinets.

### Findings and conclusion

This research evaluates the integration of an automated material logistics system and its enhancements for inventory management and operational efficiency within healthcare department logistics. By using a conceptual model based on the Markov chain method, key findings reveal the potential benefits of the combination of RFID-equipped storage cabinets with the conceptual model. In comparison to the existing statistics at ZMC, this integration results in a remarkable $93,6\%$ decrease in item stockouts, reducing them from 1600 stockouts to 102. Additionally, it leads to a substantial 60% reduction in unplanned additional replenishments, bringing them down from 20 to 8, provided that 8 additional planned replenishments are introduced. The conceptual decision strategy leads to a more reliable material logistic process. Capacity optimisation emerges as a practical approach, reducing stockouts and additional replenishments and decreasing the value of in-stock items.

Moreover, the data availability facilitated by the RFID-equipped storage cabinets offers a unique opportunity to access a wealth of previously unexplored information. This data and the insights it yields are expected to diverge significantly from the insights currently employed in known inventory management techniques, both within the manufacturing industry and healthcare facilities. As a result, this field remains open for further exploration, particularly in the context of the automated material logistics system based on the Markov chain decision strategy.

### Discussion

In the scope of this research, we delve into several limitations which could influence the outcome of the research.

1. The research provides opportunities for future research to explore the reliability of RFID-equipped storage cabinets and to investigate the feasibility of sustainable RFID tags.

2. A comprehensive cost-benefit analysis for the implementation of RFID-equipped storage cabinets is also a potential area for future research. Including precise annual values of items in stock and considering the costs associated with additional replenishments could enhance the research outcomes.

3. The simulation model's predictions are currently based on replenishment patterns. Future research may consider integrating actual usage patterns to provide a more comprehensive analysis.

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Bente van Velze,
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# Contents

# List of acronyms

**Coppa** Coppa Consultancy BV. i, iv, vi, 1, 6

**ERP** Enterprise Resource Planning. vi, 1

**FMIS** Financial Management Information Systems. vi, 1

**KPIs** Key Performance Indicators. vi, 3–5, 7, 11, 14, 16, 18, 28, 34–36, 39, 44, 46, 48, 51, 52, 67

**NFC** Near Field Communication. vi, 19–21

**OR** Operating Room. vi, 2, 28, 32, 33

**P2P** Procurement-to-Pay. vi, 2, 31, 81

**QQ** Qualitative and Quantitative. vi, 4, 13

**RFID** Radio-Frequency Identification. ii, iii, vi, 19–22, 25, 27, 45, 47, 68–72

**STO** Strategic, Tactical, and Operational. vi, 4, 12

**ZMC** Zaans Medisch Centrum. i, ii, iv, vi, 1–3, 5, 6, 9, 28–36, 38, 41, 46, 47, 50–53, 66, 68–72

# List of terms

**CoperniCare**

CoperniCare is a stock tracking system specialising in traceability and comprehensive registration of medical devices, disposables, and instruments. It offers full stock management, optimisation of goods flow, and ordering advice. vi, 32

**Kanban**

The Kanban method is based on just-in-time manufacturing and operates as a pull system. This means that work is only introduced into the system when the team has the capacity for it.. vi, 2, 3, 9, 15

**Markov chain**

Markov chain is a process that consists of a finite number of states with the Markovian property and some transition probabilities pij, where pij is the probability of the process moving from state i to state j.. ii, iii, vi, 5, 25–27, 38, 44, 45, 48, 50, 51, 55, 68, 69, 71–73

**modular carts**

Modular carts are positioned in the department's hallway and facilitate easy transportation of items to patients. vi, 30, 73

**ProQuro**

ProQuro is a software solution that specialises in procurement and supplier management across various industries, including health care. vi, 29, 32–37

**purchased items**

Purchased items are not initially stocked in the warehouse in Wormerveer. vi, 28, 29, 32–34, 36

**stocked items**

Stocked items are stored in the warehouse in Wormerveer and can be ordered by departments when needed. vi, 8, 28, 29, 32–34, 36, 37

**storage cabinets**

Storage cabinets are situated within an enclosed room in the department, serving as secure storage space for items consumed by the respective department. i–iii, vi, 1, 4, 9, 10, 12, 14, 15, 18, 21, 22, 25–28, 30–32, 34, 36, 39, 43–49, 51, 53, 55–59, 61, 62, 64, 66–73

# 1 Introduction

The problem of this research addresses the material logistic processes for the purpose of replenishing the storage cabinets at the department. Current limitations of the material logistic techniques in healthcare establishments give room for improvements [4; 30]. The identified limitations lead to imprecise replenishment estimates, wasted time, inefficiency, and a lack of strategic decision-making and data analysis capabilities. Consequently, the problem might lead to financial waste, fluctuations in stock levels, and disruptions in the continuity of care. This chapter provides a brief introduction concerning the participating parties Coppa and Zaans Medisch Centrum in Section 1.1 and 1.2, respectively. Section 1.3 describes the rational motivation for this research, and Section 1.4 outlines the research objective. Section 1.5 outlines the proposed approach, the related research question, and sub-questions.

## 1.1 Introduction to Coppa

The research is conducted in collaboration with Coppa, a purchasing consultancy company within the health care and government sectors [11]. The company was founded in 1997 by Bas Bouwman together with Marco Plasier [12]. In 2008, Jeroen Meijer and Paul Gelderman joined the management team, and since then, Bas, Jeroen, and Paul have been leading Coppa [12]. During the 25 years of existence, Coppa expanded to approximately a hundred professionals working collaboratively in various teams. According to the website of Coppa [10], the company contains a variety of teams. A list of Coppa's teams is shown in Appendix A.

We focus our collaboration on "*Team Business Consultants Implementaties*". This team advises organisations on selecting, implementing, and optimising the Enterprise Resource Planning (ERP) Systems and Financial Management Information Systems (FMIS). These systems enable institutions to improve insights into item consumption and associated costs. In addition, the material logistic processes automated by these systems reduce labour intensity and increase efficiency.

## 1.2 Introduction to Zaans Medisch Centrum

With the help of Coppa, a second collaboration is established with Zaans Medisch Centrum. ZMC is a hospital serving the region *Zaanstreek* and is located at Zaandam. The hospital resulted from a merger between the Municipal Hospital and the

St. Jan Hospital [9], established in 1931 and 1932, respectively. This merger occurred in 1974, and the hospital was subsequently known as Foundation Hospital *de Heel* [9]. Since 2004, it is officially called Zaans Medisch Centrum [9]. Currently, the hospital consists of 53 various care departments [65], along with various support departments that contribute to providing comprehensive patient care, Figure A.1 in Appendix A shows the organogram of ZMC. The primary objective of the hospital is delivering the highest quality of care to the residents of the region *Zaanstreek* [66].

The two involved teams, the Logistics and Soft Services team and the Procurement-to-Pay (P2P), play an essential role in ensuring an efficient material logistics process within the ZMC. Meetings are held with both teams to gather a profound understanding of their utilised techniques and the monitoring processes within the material logistics to gain deeper insights into the operational procedures of the ZMC hospital. See Chapter 4 for deeper insights into the material logistic process of ZMC.

## 1.3 Case description

Given the expanding demand for healthcare services, which is expected to grow in quantity, quality, and complexity, healthcare decision-makers are facing a pressing need to develop more efficient and effective healthcare systems[1]. As part of this growth, healthcare costs also increase [63; 7; 53]. In the hospital setting, efficient and effective system operations focus on patient care. To ensure the organisation's service provision, systems are optimised to minimise wasted time, financial resources, and employee energy. All while guaranteeing the provision of patient care and emphasising the provision of high-quality service to patients [33].

Among the various expenses incurred within healthcare establishments, logistics-related costs emerge as the second-largest cost category [63; 53]. Hence, optimisation is also needed in the hospital environment's material logistics context. In a hospital setting, materials are often stocked at three logistical segments: (A) inventory situated within the Operating Room (OR), (B) inventory directly held by the individual departments, and (C) a centralised storage point [18]. All three segments of the material logistic process are directed towards maximising the delivery of patient care. In the context of this research, we focus on the material logistics within the individual hospital departments. To address the healthcare expansion at the department level, numerous studies analyse the influential factors and their patient characteristics impacting inventory control systems. With the help of data analysis, these insights enable them to identify improvement areas and make well-informed decisions that lead to favourable positive outcomes for patients and the organisation. A substantial body of research has already delved into this area, aiming to find a viable solution [51]. Subsection 3.2 concisely describes these methodologies.

Currently, the most prevalent technique employed in the material logistic process within the hospital department is the Kanban method [33; 18]. This approach operates as a pull method, enabling staff members to replenish inventory following predetermined minimum and maximum stock levels [33]. A prompt is triggered to initiate replenishment whenever stock levels dip below the designated minimum. The adoption of this technique is based on its primary objective of ensuring patient safety. The secondary goals of the implementation of the Kanban method are accounting for the inventory shortage costs and capacity considerations [18]. Notably, this methodology does not account for the costs associated with staff coordinating replenishment or the potential errors introduced by personnel, which might impact the effectiveness of the Kanban method [42]. An automated material logistics process is required to reduce personnel's influence. That is why healthcare decision-makers are looking for an automated improvement and refinement of a technique that aligns primary, secondary, and overlooked objectives [18]. The determination of the priority among these objectives depends on the hospital's preferences. The objectives can be evaluated using Key Performance Indicators (KPIs); the most common ones, as identified in relevant literature studies, are defined in Section 2.2.

## 1.4 Research goal

This research aims to analyse and improve the material logistics process within hospital departments. The primary objective is to develop a technique that improves the accuracy of reorder quantity estimations and enhances operational efficiency. The technique should provide the flexibility to tailor the primary goal, allowing hospitals to define their own KPIs and simultaneously concentrate on multiple KPIs. The study involves exploring various methods and models utilised in previous literature. The key goal is to develop an automated, data-driven model capable of determining optimal reorder quantities for each specific item based on the KPIs selection. To streamline our data analysis and model testing efforts, we perform a case study at ZMC and focus our research on the department within the hospital with the highest turnover of stocked items. This department is the surgical department of ZMC. The following main research question is posed:

*"How can integrating an automated material logistics system efficiently track inventory and improve operational efficiency in the department's material logistics process?"*

## 1.5 Problem approach and research questions

This section provides an overview of the research questions and the proposed approach to address them. The research questions serve as a foundation to achieve the research goal by acquiring the necessary knowledge to solve the research problem. Examining the findings for each sub-question provides a comprehensive understanding of the context and helps identify the factors to consider before reaching a solution. The proposed sub-questions are categorised into four main research questions, each corresponding to a chapter. Sub-questions further support the research questions, and their answers will contribute to addressing the main research questions.

Chapter 1, the introduction offers an overview of the parties and teams engaged in the research collaboration. Chapter 1 defines the case description of this research, defines the research goal and outlines the research approach and questions. Chapters 1 and 2 address the first research question.
Research question I. *What traditional material logistic process techniques are currently employed in healthcare organisations, and what measures can be taken to enhance their operational effectiveness?*

1. *What plan of approach can be taken to address the described problem effectively?*
2. *What issues arise within the traditional hospital approach, particularly at the department level, and what are the resulting consequences of the current methodology?*
3. *What Key Performance Indicators (KPIs) are relevant for assessing the effectiveness and efficiency of the techniques in addressing the main issue?*
4. *How can the described problem be categorised within the Strategic, Tactical, and Operational (STO) and Qualitative and Quantitative (QQ) framework?*

Chapter 2 aims to facilitate a problem analysis to explore possibilities for improving the efficiency and accuracy of the hospital's material logistic process. It outlines the common KPIs for this research.

Chapter 3 involves analysing previous literature review studies to examine supply or logistics management methods that have been investigated and identify the characteristics associated with these methods. Chapter 3 addresses the second research question.
Research question II. *"What methods are examined in previous research to improve the material logistics process of hospitals, in terms of supply management or other logistics management methodologies?"*

1. *What state-of-the-art techniques are employed to organise material logistics processes within healthcare institutions?*
2. *How are state-of-the-art techniques applied to assess the turnover of material logistics process management, particularly at the department level of hospitals?*
3. *Which techniques are utilised to analyse the data of replenishment quantities and identify significant characteristics?*
4. *What automated and data-driven material logistic process is best suited for supplying the storage cabinets of hospitals?*

This chapter will explore the similarities among these methods and evaluate other commonly used methods in hospitals to determine their suitability for the material logistics process and their applicability within hospitals.

Chapter 4 includes a description of the existing material logistic process within ZMC and addresses the third research question.
Research question III. *"How is the current material logistic process organised at the department level in ZMC?"*

1. *What is the overall structure of the material logistics process within ZMC?*
   - *Which steps does ZMC follow when they receive deliveries?*
   - *How are items distributed throughout the hospital?*
   - *Which methods are used to track, replenish, and distribute articles within the hospital?*
2. *What problems arise within the current approach at the department level of ZMC, and what are the resulting consequences of the current methodology?*
3. *What Key Performance Indicators (KPIs) does ZMC consider relevant for evaluating the effectiveness and efficiency?*
4. *What parameters are included within the dataset provided by ZMC*

The chapter aims to clarify the current context by implementing interviews that answer the four sub-questions.

Chapter 5 analyses the methods identified in the previous chapter and provides insights into answering the fourth research question.
Research question IV. *"Which predictive methodology will be investigated in this research as the implementation of a conceptual model within the material logistics process at the department level of ZMC?"*

1. *Which key parameters of the dataset of ZMC can be included into the conceptual model?*
2. *In what ways can the data characteristics of the dataset be included in the conceptual model?*
3. *How can the Markov chain process technique be transformed into an automated, data-driven conceptual model suitable for implementation within hospitals?*
4. *What methods can be employed to analyse and evaluate the KPIs of the conceptual model?*
5. *How is the structure and configuration of the simulation model constructed?*

The chapter describes the solution design and presents the data analysis findings to develop the conceptual model.

Chapter 6 examine the added value of the conceptual model and introduce the fifth research question:
Research question V. *"What are the outcomes, impact, and effectiveness of the conceptual model for the material logistics process at the department level of ZMC?"*

This assessment is achieved through a case study, aiming to obtain the results generated by the conceptual model. The results will be validated and analysed to evaluate their potential added value.

Finally, Chapter 7 conclude the report with additional information gathered during the research period. The conclusions and recommendations sections summarise the findings and provide recommendations for Zaans Medisch Centrum, hospitals in general, Coppa, and future research. The discussion offers an interpretation of the results and critical reflection on the proposed solution.

# 2 Context analysis

This chapter presents a context analysis regarding the investigated problem correlated with the material logistic process of healthcare institutions. It also outlines the causes and consequences of our investigated problem. The chapter categorises the type of problem represented and outlines the Key Performance Indicators. Section 2.1 outlines the causes and consequences of the issues, Section 2.2 outlines the key performance indicator related to the consequences and Section 2.3 categorises the type of problem represented. A summary of this section is given in Subsection 2.4.

## 2.1 Problem context

To comprehensively understand the problem being investigated in this research, we analyse the problem from three perspectives: the customer, financial, and internal process. These perspectives are derived from the balanced scorecard framework [25], a management tool used to measure and monitor organisational performance. Developed by Robert Kaplan and David Norton, the balanced scorecard can also be applied in healthcare institutions [25]. Unlike traditional financial indicators, the balanced scorecard incorporates non-financial indicators crucial for long-term success [25]. By applying the different perspectives of the balanced scorecard, the aim is to analyse the problem thoroughly and identify its root causes and consequences [25].

The chosen perspectives — the customer, financial, and internal process — have been selected for specific reasons. The customer perspective is relevant since stock levels directly affect department employees' and patients' needs and satisfaction. The financial perspective is relevant since the manual inspection and estimate of inventory requirements can affect the cost and financial efficiency of the material logistic process. The internal process perspective is important since the manual control and estimation process directly influences material logistics' overall operation and performance. Assessing this perspective allows evaluating the material logistics process's efficiency, effectiveness, and quality. By examining the problem from these perspectives, a comprehensive understanding of its causes, impacts, and consequences can be achieved, enabling appropriate actions and improvements to be implemented. Figure 2.1 provides an overview of the problem cluster.

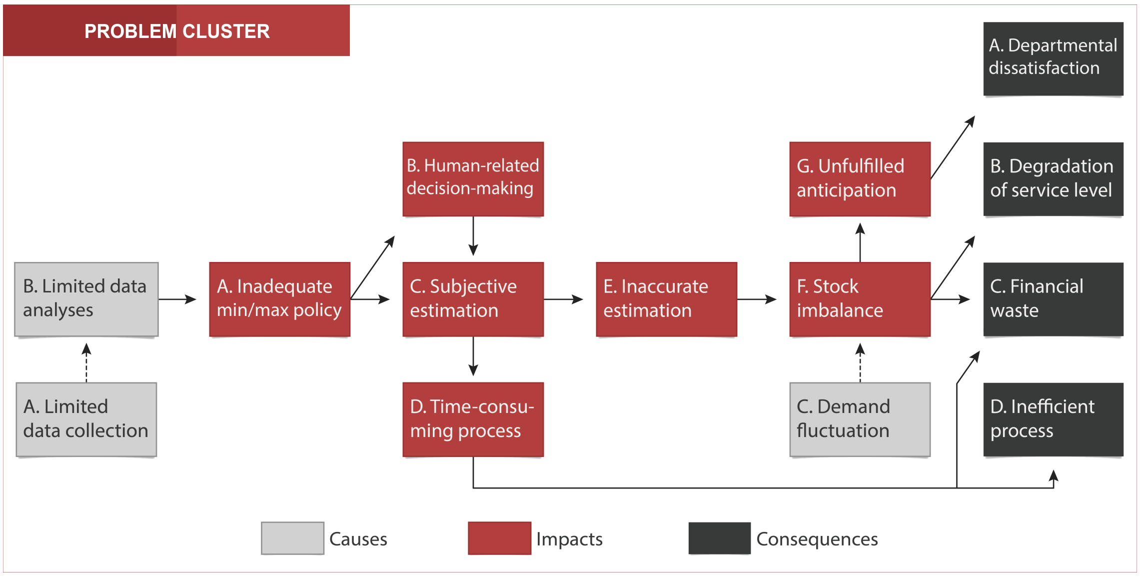



FIGURE 2.1: The problem cluster represents the causes, impacts, and consequences of hospitals' traditional materials logistics process. Each element is explained in detail in Section 2.1.

The problem cluster represents the causes, impacts, and consequences of hospitals' traditional materials logistics process. Each of these elements is explained below the figure.
The problem cluster includes various colours: grey, red, and black. Within the cluster, the grey elements represent the causes of the problem, each exerting distinct impacts. These impacts are visually depicted in red. Ultimately, the red elements lead to outcomes that are represented by the four black elements, which are defined from the three different perspectives described above. The causes and impacts of the problem are clarified below. As well, the outcomes represented by the black elements are explained below from three distinct perspectives.

### Causes and impacts of the problem

Below, you'll find a more detailed explanation of the causes and their impacts of the problem cluster.

#### Causes

(A) *Limited data collection.* During the consumption of materials within the hospital, particularly stocked items, it is common practice not to record the materials per patient but rather to register the average weekly or monthly data. This practice limits the data obtained, consequently restricting data analyses [17]

(B) *Limited data analyses.* The lack of detailed information regarding future demand for specific items challenges accurate stock forecasting and planning. Departments are constrained to rely on average historical data from the past year instead of utilising dynamic and predictive future values to establish the minimum-maximum stock policy.

(C) *Demand fluctuation.* In hospitals, the consumption of materials is often characterised by unpredictability. For instance, a sudden rush in the consumption of a specific item can rapidly exhaust articles, surpassing the predictions made by the minimum-maximum stock policy. Conversely, there may be instances where materials are used sparingly, resulting in excessive stock levels. These fluctuations in consumption patterns make it challenging to maintain balanced stock levels.

**impacts**

(A) *Inadequate min-max policy.* As previously explained, limited data analyses hinder the compliance of Kanban policy. Consequently, the levels may not align with actual consumption in specific scenarios, making the levels unreliable. As a result, logistics team members must rely on their judgment to determine the reorder size per item instead of depending solely on the established thresholds [29].

(B) *Human-related decision-making.* The existing process lacks the incorporation of advanced data analytics or predictive models to enhance the accuracy and automation of stock forecasting. The absence of data-driven decision-making hinders the efficiency and effectiveness of the material logistics process, forcing logistics team employees to make decisions resulting in time-consuming tasks and human-related mistakes manually [18].

(C) *Subjective estimation.* The employees responsible for inspecting the storage cabinets encounter inadequate minimum-maximum stock levels, which force them to rely on subjective estimates when determining the required reorder quantities. This can result in inconsistencies and variations in the reordering decisions, as different employees may make other estimates. As a result, there is a risk of experiencing shortages or accumulating excess stock levels.

(D) *Time-consuming process.* Manually checking the storage cabinets and estimating reorder requirements is time-consuming. Employees must physically visit each department within ZMC, scan the articles, and estimate the need for reordering. This process consumes a significant amount of time and impacts the overall productivity of the logistics team, potentially leading to additional unnecessary costs.

(E) *Inaccurate estimates.* Employees encounter challenges in accurately determining whether to reorder or wait. This challenge becomes even more complicated when unexpected changes occur, of which they may be unaware, such as a sudden spike in the consumption of a specific item. These factors contribute to the inaccuracy of estimates, which can result in shortages or excessive stock levels, commonly referred to as stock imbalance.

(F) *Stock imbalance.* As previously mentioned, the introduction of inconsistencies and variations in reordering decisions, influenced by different employee estimates and demand fluctuations, can result in imbalanced stock levels. Such imbalances can lead to misperceptions among employees who rely on stock consistency. Additionally, this situation can cause financial waste due to potential shortages or excessive stock levels.

(G) *Unfulfilled anticipation.* Stock imbalance can lead to stock level shortages, undermining the consistency of relying on stock levels. This situation can cause dissatisfaction among department employees who anticipate having the required items readily available.

Below, you'll find a more detailed explanation of the consequences resulting from the causes and their impacts within the problem cluster.

### Customer perspective

From the customer's perspective of the problem cluster, two of the consequences can be categorised within the customer's perspective. First, inaccurate inventory estimates might result in unforeseen shortages, potentially leading to dissatisfaction among departments relying on their stock in the storage cabinets, consequence A. Second, stock imbalance might cause delays in patient care and a decrease in the quality of service provided, ultimately degrading the service level, consequence B.

