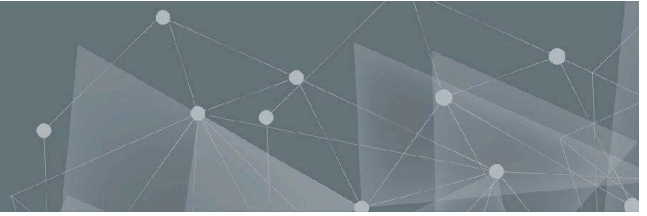




CHALMERS
UNIVERSITY OF TECHNOLOGY



Process Improvement and Physical Automation Selection for a Healthcare Warehouse: The Case of VGR

Master's thesis in Supply Chain Management

**HAMIDREZA SABERI
NIMA HAGHNEGAHDAR**

DEPARTMENT OF TECHNOLOGY MANAGEMENT AND ECONOMICS
DIVISION OF SUPPLY AND OPERATIONS MANAGEMENT

CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2026
www.chalmers.se

From diagnosing the current state,
suggesting improvements in manual setting and
establishing gap assessment between the current
and future state to use a framework to select
suitable physical automation technology solutions.

HAMIDREZA SABERI
NIMA HAGHNEGAHDAR

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NIMA HAGHNEGAHDAR

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Department of Technology Management and Economics
Chalmers University of Technology
SE-412 96 Gothenburg
Sweden
Telephone + 46 (0)31-772 1000

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HAMIDREZA SABERI
NIMA HAGHNEGAHDAR

Department of Technology Management and Economics
Chalmers University of Technology

SUMMARY

This master's thesis investigates improvements in manual warehouse operations and physical automation selection for the Västra Götalandsregionen (VGR) healthcare distribution center. The current manual warehouse faces operational challenges, including low inventory level accuracy. To address the issues, the study highlights the importance of a structured, four-phase framework consisting of Diagnose, Improvement in Manual Setting, Performance Gap Assessment and Technology Matching stages. The diagnostic stage utilizes Material Flow Mapping (MFM) to evaluate the baseline operations. The thesis proposes thirteen process improvements in manual operations that can successfully increase the performance indicators. However, because manual changes alone cannot satisfy long-term storage density mandates or high-accuracy requirements, a Multi-Criteria Decision-Making (MCDM) framework was used and developed to evaluate physical automation alternatives.

Keywords: healthcare distribution center, warehouse process improvement, Material Flow Mapping (MFM), Best-Worst Method (BWM), warehouse physical automation, qualifying-comparable factors decision-making framework.

ACKNOWLEDGEMENTS

We would like to express our sincere gratitude to the individuals and groups who supported us during this thesis project.

First, we extend our appreciation to our supervisors, Robin Hanson from Chalmers University of Technology and Johanna Linder from Västra Götalandsregionen (VGR). We also thank Jonas Carlsson and Artur Plucinski from the VGR management team. Their guidance, expertise, and continuous encouragement throughout the process were invaluable.

Our sincere thanks go to all the colleagues at VGR who welcomed us and showed great interest in our work. Their encouragement and practical feedback were highly valuable to the study. We also acknowledge our opponents, Elise Mellbin and Pontus Larsson, for their insightful feedback and constructive criticism.

Finally, we express our deep gratitude to our families and loved ones for their support throughout this journey. Their constant encouragement and moral support played a key role in keeping us motivated and focused.

Thank you all for your invaluable contributions to our thesis.

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1. Introduction

Västra Götalandsregionen (VGR) faces a need to enhance productivity within its healthcare logistics operations in Sisjön Distribution Centre, which is operated predominantly manually. It is constrained in its ability to meet increasing throughput demands while maintaining required accuracy and reliability. With daily dispatches of approximately 300 transport cages to over 4,000 healthcare units, operational efficiency is critical. Sisjön Distribution Centre is planning to relocate and this master's thesis will evaluate warehouse automation technologies in the future facility to determine which automation systems are necessary to address performance gaps that cannot be solved through improvements in manual operations alone. This is done to ensure VGR's new distribution center can meet future performance requirements and regulatory mandates, such as the 2027 inventory reserve law.

1.1 Background

For VGR, the Sisjön warehouse facility serves as a critical node in the regional healthcare supply chain, managing the distribution of consumables to medical facilities across the Västra Götaland region. It serves as the primary logistics hub connecting healthcare suppliers with hospitals and other clinical points of care. Healthcare supply chains play a critical role in supporting clinical operations by ensuring that medicines and medical supplies are available at the right place and time. High productivity, accuracy, and reliability in logistics operations are essential, as inefficiencies or errors can directly affect service quality and patient safety (Golan et al., 2022). As healthcare systems expand, distribution centers are required to handle increasing volumes while maintaining strict quality and service requirements.

At the same time, healthcare supply chains are increasingly exposed to uncertainty and external disruptions, while facing rising demand, particularly during crises. These challenges are further intensified by regulatory requirements. For instance, from 1 January 2027, all Swedish regions are legally responsible for maintaining at least one month of normal healthcare consumption close to the point of care. This requirement is part of the national objective to ensure “good care in everyday operations” and significantly increases storage volumes and handling requirements within the regional centers (Regeringskansliet, 2025).

As a public-sector organization, VGR's logistics operations emphasize efficiency and delivery reliability within public procurement, reflecting a strong responsibility to ensure an uninterrupted supply of materials that are critical to patient care (Västra Götalandsregionen, 2026).

To meet increasing volume and performance requirements, healthcare distribution centers are increasingly exploring warehouse automation technologies. Solutions such as Automated Storage and Retrieval Systems (AS/RS), goods-to-person systems, and automated picking have been shown to improve throughput, increase space efficiency and reduce picking and packing errors by standardizing material flows and reducing manual handling (Preziosa et al., 2025).

Currently, Sisjön depot suffers from performance gaps with industrial standards, for instance, there is a high risk of inaccurate inventory levels. Furthermore, VGR is planning a move to a

new facility. The current warehouse facility faces several challenges related to accessibility and efficient use of space, as operations are distributed across multiple levels. Goods are stored on different floors, resulting in unnecessary internal transportation and administration activities. In addition, parts of the warehouse are elevated on pillars, which impose structural load limitations. These constraints are key reasons for relocation. The planned facility will have the same space footprint as the existing warehouse but will eliminate the current facility structure limitations.

1.2 Problem description

The Sisjön Distribution Center currently manages the logistics flows for VGR. The operations are characterized by a relatively high proportion of fast-moving items with stable demand, placing strong demands on throughput, accuracy, and operational stability.

The existing operations are mostly manual and were not designed to accommodate the increased volumes and performance requirements associated with future targets. Current operational performance indicates room for potential improvements, specifically in inventory level accuracy, which is around 80% and falls below industry benchmarks. Furthermore, the shop floor can only accommodate a limited number of operators before congestion and traffic reduce efficiency. Combined with an order volume that the current process design cannot absorb within regular hours, this forces the operation into frequent overtime. As VGR prepares to relocate, these limitations risk constraining its ability to meet future productivity and quality requirements in a new distribution center.

VGR's new facility is intended to handle higher volumes. The transition is viewed as an opportunity to redesign warehouse processes, eliminate existing inefficiencies and also to implement physical automation technologies. There is a strong organizational conviction that partial and modular physical automation is required to overcome current inefficiencies and handle the projected volume increase, as a potential means to increase throughput, storage density and reduce operational errors. However, there is currently no structured, evidence-based evaluation demonstrating whether improved manual processes alone could achieve the required performance levels and bridge the gaps. Therefore, an evaluation of improvements of current warehousing techniques, such as order picking methods, process design, and slotting and storage is required. Without such an evaluation, there is a risk of committing to automation investments without a clear understanding of whether they are necessary or appropriately scoped.

1.3 Aim

This thesis aims to propose physical automation systems to fill identified performance gaps in the new facility. To achieve this, this research will evaluate the current processes, identify improvements for manual operations within the new warehouse and conduct a performance gap assessment. This assessment will then serve as the foundation for evaluating and recommending appropriate physical automation technologies.

1.4 Delimitations

To ensure a clear scope, this study defines several limitations to focus on warehouse technology decisions relevant to VGR's future distribution center and to exclude factors that fall outside the scope of the thesis.

- The research focuses on internal material flows within the new warehouse, including sequential processes of receiving, put away, storage, order picking and shipping preparation. The yellow boxes show the activities that are within our scope.