### Financial perspective

Two consequences can be classified when considering the financial perspective, resulting in financial waste. First, manual inspections and estimates of inventory needs yield inaccurate assessments, leading to excessive or insufficient stock levels. Such situations can result in financial waste caused by excess inventory, revenue loss due to shortages, or additional costs associated with emergency orders, consequence C. Second, manually verifying the stock in the storage cabinets and estimating reorder requirements is time-consuming since each department must monitor and replenish each item. This process consumes significant time, potentially leading to additional unnecessary costs, consequence C.

### Internal process perspective

One consequence arises from the internal process perspective, which can lead to an inefficient material logistic process. The manual verification and estimate of stock points are time-consuming and inefficient, requiring significant time and effort from the logistics team. Mainly due to a lack of data and insights into the material logistics process, making it challenging to formulate strategic decisions regarding inventory management. This can result in disruptions in the material logistics processes, consequence D.

### Core problem

As seen in the problem cluster, impacts are influenced by the causes: limited data collection, limited data analyses and demand fluctuations. The focus of this research is primarily placed on the enhancement of limited data analyses. A substantial amount of available data remains unexploited in its potential to enhance an automated material logistics process. The possibilities of an automated approach are extensively explored in the literature, and one of the alternatives is further elaborated on in this research. In addition, in-depth data analyses offer the opportunity to better manage the demand fluctuations. Addressing the issue of data collection is a issue that could be addressed in further research and falls beyond the current scope of this research.

## 2.2 Key performance indicator

Based on the problem context, it is possible to determine essential performance benchmarks to evaluate the methodology's performances within material logistic processes, commonly referred to as KPIs. Below, you can find a list of the most common KPIs to measure the improvement of the forecast model, as identified in relevant literature studies in Chapter 3. The specific KPIs can be determined in alignment with the preferences of the healthcare organisation and scope. Section 3.2 provides an overview of the examined KPIs and the correlated literature research.

1. *Data utilisation ratio*: Evaluates the degree to which data analytics are employed for automated decision-making. A lower level of human intervention results in a higher ratio, signifying a stronger reliance on data-driven decision-making.

2. *Emergency order cost*: Calculates the expenses incurred due to emergency orders. Reduced emergency order costs signify improved inventory planning.

3. *Forecast error*: Computes the variance between predicted demand and actual consumption, considering both overestimated and underestimated demand. Smaller forecast errors indicate more accurate demand forecasting.

4. *Inventory carrying cost*: Evaluates the cost of holding inventory, including storage and transport costs. Lower carrying costs reflect efficient inventory management.

5. *Inventory value at risk*: Estimates the potential financial risk associated with inventory value fluctuations. A lower value at risk indicates better risk management.

6. *Labour hours per replenishment*: Measures the time and effort required to complete replenishment tasks. Lower labour hours per replenishment indicate improved labour efficiency and lower labour costs.

7. *Obsolete inventory rate*: Measures the percentage of inventory that becomes obsolete or unusable. Reducing this rate demonstrates effective inventory planning and management.

8. *Patient care delay*: Assesses the time delay caused by stock outs, impacting patient care. Minimising delays enhances patient care quality.

9. *Replenishment frequency*: Evaluates the number of replenishment actions required within a specific period. Lower frequencies suggest optimised inventory levels.

10. *Stock out rates*: Measures the percentage of instances where items are unavailable when needed. A lower stock-out rate indicates better inventory accuracy and availability.

11. *Stock turnover rate*: Calculates the number of times inventory is sold and replenished within a specific period. A higher turnover rate suggests efficient inventory utilisation.

12. *Storage cabinets utilisation efficiency*: Assesses the efficiency of space utilisation of the storage cabinets for inventory storage. A higher utilisation rate indicates optimal space utilisation and efficient inventory management practices.

13. *Storage handling time efficiency*: Measures the average time items are stored in storage cabinets before being utilised or removed. Lower values indicate efficient storage practices and quicker turnover of stored items, reducing the need for excessive storage space and associated costs.

## 2.3 Type of problem

Before determining the approach to resolving the problem, it is essential to clarify the type of problem at hand. This subsection will outline whether the research involves a strategic, tactical, or operational problem in Subsection 2.3 and whether it is a quantitative or qualitative problem.

### Strategic, tactical or operational problem

To classify the problem within the Strategic, Tactical, and Operational framework, it is essential to provide a brief overview of strategic, tactical, and operational problems as experienced in hospital settings, which can be read below.

Strategic problems are characterised by their long-term focus and wide-ranging impact on the organisation [22]. They involve setting goals, establishing direction, and making decisions at the higher level of the organisation. Examples of strategic problems include defining the business strategy, restructuring the organisation, or determining the desired patient type volumes or the number of resources [22]. Strategic planning is based on historical data and forecasts[22].

Tactical problems are associated with the medium term and revolve around a planning horizon of several weeks [22]. Tactical issues relate to the way of doing the work and involve the tactics for implementing strategic plans. Examples of tactical problems include reorganising a department, creating a surgical schedule, or optimising the supply chain process [22].

Operational problems relate to the short term and revolve around the day-to-day or weekly activities and task execution within the organisation [22]. Operational issues concern addressing disruptions, enhancing customer service, and ensuring quality standards. These problems aim to increase day-to-day operational performance and address immediate challenges.

Within operational problems, a distinction is made between offline and online operational problems [22]. Offline operational problems focus on the detailed coordination of activities related to current (planned) demand and typically involve a planning horizon of a week [22]. This includes activities such as treatment selection, sequencing of appointments, and inventory management, which are predetermined before the actual execution occurs. Offline operational planning relies on known information and expected demand [22]. On the other hand, online operational problems address the unpredictable and unforeseen events that can arise during the execution of the processes [22]. It involves reactive decision-making and implementing control mechanisms to monitor the process and respond to unexpected circumstances. Online operational planning relies on real-time information and the current situation to guide decision-making. It includes triage, adding emergencies to the schedule, and restocking depleted supplies [22].

Improving the material logistic process of healthcare institutions can be classified as an offline operational problem. It directly impacts the day-to-day operations and task execution within the hospital environment, and covers a part of the workweek. In addition, the decision-making process occurs before the actual implementation of activities. This means that the information can be gathered and analysed in advance, after which decisions about reordering items and the reorder quantities are made. The process does not rely on real-time monitoring or immediate responses to unexpected events during execution.

**Quantitative or qualitative problem**

This subsection briefly overviews the aspects defining a quantitative or qualitative problem, including classifying our specific problem in the Qualitative and Quantitative framework.

A quantitative problem is when data is presented in measurable terms, such as numbers, quantities, percentages, or statistics [35]. With a quantitative problem, the analysis primarily involves collecting, analysing, and interpreting numerical data [6]. This problem often involves quantifying relationships, identifying patterns or trends, and making predictions using mathematical models [6]. Illustrative examples of quantitative problems include calculating average sales figures, evaluating the efficacy of a marketing campaign through measurable outcomes, or forecasting the consumption of items within the hospital on historical data and trends.

A qualitative problem, in contrast, involves understanding and interpreting non-numerical data, such as text, observations, interviews, or perceptions [8]. It revolves around gaining insights into the qualitative aspects of a problem, such as behaviour, attitude, opinion, or experience [8]. A qualitative problem emphasises collecting and analysing contextual data to gain meaning and profound understanding. This type of problem often focuses on identifying patterns, discovering themes, and exploring the subjective experiences of individuals [8]. Examples of qualitative problems include analysing qualitative customer feedback regarding a product, examining employees' perceptions of work culture, or understanding patient viewpoints in health care.

The problem addressed in this research can be classified as a quantitative problem. It involves determining specific numbers and quantities of articles that need to be reordered. This requires quantifying needs based on measurable data, such as historical consumption patterns, current stock levels, and expected consumption. By using numerical information, the problem focuses on making data-driven decisions and optimising material logistics processes.

## 2.4 Summary

The sections above outline the issues associated with material logistic processes within hospitals and the techniques used for inventory checking and estimating replenishment quantities for the storage cabinets at hospital departments. These problems result in inaccurate estimates, wasted time, inefficiency, and a lack of strategic decision-making and data analysis. Consequently, they might lead to financial waste, stock shortages or surpluses, and disruptions in the continuity of care. To address these issues, it is crucial to implement an automated and data-driven material logistic process. Such an approach can enhance the organisation's primary objective KPI and accommodate combinations of multiple KPIs. A dual approach combining offline operational improvements with quantitative analysis is recommended to address this issue.

# 3 Literature review

This chapter provides a literature review regarding the investigated problem of the thesis research. The sections answer the following questions: Which technique is employed to organise material logistics processes within healthcare institutions? How are state-of-the-art techniques applied to assess the turnover of material logistics process management, particularly at the department level of hospitals? Which techniques are utilised to analyse the data of replenishment quantities and identify significant characteristics? What automated and data-driven material logistic process is best suited for supplying the storage cabinets of hospitals? When addressing the literature review questions, our research focused on techniques aimed at addressing offline operational problems and techniques characterised by a qualitative framework.

Section 3.1 describes the traditional techniques currently used in hospitals within material logistic processes. Section 3.2 discusses general inventory management techniques used in healthcare institutions. Section 3.3 outlines the techniques used to define the characteristics of items in hospital departments and Section 3.4 explains how these techniques can be combined with an automatic, data-driven methodology. Section 3.5 reviews inventory management techniques based on on-hand stock levels. A summary of the relevant techniques for this study is provided in Section 3.6.

## 3.1 Traditional techniques in material logistics in health care

This section investigates the current method used in many hospitals, the Kanban technique [33; 18]. The Kanban technique, a lean technique initially developed by Taiichi Ohno at Toyota in the 1940s as part of the Toyota Production System (TPS) [41], has since evolved and found widespread application across various industries, including health care. Within the material logistic processes of the hospital's department, the technique serves as a central approach to material logistics management. The technique is based on just-in-time manufacturing and operates as a pull system. The Kanban technique enables healthcare employees to efficiently replenish inventory, aligning with predetermined minimum and maximum stock levels to maintain a smooth flow of supplies [33]. When inventory levels dip below the designated minimum, automated triggers prompt staff to initiate replenishment, thereby ensuring the availability of essential materials for the patient when needed [33]. Beyond its benefits, such as minimising waste and streamlining resource allocation, the Kanban technique focuses on the primary goals of providing high-quality service to patients and optimising hospital processes [18]. Its effectiveness in enhancing patient safety, addressing inventory shortages, and considering capacity constraints has contributed to its status as a widely adopted methodology in hospital logistics management, ultimately enhancing the continuous delivery of top-notch patient care within healthcare institutions [33; 18].

## 3.2 Review: inventory management techniques in health care

The literature includes numerous methodologies for enhancing material logistics processes and their corresponding implementation strategies. Notably, the existing body of literature focuses on addressing one individual KPI rather than providing comprehensive solutions that combine performance indicators. While conducting a literature review study, several influential factors and their associated patient characteristics and methodologies have been identified [51]. The KPIs within these studies are extracted from the influential factors and the reviewed literature studies can be classified within these influential factors, along with their corresponding KPIs. The subsequent influential factors and their corresponding methodology approaches are listed below, with references to the KPI numbers mentioned in Section 2.2:

1. Variation in demand for healthcare items, refer to KPI 3.
   The consumption of healthcare items can be categorised into stationary and non-stationary demand. Stationary demand pertains to items such as vaccines and examination gloves and is relatively easy to predict using forecasting techniques [37]. In the literature, predictive methods such as the Economic Order Quantity (EOQ) method [32; 27] and the Mixed Integer Programming (MIP) optimisation technique [23; 55] are commonly employed for these types of demand predictions. To determine the non-stationary demand, a technique is conducted to predict the dynamic and uncertain nature of non-stationary demand. The non-stationary demand depends on various sources of randomness, such as the number of patients in hospital care units, patient treatment stages, patients' conditions, reaction to the medication, and physicians' recommendations [62]. For this non-stationary demand, the literature investigates probability distributions like Normal [36], Poisson [20], and Negative Binomial [48] to predict the variation in demand.

2. Type variation of health care inventory items, refer to KPI 11.
   Various characteristics influence the consumption of healthcare items and show different behaviours. Given the variations among items, a distinct approach is necessary to forecast demand for each item. Therefore, literature studies investigate the classification of items based on their characteristics. Employed methodologies are ABC analysis [21; 31] and VED analysis [21; 31], decision tree analysis [13], or a combination of ABC and critical analyses [3].

3. Distribution of inventory within the storage facility, refer to KPI 12.
   In a healthcare system, inventory is distributed among different departments

or locations, leading to the implementation of multistage inventory systems [26; 62]. Distinct healthcare items may require specific storage conditions, such as temperature maintenance, and the consumption of healthcare items varies based on the characteristics of each department or location within the system [26]. Moreover, the space in various storage facilities within a healthcare system is limited, and it is necessary to maximise its utilisation. To address this, researchers are exploring an approach that distributes storage space across multiple healthcare items [38; 5]. Employed methodologies for achieving optimal storage utilisation are a capacity model based on a simple inventory rule to determine reorder levels and order quantities [5], nonlinear programming (NLP) [61], constraint programming (CP) [36], and chance-constrained programming (CCP) [38], model predictive Control (MPC) [38].

4. Inventory replenishment policies, refer to KPI 7, 9, 10.
   The literature review study employs various methodologies to determine the optimal replenishment quantity for items based on continuous assessment, periodic assessment, or a combination of both [51]. In the case of continuous assessment, the analysis focuses on factors such as reorder level and order quantity, also known as the (s,Q) policy [45; 49], or the (s,S) policy [28]. When employing periodic assessment, metrics such as review period, order-up-to-level, and reorder level are considered, using policies such as (R,S) [19] or (R,s,S) [5]. This extensively researched topic has implications not only for hospitals but also for other industries and sectors. Within health care, hybrid strategies are utilised, which incorporate both continuous and periodic review policies, along with joint replenishment criteria for multiple items [51; 49; 50].

5. Maximisation of service level of the hospital, refer to KPI 8.
   Ensuring continuous availability of products within a hospital is crucial to ensure uninterrupted care provision to patients and prevent any delays or shortages experienced by healthcare employees. The objective is to achieve a 100% service level to avoid backorders that can entail significant costs [5]. The methodologies employed to maximise the service level of the hospital align with the methods described for the influence factor of inventory replenishment policies.

6. Variation of the patient medical conditions and their response, refer to KPI 3, 11.
   In healthcare settings, the consumption of healthcare items is determined by the correlation between medicine requirements and the patient's medical condition and response [62; 51]. The daily demand for healthcare items is influenced by various patient characteristics, including the patient arrival rate [2], the severity of their illness [62], their medical condition [62], the medication the patient is already taking (multi-morbidity) [14; 15], transfers to other care units [2], and the length-of-stay in the hospital [57]. One methodology employed to address the variation in patient medical conditions and their response is the Markov decision processes (MDP) [52].

7. Variation in physicians' prescribing behaviour, refer to KPI 3, 11. Within

the hospital, physicians are the primary customers of the healthcare items. The demand for these items is dependent on the prescriptions provided by the physicians. This influencing factor must be considered in inventory management, however, it is currently an unobserved aspect [40].

When one carefully reviews the methodology mentioned above and takes note of the KPIs, it becomes evident that KPI numbers 2, 4, 5, 6, 13 are absent. KPIs 2, 4, and 5 pertain to the costs reduction associated with inventory management, which are considered as secondary objectives in the methods outlined above, for example, when addressing influential factor *Inventory replenishment policies*. KPI 6, *labour hours per replenishment*, is commonly regarded as the costs incurred for employee compensation, aligning it with the secondary objectives of the studies. KPI 13 is comparable to KPI 11. KPI 13 focuses on assessing the average time items remain in storage cabinets, providing insights into the handling time associated with the turnover.

Many of the above-mentioned techniques mainly focus on analysing individual KPIs. Only a few techniques focus on combining KPIs encompassing disparate aspects. Notably, many of these techniques predominantly focus on historical data as their primary input, often overlooking the inclusion of real-time inventory levels. This observation becomes clear when closely examining the operations within hospitals. The materials are utilised for patient treatments at the department level of hospitals. Essential items required for these treatments are retrieved from storage, and any remaining supplies are returned to their designated locations. Materials such as bandages, gloves, and syringes do not need to be linked to specific patients. Consequently, it proves impractical for doctors or nurses to accurately record the consumption of such items for each patient, considering the significant time investment involved. Time efficiency is superior within hospital settings, where time is directly translated into monetary value. As a result, this crucial step is often omitted, leading to the need for manual stock counting for each department to determine the on-hand inventory levels. This manual approach introduces limitations within the material logistics process. The following section will explore potential solutions aimed at addressing this issue.

Section 3.2 reviews inventory management techniques in healthcare, focusing on individual KPIs. These KPIss align with specific influential factors and methodologies, covering demand variation, healthcare inventory types, distribution, replenishment policies, service level maximisation, patient condition impacts, and physician prescribing behaviour. However, certain KPIss related to cost reduction and labour efficiency are not fully addressed, and many techniques predominantly rely on historical data, often overlooking real-time inventory levels. The next following section explores potential solutions to address these limitations and improve healthcare material logistic processes.

## 3.3 Material logistics turnover techniques at the hospitals department level

This section examines possible techniques for automated determinations of the on-hand inventory levels at a specific hospital department. A list of possible techniques includes:

1. 2-bin policy: The 2-bin policy is a lean inventory management technique. It involves having two bins or containers for each item in inventory. The first bin contains the current stock, while the second holds reserve stock. When the first bin becomes empty, it signals the need to reorder or replenish the item. In the meantime, the second bin is utilised. This method promotes visual inventory control and helps prevent stock-outs.

2. Doctor-managed consumption tracking: In this approach, doctors and medical staff are responsible for keeping track of the medical supplies or items they consume during patient care. It can be a simple way to monitor the consumption of certain high-value or specialised items and can help raise awareness of resource utilisation among healthcare professionals.

3. Electronic shelf labels: Electronic shelf labels are digital price tags that can also be used for inventory tracking. They provide real-time information on product availability, prices, and promotions, helping staff monitor inventory levels.

4. Manual counting: This is the most straightforward method where inventory levels are determined by physically counting items on shelves or in storage areas. While simple, it can be time-consuming and prone to human errors.

5. Near Field Communication (NFC): NFC allows contactless inventory tracking using smartphones or specialised devices. It is often used for smaller, high-value items.

6. Radio-Frequency Identification: RFID tags are attached to items, and RFID readers send out radio waves to collect data from the tags. RFID allows for real-time, contactless tracking of inventory items, providing accuracy and efficiency.

7. Red and green markers: This is a simple visual tracking method where items are marked with red and green markers to indicate their inventory status. For example, a green marker may indicate that an item is in stock and does not need to be reordered, while a red marker signifies that the item is running low and requires replenishment. The physicians place these markers. The method provides a quick visual indicator of inventory levels and reorder points.

8. Weight-based inventory: Some industries use weight to indicate inventory levels. Items have known weights, and scales can measure the total inventory weight. This method is suitable for bulk goods with consistent weights.

Upon closer examination of the provided list, options 1, 2, 3, 4, 7, and 8 can be excluded. These options necessitate manual adjustments by employees, making option 1, 2, 3, 4 and 7 unsuitable for our objective of achieving automatic application. Hospitals handle a wide range of items, varying from heavy to lightweight, and often store various items together in a single drawer. This complexity makes it unfeasible to implement option 8. Options 5 and 6, NFC and RFID tags, are the more viable alternatives.

The development of NFC and RFID technologies has advanced considerably in the last decade [58; 24; 43]. Notably, the costs associated with these tags have decreased. In addition, the accuracy of these techniques has improved, with signals being less susceptible to interference, and the signal strength and range have expanded. It is worth noting that NFC has a limited range of just 4 cm and is primarily designed for short-range communication. In contrast, RFID technology offers a broader range of capabilities, with the reading range varying depending on the specific type of RFID technology used (e.g. low-frequency, high-frequency, ultra-high-frequency, etc.). In some cases, RFID can read tags throughout entire rooms, offering a more extensive reach. RFID tags have found widespread adoption in the manufacturing sector, including manufacturing, logistics, and supply chain management. Many products and items within these industries are equipped with RFID tags during manufacturing. These tags are instrumental in tracking the status and location of items, enhancing overall efficiency and traceability in these sectors.

Researchers in literature recognise significant opportunities for using RFID tags in material logistics processes [64; 13]. Nevertheless, detailed elaborations within the material logistic processes are still absent. For now, in the hospital setting, RFID tags are used for diverse applications, which can be described as follows:

1. *The "2-bin policy"*: This approach involves using two bins filled with the same item. When one bin becomes empty, an RFID tag is placed on a designated board and scanned to indicate that the bin needs to be replenished [49].

2. *Drug management sytem*: This approach is utilised within pharmacies. They used the RFID tags as an additional check on medication expenditure. This helps ensure that the correct medication is provided, especially when dealing with similar medications, and prevents potentially dangerous interactions between different medications. [59].

3. *Tracking and monitoring medical instruments*: RFID technology has been employed in literature and various hospitals to track instruments throughout the washing and moving processes. The RFID technology ensures that instruments are properly washed and sterilised [34]. The status of RFID tags is adjusted to reflect the status of instrument tents.

4. *Indoor positioning system*: This approach involves using RFID technology to locate medical equipment within medical centres or healthcare facilities. By implementing an indoor positioning system, healthcare providers can save time that would otherwise be spent searching for equipment within the hospital [60].

5. *Monitoring of nurses, doctors, or patients*: RFID technology is employed to monitor and control the activities of nurses, doctors, staff, patients, and visitors within hospitals, ensuring compliance with required protocols. For instance, RFID tags are used to track the frequency of hand disinfection by nurses or doctors and monitor their interactions with patients [44]. Additionally, RFID-based systems enable real-time monitoring of patient's medical conditions, allowing healthcare providers to promptly respond to any changes or emergencies [46; 47].

One American company provides RFID storage cabinets in the market, facilitating the scanning and counting of items within the cabinet using RFID tags and scanners [54]. These cabinets can read additional labelled information, such as temperature and expiration date details [54]. In this research, our primary focus is on automating and improving material logistics processes within hospitals. To accomplish this objective, we utilise the technology employed in RFID storage cabinets, exemplified by Terso Solutions, as an illustrative model without delving deeper into these specific technologies. Our approach centres on a technique capable of offering automated recommendations for replenishment quantities of each item stored in these cabinets, as detailed in Section 3.5. To implement this automated technique effectively, we require data similar to what RFID storage cabinets can provide. We explore various potential techniques to generate this data, as outlined in Section 3.4.
Section 3.3 explores various automated inventory management techniques for hospital departments, including the 2-bin policy, doctor-managed tracking, electronic shelf labels, manual counting, Near Field Communication, Radio-Frequency Identification, red and green markers, and weight-based inventory. RFID and NFC are potential candidates due to their automation capabilities. RFID technology has diverse applications in healthcare, such as medication management, temperature monitoring, instrument tracking, indoor positioning, and personnel monitoring. The research aims to automate hospital material logistics, with a focus on RFID technology for automated replenishment recommendations, similar to RFID-equipped storage cabinets offered by an American company.