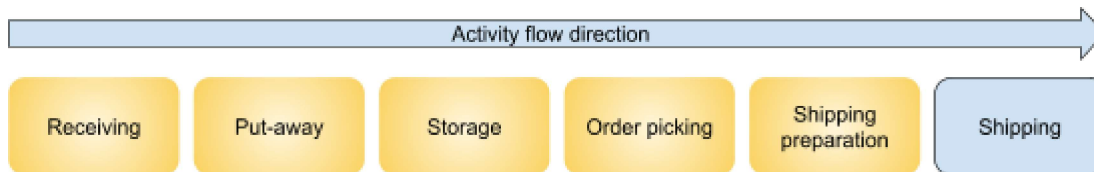


Figure 1.1: Illustration of the study scope within warehouse activities

- The study focuses on partial and modular physical automation solutions in a new warehouse. Digital automation, such as a Warehouse Management System (WMS), is considered to be a prerequisite but is not the primary object of the evaluation.
- The evaluation of current and future processes utilizes performance indicators of time, quality and productivity.
- **Exclusions:**
 - The physical building construction, property procurement and detailed facility layout are excluded from our report.
 - Detailed vendor-specific procurement, investment costs and implementation plans are excluded. The study will recommend technology types rather than specific brands.

2. Methodology

The methodology consisted of four sequential phases: **(A)** diagnosing current processes and performance, **(B)** identifying improvement opportunities in manual processes, **(C)** assessing remaining performance gaps, and **(D)** matching operational requirements to suitable automation technologies.

- A. Diagnose:** The current warehouse operations were evaluated using the empirical findings presented in Chapter 4. This phase combined data collected through observations, interviews, warehouse master data, transactional data analysis, and Material Flow Mapping (MFM) to identify operational challenges, process inefficiencies, and performance limitations within the existing warehouse.
- B. Improvement in manual processes:** Based on the identified challenges, an improved manual process was developed. The proposed improvements were primarily derived from the Material Flow Mapping analysis and supported by findings from observations, interviews, and discussions with VGR personnel. To strengthen the proposed solutions, relevant warehouse management and logistics literature was reviewed and used where appropriate to provide additional theoretical and empirical

support.

- C. Performance gap assessment:** In this step, it was checked if improving the manual processes was enough to meet VGR's future goals. The data from the Material Flow Mapping (MFM) were used to estimate how much the warehouse performance will improve. Then, we compared these improvements against future targets, such as handling 10,000 daily order lines and the inventory reserve rule. This comparison helped find the operational problems that manual changes alone cannot fix. These remaining gaps were then turned into clear requirements, which guided us in choosing the right automation technologies in the next stage.
- D. Technology matching:** For gaps that cannot be filled through manual operation improvements, remaining requirements were mapped against the capabilities of automation technologies. This involved evaluating available technology solutions using Decision-Making Framework Based on Qualifying and Comparable Factors.

2.1 Literature review

Literature review served as a foundational research method for building on existing academic knowledge. As Snyder (2019) argued, literature review is increasingly relevant in current business research as it enabled researchers to assess collective evidence in specific areas and remain at the forefront of evolving knowledge. Through systematic assessment of published research, literature reviews have provided a comprehensive understanding of a field's current state and established theoretical foundations that guide empirical investigations (Tranfield et al., 2003).

In the context of operations management research, literature reviews were used for several functions. First, they enabled researchers to make findings from multiple studies, identifying patterns and contradictions (Snyder, 2019). Second, literature reviews established the theoretical and methodological foundations necessary to find best practices, validated frameworks and proven analytical approaches (Tranfield et al., 2003).

For this research, a literature review was employed to serve two purposes. First, the literature review was used to propose improvement of manual warehouse processes, including order picking methods, storage allocation policies, and material handling techniques. By reviewing this knowledge, the research could identify opportunities to improve VGR's current manual processes before considering automation investments.

Second, the literature review provided essential knowledge for evaluating and proposing automation solutions suitable for VGR's operations. Research on warehouse automation technologies, including automated storage and retrieval systems, goods-to-person systems, and various picking technologies, has expanded in recent years as organizations seek efficiency improvements through technological solutions (Jaghbeer et al., 2020). The literature review enabled a systematic examination of different automation technologies, their performance characteristics, implementation requirements, and context factors that influence their suitability for specific operational environments.

2.2 Data collection methods

This study employed a multi-method approach to data collection, triangulating qualitative and quantitative data to ensure a comprehensive understanding of VGR's operations and to strengthen the validity of the findings (Yin, 2018). Data was collected through three primary methods: site observations, semi-structured interviews, and analysis of master data and transactional data.

2.2.1 Direct and video-based observations

Site observations served as a critical data collection method for understanding VGR's current warehouse operations. Observations were particularly valuable in operations research as it allowed researchers to directly witness operational processes, physical constraints and workflow patterns that were not fully visible through interviews or documented procedures. As Lawrenz et al. (2003) argued, site visits provided researchers with the opportunity to gather empirical evidence about how operations actually function at a daily level.

Multiple site visits were conducted at VGR's distribution center throughout the research period. These visits focused on observing several key aspects of warehouse operations: The physical layout and infrastructure of the facility, material flow processes, order picking procedures and storage allocation practices. Direct observation enabled the identification of operational inefficiencies and constraints that warehouse personnel might not routinely notice or mention during interviews (Lawrenz et al., 2003).

To support the Material Flow Mapping analysis, the observations were supplemented with video recordings and time measurements of the selected material flows. Video recording is well-suited to the analysis of manual work in logistics environments because it has captured the complete sequence of activities as they occur, enabled precise time measurement of individual tasks, and allowed for repeated review of complex or fast-moving operations (Engström & Medbo, 1997). The video material provided a permanent record that could be revisited during the analysis phase to verify activity classifications, resolve uncertainties, and ensure consistency across the four mapped flows. In addition, activity count and duration measurements were used to find and prioritize the activities with the most effect on improving the performance metrics. For example, time measurements were used to calculate the saving time by eliminating or changing the processes after improvements.

2.2.2 Interviews

Interviews served as a method for collecting empirical data in this research, enabling exploration of VGR's warehouse operations, performance challenges and organizational perspectives on manual operation improvements and automation technologies. As a qualitative data collection technique, interviews were well-suited for case study research where the objective was to understand complex operations within a real-world context, since they provide access to participants' knowledge (Yin, 2018). Semi-structured interviews were selected as the specific interview format for this study, balancing the need for systematic data collection with flexibility to explore new subjects (Pin, 2023).

The use of interviews in operations management research was recognized for its ability to capture both objective information about processes and subjective insights regarding organizational practices, challenges and logic behind decision-making (Barratt et al., 2011). In warehouse and logistics research specifically, interviews with operational personnel and management provide an essential understanding of the context, including workflow inefficiencies and technological constraints.

The interview data served multiple purposes within the research methodology. Interviews with VGR's management team provided empirical evidence for diagnosing current performance gaps, understanding the limitations of existing manual processes and identifying organizational requirements for the new distribution center. Interviews also enabled validation of findings from site observations and data analysis and also validation of improvement suggestions in terms of feasibility and practicality and thereby strengthening the reliability and validity of the research conclusions (Yin, 2018).

2.2.3 Master data and transactional data

Master data and transactional data formed important quantitative inputs for re-designing warehousing techniques and activities and physical automation technology selection decisions. Master data refers to the core business objects and their attributes, such as stock keeping unit (SKU) characteristics, including dimensions, weight, and storage requirements (De Koster et al., 2007). Transactional data captures the dynamic operational events and activities within the warehouse. Together, these data sources provided an empirical foundation for analyzing the current operational performance.

In warehouse operations research, master data and transaction history enable data-driven analysis of storage allocation strategies, material handling requirements, and process design decisions (Gu et al., 2007). SKU characteristics, including product dimensions, weight classifications, and handling constraints, directly influence decisions regarding physical automation technologies. Historical transactional data, including picking frequencies, order patterns, and demand variability, shape allocation policies and capacity planning for both manual and automated systems (De Koster et al., 2007). This data-driven approach ensures that warehouse design recommendations are grounded on empirical evidence rather than assumptions.

For this research, master data and transactional data served two purposes aligned with the thesis methodology. First, analysis of SKU characteristics and historical order data supported the optimization of manual warehouse processes. Gu et al. (2007) show that data-driven storage allocation strategies shaped by SKU analysis, turnover analysis and order pattern can significantly improve manual picking efficiency.

Second, master data analysis provided essential inputs for evaluating automation technology requirements and specifications. Warehouse automation technology selection depends on understanding SKU characteristics, volume requirements and operational patterns that determine system specifications and feasibility (Baker & Halim, 2007). For instance, SKU dimensional data determined whether products are suitable for automated storage and retrieval systems with standardized bin sizes. While historical transactional data established capacity requirements for automated equipment. Order pattern analysis revealed whether

demand characteristics aligned with automation strengths or whether manual flexibility was still advantageous. Therefore, master data analysis enabled evaluation of which warehouse processes and SKU categories were suitable candidates for automation versus those better served by improved manual operations.

VGR provided access to the most necessary data from the warehouse management system, including SKU master data covering items stored at Sisjön Distribution Centre and a one-year transactional data. This quantitative data was analyzed using statistical methods and data mining techniques to identify SKU classification (picking frequency and demand volatility), slotting improvement opportunities, and performance metrics calculations. They were used both for manual process improvements and warehouse physical automation technology recommendations for the new distribution center.

2.3 Data analysis

The purpose of the data analysis phase was to transform the collected qualitative and quantitative data into actionable insights regarding the current performance of VGR's warehouse operations. By combining material flow mapping, statistical analysis of master and transactional data, and qualitative assessment of operational processes, the study identified performance gaps, operational constraints, and improvement opportunities. The analysis served as the foundation for evaluating both manual process improvements and physical automation technologies capable of supporting VGR's future operational requirements.

2.3.1 Material Flow Mapping (MFM)

MFM is a specialized tool derived from lean production principles designed to assess the performance of material flows within supply chains (Finnsgård et al., 2011). Unlike traditional Value Stream Mapping (VSM), which prioritizes value-adding steps, MFM is tailored for logistics environments where most activities are non-value-adding but essential for material delivery (Finnsgård et al., 2011).

This methodology utilizes the HATS framework, which categorizes activities into four distinct entities (Finnsgård et al., 2011):

- **Handling:** Rearranging materials within a location, such as picking, packing, and sorting.
- **Administration:** Information management activities, including barcode scanning, documentation, and labeling.
- **Transport:** Physical movement of materials between facility zones or locations.
- **Storage:** Points where materials are kept waiting, even for short durations.

In this study, MFM was applied by first identifying and recording every activity within the selected material flows through site observations and video analysis. Each activity was then classified according to the HATS framework, enabling us to count the number of handling, administration, transport, and storage events in each flow. By mapping the flows in this detailed manner, the current process design becomes visible, non-value-adding steps are exposed, and specific opportunities to change or eliminate activities can be identified.

The mapping focused on four representative flows: Shelf Picking, Sterile Refill, Sterile, and Bulk. These four were selected because they together cover the large majority of the material movements within the warehouse. VGR's management validated that these flows capture a sufficiently large proportion of total warehouse activity to serve as a reliable basis for analysis and improvement recommendations.

To ensure that no relevant work was overlooked, each activity was further broken down into fine-grained steps. Activities were also assigned a flow tier, Primary or Support, where Primary activities directly move the goods forward (e.g., picking, replenishment) and Support activities enable or assist the primary flow (e.g., activating voice devices, fetching reach trucks). This dual classification captures a broader set of activities than a primary-only mapping would, thereby exposing more opportunities for improvement.

The research indicates that moving materials through intermediate facilities or multiple levels significantly increases the number of handling and administrative activities, often doubling the number of storage points compared to direct flows (Hanson et al., 2016). By quantifying the HATS entities in the current state and identifying inefficiencies, the study lays the foundation for evaluating whether manual process improvements can raise performance sufficiently or whether physical automation is required to overcome the constraints inherent in the current flow design.

2.3.2 Quantitative assessment

Quantitative data analysis establishes performance metrics for VGR's current warehouse operations using the master data and transactional data provided by VGR and also activity and time measurements through material flow mapping. This data quantifies current operational performance across the key performance dimensions identified in the coming sections. Specifically, the analysis includes categories below with examples:

- **SKU classification:** First, the number of active SKUs derived from one-year transactional data was determined. Except around half of the item's volume, the other characteristics, including weight, dimension and volume for the other half are missing in the master data. However, the diversity of shapes and dimensions were validated through interviews. Even though the warehouse uses different zones for various storage needs such as sterility, temperature or safety, only normal and sterile items were considered as the focus of the study. This means SKU sterility is taken into account for both the material flow mapping and the productivity calculations. Picking frequency (ABC analysis) and item association analysis (frequent co-picked SKUs) which are used for suggesting manual operation improvements in section 5.2.6 Velocity Based Slotting and Item Association Based Slotting are also calculated.

To complement the velocity classifications, Association Rule Mining (ARM) is introduced as a data-driven method to discover correlations in ordering patterns (Li et al., 2021). According to the authors, ARM evaluates product affinities using three core metrics: Support (the frequency of an item pair across all transactions), Confidence (the probability that a paired item is needed once the trigger item is selected), and Lift (the absolute correlation strength between the items). A lift number

greater than 1 indicates a significant statistical relationship where items are positively correlated and ordered together more frequently than random chance (Li et al., 2021).

- **Demand characteristics:** Demand volatility during a one-year operation, and number of order lines and physical volume per order are measured and are used to both propose potential manual process improvements and also as a demand complexity and profile input when selecting factors to evaluate different physical automation technologies.
- **Picking productivity:** Order lines picked per labor hour and per zone were calculated to determine how operational efficiency gains translate into higher throughput. By identifying and removing non-value-added activities from the material flow maps, the study quantifies how reclaiming wasted time increases actual picking capacity. For example, if an inefficient process step is eliminated, that time is redirected to productive picking, allowing for a direct estimation of additional order lines that can be fulfilled daily. These process improvement strategies are detailed in Section 5.2 Manual (Non-Automated) Improvement Suggestions.

This assessment provides the quantitative foundation for identifying performance gaps relative to VGR's future expectations. The metrics establish the current state against which manual operation improvements and automation alternatives can be evaluated.

2.3.3 Qualitative assessment

The qualitative assessment phase focused on analyzing descriptive field data to identify operational problems and develop practical improvement options. As highlighted by Barratt et al. (2011), data analysis is a core part of qualitative research that ensures objectivity when translating collected qualitative data and information into final research conclusions. In this study, the qualitative analysis allowed for a deep understanding of warehouse activities and processes.

According to Voss et al. (2002), qualitative field data is highly effective for answering "what, why, and how" questions to capture the actual complexity of a logistics system. The qualitative data were analyzed using three progressive steps:

- **Process design comprehension:** First, the recorded descriptions of warehouse operations were organized chronologically to establish a clear picture of current workflows. This step outlined how tasks are structured across storage zones. The resulting process description was later presented in the material flow map in Section 4.1.3 and served as a foundation for the subsequent analysis and development of improvement suggestions for manual operations.
- **Activity challenging:** Second, individual warehouse activities were evaluated by questioning what tasks are performed and why they exist. Following the recommendations of Voss et al. (2002), it is necessary to challenge conflicting or incomplete descriptions from the field to clarify operational information. This process

helped expose hidden process gaps, such as double-handling and non-standardized routines, as well as critical friction points in human-system interaction (such as WMS voice-picking failures due to background noise). The identified non-value-adding activities were subsequently addressed through process redesign and improvement proposals presented in Section 5.2.

- **Inefficiency and constraint categorization:** Third, the qualitative data were used to connect errors and inefficiencies to the overall process design that leads to understanding these contemporary operational issues (Barratt et al., 2011). This step helped isolate physical warehouse constraints and system communication gaps. Crucially, these categorized operational constraints and strategic realities were used to build an initial baseline of decision criteria. In collaboration with the VGR management and operational team, this initial list was reviewed, allowing them to either confirm our selections or adjust the parameters based on practical constraints. This collaborative process established the finalized binary qualifying gates and comparable logistics criteria used within the multi-criteria decision-making framework (Section 5.4) to systematically evaluate and select the physical automation technologies.

The results of this qualitative assessment provided a direct foundation for the upcoming sections of the thesis. First, identified wastes that do not require technology were used to design manual improvement suggestions. Second, the identified operational constraints and process requirements are converted into qualifying and comparable factors. These factors were subsequently used in the later sections to evaluate and select the most appropriate physical warehouse automation solutions.

2.4 Framework for empirical findings structure

In order to organize and analyze the empirical findings, Chapter 4 is divided into three main sections. This choice of structure follows the classic warehouse decision hierarchy established in logistics literature (van den Berg & Zijm, 1999). In their framework, they explain that warehouse management problems can be separated into distinct decision categories, which include "warehouse design", "inventory management under space restrictions", and "assignment and scheduling of warehouse operations".