## 3.4 Turnover simulation techniques at the hospitals department level

This research investigates the viability of implementing an automated decision-making technique in combination with a RFID storage cabinets. It is essential to initially evaluate the model within a realistic context to formulate recommendations. Ideally, the data acquired using RFID storage cabinets, capable of precise consumption measurement, should be employed for model testing. Unfortunately, this data is unavailable, so this section investigates techniques that can be applied to simulate the RFID storage cabinets in hospitals with the help of existing data at the department level of hospitals. When usage is high during a particular week, the corresponding replenishment quantity is also high, and vice versa. The existing data within hospitals consists of replenishment quantities for each item without the precision of tracking the exact time and date of item consumption. Nonetheless, it offers the possibility to analyse and simulate the throughput of a storage cabinets in a manner that enables automatic estimation of expected on-hand stock levels within these cabinets.

We have divided this section into two subsections to determine the possible technique to simulate the on-hand data of the RFID-based storage cabinets. Subsection 3.4.1 outlines the essential characteristics of the provided data in the context of modelling and analysis. Subsection 3.4.2 delves into the various techniques that can be employed to simulate RFID-based storage cabinets.

### 3.4.1 Data characteristics

It is crucial to observe the data set's characteristics to determine the composition of the hospital's material logistic data set and its potential applications. By defining these characteristics, you can effectively identify the data set's practical uses. This subsection describes the various characteristics that can be distinguished and the characteristics of the existing hospital data [39]. The various characteristics are: (A) Deterministic vs. Stochastic, (B) Static vs. Dynamic, (C) Continuous vs. Discrete, (D) Transient vs. Steady State, (E) Terminating vs. Non-Terminating, (F) Cyclical vs. Non-cyclical, (G) Markovian vs. Non-Markovian. In this subsection, we briefly explain characteristics A-G and ascertain the characteristics that align with the data set presently available from hospitals.

(A) *Deterministic vs. Stochastic*: In deterministic data sets, outcomes are precisely determined by known rules or inputs, making them highly predictable. Stochastic data sets introduce randomness or unpredictability, often influenced by external factors or chance events, making predictions less precise.

(B) *Static vs. Dynamic*: Static data sets remain constant without significant changes, making them suitable for historical analysis. Dynamic data sets evolve with time, capturing fluctuations, trends, and real-time variations, allowing for the study of evolving processes.

(C) *Continuous vs. Discrete*: Continuous data sets consist of an unbroken flow of data points within a range (e.g., temperature measurements), while discrete data sets comprise distinct, separate values (e.g., counts of items) with gaps between them.

(D) *Transient vs. Steady State*: Transient data sets depend on temporary fluctuations or changing conditions, making them suitable for studying transitions or disruptions. Steady-state data sets represent stable, unchanging conditions, often used to analyse long-term stability.

(E) *Terminating vs. Non-Terminating*: Terminating data sets have a finite duration or endpoint, typically signalled by a specific natural event that marks the end of a simulation run, making them suitable for analysing particular time periods. In contrast, non-terminating data sets continue indefinitely, often characterised by performance measures linked to continuous steady-state cycles, facilitating ongoing analysis and trend monitoring. If there is no steady state behaviour, consider its type as terminating simulation.

(F) *Cyclical vs. Non-cyclical*: Cyclical data sets display recurring patterns, resembling waves, or loops, which help forecast seasonal trends or cyclic behaviour. Non-cyclical data sets lack repetitive patterns and may show erratic, irregular variations, making them suitable for complex, unpredictable scenarios.

(G) *Markovian vs. Non-Markovian*: Markovian datasets adhere to the Markov property, where future states solely depend on the current state, simplifying predictions and modelling. Non-Markovian datasets incorporate historical dependencies, requiring consideration of past states to forecast future outcomes or analyse systems with memory effects accurately.

**Replenishment quantities data set characteristics description**

Table 3.1 shows the identified characteristics for our data set:

TABLE 3.1: The identified characteristics associated with the dataset of replenishment quantities.

**Data set characteristics definition**

| Characteristic class | Choice |
|---|---|
| A | Stochastic |
| B | Static & Dynamic |
| C | Discrete |
| D | Transient |
| E | Non-Terminating |
| F | Cyclical |
| G | Non-Markovian |

Our data set is:

(A) *Stochastic*. The data set is stochastic, reflecting the inherent randomness and variability in the consumption patterns of medical items for patient treatment.

(B) *Dynamic & Static*: The dataset exhibits both dynamic and static characteristics. It is dynamic due to the varying replenishment quantities over time. However, these quantities tend to hover around an average replenishment quantity, representing a static aspect of the data set.

(C) *Discrete*: The data set is discrete since replenishment quantities are typically distinct, countable values.

(D) *Transient*: The data set depends on temporary fluctuations or changing conditions, such as the item preferences of doctors and nurses.

(E) *Non-Terminating*: The data set is ongoing and has no predefined endpoint. It represents a continuous or open-ended collection of replenishment quantities with no specified final date or time.

(F) *Cyclical*: The data set consists of the frequency and regularity of fixed-order days, displaying a cyclical pattern.

(G) *Non-Markovian*: The data set exhibits non-Markovian behaviour since future replenishment quantities and order days may depend on historical context or past occurrences.

Considering the data characteristics, we can proceed to explore the turnover simulation techniques, as detailed in Subsection 3.4.2.

### 3.4.2 Turnover simulation techniques

When determining on-hand stock levels, the logistical choice for handling the dynamic and uncertain nature of demand is the utilisation of probability distributions. A possible technique to predict non-stationary demand, and the associated dynamic and uncertain nature of non-stationary demand, is the probability distributions like Normal [36], Poisson [20] and Negative Binomial [48]. The non-stationary demand depends on various sources of randomness, such as the number of patients in hospital care units, patient treatment stages, patients' conditions, reaction to the medication, and physicians' recommendations [62]. In addition to the Normal, Poisson, and Negative Binomial distributions, numerous other known and slightly unknown distributions exist. Table 3.2 shows multiple distribution options and the corresponding characteristics.

TABLE 3.2: The characteristics related to the potential distributions.

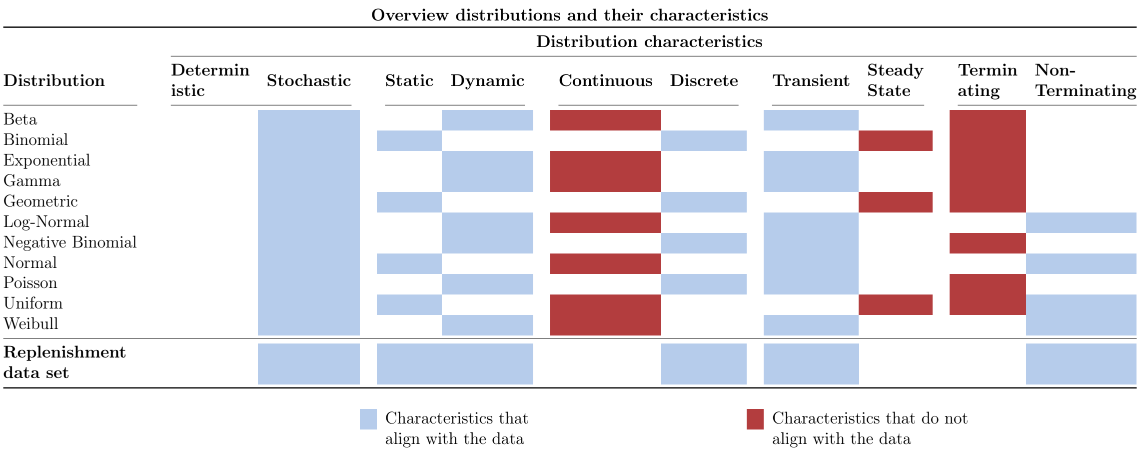



Table 3.2 shows the characteristics associated with these distributions. The characteristics of our data set have been incorporated into the illustration. Within the figure, the blue boxes represent distribution characteristics that do not align with our data set, while the red boxes depict characteristics of the distributions that align with our data set. As depicted in the figure, not all characteristics overlap

with those of the replenishment quantities data set. When evaluating the purpose of distributions for our research objective, the following distributions are not well-suited for our intended application: beta, binomial, exponential, gamma, geometric, Negative Binomial, Uniform, and Weibull. These distributions revolve around the probability of events, time, or the number of successes and failures, which do not align with the purpose of this simulation. After elimination, the three options left are the Log-Normal, Normal, and Poisson distributions. These distributions could be employed for simulating on-hand replenishment quantities.

Section 3.4 explores the feasibility of combining automated decision-making techniques with RFID storage cabinets in hospitals, aiming to enhance material logistics. To assess the model's performance, precise consumption data from RFID cabinets is needed. Consequently, the section investigates techniques for simulating RFID cabinets using existing department stocklevel data, focusing on data characteristics and potential simulation methods. The data exhibits stochastic, static & dynamic, discrete, transient, non-terminating, cyclical, and non-Markovian features, reflecting the variability in medical item consumption. To simulate on-hand replenishment quantities, probability distributions like Log-Normal, Normal, and Poisson are considered.

## 3.5 Inventory management techniques based on on-hand stock levels

With the capability to simulate a realistic setting of on-hand stock levels, the final step involves developing a model based on the data collected from the RFID storage cabinets, which can offer guidance regarding replenishment quantities. Numerous methods can be appropriate for this purpose, as outlined in this section:

1. Agent-based modelling: Agent-based modelling involves creating virtual agents representing items or products within a storage cabinet. These agents interact with each other based on predefined rules and policies, simulating real-world rotations and usage patterns.

2. Discrete event simulation: This technique models discrete events and their impact on the system. In the context of storage cabinet rotation, it can simulate item restocking, emergency reordering, and the overall flow of items through the cabinet, providing insights into usage patterns and efficiency.

3. Markov chains: Markov chains can be used to model the transition of items between different states within a storage cabinet. By defining states (e.g., number of items in stock) and transition probabilities, you can simulate how items move and rotate over time.

4. Monte Carlo simulation: Monte Carlo simulation is a probabilistic modelling technique that can be applied to simulate the rotation of items within storage cabinets. It generates random scenarios based on input parameters like

demand patterns, usage rates, and restocking policies. By running many simulations, you can estimate the distribution of item usage and identify potential stock-out risks.

5. Optimisation algorithms: Some optimisation algorithms, such as genetic algorithms or particle swarm optimisation, can be applied to find optimal stocking policies that maximise rotation and minimise waste in storage cabinets. These algorithms iterate through different strategies to find the best approach.

6. Queuing theory: Queuing theory can be applied to simulate the movement of items in and out of storage cabinets. It focuses on analysing wait times, service rates, and the overall flow of items, which can help optimise cabinet configurations and stocking strategies.

When examining the options listed above, one reason to select Markov chain from the list of modelling techniques for the context of storage cabinets turnover is that Markov chains are particularly well-suited for modelling systems with discrete states and probabilistic transitions. These characteristics align with the dynamics of item movement and rotation within a storage cabinets, precisely mirroring the input that our data can furnish. Unlike the Markov chain, Monte Carlo simulation is commonly employed for continuous data when the goal is to estimate probabilities and outcomes across a continuous range of values. Queuing Theory and discrete event simulation typically centre around the timing or waiting/service times of the simulation, which does not align with the primary focus of our research. Optimisation algorithms can sometimes be less transparent in revealing the underlying processes within the algorithm. This lack of clarity is why this algorithm is not utilised for this research. Lastly, Markov chains are particularly well-suited for systems characterised by discrete and clearly defined states, along with probabilistic transitions between these states. If a problem can be accurately represented using states and transitions, a Markov chain may provide a more straightforward and efficient approach than Agent-based modelling. Hence, we employ the Markov chain as the chosen technique for this research.

### 3.5.1 Markov chain method

This subsection provides a brief overview of the Markov chain model implementation. Markov chains are excellent for modelling the items' transition between different states within a system [56]. In the context of storage cabinet rotation, it is possible to define states such as the number of items in stock or the occupancy level of the cabinet. By specifying transition probabilities between these states, it is possible to simulate how items move and rotate over time. Markov chains rely on probabilities to dictate transitions between states. This is advantageous when dealing with uncertain factors such as demand patterns, usage rates, or restocking policies, which can significantly influence the rotation of items in storage cabinets. Markov chains allow the possibility to incorporate this uncertainty into the model. Defining the transition probabilities between these states makes it possible to simulate the movement and rotation of items over time. This enables examining the current state and the likelihood of transitioning to other states. Additionally, recommendations for replenishment and reorder quantities can be formulated based on the Markov chains. Markov chains capture dynamic behaviour as they evolve over time. This is valuable in understanding how items move and rotate within the cabinet as conditions change. For example, it is possible to assess how different restocking policies or demand patterns affect item rotation and usage. Markov chains can provide insights into the long-term behaviour of the system. By simulating transitions over many time steps, you can assess the steady-state behaviour of the storage cabinet, helping you identify trends and patterns in item rotation.

Section 3.5 delves into inventory management techniques centred on on-hand stock levels, primarily within RFID storage cabinets. It presents a range of methods, including agent-based modelling, discrete event simulation, Markov chains, Monte Carlo simulation, optimisation algorithms, and queuing theory. From these options, Markov chains are chosen because they are well-suited for handling discrete states and probabilistic transitions in the context of item transitions between different states within a system. Subsection 3.5.1 offers a concise overview of the Markov chain method.

## 3.6 Summary

Chapter 3 explores various techniques employed within material logistics processes in hospital settings relying on historical data. This research tries to identify another possible method to improve material logistic processes at the department level of hospitals. To establish a foundation for this optimisation, the initial step involves exploring potential methods to create a suitable data set. The objective is to acquire direct on-hand inventory levels, a critical component in improving the material logistics process. The ideal source for this data is RFID storage cabinets, which can provide real-time insights into inventory status. However, data is unavailable since such storage cabinets are not yet used. An alternative approach is considered: simulating the data. After evaluation, the decision is made to employ three probability distributions – Log-normal, Normal, and Poisson – to simulate the data. These distributions align with the characteristics of the data set, facilitating the simulation of on-hand stock levels within hospital storage cabinets. Last, the Markov chain method is the foundation for the forecasting model's design. The Markov chain method is suitable for modelling systems with discrete states and probabilistic transitions, making it an appropriate selection for simulating item stock levels and replenishment quantities.

# 4 Case study: Background information Zaans Medisch Centrum

To assess our forecasting model, we conduct a case study with the assistance of the Zaans Medisch Centrum. Before delving into the specifics outlined in Chapter 5, it is essential to provide an overview of the hospital and its operations. Section 4.1 explains the material logistics processes within ZMC. Subsection 4.1.1 outlines the operational aspects of distinguishing between three logistic segments: (A) inventory located within the Operating Room, (B) inventory directly managed by individual departments, and (C) a centralised storage point [18]. Subsection 4.1.2 describes the distinction among various items, and Subsection 4.1.3 provides further insights into the inventory ordering systems of ZMC. Subsection 4.1.4 provides a summary of the first section of this chapter. Section 4.2 provides a concise problem description within ZMC, Section 4.3 defines the KPIs of this case study, and Section 4.4 describes the data contents of the provided data by ZMC. Section 4.5 offers an overview of the key points in this chapter.

## 4.1 Process description

First, in Subsection 4.1.1, a comprehensive description of the material logistics at Zaans Medisch Centrum along with the diverse storage facilities is presented. ZMC possesses diverse storage facilities supplemented by external suppliers or internal storage locations within the organisation. In addition, Subsection 4.1.2 describes the hospital items, categorised into two subgroups: stocked items and purchased items. Lastly, the order process is explained in Subsection 4.1.3, providing an overview of how procurement is conducted at ZMC. The subsections cover the key processes essential for understanding the material logistics within ZMC.

### 4.1.1 General overview of supplies within ZMC

During our visits to the ZMC, we arranged meetings with, among others, the Head of Logistics and Soft Services and the Head of OR Care. Following these meetings, we oversee the material logistics within ZMC. ZMC possesses three different storage facilities: a warehouse situated at an external location of the hospital in Wormerveer, storage cabinets placed within each department at the hospital, and a warehouse for the Operation Rooms in the hospital. Figure 4.1 shows a visual representation and schematic overview of the storage facilities at ZMC.

**Warehouse located in Wormerveer**

ZMC uses an external warehouse located in Wormerveer, serving as a central point for receiving all orders from external suppliers, except for emergency orders, hazardous materials, and large equipment, which are directly delivered to the hospital. Within the warehouse, items are sorted, monitored, and replenished as needed, with assistance from the ProQuro software program. For a more comprehensive explanation of the ProQuro software application, read Subsection 4.1.3. When using an external warehouse, ZMC can place substantial orders with suppliers, temporarily store the orders and replenish the hospital's stock with smaller quantities. The external warehouse's purpose is to streamline hospital supply operations, enhance reliability, and reduce supplier costs, ensuring a more efficient and cost-effective supply chain.

ZMC categorises items for material logistics into two distinct categories: stocked items and purchased items. Stocked items are stored in the warehouse in Wormerveer and can be ordered by departments when needed. Purchased items are not initially stocked in the external warehouse. When a department orders purchased items, the order is sent to the supplier, after which it is first delivered to the warehouse and subsequently included in the next delivery to the respective department. In addition, the stocked items stored in the warehouse in Wormerveer are further categorised into medically sterile items, non-sterile items, and liquids, each with a dedicated section within the warehouse for storage. This systematic division ensures efficient organisation and management of various items.

When a department at the hospital places an order, the order is processed and prepared at the warehouse. On weekdays, a delivery truck travels three times each day from the external warehouse to the hospital, following a predetermined schedule, dividing the departments into specific blocks. In the morning, the warehouse receives a request from the departments for that relevant day, specifying the required quantity of the items. Those orders are then prepared in the warehouse and collected at the assigned time by the truck, which transports them from Wormerveer to the hospital. Occasionally, the external warehouse receives emergency orders from departments that are not scheduled for that specific day. In the context of this research, we will refer to these as additional replenishment or additional orders. In such cases, those additional orders are included in the next trip departing from the warehouse. However, that only applies to additional orders for items stocked in the external warehouse. If an additional order is placed for an item not currently available in the warehouse, it is directly delivered to the hospital by the supplier. The described logistical process ensures the smooth delivery of items from the warehouse in Wormerveer to the various departments within the hospital in Zaandam.

The replenishment of stocked items in the external warehouse follows a system based on minimum and maximum stock thresholds, which are predetermined for each item. When an item's quantity falls below the minimum level, an order is initiated at the

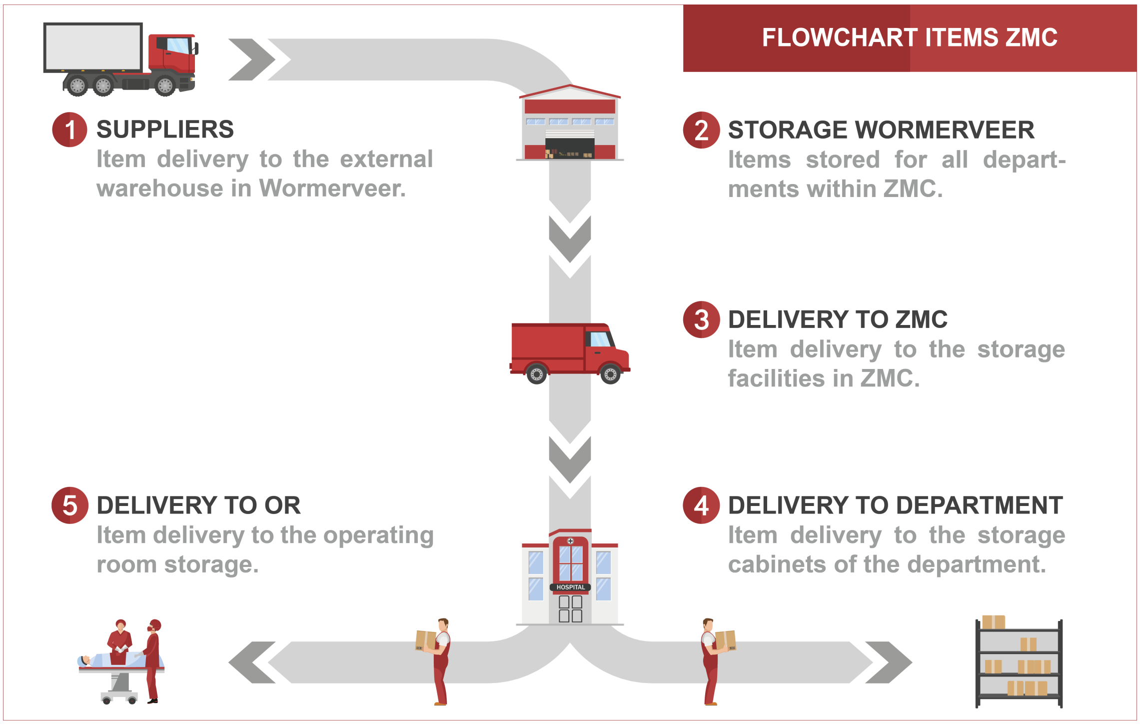



FIGURE 4.1: A flowchart of the material logistic processes for items at Zaans Medisch Centrum.

supplier to replenish the stock to the maximum level for that specific item. The warehouse aims to place orders at suppliers once a month, resulting in twelve orders per year. Determining the minimum and maximum ranges is aligned with the monthly ordering frequency, ensuring efficient stock management and supply replenishment.

### Storage cabinets in the department

In ZMC, every department stores its items in the storage cabinets situated within an enclosed room. In addition to the regular storage cabinets, departments also have access to modular carts that are replenished directly from the storage cabinets. These carts facilitate easy transportation of items to patients. When managing the stock, it is essential to find the right balance between the capital invested and the prevention of shortages. Excessive stocking of items should be avoided as it leads to substantial capital investment and occupies significant stock space. However, it is equally important to avoid running out of essential items. The expiration dates of products, especially food and sterile materials, must also be considered. Insufficient purchases of a product lead to additional orders, incurring additional costs. Conversely, a large capital investment also comes with additional expenses. Each department, together with team Logistics and Soft Services, is responsible for maintaining the storage cabinet, emphasising the importance of accurate supply management.

To ensure an adequate stock level, each item in the department has a minimum-maximum stock threshold determined and monitored by the Logistics and Soft Services team. Depending on the throughput in the department, supplies are checked by a logistic employee 1-3 times a week. Larger departments receive supplies three times a week, while smaller outpatient clinics are supplied once a week. The team has developed a weekly schedule for delivery and monitoring, taking into account the specific needs of each department. Table B.1 in Appendix B displays this replenishment schedule. It is important to note that deliveries and inspections occur only on weekdays, and there are no standard deliveries to ZMC over the weekend. Inspections are conducted on the morning of the delivery day, which aligns with the day of the transport of supplies from the external warehouse to the hospital in Zaandam.

During the stock control process, the logistic employee scans all items in the department's storage cabinets. After scanning, the inspector estimates whether additional items should be ordered and determines the appropriate quantity if necessary. While the minimum-maximum stock threshold provides a useful guideline for estimating stock needs, some employees may find it challenging to decide whether to place a reorder or wait until the next stock control. Moreover, unexpected changes, such as sudden increases in item consumption, can make the estimate less accurate. To support employees in making informed choices, a department-wide supply check is conducted every six months to verify the minimal-maximal stock threshold. If any shortages or surpluses are identified during the stock control, the department and logistics teams collaborate to discuss and adjust the threshold accordingly. In the meantime, the logistic employee has the authority to order more or less than the threshold to ensure that the supply meets the consumption demands. Ultimately, the Logistics and Soft Services team is responsible for ensuring that each department has sufficient supplies to meet the required standards.

Placing additional orders entails additional costs, which include the expenses of an extra delivery by the supplier and the labour costs associated with fulfilling the additional order and delivering it to the department. Additional orders may be necessary for various scenarios, such as when the department has been late with its ordering process, when more materials have been consumed than anticipated, or when the internal or external supplier fails to meet the agreed delivery time. If the item is unavailable at the external warehouse, a direct order is made with the supplier. In the other cases, an additional order is placed at the warehouse in Wormerveer. Department secretaries handle additional orders, which are reported to the P2P team for processing. When the item from the additional order is directly ordered from the external supplier, the supplier delivers it straight to the hospital in Zaandam. Any additional costs associated with the delivery must be approved in advance by the department, considering their set budget and ensuring it is not exceeded. To minimise unexpected additional charges in a department, it is crucial to minimise the occurrence of additional orders.

**Operating Room warehouse**

Orders are placed immediately within the supply organisation of the OR warehouse upon consumption of items. Throughout the day, those individual orders are collected and gathered into a singular order and sent to the external warehouse. While both stocked items and purchased items coexist in the OR warehouse, the reordering process for both types of items follows a similar approach to the logistics process outlined for purchased items in subsection 4.1.1 - *Storage cabinets in the department*. It can be observed that the supply management in the OR warehouse differs from the external warehouse and storage cabinets.

The replenishment process for both stocked items and purchased items in the OR warehouse is facilitated through the CoperniCare software system. This application allows the tracking of individual orders of the OR. Moreover, CoperniCare is integrated with ProQuro, enabling the automatic transmission of orders between the two systems. The combined orders are transmitted via ProQuro to the external warehouse in Wormerveer, where it is prepared on the day when the delivery truck is scheduled to transport the items to the OR department.

In addition to stocked items and purchased items, the OR department also utilises a consignment inventory system. This type of inventory management involves the supplier being responsible for supplying and maintaining the inventory in the OR warehouse. An example is prostheses in various sizes, from which only one specific size is used during the operation. The supplier stocks a certain quantity of each size of prostheses in the hospital, but this inventory remains the supplier's property and is not considered hospital-owned. When an item is consumed, it is deducted from the hospital's inventory. Following consumption, the supplier replenishes the stock in the hospital.

### 4.1.2 Distinction in items

As mentioned in subsection 4.1.1, the ZMC hospital classifies items into two categories: stocked items and purchased items. This subsection delves into further details about these two types of items.

Stocked items are kept available in the warehouse located in Wormerveer and are immediately ordered and delivered to the hospital whenever a department requires them. These items are stored in the warehouse if multiple departments use them or if the delivery time from the supplier is long. This approach ensures that the departments have a higher level of assurance regarding timely deliveries and helps to reduce delivery and administration costs. Stocked items are frequently used, allowing for consumption prediction and assessment of the accuracy of the current stock threshold. Examples of stocked items include medical consumables, medication and pharmaceutical products, as well as bandages.

Purchased items, on the other hand, are purchased on an ad hoc basis and typically involve items that are used infrequently or are specifically meant to treat patients with a unique treatment. When a department requires purchased items, they are immediately ordered after usage, separate from the department's stock control in the morning. Still, similar to stocked items, purchased items are delivered to the warehouse first and then included in the next delivery moment to the relevant department. The handling of purchased items within the warehouse is facilitated by a purchasing number, which allows the external warehouse employees to identify the department that placed the order. The purchasing number also enables determining whether the item is needed earlier than the scheduled delivery. In such cases, the item will be delivered to the hospital during the next delivery of that day. Examples of purchased items include medication and pharmaceutical products that are not regularly used and consumables specific to certain procedures, such as catheters, prostheses, or implants.

### 4.1.3 Placing orders

In the section above, orders are placed either from the external warehouse or by a specific department at ZMC, utilising the ProQuro software program. ProQuro is a software solution specialising in procurement and supplier management across various industries, including health care [16]. It offers features and tools to streamline the procurement process, enhance supplier relationships, and optimise the cold supply chain [16]. The ProQuro platform enables organisations to improve the efficiency of their procurement processes and gain better control over expenses.

Within ZMC, ProQuro is utilised for placing and tracking item replenishment orders. Those orders are initiated by either a member of the Logistics and Soft Services team or one of the department secretaries. During the ordering process, the order is related to a specific cost centre, corresponding to the relevant hospital department. Once the order is placed, it requires approval from the budget holder of the department. After obtaining the necessary approval, the order is forwarded to the external warehouse (in the case of hospital orders) or the supplier (for orders made by the external warehouse) for further processing and fulfilment.

### 4.1.4 Summary

This section offers a comprehensive understanding of Zaans Medisch Centrum's material logistics, from the storage facilities and item categorisation to the ordering processes, setting the stage for a more in-depth exploration of the hospital's logistics operations. The section is subdivided into three subsections, each focusing on a critical aspect of the material logistics within the hospital.

The first subsection offers a comprehensive overview of ZMC's material logistics, emphasising the various storage facilities. ZMC utilises three storage facilities: an external warehouse in Wormerveer, storage cabinets within hospital departments, and a dedicated warehouse for the Operating Room. These facilities serve different roles in managing the hospital's supplies.

The second subsection delves into the categorisation of items at ZMC. Items are classified into two primary groups: stocked items and purchased items. Stocked items are readily available in the external warehouse and can be ordered by departments when needed. Purchased items are ordered as required and are not initially stocked in the external warehouse. The distinction between these two categories influences the procurement and supply processes.

The third subsection provides an insight into the ordering process at ZMC. It discusses the software solution, ProQuro, used for placing and tracking item replenishment orders. The order process is explained, highlighting the involvement of various personnel, including the Logistics and Soft Services team and department secretaries.

## 4.2 Problem description

As described in Section 4.1.1, the storage cabinets undergo manual inspections carried out by a logistics team member. During these inspections, the employee scans each item in the department's storage cabinet, and based on the findings, the inspector evaluates whether reordering is necessary and, if so, determines the appropriate quantity. While many employees can accurately estimate the need for reordering using the minimum-maximum stock threshold, some may struggle with making this decision. Additionally, unforeseen shifts in item consumption can occur, further undermining these estimates' precision. Manual inspections and estimates of inventory needs in department storage cabinets result in various challenges and potential issues.

## 4.3 Key performance indicators in the case study

When testing the model using the case study, our attention is directed towards a subset of Key Performance Indicators selected from the list provided in Section 2.2. During discussions with the Head of Logistics and Soft Services and the Head of Operating Room (OR) Care, it became clear that they are interested in a reliable automated technique to determine replenishment quantities. Their definition of reliability revolves around a model's ability to prevent stockouts. They emphasise the risks associated with an excessive stock in the storage cabinets. This risk necessitates a trade-off between guaranteeing the provision of patient care and keeping a low invested capital within the storage cabinets. To measure the effect of these requirements, relevant KPIs are formulated. The following KPIs are in line with the requirements mentioned above:

1. *Additional replenishment frequency.*

2. *Stock out rates.*

3. *Inventory carrying costs.*

4. *Storage handling time efficiency.*

Our model's evaluation revolves around assessing the outcomes of these KPIs.

## 4.4 Data contents

ZMC provides data regarding replenishment activities across the hospital's departments. Within ZMC, the logistics team monitors the stock levels in every department. As described in Section 4.1.1, our research focuses on a specific department within ZMC known as the surgical department. The logistics team oversees replenishment for this department twice a week — Mondays and Thursdays. Period 1 represents consumption spanning from Mondays to Wednesdays, while period 2 represents consumption from Thursdays to Sundays. Notably, orders on Thursday mornings reflect consumption in period 1, whereas orders on Monday mornings mirror consumption in period 2. Additionally, the surgical department occasionally places additional orders to avert shortages. Whenever the logistics team initiates an order, the corresponding quantity is recorded; conversely, 0 is recorded when no order is placed. All orders are tracked using the ProQuro software system. The data required for this research is sourced from the ProQuro system.

The data contains information about the ordering behaviour and items of the departments from January 1, 2020, to December 31, 2022. The essential information within the data set is described as the following:

1. *Cost centre*: The cost centre describes the department in which the costs are incurred. In our case, this is the surgical department.
2. *Cost category*: The cost category describes the type of costs of the item. For example, medicines, bandages, or administrative costs.
3. *Item name*: The item name describes the item, such as Glove size L, NITRILE SensiCare-Mediguard, Sterile suture removal kit, and Hip bandage large.
4. *Order date*: The order date indicates the date the item was ordered.
5. *Quantities*: The quantities indicate the quantity ordered per item on the order date.
6. *Price per unit*: The price per unit represents the item's cost per unit on the order date.
7. *Total costs (incl. VAT)*: Total costs are the expenses for the total number of one item per order date, including VAT.
8. *Unit*: The unit specifies the unit of which one quantity of the item consists. For example, gloves come in a box containing 200 pieces; the unit for 1 number of gloves is 200 pieces.

### 4.4.1 The items in the storage cabinets

In the year 2022, the surgical department distinguished 37 cost categories. Table C.1 in Appendix C shows a comprehensive overview of all these cost types. Some of these cost types encompass items available in the storage cabinets, while others include administrative expenses or one-time purchases of assets. In this research, our focus is primarily directed to the cost types predominantly consisting of items located within the storage cabinets. This choice is made since it allows the development of an automated, data-driven forecast model tailored to the specific item usage of the surgical department.

Next, we compare the items belonging to the remaining cost categories and those listed in the assortment lists. The items in the assortment list are stocked in the storage cabinets and exclusively contain stocked items. These are closely monitored and replenished by the logistics team. We exclude any items not found on this list from our comprehensive order overview. In some instances, the same item might be listed under two different names, or the same item might transition to another brand midway through the year. To address this, we have consolidated the order history and quantities, presenting the item's consumption overview while accounting for both the old and new item units. This execution of items forms a comprehensive overview of all items stored in the storage cabinets. A total of 267 distinct items emerge from this process, encompassing all items present in the storage cabinet of the surgical department. The cumulative cost for all the selected items, as incurred in 2022 by the surgical department, amounts to € 132 963. This sum constitutes 89% of the total costs, which is €149 658, spent by the surgical department throughout 2022.

## 4.5 Summary

The first section of this chapter provides a detailed overview of material logistics at ZMC. The section serves as a foundation for understanding ZMC's logistics operations and is divided into three subsections:

1. Subsection 4.1.1 outlines the hospital's storage facilities, including an external warehouse, departmental storage cabinets, and an OR warehouse.
2. Subsection 4.1.2 explains the classification of items into stocked items and purchased items.
3. Subsection 4.1.3 delves into the ordering process using the ProQuro software, involving various personnel and approval procedures.

The second subsection addresses the manual inspection of storage cabinets, as outlined in Section 4.1, and highlights the associated issues. During the inspections, employees scan items and determine if reordering is necessary. While some employees can estimate reorder needs accurately, others face challenges. In addition, unforeseen shifts in item consumption can also complicate estimates, resulting in additional costs and possible shortages.

The third section discusses the selection of Key Performance Indicators for the case study. The selected KPIs are in line with the requirements of hospital management and include the following:

1. *Additional replenishment frequency.*
2. *Stock out rates.*
3. *Inventory carrying costs.*
4. *Storage handling time efficiency.*

Section 4.4 describes the data used for the research. The data, sourced from the ProQuro system, covers department ordering behaviour and item details from January 2020 to December 2022. The focus is primarily on cost types associated with items stored in storage cabinets (stocked items), amounting to 89% of the surgical department's total costs in 2022, totalling €132 963 out of €149 658.

# 5 Forecast model

This chapter provides a written description of the conceptual forecast model developed for this research. Section 5.1 provides a written description of the conceptual forecast model developed for this research. It offers an overview of all the sections described in this chapter. Section 5.2 explains the data preprocessing steps. Section 5.3 clarifies the selection process of the distributions for the individual items. The explanation of the revised capacity determination and the implementation of the Markov chain decision strategy can be found in Section 5.4 and Section 5.5, respectively. Section 5.6 provides details on the setup of the three experimental designs, while Section 5.7 explains the functioning of the conceptual forecasting model. Section 5.8 concludes this chapter with a summary.

## 5.1 Chapter overview

This chapter outlines the research approach for the development of the conceptual forecast model and serves as an essential guide to understanding the methodology and steps involved, from data preprocessing to experimentation and modelling. The chapter consists of the following key steps:

1. *Data preprocessing, Section 5.2*: Before determining item distributions, data preprocessing is conducted to select crucial items based on criteria such as cost type, article name, total costs, and replenishment frequency. The ABC-Replenishment matrix is used for classification, and further preprocessing is explained for data from 2020-2021.

2. *Determining distributions for each item, Section 5.3*: The distribution for each item is determined based on a two-period consumption pattern derived from the data collected at ZMC. These distributions are validated using the chi-square test.

3. *Revised capacity, Section 5.4*: The assigned capacity for items is revised to better match actual usage. This revised capacity is determined based on the average maximum consumption observed across simulations.

4. *Markov chain model, Section 5.5*: A Markov chain decision strategy is implemented to decide replenishment quantities based on probability thresholds. The probability threshold assesses the likelihood that the usage will be equal to or less than the in-stock items for the upcoming period.

5. *Experimental designs, Section 5.6*: Three experiments are conducted to optimise the decision-making strategy. These experiments focus on the probability threshold values, additional replenishment days, and capacity adjustments.

6. *Forecast model, Section 5.7*: The simulation model is described, including the material logistics process, consumption patterns, ordering methods, and the implementation of KPIs. The chapter also delves into various experiment setup details, including the number of replications, random number streams, warm-up periods, and batching approach for modelling items.

## 5.2 Data preprocessing

Before determining the distribution of each item for the storage cabinets simulation, it is essential to conduct data preprocessing on the acquired data. This preprocessing involves the selection of crucial items based on criteria such as cost type, article name, total costs, and the number of replenishments. For this process, we process the data from the year 2022, representing the most recent complete cycle. The determination of the most suitable items for simulation is explained in Subsection 5.2.1, utilising the ABC-Replenishment matrix. Further details about additional preprocessing steps, carried out after analysing the entire available data from 2020 to 2022, are provided in Subsection 5.2.2.

### 5.2.1 ABC-Replenishment matrix

After identifying the items present in the storage cabinets, a total of 267 distinct items remain. This is still a long list, implying that replicating a storage cabinets simulation would be a labour-intensive and time-consuming task. By implementing a categorisation strategy that classifies items into three groups based on their replenishment frequency and revenue data (ABC analysis), we streamline this process and reduce the number of items.

#### Inventory classification based on replenishment frequency

A sufficient amount of data is necessary to establish a distribution of the replenishment for each item. By considering the frequency of replenishments, we can classify items into different groups, often labelled as "High Replenishment Frequency," "Medium Replenishment Frequency," and "Low Replenishment Frequency,".

1. High Replenishment Frequency: $\geq 48$ replenishment.
   Items in this category are replenished frequently throughout the year, averaging at least once a week. This implies a high level of demand for these items, and they require more frequent stock replenishment to meet this demand.
2. Medium Replenishment Frequency: $48 \geq 24$ replenishment.
   This category includes items with a moderate level of replenishment. They are replenished roughly two to four times a month. This suggests a balanced demand for these items and a more measured stock replenishment approach.

3. Low Replenishment Frequency: 24 > replenishment.
   Items in this category experience infrequent replenishment, with an average of less than twice a month. This indicates lower demand or longer shelf life, allowing for a more relaxed stock replenishment schedule.

For this research, we define the minimum requirement as 24 replenishments within a year. This means that the specific item is replenished at least twice a month.

**Inventory classification based on the ABC analysis**

The ABC analysis ranks items according to their revenue or cost data, focusing on their contribution to overall value. This strategy initially arranges all items in descending order based on their revenue or cost. For which the total percentage is computed. A prioritised list is formulated with the cumulative revenue or cost calculations. The outcome of the ABC analysis classifies items into three primary groups:

1. Category A: 80% of total revenue or cost.
   This category includes the most valuable items. Although they constitute a relatively small fraction of the overall item count, they significantly contribute to the overall sales.
2. Category B: 15% of total revenue or cost.
   This category includes items that provide a moderate value contribution to total sales.
3. Category C: 5% of total revenue or cost.
   This category includes items with the lowest individual value contribution. They often make up a substantial percentage of the overall item count.

Combining both categorised groups provides the opportunity to differentiate the items. This differentiation is depicted in Table 6.1.

### 5.2.2 Additional data preprocessing based on 2020-2021

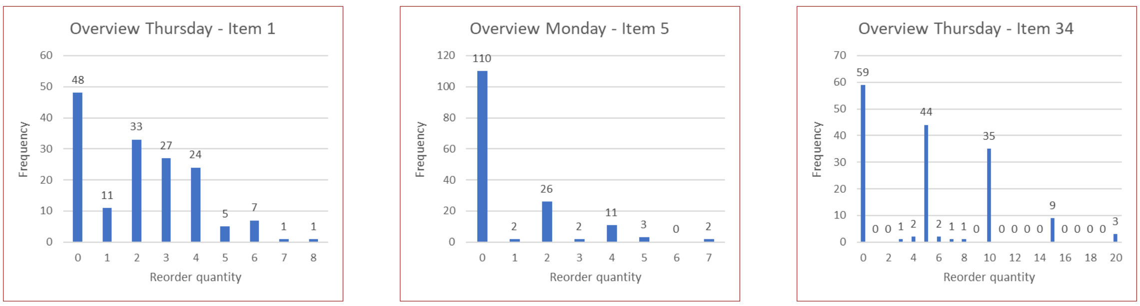
The item selection mentioned earlier is established upon the replenishment data of 2022. Upon examination of the data from 2020 and 2021, it becomes clear a refined subset of 43 items remains suitable out of the initially identified 56 distinct items — various factors cause this refinement. For instance, the turnover of certain items during 2020-2021 is comparatively lower than that of 2022, or certain items were not stocked at all within 2020-2021. One illustrative example is the item "OttoMatic BEPA 5 ltr can". Moreover, it is crucial to acknowledge that the COVID-19 pandemic has influenced the consumption of specific items. Notably affected are items such as "Sterillium gel pure 475ml 9813152" and "INT Mask Blue Earloop EN14683 Type IIR." Consequently, the data generated during this period is not representative due to the exceptional circumstances, so these specific items are excluded from the final selection. The final selection consists of 43 items from the storage cabinet of the surgical department. Table 6.2 shows the statistics of this selection.

## 5.3 Determining the distributions for each item

We assume two distinct periods within a week when determining the distribution of each item's consumption. This approach involves considering additional orders as part of the period in which they occur. We further assume that the consumption patterns in periods 1 and 2 between 2020 and 2022 are similar and can be treated as distinct measurement instances within a unified period. All these measurement instances from periods for both periods 1 and 2 are combined sequentially. To achieve this, we sequentially record all replenishment quantities for each day, as provided in data from ZMC. Thereafter, all replenishment quantities within one period of one week are summarised and listed in a new overview. This overview can be used to create visual representations such as histograms or frequency overviews to better understand the distribution of replenishment quantities over time and enables the derivation of a distribution for each item per period.

When examining the attributes of the data, it becomes clear that the decision-making of the logistics team members impacts the measurement instances. Figure 5.1 illustrates a visual explanation of the influence of the logistics employee's replenishment behaviour. The influence of the team members can be categorised into three distinct factors:

1. Item reorder quantities such as 1, or occasionally 2, are seldom ordered. The team member responsible for logistics tends to wait until the subsequent ordering opportunity, at which point a larger quantity is ordered in a single instance.
2. Certain reorder quantities, such as 2, 4, or 5, are inherently more straightforward to order than items like 3 or 6. The preferences of the logistics team members influence the selection process.
3. Various articles are ordered in specific quantities such as 5, 6, 10, etc., often based on convenience or due to items being supplied in certain quantities, like strips.




(1) Seldom ordered quantities

(2) Preferences ordered quantities

(3) Strip size ordered quantities

FIGURE 5.1: Illustration of factors 1, 2, and 3 influencing the decision-making process of the logistics team members.

The factors above significantly impact the shape of the distribution. Despite these influences, it is essential to derive a distribution from the acquired data. To achieve this, the interval used to categorise data points in a histogram or frequency distribution must be adapted following the effects of factors 1, 2, or 3. There are also instances where a combination of these factors might influence the item reorder quantity. For example, an item is supplied in strips of six (factor 3), and the logistics team member delays ordering if only one strip has been utilised (factor 1).

A common heuristic for determining the bin range is $\sqrt{Number\ of\ measurements}$ [39]. This choice helps strike a balance between the level of detail in the histogram and its ability to reveal patterns or structures in the data. The reasoning behind this heuristic is that if you have too few bins (underspecified), the histogram might not capture important details in the data. On the other hand, if you have too many bins (overspecified), the histogram may become noisy and make it difficult to identify meaningful patterns.