First, Section 4.1 describes the context and design of the VGR facility, including a warehouse overview, item demand profiles, and material flow mapping. This section matches the "warehouse design" category from the van den Berg and Zijm (1999) framework. Describing the physical facility, the items, and mapping the baseline flows is necessary before analyzing active operations. These design choices establish the physical boundaries and operational limits for all daily logistics tasks.

Second, Section 4.2 focuses entirely on order picking operations at VGR. This isolation follows the "assignment and scheduling of warehouse operations" level defined by van den Berg and Zijm (1999). Order picking is placed in its own dedicated section because it is the most critical process in manual warehousing. De Koster et al. (2007) emphasize this point by stating that "order picking has long been identified as the most labour-intensive and costly activity for almost every warehouse". They point out that the cost of picking is estimated to be

"as much as 55% of the total warehouse operating expense". Because picking activities consume the most resources, any errors or low productivity will directly lower customer service and increase costs for the whole supply chain (de Koster et al., 2007). Therefore, a separate analysis is required to evaluate picker performance and picking errors at VGR.

Third, Section 4.3 covers inventory control and capacity planning. This section directly aligns with the "inventory management under space restrictions" category established by van den Berg and Zijm (1999). In warehouse operations, storage capacity cannot be studied without considering how inventory levels are managed. This section shows inventory policies and capacity planning together to help understanding of how administrative control rules affect the physical reality.

2.5 Multi-criteria decision-making

Multi-criteria decision-making (MCDM) is a specialized branch of decision science that provides structured methodologies to evaluate complex operational problems that involve multiple conflicting objectives. As Liang (2021) notes, MCDM models are fundamentally categorized into continuous and discrete methods. Discrete MCDM techniques are highly applicable to supply chain planning and industrial logistics systems where an organization must evaluate, rank, or select a finite number of physical options against a predefined set of performance requirements (Liang, 2021). In this master's thesis, a discrete MCDM approach is used to structure the technical evaluation of warehouse physical automation technologies for the VGR Sisjön Distribution Centre relocation project.

This research adapts the structured selection framework developed by Johansson and Persson (2023) to match warehouse operational requirements with specific technological capabilities. In their original study, Johansson and Persson (2023) used a fixed arrangement of four qualifying factors and eight comparable factors to evaluate physical systems. However, a major methodological choice in this thesis is that the exact criteria used by Johansson and Persson (2023) will not be direct copies. Instead, this study will select and define entirely new qualifying and comparable factors in the upcoming analysis chapter. These specific criteria will be chosen based on the actual empirical observations, item and demand characteristics, and from the VGR facility rather than relying on a generic industrial list (Johansson & Persson, 2023).

2.5.1 Best-worst multi-criteria decision-making

To obtain the weights for each criteria the best-worst method (BWM) was utilized. BWM was selected since it requires less comparison data and is more consistent compared to other MCDM methods (Rezaei, 2015). The BWM is a discrete multi-criteria decision-making technique used to calculate the exact importance weights of evaluation criteria through a structured pairwise comparison process. Rezaei (2015) originally developed the BWM to overcome the mathematical inconsistencies that frequently occur in older, matrix-based comparison models. BWM simplifies the weighting process by using only two reference vectors (Best-to-Others and Others-to-Worst), reducing comparison fatigue.

In the context of this project, BWM is integrated into the technology matching methodology to determine the precise weights for the new comparable factors identified for VGR. In line with the application steps outlined by Johansson and Persson (2023), the execution of BWM led to focus on highly customized operational needs. When executing the framework in the analysis section of this report, the decision-makers will follow the standard five-step mathematical procedure established by Rezaei (2015):

- **Step 1:** Finalize the set of customized comparable logistics criteria $\{C_1, C_2, \dots, C_n\}$ derived from the VGR empirical findings.
- **Step 2:** Identify the single most important factor (the best criterion, C_B) and the single least important factor (the worst criterion, C_W) from the chosen list based on organizational goals.
- **Step 3:** Determine the operational preference of the best criterion (C_B) over all other individual criteria using a standard integer scale from 1 (equal importance) to 9 (extreme unimportance) to generate a Best-to-Other vector.
- **Step 4:** Determine the preference of all individual criteria over the designated worst criterion (C_W) using the same 1–9 integer scale to generate an Other-to-Worst vector.
- **Step 5:** Solve a mathematical optimization model to calculate the optimal weights ($w_1, w_2, \dots, w_n$) by minimizing the maximum absolute differences between the actual weight ratios and the target preference vectors.

Once these optimal criteria weights are calculated, they will be combined with the technical performance scores assigned to each qualified technology option (Johansson & Persson, 2023). This mathematical aggregation will provide a final suitability score for each technology configuration, allowing a clear, data-driven recommendation on which physical automation systems can best bridge VGR's operational performance gaps.

2.6 Qualifying-comparable factors decision-making framework

To transition VGR's Sisjön Distribution Centre from mainly manual operations to a high-performance, partially automated design in the new facility, a structured and objective selection method is required. This master's thesis utilizes the qualifying-comparable factors decision-making framework formulated by Johansson and Persson (2023) as its central methodology to guide this selection process.

The framework is a specialized, two-stage discrete multi-criteria decision-making (MCDM) model. In the first stage, it uses non-negotiable criteria, known as qualifying factors, as binary filters to eliminate unfeasible technology options. In the second stage, it applies weighted comparable factors to score and rank the remaining qualified options. While this study adopts the structural logic of the Johansson and Persson (2023) framework, it does not use the generic industrial criteria from the original research. Instead, the framework is adapted as a general guide, using customized qualifying and comparable factors derived directly from VGR's specific context and design.

The selection of warehouse physical automation is highly dependent on the relationships between three core dimensions: **context, performance, and design**. The relationship between these dimensions is central to the framework's logic:

- **Context:** This dimension defines the external and internal boundaries of the system. For VGR, the context includes SKU and demand characteristics.
- **Performance:** This dimension represents the specific operational goals the organization wishes to achieve. It is represented by key performance indicators (KPIs) covering productivity, quality and accuracy.
- **Design:** This dimension is the selection and configuration of the physical automation hardware. It represents the technical options available in the market to meet performance goals within the context.

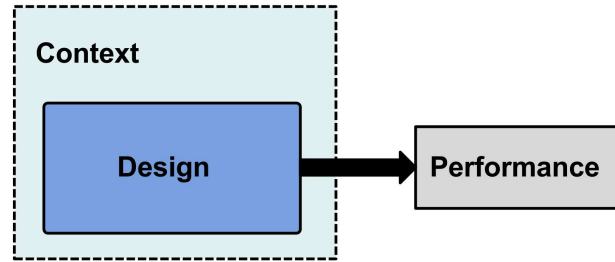


Figure 2.1: Visualization of the three different dimensions utilized to support the analysis

The framework acts as an analytical bridge between these dimensions. The operational context determines the performance expectations and its requirements. By assessing physical automation technologies through this lens, VGR can ensure that any selected system is both technically appropriate and aligned with its goals.

2.6.1 The binary qualifying stage

The first stage of the decision-making framework acts as a binary gatekeeper. Qualifying factors represent the strict physical, financial, and regulatory constraints that a technology must satisfy. Each technology alternative ($t_1, t_2, \dots, t_n$) identified from the list of available warehouse physical automation technologies in previous chapters is evaluated against these factors. If a technology fails to meet even one qualifying factor, it is immediately disqualified and removed from further analysis.

In their original work, Johansson and Persson (2023) defined four standard qualifying factors: item characteristics, investment budget, size limitations, and warehouse capacity. For the VGR's relocation project, these categories will be customized to align with the empirical findings.

2.6.2 The weighted comparable stage

Technologies that pass the binary qualifying stage are classified as qualified solutions. In the second stage, these qualified alternatives are evaluated and compared quantitatively. Comparable factors represent criteria that are highly important to the business case but allow for performance trade-offs. Here again, customized comparable factors will be used. These factors are designed to bridge the specific performance gaps identified at the Sisjön facility.

The evaluation of comparable factors requires assigning a performance score (p_{ij}) to each qualified technology j for each comparable factor i . This score indicates how effectively a specific technology meets that criterion.

2.6.3 BWM integration and mathematical scoring

To rank the qualified technology options, the framework utilizes the BWM to assign mathematically objective weights (W_i) to each comparable factor. As outlined earlier, BWM requires decision-makers to identify the single most important (best) and single least important (worst) comparable factors from the customized list. Pairwise comparisons are then made on a standard scale from 1 (equal importance) to 9 (extreme unimportance).