However, to account for the impact of these factors, the bin length is adjusted to counterbalance the effect or a combination of these factors. The procedure for adjusting the bin length is as follows:

1. Bin length multiplication: The bin length is multiplied by a factor of two, resulting in a bin range that accommodates double the item count. In cases where a combination of factors occurs, such as factors 3 and 1, when an item is ordered in quantities of five, the bin length is adjusted to ten.
2. Bin length shift: The bin length is shifted to align with item quantities ordered less frequently. Precisely, the bin range is adjusted so that the next or previous item quantity encompasses the less frequently ordered item quantity. For instance, when item reorder quantity three is often rounded to four by the logistics team, the bin length is fine-tuned to ensure that reorder quantity three and four fall within the same bin range.
3. Preferred Quantity Bin Length: The bin length is set based on the item's strip size or preferred order quantity (e.g. reorder quantity of ten). By adjusting the bin length to match the preferred quantity or strip size, the distribution is influenced, and orders that occasionally deviate from this pattern are aligned with the more frequently made choice.

To determine which distribution suits each item, we conduct a validation procedure utilising the chi-square test. This test serves to evaluate the null hypotheses. In this context, the null hypothesis posits that the examined distribution fits the characteristics of the observed item. The chi-square test assesses the variance between expected and observed frequencies within the data set. It quantifies how much the data deviates from what would be expected under independence. This Chi-Square statistic is compared to the critical value derived from the Chi-Square distribution. If the Chi-Square statistic surpasses the critical value, it signifies the rejection of the null hypothesis, indicating a lack of significant association between the variables. If the Chi-Square statistic does not exceed the critical value, this distribution can be employed for simulating on-hand stock levels. These outcomes are illustrated in Section 6.3 Table 6.4.

## 5.4 Revised capacity

When observing the replenishment data, it became clear that the assigned capacity does not always align with the actual item usage. While shadowing the logistics team member during a department checkup, it became clear that the specified capacities are not always accurate for every item. The logistics team members often use their insights into which items are being used more rapidly or slowly than the assigned capacity indicates. They manually adjust the replenishment quantities as needed. We seek to incorporate a revised capacity within our simulation to achieve a more realistic representation. This revised capacity is determined based on the average maximum consumption observed across twenty simulation replications.

## 5.5 Markov chain model

The conceptual model is based on the methodology selected in the last subsection of Chapter 3. The replenishment quantities are based on a predetermined probability threshold. When determining the replenishment quantity, the method assesses the likelihood that the usage will be equal to or less than the in-stock items for the upcoming period, denoted as $P(Usage <= InStock)$. This decision is based on the probability that the current stock in the storage cabinets is sufficient to cover the period until the next scheduled ordering moment. If this probability is less than the selected probability threshold, the stock is replenished to its maximum capacity, considering the order size at which individual items are packaged. Only multiples of this order size are placed as orders. If $P(Usage <= InStock)$ exceeds the probability threshold, no order is placed, and the system waits until the next scheduled ordering moment. The determination of $P(Usage <= InStock)$ relies on the distribution used to characterise the item. The following formula applies to the Poisson distribution, where $x$ represents the current stock level (InStock):

$$P(Usage <= x) = \frac{\lambda^x * e^{-\lambda}}{x!} \tag{5.1}$$

The following principles apply when calculating $P(Usage <= InStock)$ for the Normal distribution, with $x$ representing the current stock level (InStock):

$$\phi(z) = P(Usage <= x) = \frac{1}{\sqrt{2\pi}} * \exp -\frac{x^2}{2} \tag{5.2}$$

When consulting the standard Normal probability table for the result of $\phi(z)$, you obtain $P(Usage <= x)$.

## 5.6 Experimental designs

We evaluate and measure the optimisation of the conceptual decision-making strategy through three diverse experiments. The first assesses the Markov chain decision policy implementation on traditional replenishment days (Monday and Thursday). The second evaluates the implementation of the Markov chain decision policy on traditional replenishment days (Monday and Thursday) and its application on additional replenishment days (Tuesday, Wednesday, and Friday). The third experiment aims to optimise the capacity of items stocked in the storage cabinets.

**First experimental design: implementation of the Markov chain model**

The replenishment decision is driven by the probability $P(Usage <= x)$, which assesses the likelihood of the current stock meeting upcoming care requirements. A threshold specific to each experiment is defined to guide the decision-making process. Replenishment is initiated when the $P(Usage <= x)$ falls below the defined threshold. This threshold represents the point at which the probability of adequately meeting care demands becomes too low, signifying an unacceptable level of risk in starting the period with the current stock levels. In the first experiment, a threshold of 50% is applied, with subsequent experiments incrementally increasing the threshold by 1% until reaching the maximum value of 100%. This systematic progression results in 51 unique experiments, each comprising a hundred replications.

**Findings after first experimental design**

When examining the first experiment's results, it becomes evident that a trade-off must be considered between the KPIs representing the frequency of stock outs and the associated costs within the inventory. The performance is determined by a balance between these two KPIs. After a thorough analysis of the results, four options emerge:

1. Maintaining certainty: When prioritising certainty, opt for a probability threshold of 100%, even though this comes with higher inventory costs. This approach aligns with the current method, where inventory levels are consistently replenished to their maximum capacity.

2. Accepting a slight risk for cost reduction: To reduce costs while accepting a small degree of risk, choose a probability threshold lower than 100%. This will lead to an increase in stockouts but a decrease in the total inventory value.

3. Predictive stock-out prevention: Conduct an experiment to explore whether predicting stock-outs in advance during the period is feasible, allowing for timely additional replenishments. This proactive approach aims to prevent stockouts from occurring within the department itself.

4. Alternative cost reduction measures: Conduct an experiment to investigate alternative methods for reducing costs while maintaining the certainty of a 100% probability threshold.

The last two options are examined before providing the results and a recommendation. The approach for these options is described in the following two subsections.

**Second experimental design: additional replenishments**

One of the advantages of implementing RFID-equipped storage cabinets is the continuous visibility of the quantities of items within the storage cabinet at any given time. This means that when orders are not traditionally placed, it is possible to monitor the inventory levels within the cabinets. This contrasts with the current practice where item counts are conducted only on Mondays and Thursdays, and replenishments are determined based on those counts.

With these real-time insights, the Markov chain model can be employed to assess whether a replenishment should occur on non-traditional ordering days. Similar to the approach used on Mondays and Thursdays, this decision is based on the probability that the current stock in the storage cabinets is sufficient to cover the period until the next scheduled ordering moment. When the $P(Usage <= x)$ falls below the predefined threshold, an additional replenishment is triggered, and the stock is refilled.

For the second experimental design, we employ two distinct probability thresholds. The probability threshold for guiding replenishment decisions on Mondays and Thursdays is set at 94% and remains fixed. The second probability threshold is utilised to determine replenishments on the remaining days. We conduct 51 experiments, starting with a probability threshold of 50%. Subsequently, each successive experiment increases the threshold by 1% until reaching the maximum of 100%. This results in 51 unique experiments, which aim to explore the potential of predicting stockouts in advance on non-traditional ordering days.

**Third experimental design: optimise capacity**

A capacity adjustment is an alternative approach to cost reduction while ensuring the certainty of a 100% probability threshold. In our simulation, when a 100% probability threshold is selected, the average quantities of stockouts amount to an annual average of four over a hundred replications. The average annual inventory value costs amount to €3 100, representing a 14% increase compared to a 99% probability threshold.

The third experimental design aims to maintain certainty while exploring an alternative approach to cost reduction. The solution focuses on the capacity of each item. A fractional factorial design is employed, conducting experiments that adjust the capacity of individual items within the storage cabinets. In many cases, the capacity of each item is either reduced or maintained. However, in some instances, the capacity is increased to enhance the stockout outcomes. The simulation is halted if no cost reduction is observed without an increase in stockouts exceeding six.

## 5.7 Forecast model

After selecting the distribution models for individual items, the subsequent step involves constructing the simulation model within Plant Simulation. Figure D.1 and Figure D.2 in Appendix D provides an overview of the final output within the model frame of the simulation. The model frame is divided into two parts. The first part depicts the flow of items in the material logistics process, encompassing item delivery by suppliers, stock placement in the external warehouse in Wormerveer, item packaging, and subsequent storage in storage cabinets. Additionally, the simulation system visually represents its status. For instance, when items arrive from suppliers at Wormerveer, the status is denoted as *LoadStock*, and when replenishment of the storage cabinets occurs, the replenishment day is indicated. Item usage is depicted by tracing the consumption of items after they are allocated to patients. The second part of the model frame presents the model's settings, inputs and outputs, with various methods, variables and tables. Additionally, this section features simulation run-time settings and buttons for resetting and initiating the simulation.

The subsections within this section provide in-depth insights into the implementation of various methods, as well as the settings, and input and output employed in the simulation. The material logistics process consists of different parts, the simulation of the first two parts, supplier and external warehouse, are explained in Subsection 5.7.1. Subsection 5.7.2 explains the simulation of the storage cabinets using distributions. Subsection 5.7.3 describes the implementation of the present state method and the conceptual method. Subsection 5.7.4 explains the implementations of the KPIs and how results for this research will be obtained. Subsection 5.7.5 describes what the setup of the experiment will look like.

### 5.7.1 Implementation of the simulation of supplier and external warehouse

This research proposes a simulation model to analyse the throughput and consumption of the storage cabinets. The process starts at the supplier, where items are requested from various departments. Once the supplier fulfils the order, the stock is transported to Zaans Medisch Centrum's external warehouse. Our simulation assumes that an ample supply of items is always available to satisfy departmental demands. To ensure that the simulation is not constrained by stock shortages in the external warehouse, the order size for the external warehouse is set equal to the cumulative number of items utilised throughout the entire simulation, plus twice the storage cabinets capacity for extra safety stock. The quantities for these orders are determined using the *SetDelivery* method, and the specific quantities are documented in the *Delivery* table. The item quantities outlined in the *Delivery* table define the quantities for each item entering the system. The *SetDelivery* method calculates the quantities consumed over the entire simulation period, drawing information from the *Forecast* table. The supplier delivers the stock to ZMC's external warehouse at the simulation's onset. Subsequently, using the *Stocking* method, the items are allocated to their respective storage locations within the external warehouse. Once this stocking process for all items is concluded, the simulation progresses to simulate the replenishment and consumption of items within the storage cabinets.

### 5.7.2 Implementation of the simulation of the storage cabinets

The simulation of the storage cabinets is achieved through moving items, encompassing consumption, stock level tracking, and replenishment procedures. At this stage of the simulation, an inventory of items exists at a remote location, while another inventory remains at the respective department. However, before the simulation can start, it is essential to establish an initial stock within the surgical department's storage cabinets. This is accomplished using the *CreateStock* model, which ensures that, before initiating the simulation, all items are replenished to the maximum allowable quantity within the storage cabinets. Subsequently, the *Usage* method manages the periodic consumption of items from the cabinets to the *Patient*. The consumption pattern is determined based on the distributions outlined in the preceding section. The *SetForecast* method examines the distribution associated with each item and period and the input required for a single observation. Every observation is recorded in the *Forecast* table, encompassing all observations for each item at each replenishment moment throughout the simulation. These observations serve as predictions for consumption on the relevant days. During the simulation, the system retrieves the consumption data from the *Forecast* table for the relevant date of each item stocked in the storage cabinets. These items are allocated to the *Patient* when used and subsequently exit the simulation. This approach aims to replicate the flow of items within the RFID-equipped storage cabinets.

### 5.7.3 Implementation of the automated ordering process

On each day when replenishment occurs, verifying the quantities still present in the cabinet within the simulation becomes feasible. This information is then used to determine the replenishment quantity. These replenishment quantities are determined using the *PresentStateMethod* or the *ConceptualMethod*. The approaches of both methods are explained in Subsection 5.7.3 and Subsection 5.7.3, respectively. The selection of the simulation model is determined through the checkbox labelled *Conceptual Model Simulation*. When this checkbox is selected as *true*, it signifies the intention to execute a simulation employing the *ConceptualMethod* method. Conversely, if the checkbox is marked *false*, it utilises the *PresentStateMethod* method. Subsection 5.7.3 explains the additional replenishment ordering process within our model frame.

#### Present state model

The present state model represents the current material logistics process employed in departments at Zaans Medisch Centrum. At the surgical department, item quantities in the cabinets are checked every Monday and Thursday morning, and they are replenished to reach the maximum capacity of the items. The *PresentStateMethod* method executes the replenishment strategy as described above, creating the present state model.

#### Conceptual model

The conceptual model is based on the Markov chain decision strategy as defined in Section 5.5. The probability threshold can be modified using the dropdown list. Within this list, you can select a probability ranging from 50% to 100%. Opting for a threshold of 100% signifies a choice to avoid risk and consistently replenish to ensure that $P(Usage <= x)$ equals 100%. Conversely, as the threshold decreases, the greater the risk.

To consult the standard Normal probability table for the result of $\phi(z)$, both the positive, *Pos_StdNormal*, and the negative standard Normal probability tables, *Neg_StdNormal*, have been incorporated into the simulation.

#### Additional orders

Aside from the standard replenishment process, there are instances where stock shortages occur during a given period. To maintain continuous care provision, additional orders are initiated. These additional orders are sourced directly from the stock in Wormerveer and are utilised for patient care. The count of additional orders is maintained in the *StockOut* table.

### 5.7.4 Implementation of the key performance indicators outcomes

The data is recorded in tables to capture essential information required for the KPIs during the simulation. In Section 4.3, you can find the KPIs specifically formulated for this case study.

Within the tables under the *Usages* section, we record the consumption and average consumption data throughout the simulation. In the *Capacities* section, we record various applications of capacities. The tables in the *StockOuts* section store data on the average occurrences of stockouts per item throughout the entire simulation. It also provides information on the average service level for the whole duration and for all items. The tables in the *Costs* section offer insights into the average value of items in stock. Meanwhile, the tables in the *HandlingTimes* section monitor the average handling time of items within the storage cabinets. The annual average values of all replications of one experiment are logged in the tables *MultiLevelCapacity* and *MultiLevelOutcome*.

### 5.7.5 Experiments setup

#### Number of replications

The output of a simulation model, in the form of the performance measures, is a complex function of the input. Given the uncertainty in the input of a simulation model, the output also has a random character. The output only provides point estimates of the system performance. This is similar to having one respondent in a questionnaire. Statistical rules apply: the more observations from the simulation model, the more accurate the performance measures are estimated. An indication of the accuracy is confidence intervals. The confidence interval gets smaller with more replications. The idea is to perform replications until the width of the confidence interval, relative to the average, is sufficiently small. When determining the number of replications for our simulation, selecting a value that ensures the simulation's accuracy falls within the 95% confidence interval is essential. This number can be calculated using the sample t-approach. With each additional replication, the sample size increases, and this process is repeated until the error falls and consistently stays below 5%.

In our simulation, this level of accuracy is achieved after seven replications. However, our simulation is not computationally intensive, and each run takes less than a second, so we opt to conduct each experiment with a hundred replications. This decision provides an extra layer of assurance and helps further reduce the potential impact of external influences.

#### Random number stream

For each replication of each experiment, we employed a unique random number stream. This approach is implemented to reduce the influence of external factors, ensuring that the selected probability threshold remains the predominant factor influencing the outcomes.

#### Runlength and warm-up period

Each replication is conducted over precisely one year to maintain comparability in our findings. A fixed warm-up period of two periods is established for this simulation. Only the output from the first two periods is not stored as part since the outcomes of the subsequent period are influenced by the number of items in the storage cabinets. After two periods, the results of the items are entirely dependent on the specific experiment's settings.

#### Batch of Items

In this research, a Student License for Plant Simulation is employed, which imposes a limitation of utilising a maximum of 80 objects. However, for our simulation, we aim to model 43 distinct items. We use a batching approach to accommodate all these items in the simulation. Batch 1 encompasses item numbers 1 through 22, and batch 2 contains 23 through 43. The simulations for batch 1 and batch

2 are executed sequentially, employing identical settings, and are considered as a single run. After the simulation for batch 2 is completed, adjustments are made to the simulation setup. A checkbox labelled "*Batch of Items 1-22*" is employed to determine which batch is currently being simulated. When *true* is selected in the checkbox, it signifies that a simulation is being conducted for batch 1. Conversely, selecting *false* indicates that the simulation is based on batch 2.

### Revised capacity

When *true* is selected in the checkbox labelled *Use Revised Capacity*, it indicates that the simulation is being conducted with the revised capacity. Conversely, selecting *false* indicates that the simulation relies on the capacity assigned by ZMC.

## 5.8 Summary

This chapter provides a detailed account of the conceptual forecast model developed for the research. It offers an overview of all the sections within the chapter and covers essential topics, starting with data preprocessing, distribution determination for individual items, revised capacity, and the Markov chain model. The chapter also explains the setup for three experimental designs: one focused on the implementation of the Markov chain decision policy on traditional replenishment days, another exploring the implementation of the Markov chain decision policy on additional replenishment days, and the third aiming to optimise the capacity of items stocked in the storage cabinets. It further describes the forecasting model's implementation. These experiments are conducted with the number of replications set to one hundred, using unique random number streams, with a warm-up period of two periods, and a batching approach involving two batches to model the items.

# 6 Results

This chapter presents the quantitative outcomes of this research. These results ultimately answer the question of whether integrating an automated material logistics system based on the Markov chain decision strategy can efficiently track inventory and improve operational efficiency in the department's material logistics process. This question is answered by evaluating the results of the four established Key Performance Indicators (KPIs) comprehensively.

Section 6.1 shows the statistics of the final item selection based on the data preprocessing. Section 6.2 explores the current performance of ZMC of the selection of items. The results of the determined distributions are shown in 6.3. Sections 6.4 to 6.6 provide insights into the findings derived from the outcomes of the conceptual forecast model. Section 6.4 assesses the Markov chain decision policy performance on traditional replenishment days (Monday and Thursday). Section 6.5 evaluates the performance of the Markov chain decision policy on traditional replenishment days (Monday and Thursday) and its application on additional replenishment days (Tuesday, Wednesday, and Friday). Section 6.6 shows the findings of the optimised capacity of items stocked in the storage cabinets. To conclude, Section 6.7 compares the results of the experiments and the statistics of ZMC and Section 6.8 provides a conclusion of the obtained results.

## 6.1 Results step 1: Data preprocessing

Table 6.1 shows the results of the inventory classification based on the replenishment frequency and ABC analysis. During the item selection, our focus is directed towards items within the categories 'A-High', 'B-High', and 'A-Medium'. These categories collectively result in a selection comprising 56 distinct items. In 2022, the cumulative cost for this selection equals € 104 464, which is 70% of the overall cost of all items, which is € 149 658. This is still a representative portion of the turnover in the surgical department, and the number of items has been reduced back to a more manageable quantity for simulation of the storage cabinets.

Table 6.1: The results of the combination of the ABC and replenishment classification, highlighting the selected group for this experiment in blue.

**ABC-Replenishment matrix - Number of items**

| | High | | Medium | | Low | | | |
|---|---|---|---|---|---|---|---|---|
| | Combined category | Number of items | Combined category | Number of items | Combined category | Number of items | Total number of items | Percentage of items |
| A | A-High | 31 | A-Medium | 12 | A-Low | 6 | 49 | 18% |
| B | B-High | 12 | B-Medium | 14 | B-Low | 50 | 76 | 28% |
| C | C-High | 1 | C-Medium | 14 | C-Low | 127 | 142 | 53% |
| | | 44 | | 40 | | 183 | 267 | |
| | | **16%** | | **15%** | | **69%** | | **100%** |

**ABC-Replenishment matrix - Cost**

| | High | | Medium | | Low | | | |
|---|---|---|---|---|---|---|---|---|
| | Combined category | Costs | Combined category | Costs | Combined category | Costs | Total costs | Percentage of costs |
| A | A-High | € 86 028 | A-Medium | € 14 973 | A-Low | € 5 520 | € 106 520 | 80% |
| B | B-High | € 3 354 | B-Medium | € 3 942 | B-Low | € 12 372 | € 19 668 | 15% |
| C | C-High | € 109 | C-Medium | € 986 | C-Low | € 5 680 | € 6 775 | 5% |
| | | € 89 491 | | € 19 900 | | € 23 572 | € 132 963 | |
| | | **67%** | | **15%** | | **18%** | | **100%** |

### 6.1.1 Results step 1: Additional data preprocessing

Upon examination of the data from 2020 and 2021, it becomes clear a refined subset remains suitable out of the initially identified 56 distinct items. The final selection consists of 43 items from the storage cabinet of the surgical department. Table 6.2 shows the statistics of this selection.

Table 6.2: The statistics of the selection of 43 items compared to the total number of items and costs of the surgical department in 2020-2022.

**Overview number of items and costs 2020-2022**

| | Items | | | Costs | | |
|---|---|---|---|---|---|---|
| **Year** | **Total** | **Selection** | **Percentage** | **Total** | **Selection** | **Percentage** |
| 2020 | 336 | 43 | 13% | € 154 927 | € 77 901 | 50% |
| 2021 | 308 | 43 | 14% | € 175 254 | € 95 459 | 54% |
| 2022 | 398 | 43 | 11% | € 149 658 | € 81 441 | 54% |
| **Total** | **1042** | **129** | **12%** | **€ 479 839** | **€ 254.801** | **53%** |

## 6.2 Results step 2: Current performance Zaans Medisch Centrum

To obtain the current performance of Zaans Medisch Centrum based on the determined Key Performance Indicators entails utilising the data sourced from ZMC. In this research, our focus centres on the surgical department, and our data input encompasses the years 2020 to 2022. As depicted in Table 6.3, it is shown that an average of twenty unplanned additional replenishments take place annually. The cumulative reorder sizes indicate approximately 1600 instances of stockouts annually, and the estimated value of items in stock amounts to €2 175, providing an average valuation of the items held in stock. While shadowing the logistics team member during a department checkup, it became clear that the specified capacities are not always accurate for every item. The logistics team members often use their insights into which items are used more rapidly or slowly than the assigned capacity indicates. Consequently, they manually adjust the replenishment quantities as needed. As a result, the value of the items in stock can only be estimated, and it is impossible to compute an actual annual average.

Stockouts result in additional costs, which are associated with the expenses for extra replenishments. These costs are not tracked within ZMC. Therefore, the supplementary costs cannot be integrated into the comprehensive overview. As a result, our focus remains on the value of the items in stock, and we do not include the expenses associated with unplanned additional replenishments.

Table 6.3: The statistics of the annual averages of the number of unplanned additional replenishments, replenishment quantities and the value of the items in stock at Zaans Medisch Centrum over the year 2020-2022.

**The annual averages of the KPIs at ZMC**

| | Number of additional replenishment | Replenishment quantities | Value of in stock items |
|---|---|---|---|
| 2020 | 25 | 2383 | € 2.175 |
| 2021 | 15 | 890 | € 2.175 |
| 2022 | 20 | 1528 | € 2.175 |
| **Average** | **20** | **1600** | **€ 2.175** |

The data presented in Table 6.3 includes the items utilised in this simulation. The selected items represent 12% of the total inventory within the storage cabinets. Despite their relatively small share, these items contribute significantly to the annual revenue, accounting for approximately 53% of the total revenue.