An optimization model is solved to calculate the weights ($W_1, W_2, \dots, W_k$) for the k comparable factors, ensuring high consistency in decision-maker preferences. Once these weights are calculated, the decision-maker structures the evaluation problem using a discrete MCDM matrix.

2.6.4 Discrete MCDM performance matrix structure

The interaction between the qualified physical automation technologies and the comparable factors is represented mathematically in the matrix below:

	C_1	C_2	$\dots$	C_k
t_1	P_{11}	P_{21}	$\dots$	P_{k1}
t_2	P_{12}	P_{22}	$\dots$	P_{k2}
$\dots$	$\dots$	$\dots$	$\dots$	$\dots$
t_n	P_{1n}	P_{2n}	$\dots$	P_{kn}

Using the weights (W_i) derived from the BWM step and the performance scores (P_{ij}), the total suitability score (S_j) for each qualified physical automation technology is calculated using a weighted sum aggregation:

$$S_j = \sum_{i=1}^k P_{ij} W_i$$

The physical automation technology that achieves the highest total suitability score is recommended for implementation.

3. Theoretical frameworks

This chapter presents the theoretical foundations that support the analysis and evaluation conducted in this study. The reviewed literature covers warehouse performance measurement, warehouse physical automation technologies, and decision-making frameworks for technology selection. Together, these theoretical perspectives provide the analytical basis for assessing VGR's current warehouse operations, identifying performance gaps, and determining whether improvements in manual processes or physical automation technologies are required to meet future operational requirements.

3.1 Performance metrics

Performance metrics provide the analytical foundation required to evaluate operational efficiency, identify bottlenecks, and guide design decisions in warehousing systems. According to Kusrini et al. (2018), establishing clear performance indicators is essential for warehouse managers to diagnose areas for improvement and implement targeted corrective actions. When undertaking facility re-design or technology implementation, performance evaluation models serve a dual purpose: they benchmark the existing manual processes and establish the structural criteria needed to assess alternative system configurations (Gu et al., 2010).

To ensure a comprehensive evaluation that aligns both improvements in manual processes and physical automation selection, this thesis reorganizes the performance metrics of the VGR distribution center. The metrics are structured around the qualifying and comparable decision factors relevant to the case environment (Johansson & Persson, 2023). Consequently, the following subsections analyze the facility's performance across two primary dimensions: productivity and capacity and quality and accuracy.

3.1.1 Productivity and capacity

Productivity in warehouse operations represents the operational efficiency with which resource inputs are converted into functional outputs. Following the established Frazelle warehouse model utilized by Kusrini et al. (2018), productivity is tracked quantitatively across specific activity categories, such as measuring the number of put-aways or order lines picked per man-hour. Material handling is fundamentally classified as a non-value-adding activity. Therefore, improving labor productivity in manual settings depends heavily on minimizing internal travel time and travel distances.

While productivity analyzes labor performance, warehouse capacity represents the physical processing and volume limits of the system layout. According to Johansson and Persson (2023), warehouse capacity is defined by two key considerations: throughput and storage capacity. Throughput dictates the total volume of transactions or goods that a warehouse configuration can process within a specific timeframe. This capacity metric determines whether a facility can handle volatile demand patterns without creating operational bottlenecks. Storage capacity, on the other hand, determines the maximum number of Stock Keeping Units (SKUs) that can be safely housed in the facility.

3.1.2 Quality and accuracy

Quality in warehouse execution refers to the system's capability to eliminate errors and assure data integrity. According to the traditional logistics models evaluated by Kusrini et al. (2018), quality is primarily verified through perfect process execution across warehouse activities. In fulfillment operations, this is measured directly through picking accuracy, which monitors the percentage of perfect picking lines completed without errors. High picking accuracy ensures that downstream processes run smoothly and customer requirements are met without costly correction loops.

Beyond physical picking execution, quality also encompasses inventory level accuracy. Information discrepancies frequently occur when the digital stock records in a warehouse management system deviate from the actual physical items on the shelves. In manual warehousing environments, undetected inventory discrepancies cause an operational domino effect, leading to unexpected stockouts, delayed fulfillment cycles, and incorrect replenishment planning. Therefore, tracking locations without inventory discrepancies is vital to maintaining data accuracy.

3.2 Warehouse physical automation technologies

According to Kwak et al. (2025), the healthcare industry faces pressure to optimize operational efficiency and fulfillment accuracy within its internal logistics processes. Although these logistical functions are vital to overall healthcare supply chain performance, the sector demonstrates a slow adoption rate for advanced warehouse automation, maintaining a technology investment ratio of only 14.9%, which sits below the broader industrial baseline of 18% (Kwak et al., 2025). As Kwak et al. (2025) observe, this implementation gap is heavily driven by strict regulatory compliance mandates and severe product heterogeneity.

Healthcare inventories encompass an enormous variety of individual items that differ drastically in their physical dimensions, shapes, weights, fragilities, packaging structures, and environmental sensitivities (Kwak et al., 2025). To overcome these complex product variations and eliminate intensive manual handling, modern distribution facilities are increasingly deploying specialized warehouse physical automation technologies designed to maximize cubic storage space and accelerate material workflows.

To evaluate the potential solutions, this section reviews eight available physical automation technologies. Consequently, this section tries to evaluate each technology's technical specifications, structural requirements, and operational suitability within the healthcare context.

Furthermore, although pallet shuttle systems are technically a sub-system within the broader shuttle-based technology family, this report explicitly evaluates them as two separate categories in Section 3.2.3 and Section 3.2.8. This choice is based on distinct operational and technical realities. First, these systems handle different load units and fulfill separate functional roles. Tote-based multi-shuttles manage small containers for dynamic, high-throughput piece picking, while pallet shuttles manage full pallet unit loads for deep-lane bulk storage and replenishment. Second, separating them avoids terminology

ambiguity during the literature review, as both systems are grouped under the generic term "shuttle systems" in logistics research. Finally, this division allows for a more granular evaluation within the multi-criteria decision-making framework, ensuring that performance scores for versatility handling and storage density reflect the unique attributes.

3.2.1 Crane-based automated storage and retrieval systems

Crane-based automated storage and retrieval (AS/R) systems serve as a foundational technology for modern industrial facilities. Azadeh et al. (2019) explain that these systems were originally developed to handle bulk stock stored on unit loads. de Koster (2018) explains that AS/RSs handle unit loads, such as bins and pallets, using an aisle-captive crane that automatically places and retrieves items in racks reaching heights of up to 30 meters. Roodbergen and Vis (2009) explain that an automated storage and retrieval system (AS/RS) utilizes fixed-path storage and retrieval machines operating on rails between fixed arrays of storage racks. These automated storage and retrieval machines, commonly referred to as cranes, autonomously handle unit-loads within dedicated warehouse aisles (Roodbergen & Vis, 2009). To optimize cycle times, these cranes perform driving and lifting movements simultaneously.

System throughput can be improved further by using dual command cycles, which combine a single storage and retrieval command to save one operational movement per cycle (de Koster, 2018). While classic logistics literature identifies typical system designs as having horizontal travel speeds up to 3 m/s (180 m/min) and vertical travel speeds up to 0.75 m/s (45 m/min), modern commercial technology has significantly surpassed these operational thresholds. Specifically, an industry report by Daifuku Europe Ltd. (2008) highlights that modern high-throughput crane configurations can achieve horizontal travel speeds of up to 400 m/min and vertical lifting speeds of up to 60 m/min (Daifuku Europe Ltd., 2008). Tarasiuk (n.d.) highlights that a vital element of crane-based configurations is the automatic pallet control station, which verifies the weight and contour of each pallet prior to storage.

By utilizing vertical high-bay racks that standardly range between 20 and 40 meters in height, AS/R systems maximize space utilization and reduce the building footprint in regions where industrial land is scarce. Furthermore, replacing traditional manual warehouse layouts with these automated systems helps operations handle large product assortments while mitigating rising labor and picking challenges (Azadeh et al., 2019). Stacker cranes operate effectively within extreme cold-chain environments, such as the Keller Logistic facility in Romania, where pallet conveyor systems transfer inventory through specialized airlocks into dual cold chambers operating from +5°C to -22°C and down to -27°C (Tarasiuk, n.d.). For temperature-controlled healthcare inventories, the system must be compatible with cold storage or refrigerated environments (Ji, M., & Guo, Y., 2017).

As highlighted in the empirical fieldwork by Kwak et al. (2025), Case 5, representing the Korean business unit of a Swiss pharmaceutical logistics provider, demonstrated that a crane-type AS/RS offered exceptional operational productivity during inbound sorting and inventory replenishment cycles across two decades of continuous use. However, Azadeh et al. (2019) state that conventional crane-based compact storage systems lack flexibility regarding the volume of goods they can handle. The throughput capacity of these automated systems is

inherently restricted because a single crane is responsible for handling all material movements at every vertical level within a given storage aisle (Azadeh et al., 2019). Consequently, crane-based systems cannot scale their operational capacity dynamically to match volatile demand variations, which contrasts with modern shuttle-based systems where capacity can be adjusted simply by changing the number of active vehicles (Azadeh et al., 2019).

The installation of a crane-based AS/RS requires vertical space, with taller systems offering higher cubic density at proportionally greater investment cost, making height a key economic variable rather than a fixed technical requirement. The system relies on an integrated Warehouse Control System (WCS) synchronized in real time with a WMS to coordinate crane paths and prevent mechanical collisions. Despite these long term operational benefits, third-party logistics (3PL) companies face unique structural barriers, they often hesitate to commit capital to fixed automation infrastructure because short-term client contract renewals introduce severe financial investment risks (Kwak et al., 2025).



Figure 3.1: Automated high-bay warehouse layout with aisle-bound unit-load stacker cranes (Logistiksysteme, 2018)

3.2.2 Cube-based automated storage and retrieval systems

As outlined by Kwak et al. (2025), cube-based layouts (frequently implemented via AutoStore technologies) utilize a robot-based compact storage and retrieval system (RCS/RS) architecture to maximize warehouse cubic space utilization. This design organizes inventory within standardized plastic bins that are arranged in vertical stacks inside a dense grid framework (Kwak et al., 2025). Dedicated robots navigate across the top interface of the grid to retrieve storage bins, utilizing software controls to handle the inherent Last-In-First-Out (LIFO) sorting sequences when digging for specific SKU (Kwak et al., 2025). “Cube-based AS/RS is increasingly found in e-commerce fulfillment and pharmaceutical distribution where space efficiency and rapid access to many SKUs are critical” (Kwak et al., 2025).

Optimizing the physical dimensions of the grid layout is critical when designing robot-based compact storage and retrieval (RCSR) systems. In a comprehensive industry review, Azadeh et al. (2019) highlight mathematical modeling developed by Zou et al. (2016) regarding system shape optimization. This research demonstrates that a grid width-to-length ratio of approximately $2/3$ minimizes throughput times (by optimizing travel distances and congestion

reduction) when operations deploy a random storage stack configuration (Azadeh et al., 2019; Zou et al., 2016). If the facility switches to a zoned storage strategy, a slightly larger dimension ratio is required to maintain optimal configuration performance (Azadeh et al., 2019).

Within the specialized pharmaceutical wholesale sector, automated storage configurations are increasingly evaluated to address strict service level demands and regulatory mandates (Kwak et al., 2025). In the empirical findings presented by Kwak et al. (2025), Case 6 highlights a clinical trial logistics provider that evaluated the integration of an AutoStore system while planning a warehouse relocation due to an expiring facility lease. The center's operations manager emphasized that clinical trial logistics functions as a high-cost, high-service sector. Rather than managing a standard commodity flow, the organization handles specialized pharmaceuticals destined for regulatory approval pathways. By exploring cube-based automated storage and retrieval system (AS/RS) options during their request for proposal (RFP) stage, the firm expects to optimize storage density within expensive, temperature-controlled footprints while establishing segregated storage zones tailored to unique customer requirements (Kwak et al., 2025).

In terms of physical facility parameters, a Robot-based Compact Storage and Retrieval System (RCSRS) has distinct vertical clearance requirements, as it must have a higher ceiling layout to utilize the total volume of an existing warehouse footprint effectively (Johansson & Persson, 2023). Unlike traditional high-bay AS/RS, cube storage does not require high ceiling heights, it is highly adaptable to standard industrial heights. For example, an AutoStore system can achieve a total operating height of between approximately 7.4 and 8.2 metres (Element Logic, 2024). Additionally, the robots require charging and maintenance windows, meaning the warehouse must schedule operational shifts to allow for battery recovery (Zou et al., 2018).

The system requires strict integration with warehouse control software to manage the sorting and optimization of bin sequences. Johansson and Persson (2023) showed that while digital connectivity is expected in automated designs, the technical integration between new physical configurations and the local WMS was surprisingly brief or absent in practitioner accounts, showing it may not be a primary focus area during initial industrial evaluations.

However, cube-based storage systems have strict qualifying constraints when evaluated for healthcare logistics environments. According to Johansson and Persson (2023), cube-based automated storage configurations possess clear material limitations, meaning that dangerous goods cannot be stored within a cubic solution. Additionally, fire safety design is a critical operational factor. These systems utilize non-perforated bins that restrict airflow during a fire, which allows sprinkler systems to suppress flames more effectively (a design condition that both insurance companies and fire protection engineers expect suppliers to evaluate) (Johansson & Persson, 2023).



Figure 3.2: Cube-based ultra-high-density automated storage and retrieval system with robots operating on a grid structure (Euku, 2025)

3.2.3 Shuttle-based storage and retrieval systems (AVS/RS and Multi-Shuttles)

de Koster (2018) states that autonomous vehicle-based storage and retrieval (AVS/R) systems, also referred to as shuttle-based retrieval (SBR) systems, are aisle-based configurations that operate without traditional cranes. Instead, these designs utilize shuttles that can drive independently in the x and sometimes also in the y-direction on any racking level within the storage aisle to handle unit loads, such as bins. Integrated vertical lifts stationed at the front of the structure transport either the individual shuttles or the unit loads between the levels and the designated depot. This setup differs from the operational layout from traditional crane-based AS/RS, where driving and lifting movements occur simultaneously via a single crane mechanism.

Shuttle-based technologies separate horizontal and vertical material movements. In these configurations, autonomous vehicles handle horizontal travel within a specific tier, while dedicated lifts manage vertical movement across levels (Azadeh et al., 2019). Because AVS/R (autonomous vehicle-based storage and retrieval) infrastructure allows multiple shuttles to move at the same time, these systems yield a higher retrieval capacity and provide scalable operational flexibility (de Koster, 2018).

Unlike rigid crane-based configurations, AVS/R systems provide a modular and highly scalable alternative. Azadeh et al. (2019) state that “such systems are increasingly popular because the required investment is similar to that of AS/R systems, although they offer a much higher retrieval capacity and are also significantly more flexible in capacity”. Because storage capacity and throughput capacity are completely decoupled in an AVS/R framework, system performance is not restricted by fixed aisle cranes. Consequently, when seasonal throughput peaks occur or demand variability fluctuates, managers can scale transaction capacity independently by adjusting the number of active autonomous shuttles within the boundaries of the existing rack structure (Azadeh et al., 2019).

However, this decoupling is subject to physical limitations when planning macro facility expansions. Shuttle-based storage and retrieval systems present specific structural constraints, as they conventionally bind each autonomous vehicle to a designated aisle. As highlighted by

Johansson and Persson (2023), this configuration creates operational challenges during facility expansions because scaling storage capacity and throughput capacity are often tightly coupled, preventing organizations from expanding them independently once the physical capacity limits of the initial rail layout are reached.

Coordinating movements is critical to avoid system bottlenecks. As highlighted by Azadeh et al. (2019), mathematical models developed by Roy et al. (2015b) are vital to evaluate these congestion effects, specifically capturing how blocking delays occur at cross-aisles and aisle nodes. To evaluate overall system performance, Heragu et al. (2011, as cited in Azadeh et al., 2019) demonstrated that an open-queueing network approach can successfully estimate transaction cycle times. Specifically, their research utilized a manufacturing performance analyzer tool to compare tier-captive AVS/R system performance directly against traditional crane-based configurations (Azadeh et al., 2019).

Modern shuttle-based automated storage and retrieval systems, such as the OSR Shuttle Evo developed by KNAPP, store inventory in totes or cartons with weights reaching up to 50 kg (Tarasiuk, n.d.). Tarasiuk (n.d.) highlights the application of this technology in footwear logistics through its deployment at the ASICS distribution center in Garons, France. In this facility, intelligent shuttle robots retrieve items and deliver them to Pick-it-Easy workstations, which are ergonomic picking stations operating on the goods-to-person principle. These workstations integrate pick-to-light systems, weight checks, and image inspections to verify order correctness. According to Tarasiuk (n.d.), utilizing this integrated system successfully reduces operational errors, shortens order lead times, and increases employee picking productivity.