## 6.3 Results step 3: Determining the distributions for each item

Table 6.4 shows the final selections for the distributions and shows the influencing factors upon which the items depends.

TABLE 6.4: Overview of distribution selection and influential factors for 43 selected items in the surgical department from 2020 to 2022.

**Overview of types of costs of the surgical deparment of ZMC**

| | **Normal DF** | | **Poisson DF** | | |
|---|---|---|---|---|---|
| **Name of the article** | **Monday** | **Thursday** | **Monday** | **Thursday** | **Influence factor** |
| Afvalzak, blauw (80 x 110 cm) | | | | | 1 |
| Afvalzak, groen 75x65cm. 20st. | | | | | 3&4 |
| Bloedafnameset Safety-Lok 21G 178mm | | | | | 3&4 |
| Braakzak, Mediplast | | | | | 4 |
| Cath.ballon ch16 silk.tieman rusch | | | | | 1&2 |
| Cutisoft onsteriel 10x10cm. 4 laags | | | | | 3&4 |
| DISCOFIX® C 3-WEGKRAAN 10 CM | | | | | 3&4 |
| Elastomull 4m x 10cm. | | | | | 3&2 |
| Elastomull 4m x 8cm. | | | | | 3&2 |
| Elastomull 4m x6cm. | | | | | 3&4 + 3&2 |
| Handschoen maat M, NITRILE | | | | | 3&2 |
| Handschoen maat S, NITRILE | | | | | 2 |
| Hechtingverwijderset, steriel | | | | | 3&4 |
| Heupverband large | | | | | 2 |
| Incidin Oxywipes | | | | | 2 |
| Infuussysteem, belucht met male luerlock | | | | | 3&2 |
| Isolatiejas XXL elastisch manchet | | | | | 3&2 |
| Kidney Bowl - Nierbekkenschaaltjes | | | | | 2 |
| Naald, Injectie Eclipse Oranje 25G 5/8" | | | | | 3&2 |
| Naald,transfer 2xstalen naald 1,5/8-22mm | | | | | 4 |
| Naaldencontainer Sharpsafe 3 liter | | | | | 1&2 |
| NACL 0,9% Inf.vloeistof freeflex 100ml. | | | | | 3 |
| NACL 0,9% Inf.vloeistof freeflex 500ml. | | | | | 3&2 |
| NACL 0,9% Inf.vloeistof freeflex 50ml. | | | | | 3&4 |
| NACL 0,9% Spoelvloeistof 3000ml. | | | | | 3&1&4 |
| Onderlegger Molinea 60x60 pak | | | | | 3&2 |
| Oordopjes tbv oorthermometer Genius 2 | | | | | 1 |
| Pleister Leukopor 9.2m x 2.50cm. | | | | | 3 |
| Pleister, Leukomed IV film 7x9cm. | | | | | 4 |
| Schaar chirurgisch disposable spits/stomp | | | | | 3&2 |
| Spuit, 20ml. | | | | | 3&2 |
| Spuit, 3ml, luer tip, centrisch | | | | | 3&1 |
| Spuit, 50ml ct | | | | | 3&2 |
| Spuit,10ml, luer tip, centrisch | | | | | 3&4 |
| Spuit,50 ml ll | | | | | 3&1&4 |
| STERICAN MIX 18G,1.20X40MM | | | | | - |
| TDS Basic, belucht, 200µ, naaldloos | | | | | 3&4 |
| TDS Plus, belucht, 200µ, naaldloos | | | | | 3&1 |
| Tissues facial | | | | | 1 |
| Urinemeter, 2 kamers, 450ml + 2000ml | | | | | 2 |
| VASOFIX® SAFETY 20 G X 33 MM | | | | | 3&2 |
| Washandjes Tena doos 8x30stuks | | | | | 2 |
| Wasset 4x2.0 gr non-woven steriel | | | | | 3&4 |
| **Total** | **36** | **34** | **7** | **9** | |

Chosen distributor for Mondays

Chosen distributor for Thursdays

## 6.4 Results step 4: Implementation of the Markov chain model

To evaluate the performance of the Markov chain model implementation, we conducted 51 experiments across a range of the probability thresholds from 50% to 100%. This probability threshold assesses the likelihood that usage will be equal to or less than the in-stock items for the upcoming period, denoted as P(Usage <= InStock). Each experiment consisted of a hundred replications, and we employed a unique random number stream for each replication of each experiment. This approach is implemented to minimise the influence of external factors, ensuring that the chosen probability threshold remains the primary determinant of the outcomes. The comprehensive results of all 51 experiments are visually presented in Figures 6.1 through 6.4.

Figures 6.1, 6.2, 6.3, and 6.4 present two distinct baselines. The first baseline, depicted in blue, is based on the results of the present state, where on every traditional ordering day, the items in the storage cabinets are replenished to their maximum capacity. The second scenario, highlighted in red, is based on the results of the present state & revised capacity, where on every traditional ordering day, the items in stock are replenished to their maximum revised capacity. Additionally, each figure illustrates a trendline that shows the experiment's outcomes. This experimental approach initiates with a probability threshold of 50% and progressively increases it by 1% until it reaches the maximum threshold of 100%. This comprehensive representation allows for a detailed examination of how different probability thresholds impact the results across various aspects of the experiment.

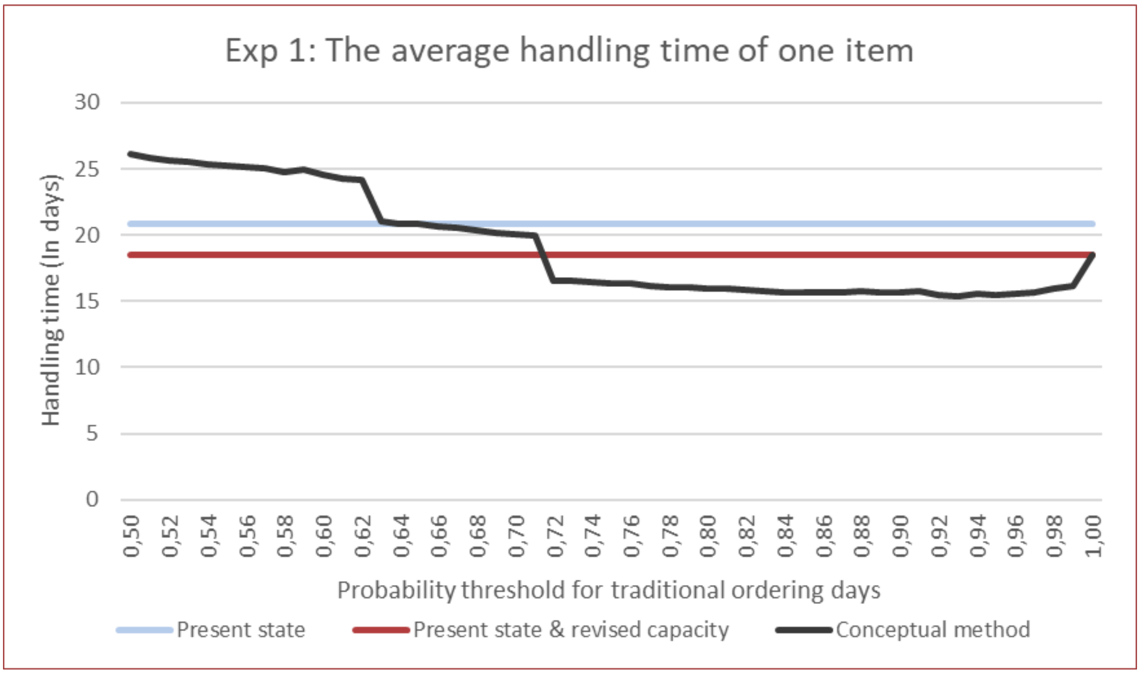



FIGURE 6.1: Comparison of average handling time for one item in storage cabinets: present state, present state & revised capacity, and Markov chain decision strategy with probability threshold.

Figure 6.1 displays the average handling time of items in the storage cabinets as a function of the probability threshold used for item replenishment decisions. The figure reveals a trend where the handling time decreases as the probability threshold increases. This observation suggests that as the criteria for replenishing the items become stricter (higher threshold), items spend less time within the storage cabinets. This indicates an improved efficiency in managing the cabinets. In the first stages of the graph, the handling time is notably greater compared to both the baseline scenarios. However, as we progress through the graph, the handling time falls below both baseline scenarios, indicating an improvement in efficiency.

Figure 6.1 illustrates two noteworthy deviations within the trendline, consistently observed across hundred replications, indicating that they are not random anomalies. These declines seem to be associated with distinct conditions influenced by the established probability threshold, leading to an unexpected decrease in handling time. These deviations could arise from the interplay of the probability threshold, which prevents ordering a certain number of items in the cabinet, closely matching actual consumption, resulting in minimal remaining handling time of the items. This intriguing phenomenon calls for in-depth analysis and is a subject for future research to delve into its underlying factors and confirm our hypotheses.

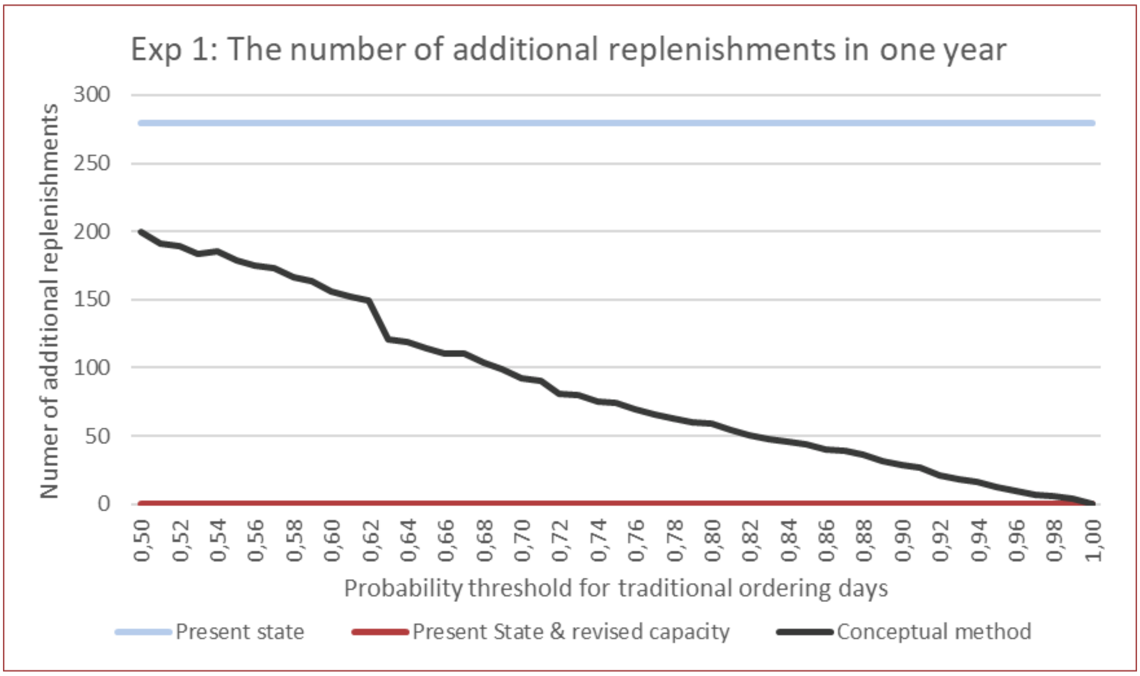



Figure 6.2: Comparison of the frequency of unplanned additional replenishment of the storage cabinets: present state, present state & revised capacity, and Markov chain decision strategy with probability threshold.

Figure 6.2 delves into the frequency of unplanned additional replenishments due to stock out at varying probability thresholds, represented as percentages ranging from 50% to 100%. The figure reveals a downward trend: as the probability threshold increases, signifying a higher probability for $P(Usage <= x)$, the frequency of unplanned additional orders decreases. This finding suggests that proactive risk management reduces critical stock shortages, leading to fewer emergency orders and improved inventory stability. The experiment's trendline consistently positions itself below the baseline of the present state and converges towards the baseline of the present state & revised capacity as the probability threshold increases.

Figure 6.2 illustrates one noteworthy deviations within the trendline, consistently observed across hundred replications, indicating that they are not random anomalies. These decline seem to be associated with distinct conditions influenced by the established probability threshold, leading to an unexpected decrease in the number of additional replenishments in one year. These deviations could also arise from the interplay of the probability threshold, which prevents ordering a certain number of items in the cabinet, closely matching actual consumption, resulting in significant reduction of the number of additional replenishment over one year.

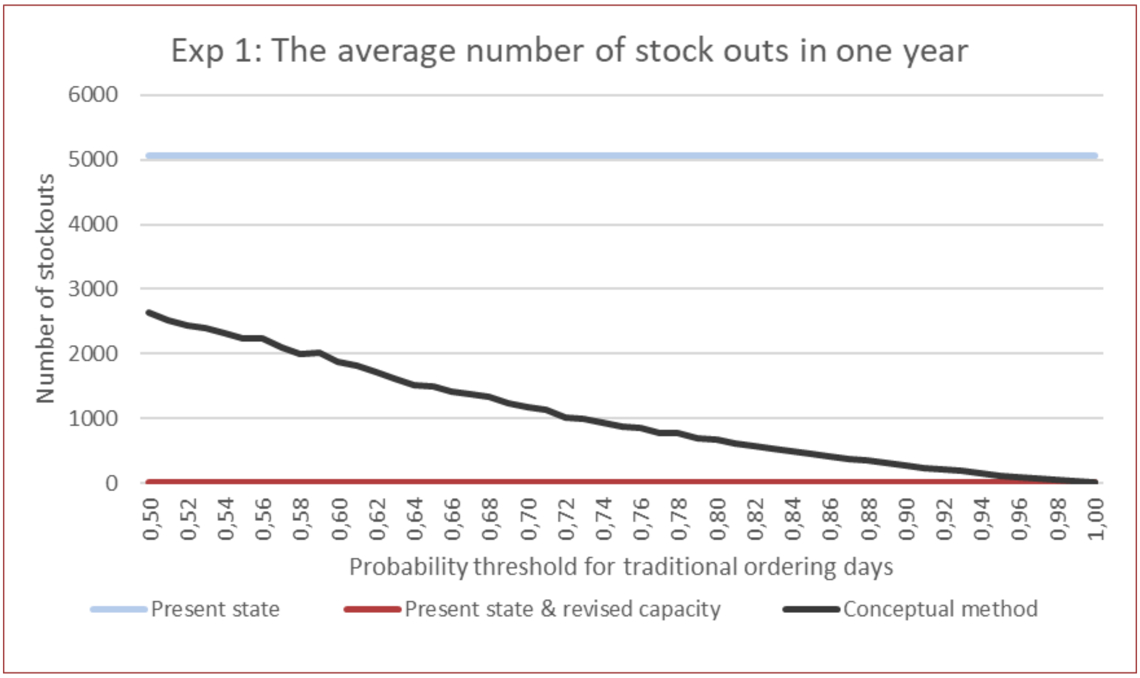



FIGURE 6.3: Comparison of the number of item stockouts: present state, present state & revised capacity, and Markov chain decision strategy with probability threshold.

In Figure 6.3, we explore the relationship between the number of stockouts and the associated risk, expressed as the probability threshold. The probability threshold signifies the likelihood that the number of items in the storage cabinets is sufficient to meet the upcoming period's consumption needs ($P(Usage <= x)$). The data presented in this figure reveals a compelling pattern: as the probability threshold increases, the quantity of items falling below the desired stock level in the cabinets decreases. This trend emphasises the significance of selecting a higher probability strategy. With lower risk, there is a reduced probability of stockouts, resulting in fewer unplanned additional replenishment orders. The experiment's trendline consistently positions itself below the baseline of the present state and converges towards the baseline of the present state & revised capacity as the probability threshold increases.

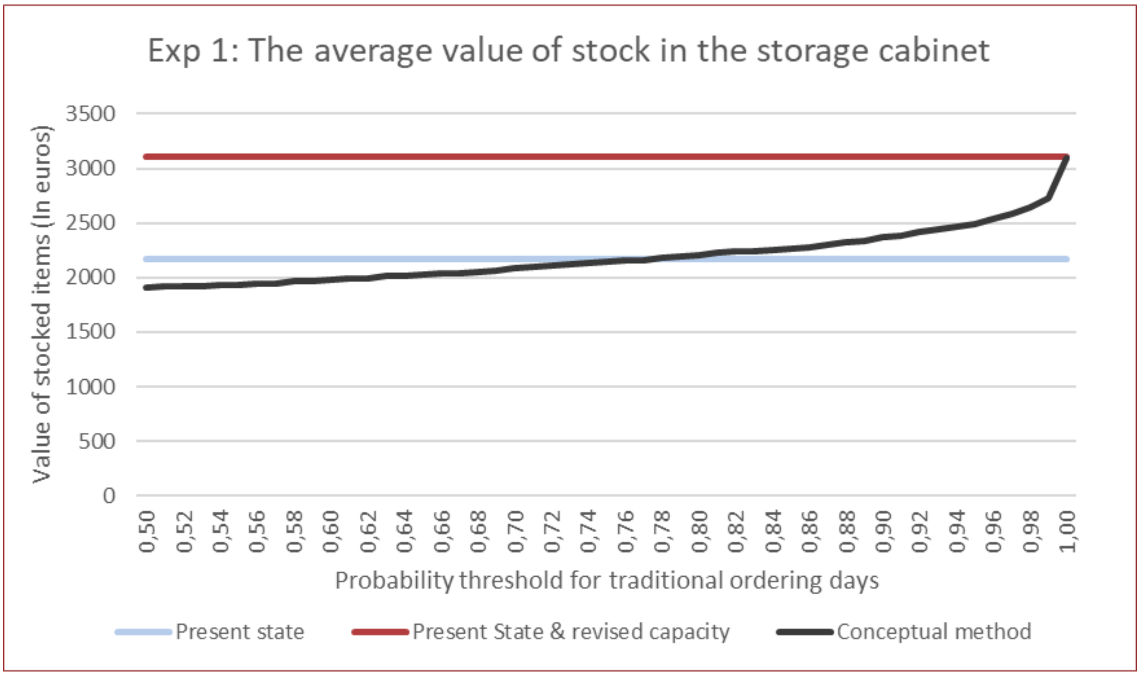



FIGURE 6.4: Comparison of the annual value of items stocked in the storage cabinets: present state, present state & revised capacity, and Markov chain decision strategy with probability threshold.

Finally, in Figure 6.4, we conduct a cost analysis with the probability threshold spanning from 50% to 100%. The data in this figure demonstrates that the associated costs increase as the probability threshold increases, with a peak at 100% probability threshold. This cost-probability threshold relationship is a critical insight for decision-makers, highlighting the financial implications of risk management strategies. As the probability threshold increases, the experiment's trendline consistently starts below the present state baseline, surpasses it halfway through the experiment, and continues converging towards the present state + revised capacity baseline.

### Summary

In summary, Figures 6.1 through 6.4 collectively emphasise the significance of risk management in inventory control. A higher probability for $P(Usage <= x)$ means lower risks. Increasing the probability thresholds is associated with reduced stock-outs, fewer unplanned additional replenishments, and increased costs. These findings emphasise the need for a balanced approach to material logistic processes considering risk reduction and cost efficiency. Further analysis and discussion of these results will be presented in subsequent sections of this research paper.

## 6.5 Results step 5: Planned additional replenishments

For the second experiment, a fixed probability threshold is set for replenishment decisions on Mondays and Thursdays. For example, consider the simulation with a probability threshold of 94%. In this scenario, the annual average number of unplanned additional replenishments over a hundred replications is 16, and the instances of stockouts amount to 146 samples. The total average value of the items in stock is €2 463, which is €637 less than the value incurred in stock compared to the €3 100 observed in the simulation with a probability threshold of 100%. The setup with a probability threshold of 94% showcases a lower in-stock value than opting for greater certainty. However, it also highlights the potential for improvement in managing stockout quantities, producing a matching setup for the second experiment, which aims to explore the possibility of predicting stockouts on non-traditional ordering days in advance.

Figures 6.5, 6.6, 6.7, and 6.8 show two distinct baselines. The first baseline, represented in blue, employs a fixed probability threshold of 100% for replenishment decisions exclusively on Mondays and Thursdays. The second scenario, shown in red, employs a fixed probability threshold of 94% for replenishment decisions on the same traditional ordering days. Both scenarios do not involve planned additional replenishments on non-traditional ordering days. Additionally, each figure illustrates a trendline that shows the experiment's outcomes. This experimental approach initiates with a probability threshold of 50% and progressively increases it by 1% until it reaches the maximum threshold of 100%. This comprehensive representation allows for a detailed examination of how different probability thresholds impact the results across various aspects of the experiment.

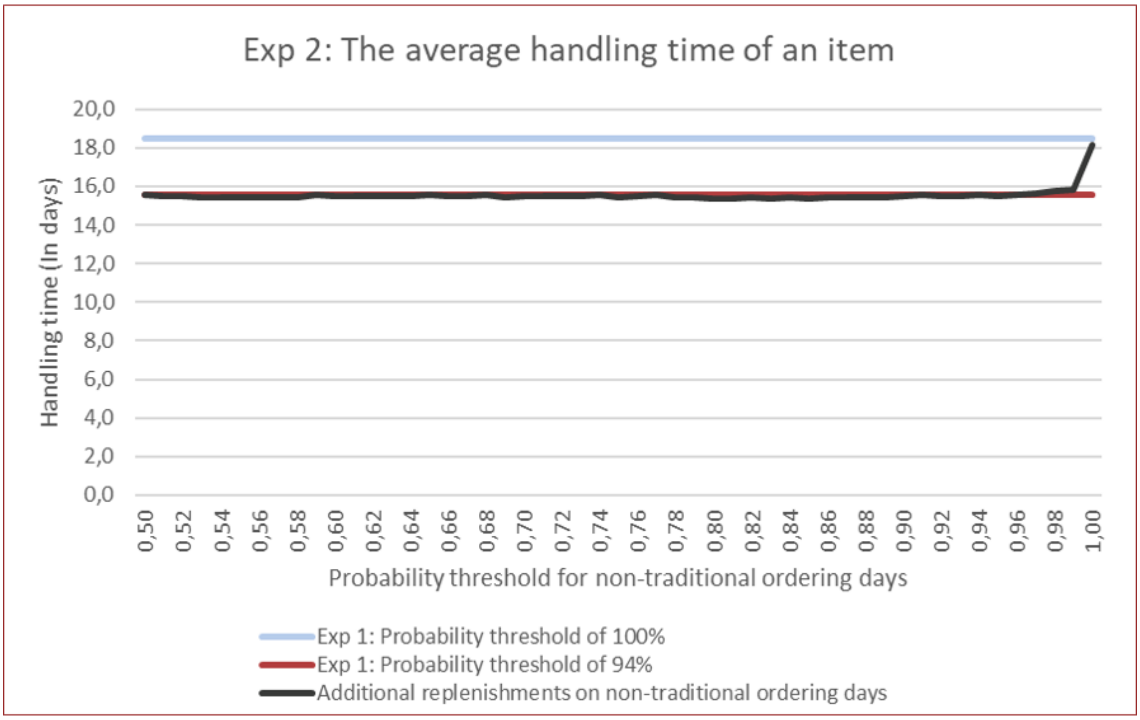



FIGURE 6.5: Comparison of average handling time for one item in storage cabinets: Exp 1: Probability threshold of 100%, Exp 1: Probability threshold of 94%, and Exp 2: Markov chain decision strategy with probability threshold on non-traditional ordering days.