In the warehouse automation literature summarized by Kwak et al. (2025), multi-shuttle infrastructure is characterized by fleets of independently operating vehicles designed to handle totes or cartons within highly dynamic, high-throughput order fulfillment environments. From an empirical perspective, Kwak et al. (2025) present the case of a third-party logistics (3PL) wholesaler (the South Korean business unit of a Swiss pharmaceutical logistics firm) that planned to develop a new mega-hub facility. To maximize internal performance, the organization evaluated combining innovative mobile robotics and automated storage systems, specifically focusing on autonomous mobile robots (AMRs) and 4-way shuttles.

However, organizational execution challenges emerged during the procurement phase. In an attempt to secure procurement cost reductions, the firm prioritized communication with automated equipment manufacturers based in China. This strategy resulted in severe language barriers and technical communication misalignments between the project teams and the technology vendors, which ultimately caused management to discontinue the automation initiative altogether (Kwak et al., 2025). Here we can see that while advanced shuttle layouts offer substantial productivity advantages, their successful deployment depends heavily on robust vendor relationship management, clear communication channels, and transparent technical support frameworks to mitigate integration risks.



Figure 3.3: Autonomous storage shuttle vehicle operating inside an automated racking matrix (Moffett, 2020)

3.2.4 Robotic mobile fulfillment systems (RMFS) and autonomous mobile robots (AMRs)

Robotic Mobile Fulfillment Systems (RMFS) represent a prominent parts-to-picker architecture that relies on fleets of autonomous mobile robots. As reviewed by Azadeh et al. (2019), these mobile units navigate facility floors dynamically to eliminate manual walking paths for warehouse operators. Under centralized software control, the vehicles drive directly underneath movable storage racks, known as inventory pods, lift them, and transport them to stationary picking or replenishment workstations (Azadeh et al., 2019). Alternatively, some material handling setups utilize Autonomous Case-handling Robots (ACRs). As explained by Tarasiuk (n.d.), these specific units move horizontally on the warehouse floor while retrieving multiple containers simultaneously from different vertical levels on a single 4-meter-high storage rack.

Real-world deployments demonstrate that mobile robotic systems generate significant operational impacts. For instance, the deployment of Exotec's Skypod system at the Renault Group distribution center in Villeroy reduced order processing times from 120 minutes to 15 minutes (Tarasiuk, n.d.). This automation integration also achieved a fourfold increase in order processing productivity alongside a 99.7% customer service satisfaction rate. Similarly, the implementation of a HAI ROBOTICS ACR system at the SF-DHL facility in Shanghai generated a 20-fold increase in the efficiency of goods receipt and a 3.5-fold increase in order picking efficiency (Tarasiuk, n.d.). This configuration utilized put-to-light shelves at automated picking workstations to help achieve an overall picking accuracy of 99.99%.

Regarding the AMR fleets themselves, according to Kwak et al. (2025), autonomous mobile robots (AMRs) provide a highly viable alternative to traditional fixed automation layouts because they offer greater investment flexibility and operational adaptability within the supply chain. Furthermore, because these mobile platforms navigate dynamically using advanced sensors rather than fixed physical infrastructure, they provide the real-time route flexibility required to manage shifting workflows and complex inventories across both distribution centers and active hospital environments (Kwak et al., 2025). The system performance depends heavily on software orchestration. Azadeh et al. (2019) note that optimizing these robot-based environments requires logistics managers to resolve complex operational decision

problems, including robot routing, pod sequencing, and automated fleet battery charging schedules.

In the empirical fieldwork presented by Kwak et al. (2025), Case 8 outlines a medical device wholesaler that experienced substantial automation challenges due to the physical profile of its inventory. The organization's warehouse manages a complex mix of bulky medical equipment alongside small, irregularly shaped consumables, such as catheters. Because the firm operates without localized digital master data for these product specifications, establishing standardized automated workflows, required for implementing AMRs, has proven highly difficult.

When integrated into collaborative picking systems, pairing human workers with AMRs helps logistics managers overcome the technical barriers presented by high product variability, diverse packaging shapes, and strict regulatory compliance mandates (Kwak et al., 2025). To address the operational boundaries imposed by high product variability, Kwak et al. (2025) highlight Human-Robot Collaboration (HRC) as a scalable, hybrid alternative to full automation. Within an HRC framework, autonomous mobile platforms or smart trolleys manage physical navigation and long-distance transport tasks. This division of labor allows human operators to focus their efforts entirely on high-value picking and essential quality validation tasks (Kwak et al., 2025).

Overall, goods-to-Person (GTP) systems affect the operational performances by delivering items directly to a stationary operator at a picking workstation, which eliminates operator travel time and can reduce overall picking times by approximately 50% compared to manual workflows in healthcare logistics settings (Kwak et al., 2025). In another place the authors emphasize again that the integration of GTP systems further optimizes fulfillment performance by routing items directly to fixed workstations. This automated delivery mechanism eliminates extensive operator transit time, which significantly improves picking productivity, enhances workstation ergonomics, and decreases the cumulative physical workload of the warehouse workforce.



Figure 3.4: Autonomous mobile drive unit robot executing transport tasks in a fulfillment warehouse (Geni, 2023)

3.2.5 Vertical lift modules (VLMs)

VLMs represent an established category of automated parts-to-picker warehousing technology. According to Azadeh et al. (2019), a VLM consists of two columns of internal storage trays separated by a central, lift-mounted inserter and extractor mechanism. When an item is requested, the automated mechanism retrieves the specific tray holding the required inventory and delivers it directly to the operator stationed at the front of the unit (Azadeh et al., 2019). This localized setup eliminates manual walking paths, enabling pickers to remain stationary and perform secondary tasks, such as product labeling or sorting, while waiting for the next tray cycle to complete.

Johansson and Persson (2023) synthesized literature showing that VLMs operate as parts-to-picker automated systems designed for the high-density storage and retrieval of small items. These configurations are increasingly adopted by industrial operators to handle rising productivity demands and achieve significant floor space savings. A VLM is built around three primary internal columns; the front and rear columns feature specialized brackets to support storage trays and totes, while the vertical center column houses an insertion and extraction mechanism that moves vertically to deliver requested materials directly to the operator (Johansson & Persson, 2023).

VLMs require vertical ceiling space, typically between 3.5 and 15 meters, with some heavy-duty models reaching up to 30 meters. The system must be placed on a standard industrial concrete floor capable of supporting the high concentrated load of the steel tower, typically requiring a load capacity of 2,500–4,500 kg/m² (Modula Asia, 2025). The VLM control software must be integrated with the WMS to track bin locations and manage real-time inventory adjustments as trays are presented (Marolt et al., 2025).

According to Kwak et al. (2025), VLMs are highly recommended for specialized wholesalers and importers operating with large SKU portfolios and low transaction frequencies. Within these high-complexity environments, vertical lift infrastructure serves as an effective mechanism for warehouse storage optimization when paired with an integrated WMS (Kwak et al., 2025).

However, empirical field evidence highlights that the physical profile of the inventory can introduce significant operational barriers. As Kwak et al. (2025) observe in Case 8, a medical device wholesaler evaluated a vertical lift system for a client's high-frequency products, yet encountered substantial hurdles when handling small, irregularly shaped consumables such as catheters. The researchers emphasize that automating the storage and retrieval of these specialized medical items remains deeply problematic because the sector often lacks standardized digital product master data (Kwak et al., 2025). Digitizing precise product specifications is a fundamental prerequisite before vertical lift systems can be successfully deployed to handle irregular medical consumables.



Figure 3.5: Automated vertical lift module (VLM) warehouse system utilizing internal tray retrieval mechanisms (WindyPrints, 2010)

3.2.6 Carousel-based automated storage and retrieval systems

Carousel systems represent a mature category of automated storage and retrieval technologies used to improve internal material flows. As defined by Azadeh et al. (2019), carousels consist of interconnected storage shelves that rotate in either a horizontal or vertical closed loop. This mechanism brings inventory directly to an operator located at a stationary picking workstation, eliminating manual travel time across the warehouse floor (Azadeh et al., 2019). These systems are highly effective for storing small to medium-sized stock profiles, such as retail goods, books, or medical items (Litvak & Vlasiou, 2010, as cited in Azadeh et al., 2019).