Figure 6.5 reveals that the handling time closely resembles the baseline with a probability threshold of 94% without planned additional replenishment. When the probability threshold reaches 100%, a noticeable peak in handling time emerges. Introducing the option for planned additional replenishments on non-traditional ordering days seems to have minimal impact on the handling time.

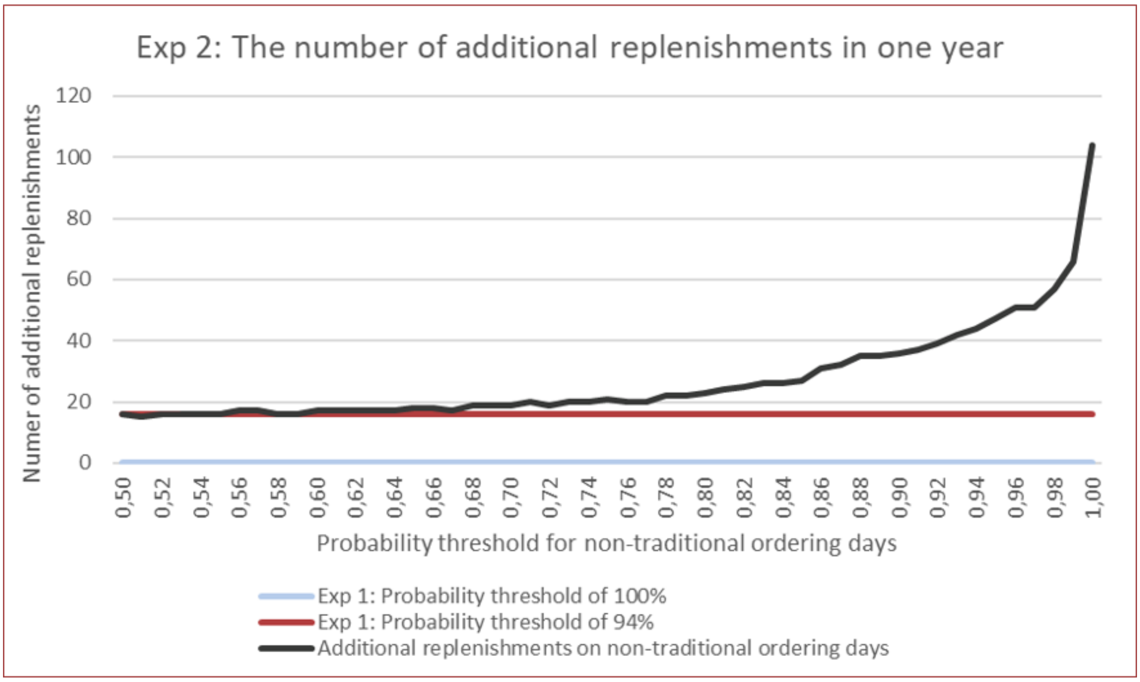



FIGURE 6.6: Comparison of the frequency of unplanned and planned additional replenishment of the storage cabinets: Exp 1: Probability threshold of 100%, Exp 1: Probability threshold of 94%, and Exp 2: Markov chain decision strategy with probability threshold on non-traditional ordering days.

When evaluating the overall impact on the total number of additional replenishments in Figure 6.6, it becomes clear that while the total number of unplanned additional replenishments decreases, the number of planned additional replenishments increases more significantly surpassing the decrease. For example, at the probability threshold of 99%, for planned additional replenishment, there is a substantial 400%, increase in the total number of additional replenishments compared to the baseline with a fixed probability threshold of 100%, and zero unplanned or planned additional replenishments. Even when the probability threshold of the planned additional replenishment days is set to 100%, the total number of unplanned and planned additional replenishments becomes equivalent to carrying out a planned additional replenishment daily. This unintended consequence highlights the importance of carefully considering the trade-offs when implementing planned additional replenishment strategies.

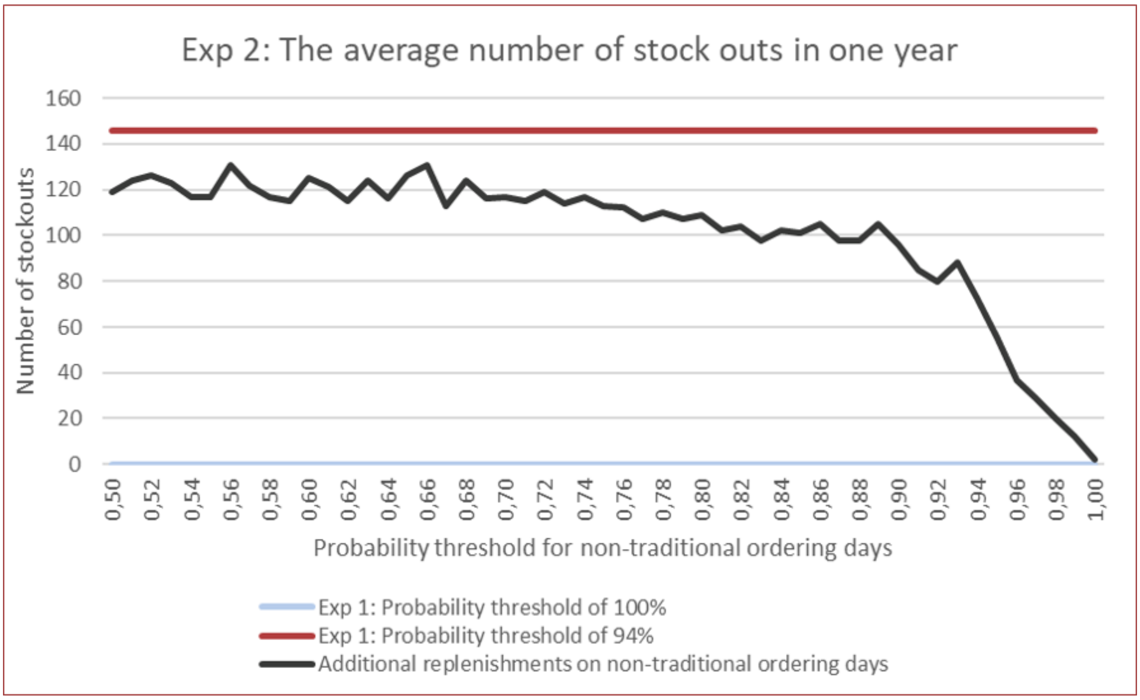



FIGURE 6.7: Comparison of the number of item stockouts: Exp 1: Probability threshold of 100%, Exp 1: Probability threshold of 94%, and Exp 2: Markov chain decision strategy with probability threshold on non-traditional ordering days.

When examining Figure 6.7, it becomes clear that despite the planned additional measurements, the reduction in the number of stockouts is minimal. The number of stockouts hardly decreases compared to the baseline with a fixed probability threshold of 94% for replenishment decisions exclusively on Mondays and Thursdays. The decrease in the number of stockouts remains consistently within the range of 20 to 30 items, maintaining this pattern until the probability threshold reaches approximately 90%. At this point, a notable decline in the number of stockouts is observed. Once the probability threshold reaches 100%, it aligns with the baseline of the fixed probability threshold of 100% for replenishment decisions exclusively on Mondays and Thursdays.

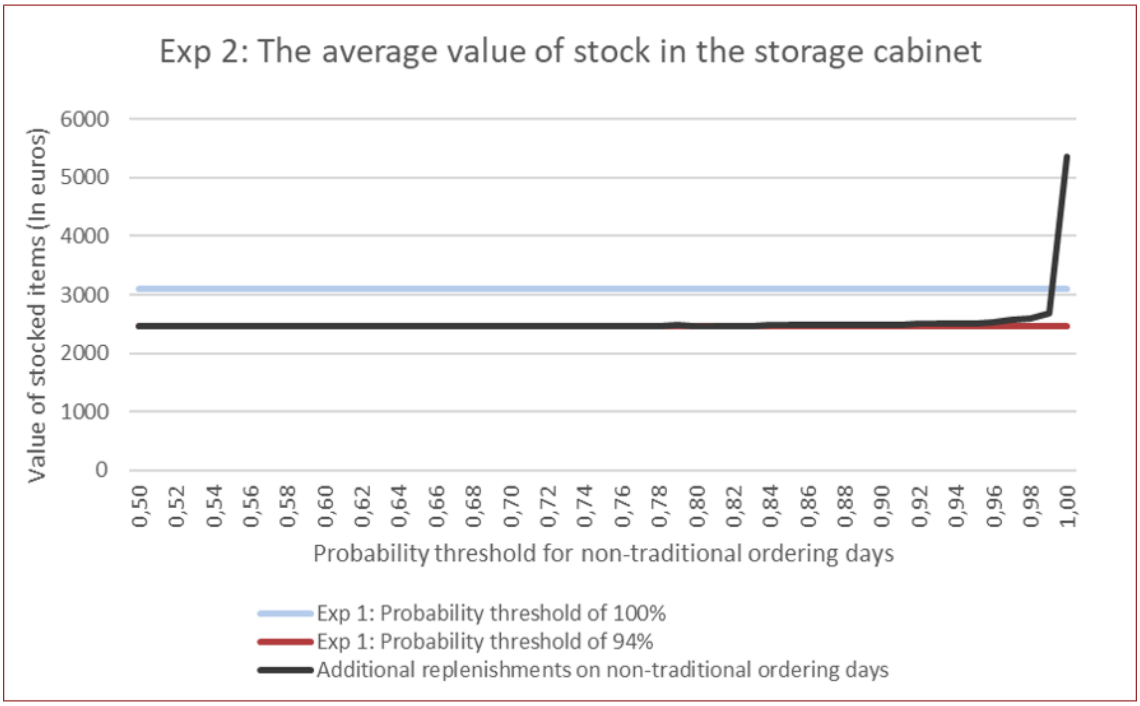



FIGURE 6.8: Comparison of the annual value of items stocked in the storage cabinets: Exp 1: Probability threshold of 100%, Exp 1: Probability threshold of 94%, and Exp 2: Markov chain decision strategy with probability threshold on non-traditional ordering days.

Figure 6.8 shows that the trends of the values of the in-stock items from the experiment align with the result of the fixed probability threshold of 94% for replenishment decisions exclusively on Mondays and Thursdays. There is a prominent peak in the in-stock value where it doubles at the probability threshold of 100% set for the planned additional replenishment decision. Besides this peak, the in-stock value remains significantly lower than those associated with the fixed probability threshold of 100% for replenishment decisions exclusively on Mondays and Thursdays. This suggests that the experimental approach still offers a more cost-effective solution while seeking a higher level of certainty.

**Summary**

In summary, Figures 6.5 through 6.8 illustrate that it is not feasible to find a probability threshold that reduces the number of stockouts to nearly zero without increasing the total number of additional replenishments to daily levels. However, when considering a trade-off, it is possible to reduce the number of stockouts by 30 while the total number of unplanned additional and planned additional replenishments remains at approximately 16.

It is also possible to opt for a total number of additional replenishments exceeding 16 replenishments, such as selecting 22 replenishments in total. This setup reduces the number of stockouts to approximately 102, representing a decrease of 30% compared to the results when no planned additional replenishments occur. The annual average number of unplanned additional replenishments over a hundred replications of this setup equals 8, and the number of planned additional replenishments equals 14. Table 6.5 summarises the results of the second experiment. The selection of the replenishment probability threshold depend on the hospital's preferences. The hospital can formulate various experimental designs with customised replenishment probability thresholds for the traditional ordering days as per their specific requirements.

TABLE 6.5: Comparison of results between the first and second experiments using the same fixed probability threshold for traditional ordering days.

| Comparison - Results experiment 1 vs. experiment 3 | | | | | |
|---|---|---|---|---|---|
| | **Number of stock outs** | **Number of additional replenisments** | **In stock value** | **Probability threshold for traditional ordering days** | **Probability threshold for non-traditional ordering days** |
| Exp 1: Only traditional ordering days | 146 | 16 | € 2 463 | 91% | NA |
| Exp 2: Additional non-traditional ordering days | 102 | 24 | € 2 471 | 91% | 81% |

## 6.6 Results step 6: optimise capacity

The third experiment explores the option of optimising the capacity while setting the replenishment policy probability at 100%. In the baseline scenario with the generous capacity, the annual average number of stockouts over one hundred replications is approximately four stockouts, and the average value of the in-stock items is €3 100. This approach to reducing the in-stock value involves determining the capacity of each item in such a way that stockouts do not significantly decrease, but the overall stock value decreases. This is accomplished through a 2k factorial design, which required 217 experiments before stopping the simulation. Table 6.6 presents the outcomes of this simulation.

TABLE 6.6: Comparison of results between the first and third experiments, with a capacity reduction in the third experiment.

| Comparison - Results experiment 1 vs. experiment 3 | | | | | |
|---|---|---|---|---|---|
| | **Number of stock outs** | **Number of additional replenisments** | **In stock value** | **Probability threshold for traditional ordering days** | **Probability threshold for non-traditional ordering days** |
| Exp 1: Only traditional ordering days with generous capacity | 4 | 1 | € 3 100 | 100% | NA |
| Exp 3: Only traditional ordering days with minimised capacity | 5 | 1 | € 2 754 | 100% | NA |

The table reveals that the quantity of stockouts and additional orders remains practically identical when comparing the optimised and generous capacity. Conversely, the in-stock costs have experienced an 11% reduction, €346, declining from €3 100 to €2 754.

## 6.7 Comparison of the statistics of Zaans Medisch Centrum and the experiment results

Let's revisit the initial scenario of our case study. This research examines the data of Zaans Medisch Centrum within their circumstances, explicitly focusing on the surgical department. We only look at the items used for our simulation within their data. Table 6.7 presents the statistic related to this selection. The selection of items includes 12% of all items located in the storage cabinets, and on an annual basis, these items generate 53% of ZMC's turnover. Throughout 2020-2022, annually, an average of 20 unplanned additional replenishments occurred, and the average total reorder sizes amounted to 1600 stockouts per year. The estimated value of the items in stock equals €2 175. Keep in mind that this value is an approximation, as elaborated in Section 4.3, and the actual value is likely higher.

Table 6.7 shows that the in-stock value of the cabinets tends to increase as the number of stockouts and total number of additional replenishments decreases. When the number of stockouts decreases, the total number of additional replenishments also tends to increase. This trade-off between these three outputs should be considered when making decisions regarding inventory management strategies. After evaluating the various experiments conducted in this research, it becomes clear that no one-size-fits-all ideal method can be universally selected. The choice of method ultimately depends on the preferences and priorities of the hospital itself.

TABLE 6.7: Comparison of results of the first, second and third experiments with the statistics of Zaans Medisch Centrum.

**Comparison - Results experiment 1 vs. experiment 3**

| | Number of stock outs | Number of additional replenisments | In stock value | Probability threshold for traditional ordering days | Probability threshold for non-traditional ordering days |
|---|---|---|---|---|---|
| Statistics Zaans Medisch Centrum | 1600 | 20 | € 2 175 | NA | NA |
| Exp 1: Only traditional ordering days with generous capacity | 4 | 1 | € 3 100 | 100% | NA |
| Exp 1: Only traditional ordering days with generous capacity | 146 | 16 | € 2 463 | 91% | NA |
| Exp 2: Additional non-traditional ordering days | 102 | 24 | € 2 471 | 91% | 81% |
| Exp 3: Only traditional ordering days with minimised capacity | 5 | 1 | € 2 754 | 100% | NA |

## 6.8 Conclusion

This research explores the optimisation of material logistics processes in healthcare facilities, with a focus on the Surgical department of Zaans Medisch Centrum. Through three experimental designs, the research examines the applicability of the Markov chain method for determining replenishment quantities. The results suggest that integrating an automated material logistics system using this method is feasible but has not yet achieved optimal operational efficiency. The comparison of the results of the first, second and third experiments with the statistics of Zaans

Medisch Centrum indicates the potential for a significant reduction in the number of stockouts. Moreover, it demonstrates the feasibility of decreasing the frequency of unplanned additional replenishments. However, these improvements are counterbalanced by an increase in the overall value of the stocked items within the storage cabinets. The findings underscore the presence of a trade-off between a reduction in item stockouts and unplanned additional replenishments, while also maintaining a minimal in-stock value.

In Section 2.1, we examined the issues within material logistic processes from three perspectives: the customer, financial, and internal process. Based on these perspectives, we also evaluate the results of the KPIs:

1. *Customer perspective*: Elimination of unforeseen shortages leads to increased departmental satisfaction and improved employee morale. In addition, the prevention of delays in patient care ensures the maintenance of service quality, thereby enhancing the overall service level.

2. *Financial perspective*: Implementation results in a significant reduction in financial waste, due to decreased handling time, fewer shortages, and the associated extra costs. Additionally, automation of the reorder decision strategy minimises wasted time spent on manual estimation of reorder decisions, as the logistics team no longer need to monitor each item individually.

3. *Internal process perspective*: The elimination of manual verification and stock point estimation simplifies the logistics process, allowing the logistics team to allocate their time to more valuable and challenging tasks.

In conclusion, the research highlights the effectiveness of automated material logistics systems in reducing stockouts and additional replenishments. Confirming that the integration of an automated material logistics system based on the Markov chain decision strategy can efficiently track inventory and improve operational efficiency in the department's material logistics process. However, the increase in in-stock value poses a trade-off. Hospitals must consider these findings and their specific preferences when making decisions about system implementation.

# 7 Conclusion and discussion

The primary objective of this research is to address the fundamental question: *"How can the integration of an automated material logistics system efficiently track inventory and improve operational efficiency in the department's material logistic process?"*. This simulation generates insights and conclusions by employing a conceptual model based on the Markov chain model, which can be found in Section 7.1 of this report. Section 7.2 also delves into a discussion of these conclusions, assessing whether they align with the initial expectations, and provides an overview of the research's limitations and potential implications. Section 7.3 outlines recommendations for future research.

## 7.1 Conclusion

This research explores various experimental designs to optimise material logistics processes at the departmental level of healthcare facilities. In our case study, we evaluated our conceptual model and its enhancements within the scope of Zaans Medisch Centrum, with specific attention directed toward the Surgical department. The results of this investigation show the importance of efficient inventory control within the context of material logistics processes at the department level of hospitals.

This research initially focuses on techniques for determining in-stock quantities of items in the storage cabinets. The utilisation of Radio-Frequency Identification-equipped storage cabinets allows tracking cabinet quantities daily or even multiple times a day, facilitating more detailed consumption data. Despite the high turnover of items within hospital cabinets, there is a scarcity of data concerning the consumption date and time of these items, as well as the precise reasons for their usage. Given the anticipated future growth and increasing complexity of healthcare demand, investing in RFID-equipped storage cabinets becomes highly valuable for in-depth data analysis. This investment contributes to the advancement of integrating an automated material logistics system, which in turn eliminates the necessity for the logistics team to perform manual cabinet content counts, resulting in significant time savings of approximately 2 hours per day for one employee. Additionally, this automation reduces the risk of counting errors and ensures that consumption data is no longer influenced by employee replenishment decision-making.
This research also delves into an automated system to enhance operational efficiency. To accomplish this, the application of the Markov chain method has been thoroughly examined through three distinct experimental designs. The first experimental design

shows the applicability of the Markov chain in determining replenishment quantities and the necessity of replenishing items on traditional order days. The findings indicate that to minimise the risk of stockouts, it is essential to maintain stock levels near their maximum capacity. So, the replenishment policy deviates minimally from the current method to achieve an optimal reduction in stockouts. It can be concluded that integrating an automated material logistics system using the Markov chain is feasible.

The utilisation of the conceptual model shows improvements in the reduction of additional replenishment and the associated stockout quantities. At the same time, this enhancement facilitated by implementing the conceptual Markov chain model leads to an increase in both the capacity and the value of in-stock items within the storage cabinets, implying that operational efficiency has not yet been reached. This implication does not imply an immediate abandonment of the integration of the Markov chain method.

An advantage of automated RFID-equipped storage cabinets is the ability to scan the cabinet contents any time during the week, allowing for temporary stock level assessments. This possibility creates a trade-off strategy, where replenishment strategies deviate from maximum replenishment on every traditional ordering day, and the in-stock level is assessed to determine if additional replenishment is required on non-traditional ordering days to prevent additional replenishments. The trade-off strategy provides opportunities to reduce the value of items in stock while still minimising the number of stockouts.

The results of the second experimental design further emphasise the difficulty of achieving zero stockouts without replenishing items to their maximum capacity on every traditional ordering day or increasing additional replenishments to a daily occurrence. Nevertheless, the implementation to stop replenishing items to their maximum capacity on every traditional ordering day and reduce the frequency of additional replenishments can still lead to a decrease in additional replenishments and stockouts. The results of this simulation conducted with the conceptual model outperform the existing statistics at Zaans Medisch Centrum.

A trade-off involving the probability threshold employed in the Markov chain method offers flexibility in material logistics process strategies addressing specific hospital preferences, thereby enhancing operational efficiency. However, this enhancement comes at the cost of incrementing the in-stock value. This increase in in-stock value does not align with the preferences of ZMC. As a result, a third experimental design is conducted to examine the impact of optimised capacity on in-stock value and the number of stockouts. The experimental findings reveal that optimising capacity can keep the number of stockouts and additional replenishments low while also resulting in an 11% reduction in the value of in-stock items. This shows the potential for cost savings through capacity adjustments. Unfortunately, it is impossible to directly compare the obtained annual value of the items in stock to the annual in-stock value at ZMC, as the determined value represents an estimated value.

In conclusion, this research demonstrates that implementing an automated material logistics system effectively reduces instances of stockouts and additional replenishments. However, this improvement is linked to an increase in the overall value of stocked items. The implementation offers significant benefits, such as saving employees two hours of daily work and reducing errors associated with manual counting. Additionally, the integration of RFID-equipped storage cabinets presents an opportunity to collect additional data with potential relevance. Ultimately, deciding to opt for the automated material logistic system is up to the hospital, as they must assess the associated costs against the achieved improvements and their preferences.

### 7.1.1 Recommendations for Zaans Medisch Centrum

Based on the findings and insights gained through this research,we propose the following two recommendations for ZMC:

1. *Evaluate and adjust the storage cabinets capacities*: One crucial area for improvement is reevaluating the capacity of storage cabinets. Often, the capacity of items in storage cabinets does not align with actual consumption, leading to frequent occurrences of either stockouts or excess inventory. By carefully reassessing and adjusting the cabinet capacity to better match consumption patterns, the hospital can significantly reduce stockouts and enhance overall inventory management.

2. *Implement automatic tracking systems*: The integration of an automatic tracking system, as demonstrated in this research, is highly valuable. Given the current scarcity of data recorded at ZMC, it provides a wealth of data that can be used to fine-tune inventory management and optimise material logistics processes. Especially since the technique shows a growing trend of improved, more efficient, and cost-effective RFID-equipped storage cabinets. Monitoring this technology's advancements and evaluating its adoption can be a valuable step in enhancing the operational efficiency.

By taking these steps, your hospital can enhance its material logistics processes, reduce stockouts, and capitalise on the wealth of data for continuous improvement.

### 7.1.2 Recommendations for Coppa

Based on the findings and insights gained through this research,we propose the following two recommendations for ZMC:

1. *Explorer the implement automatic tracking systems*: We recommend Coppa to explore opportunities for automatic stock level maintenance systems in hospital settings. While such systems are prevalent in non-hospital inventory management, they remain underutilised within healthcare due to the complexity of the system. Implementing RFID-equipped storage cabinets, as demonstrated in this research, offers a viable solution. Integrating this technology optimises material logistics processes in hospitals, generate valuable data for improved

advisory services, and ultimately enhance efficiency. Given the advancing technology related to RFID-equipped storage cabinets, it is recommended that Coppa closely monitors these developments.

2. *Additional advisory services*: Examination of our case studie reveals significant benefits in advising on capacity and safety level determinations within hospitals. Utilising straightforward methods in this context can yield substantial advantages with minimal implementations. This approach can offer additional value to the advisory services provided by Coppa.

## 7.2 Discussion

This research assumes a flawless operation of RFID-equipped storage cabinets. However, despite these cabinets' confirmed functionality, it is essential to assess the reliability of RFID-equipped storage cabinets. This assessment should include an examination of how accurately items are tracked and the time required for cabinet scanning. Moreover, considering sustainability, exploring the potential use of sustainable RFID tags and their reusability is necessary. Lastly, a thorough cost-benefit analysis is required, weighing the acquisition and maintenance costs of the RFID-equipped storage cabinets and RFID tags against the benefits derived from the automation and optimisation of the material logistics processes.

To create an informed decision, it is essential to gain insight into the current expenses associated with additional replenishments and the costs incurred for replenishments on regular ordering days. Unfortunately, the precise costs associated with additional replenishments remain unknown and, as a result, have not been factored into the findings and comparisons presented in this research. Moreover, the value of items in stock is an estimation instead of a precise measurement of the annual average value. The absence of these values adds complexity to determining the optimal approach and is likely to alter the optimal approach once these costs are known.

The consequences of planned additional replenishments still need to be investigated. Feasibility must be considered, both from the delivery from the external warehouse and from the logistics team staff. This investigation should encompass an in-depth analysis of how planned additional replenishments impact not only the overall inventory management but also the broader material logistics processes.

The item consumption of the simulation of the conceptual model is based on the replenishment quantities obtained from the replenishment data of ZMC. The replenishment decisions are influenced by employees' ordering behaviour, which results in scenarios where no consumption occurs in one period, while in another period, there is a significant consumption (e.g., 100 items). In reality, consumption typically does not exhibit such extreme fluctuations from week to week. These substantial gaps in consumption patterns affect the predictive accuracy of the Markov chain model. By incorporating precise daily usage for items withdrawn from the cabinets, it is possible to achieve a more accurate distribution prediction, and the model's performance will better align with the dynamic nature of consumption. As the consumption distributions change, the simulation's outcomes and, consequently, the results of the model's application will also change accordingly.

The reported capacities of the storage cabinets are adjusted for the simulation, and this adjustment may not align with the preferences of ZMC. Choosing different capacities will also have an impact on the experiment results. Nonetheless, it is crucial to make capacity adjustments to enhance operational efficiency. Without these adjustments, achieving zero stockouts is not feasible.

Ultimately, our research predominantly centres on capacity enhancement, which is prominently researched in the existing literature, alongside the prediction of consumption numbers. Hence, our research significantly intersects with numerous studies outlined in the literature. However, the application of the Markov chain is relatively limited research within the existing literature. After conducting this research, it becomes clear that the problem does not solely shape the research direction and prior findings within the literature but also depends on the accessibility of data for analysis and the potential to gain new insights. The availability of data facilitated by RFID-equipped storage cabinets offers a unique opportunity to access a wealth of previously unexplored information. This data and the insights it yields are expected to diverge significantly from the insights employed in known inventory management techniques, both within the manufacturing industry and healthcare facilities. As a result, this field remains open for further exploration, particularly in the context of the automated material logistics system based on the Markov chain decision strategy.

## 7.3 Future research

The utilisation of RFID-equipped storage cabinets offers the potential for more comprehensive data collection, supporting future models' development. The current data collection does not include all the characteristics related to consumption. Consequently, significant measurable factors influencing consumption may not be accounted for despite their potential to enhance predictive accuracy greatly. Obtaining this additional information allows for a more thorough examination of consumption influences, including specific consumption patterns by doctors, the date and time of the item removal and return to the cabinets and the correlation between consumption and the patient's treatment and treatment schedule. This data can then be used to investigate whether an improved consumption prediction is possible, thereby potentially reducing replenishment quantities.

In this research, we utilised fixed input parameters for the distributions. This means that the parameters were derived from historical data from 2020 to 2022, with equal weight given to each year's data. It could be interesting to investigate whether the reliability of the Markov chain model can be enhanced by adopting a time-varying Poisson and Normal processes approach. In this alternative approach, determining parameters such as the $mean$, $standarddeviation(sigma)$, and $lambda$ would place more emphasis on recent historical data than older historical data. When employing the Markov chain model within the automated material logistics system, it is crucial to accurately evolve the parameters over time to reflect the changing event rates. Consequently, conducting further research into time-varying parameters based on input data becomes essential for enhancing the performance of the automated material logistic system.

Additionally, future research can explore the feasibility of partial replenishment rather than replenishing to maximum capacity. This research could delve into the associated costs, benefits, drawbacks, as well as the potential risks and advantages of maintaining a smaller stock. This research can provide valuable insights into finding an optimal balance between stock levels and operational efficiency, allowing healthcare facilities to tailor their inventory management strategies more precisely to their specific needs.

In response to the positive results of the three future research efforts described above, a potential future application could involve storing the items in modular carts specifically prepared for each patient's treatment instead of keeping the items within the storage cabinets in the department. This creates the possibility of eliminating or joining the storage cabinets within the hospital, thereby freeing up space for patient treatments.

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# Appendix A - Organogram

**List of the teams of Coppa**

1. Team Facilitair & ICT,
2. Team Sociaal Domein & Juridisch,
3. Team Junioren Overheid en KC Zorg,
4. Team Inkoopconsultants Zorg,
5. Team Overheid,
6. Team Inkoopadvies,
7. Team Implementaties,
8. Team Outsourcing,
9. Team Procurement-to-Pay.

## Organogram of Zaans Medisch Centrum

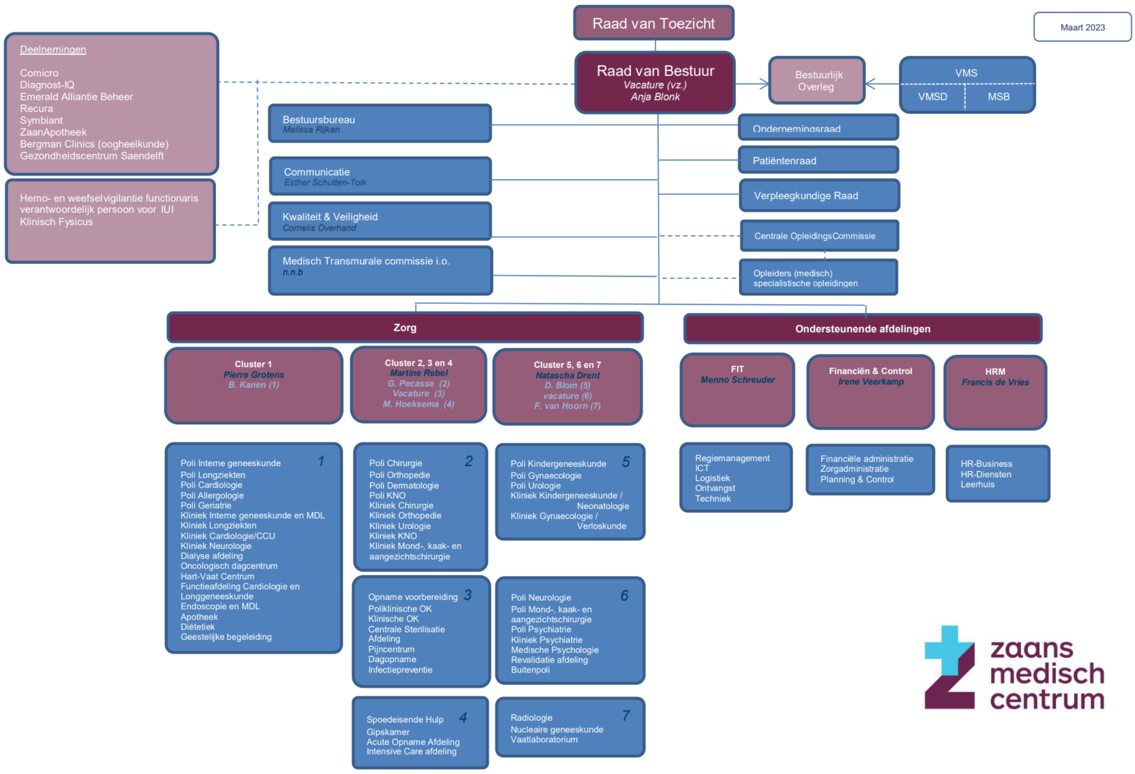


FIGURE A.1: This figure shows the organogram of Zaans Medisch Centrum.

# Appendix B - Overview schedule 'Scan and delivery day' for the dempartments within ZMC

TABLE B.1: Schedule of the replenishment days for each department of Zaans Medisch Centrum. The blue highlights indicate the scheduled days, and the department chosen for our research is highlighted in red.

**Schedule for the dempartments within ZMC - Scan and delivery day**

| Department | Monday | Tuesday | Wednesday | Thursday | Friday | Total |
|---|---|---|---|---|---|---|
| Beschouwend | | | | | | 2 |
| Dagopname | | | | | | 2 |
| Dialyse afdeling | | | | | | 3 |
| Endoscopie en MDL | | | | | | 2 |
| Gipskamer | | | | | | 3 |
| Hart-Vaat Centrum | | | | | | 1 |
| HCK | | | | | | 3 |
| Intensive care afdeling | | | | | | 3 |
| Kenniscentrum Midden | | | | | | 1 |
| Kenniscentrum Noord | | | | | | 1 |
| Kenniscentrum Zuid | | | | | | 1 |
| Kliniek Cardiologie/ Acute opname afdeling | | | | | | 3 |
| Kliniek gynaecologie/ Verloskunde | | | | | | 3 |
| Kliniek kinderafdeling/ Neonatologie | | | | | | 3 |
| Klinische OK | | | | | | 2 |
| Nucleaire geneeskunde | | | | | | 1 |
| Oncologisch dagcentrum | | | | | | 1 |
| Pijncentrum | | | | | | 1 |
| Poli allergologie | | | | | | 1 |
| Poli dermatologie | | | | | | 1 |
| Poli gynaecologie | | | | | | 1 |
| Poli kindergeneeskunde | | | | | | 1 |
| Poli KNO | | | | | | 1 |
| Poli longziekten | | | | | | 1 |
| Poli mond-, kaak- en aangezichtschirurgie | | | | | | 2 |
| Poli neurologie | | | | | | 1 |
| Poli orthopedie | | | | | | 2 |
| Poli urologie | | | | | | 1 |
| Poliklinische OK | | | | | | 2 |
| Radiologie | | | | | | 2 |
| **Snijdend** | | | | | | 2 |
| Spoedeisende hulp | | | | | | 3 |
| **Total** | 9 | 15 | 8 | 14 | 11 | |

# Appendix C - Overview of types of cost

Table C.1: This table gives an overview of the types of costs in the surgical department of Zaans Medisch Centrum. The costs highlighted in blue are the cost types predominantly consisting of items located in the storage cabinets.

**Overview of types of costs in the surgical ward of ZMC**

| **Type of costs** | **Costs** | **Type of costs** | **Costs** |
|---|---|---|---|
| 423310 - dienstkleding schoeisel | € 610 | 461910 - and. kost. onderz. funct. | € 423 |
| 423320 - specifieke kleding | € 9 497 | 462110 - geneesmiddelen | € 5 737 |
| 431310 - dieetvoeding en produkten | € 354 | 462170 - dialyse benodigdheden | € 12 017 |
| 432210 - restauratieve app./ben. | € 236 | 462610 - verband | € 30 581 |
| 441110 - schoonmaak app./ben. | € 12 352 | 462710 - hechtmateriaal | € 130 |
| 441210 - afvalverwijdering | € 2 599 | 462910 - and. kost. behand. funct. | € 994 |
| 441310 - toiletbenodigdheden | € 494 | 462920 - procedure trays | € 26 |
| 441415 - meubilair | € 39 | 464110 - pers. voorz. patienten | € 1 356 |
| 441940 - verpakk.mat+dispocebles | € 25 | 464210 - verplaats hulpmiddelen | € 96 |
| 442110 - linnengoed | € 1 455 | 464310 - incontinentie materiaal | € 5 114 |
| 442120 - dekens kussens matras | € 2 474 | 464910 - and. kst. verpleging | € 14 888 |
| 442210 - wasbenodigdheden | € 11 | 465110 - toed.- en afn.- systemen | € 12 640 |
| 451110 - kantoorbenodigdheden | € 1 563 | 465210 - katheters en sondes | € 9 506 |
| 451120 - patiëntind. benodigdheden | € 505 | 465310 - handschoenen | € 10 684 |
| 451210 - drukwerk | € 88 | 465910 - and. kst. ond. beh. verpl | € 9 245 |
| 459333 - adm. kleine orderkosten | € 45 | 466110 - instrumentarium | € 2 452 |
| 461140 - registratiemiddelen | € 397 | 466111 - onderhoudscontracten | € 60 |
| 461210 - grond- hulpstoffen lab. | € 10 | 466113 - disp. ok. lap. sc. mat. | € 308 |
| 461290 - and. kost. laboratoria | € 531 | | |
| **Total** | | | **€ 149 543** |

# Appendix D - Model frame of the forecast model

**A visualisation of the model frame of the forecast model as presented in Plant Simulation.**

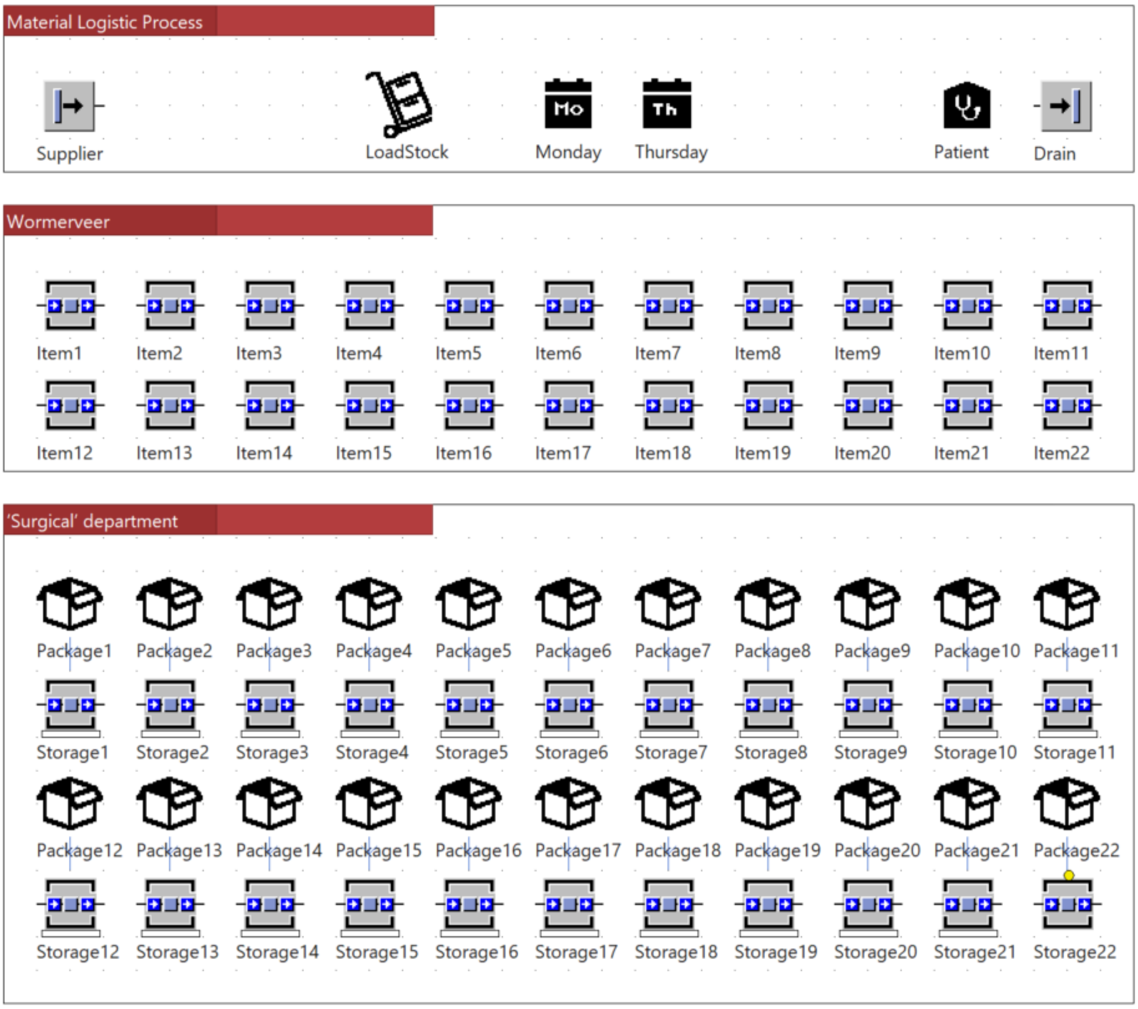


FIGURE D.1: Part 1 of the model frame: A visualisation of the model frame simulating the items.

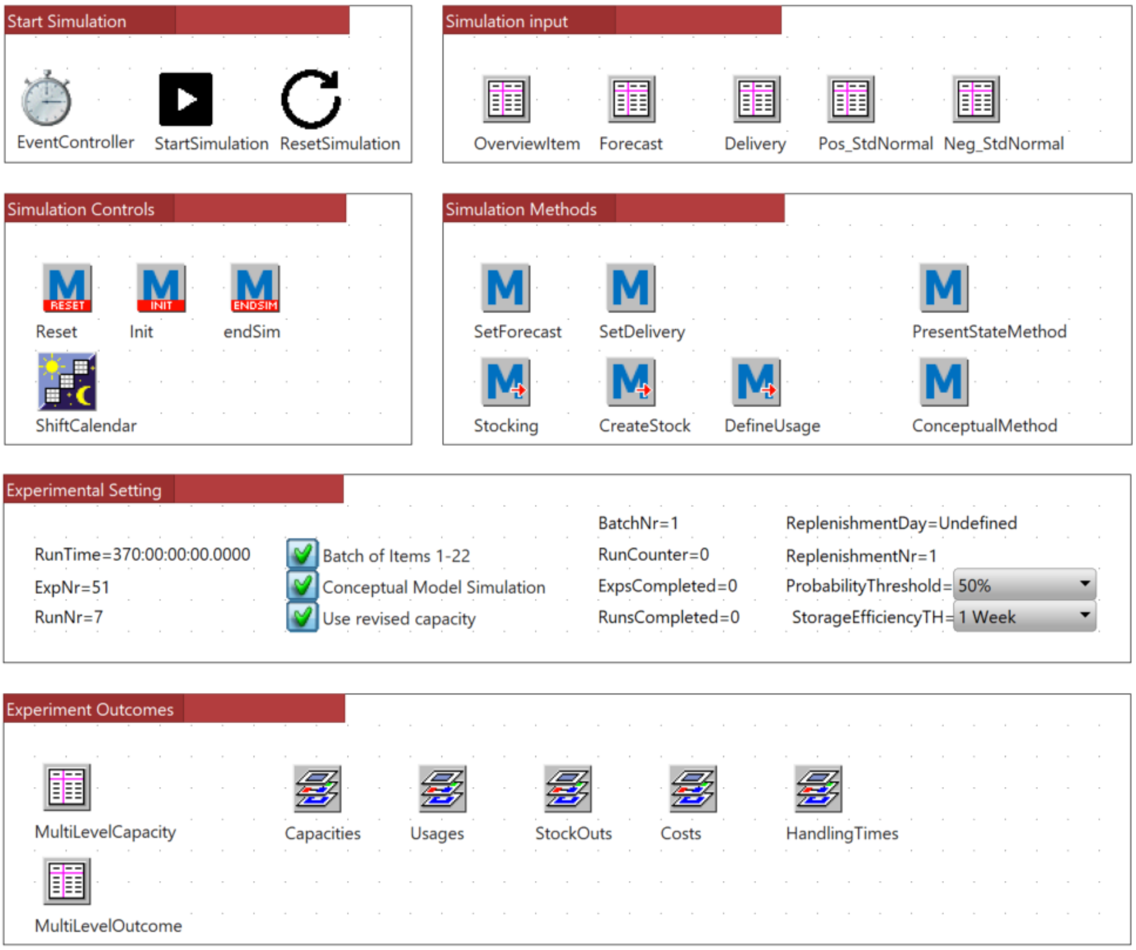


FIGURE D.2: Part 2 of the model frame: A visualisation of inputs and outputs represented in the model frame.