To improve throughput performance in these configurations, logistics managers often implement batch picking strategies. Research highlighted by Azadeh et al. (2019) demonstrates that consolidating orders into batch retrievals can reduce overall carousel cycle times by 20% compared to traditional sequential order processing (Azadeh et al., 2019). Within this parts-to-picker context, Johansson and Persson (2023) noted that a single warehouse employee frequently operates multiple carousel units simultaneously. Drawing on industrial field data, they explained that this multi-unit assignment effectively reduces or eliminates operator idle time, leading to superior picking productivity. From a facility layout perspective, vertical variations of these automated systems optimize space utilization by exploiting unused overhead air space, minimizing the physical floor footprint required for small and midsize inventory items.

Despite the productivity advantages, carousel systems introduce specific operational tradeoffs. Because the physical loads are in continuous movement during rotation cycles, carousels present a more hazardous working environment for order pickers than conventional static storage setups (Johansson & Persson, 2023). Consequently, material handling processes must be managed carefully to support industrial ergonomics and occupational safety standards. Finally, the authors emphasized that like other parts-to-picker automated configurations,

carousel systems require high initial investment capital and can introduce long-term reconfiguration difficulties if corporate operational needs and material flow requirements change.



Figure 3.6: Automated horizontal carousel storage system rotating vertical shelving carriers along a track matrix (Ingenieria-logistica, 2016)

3.2.7 A-frame automated dispensing systems

A-frame automated dispensing systems represent specialized order-picking technology designed to process large orders composed of small-sized items. As explained by Azadeh et al. (2019), this architecture consists of vertical product channels arranged in an "A" shape configuration that forms a tunnel over a central collection belt. Orders are fulfilled automatically when items drop into designated virtual windows on the moving conveyor (Azadeh et al., 2019). Although the dispensing process is completely automated, material replenishment is performed manually and can be finished without stopping active picking operations. Because of their high-volume sorting capabilities, these systems are primarily deployed within the pharmaceutical, cosmetic, and mail-order industries (Azadeh et al., 2019).

To maximize the operational efficiency of an A-frame layout, logistics managers use mathematical models to resolve complex SKU assignment and order retrieval sequencing problems (Azadeh et al., 2019). Furthermore, Kim et al. (2016, as cited in Azadeh et al., 2019) state that the choice of conveyor management strategies significantly changes system performance. An ejecting zone (EZ) represents a specific segment of the conveyor belt allocated to an individual order. Using simulation models, Kim et al. (2016) evaluated three distinct ejecting zone strategies: unequal, equal, and combined methods. Their research demonstrates that selecting the correct ejecting zone method is essential to balance order throughput times and total system energy usage (Azadeh et al., 2019).

Within healthcare distribution networks, large-scale pharmaceutical wholesalers frequently implement advanced automation infrastructure to improve operational efficiency, fulfillment accuracy, and network scalability (Kwak et al., 2025). As illustrated by the empirical findings

in Case 7, a prominent pharmaceutical wholesaler managing an extensive logistics terminal network in South Korea successfully automated its outbound operations. To streamline its downstream distribution, the organization deployed a high-speed automated sorting system referred to as an "a frame system". In this specific operational configuration, high-speed sorting machinery automatically categorizes completed shipping parcels according to their physical dimensions, ultimate destination, and shipment priority (Kwak et al., 2025). Integrating this automated sorting system into their fulfillment workflow allowed the company to significantly decrease manual handling labor and reduce parcel processing lead times across their distribution hub (Kwak et al., 2025).

3.2.8 Pallet shuttle systems

As observed by Kwak et al. (2025), the structural composition of inventory heavily dictates the selection of automation equipment within the pharmaceutical supply chain. Wholesalers typically manage massive bulk quantities of a concentrated range of high-turnover commodities on behalf of multiple client accounts (Kwak et al., 2025). This specific commercial profile results in relatively low SKU complexity per customer, but demands exceptionally large overall storage capacities and high throughput performance. Consequently, wholesale logistics strategies prioritize maximizing cubic space utilization within the facility and accelerating bulk replenishment cycles (Kwak et al., 2025).

According to Kwak et al. (2025), pallet shuttle infrastructure operates as a semi-automated, high-density storage configuration that utilizes autonomous, radio-guided platforms to transport unit loads along specialized racking channels. This layout proves exceptionally advantageous for deepplane warehousing strategies and successfully accommodates the harsh operational conditions typical of temperature controlled or refrigerated cold chain facilities (Kwak et al., 2025).

Because the self-propelled shuttle executes internal lane transfers independently, it removes the operational requirement for traditional material handling equipment, such as forklifts, to enter the dense storage aisles. Consequently, this restricted access prevents material handling machinery from colliding with the storage infrastructure, which effectively safeguards structural rack integrity. By eliminating these equipment collisions, this operational layout significantly reduces cumulative warehouse maintenance costs and lowers facility maintenance risks inside low-temperature or refrigerated cold chain footprints (Kwak et al., 2025).



Figure 3.7: High-density deep-lane storage racking infrastructure optimized for autonomous radio-controlled pallet shuttle platforms (SSTC-storage, 2026)

4. Empirical Findings

This chapter presents the empirical findings gathered from the logistics operations at the Sisjön Distribution Center. The presented data combines qualitative insights collected through direct site observations and semi-structured interviews with quantitative datasets extracted from a one-year warehouse transaction history and provided master data. These findings establish the operational baseline required to analyze performance gaps and evaluate potential manual- and automated-based improvements for the planned facility relocation.

4.1 Context and design

This section describes the physical layout, operational parameters, and material flow characteristics of VGR's Sisjön Distribution Centre. It provides the empirical baseline for understanding current performance, including facility constraints, item and demand profiles, and a detailed Material Flow Mapping (MFM) of the four main logistics flows.

4.1.1 An overview of the warehouse

The current warehouse facility encompasses a total physical storage volume of approximately 7,000 m³. Material storage and operational handling activities are divided across distinct functional zones, supported by a dock infrastructure consisting of seven gates: two dedicated to inbound receiving, four to outbound shipping, and one designated for waste management. Table 4.1 provides a breakdown of the volumetric space allocation and the distribution of SKUs across the handling, storage, and support zones.

The facility operates on a single-shift timeline where daily working hours exhibit variability, regularly from 8 to 10 hours, and occasionally extending to 12 hours during peak demand periods. Employee break intervals, such as lunch and breaks, are structurally managed within dedicated intervals to ensure continuous warehouse operations.

To control floor traffic and mitigate safety risks associated with moving material handling vehicles, warehouse management enforces a strict staffing ceiling of 29 operators on the shop floor simultaneously. This constraint limits the maximum manual throughput capacity of the current process design to an absolute ceiling of approximately 9,400 order lines per day.

Internal logistics movements, put-away routines, and order fulfillment tasks are executed using a varied fleet of industrial trucks and manual handling equipment. Table 4.2 categorizes the standard equipment types deployed on the warehouse floor.

The physical parameters presented here, including the volumetric space, gate setup, single-shift schedule, and the strict safety ceiling of 29 operators on the shop floor, establish the absolute operational limits of the current manual setup. This structural baseline is directly used in the Gap Analysis to prove that the current manual design cannot process more than 9,425 daily order lines during standard hours. Consequently, these metrics provide the mathematical justification for why the facility is forced into frequent overtime and why

Table 4.1: Functional space allocation and SKU distribution

Category	Warehouse Zone	Number of SKUs Stored	Approx. Space (m ³)
Operational Handling	Goods In / Receiving	-	500
	Goods Out / Shipping	-	500
	Consolidation	-	90
	Empty Pallet Handling	-	100
	Cart/Trolley Staging	-	30
Subtotal: Handling		-	1,220
Storage & Picking	Pallet Racking	1,000	3,170
	Picking Shelves (forward)	3,500	1,600
	Reserve Shelves	3,600	
	Sterile	2,000	400
	Vertical Lift Modules (VLM)	600	10
	Deep Stacking / Bulk Storage	15	200
	Dangerous Goods	70	100
	Cold Storage	50	55
	Order Specific / Transit	500	64
	Sterile Air-lock	-	40
	Clean Room	-	10
Subtotal: Storage		11,335	5,649
Logistics & Support	Workshop	-	100
	Returns / Claims	-	50
	Pallet Storage/ Packaging	-	20
	Forklift Charging Station	-	12
Subtotal: Support		-	182
GRAND TOTALS		11,335 *	7051
Dock Infrastructure	7 Gates (2 IN, 4 OUT, and 1 for Waste)		

**Note: While the formal master data lists approximately 11,335 SKUs, the analysis of the one-year transactional dataset reveals more than 14,000 unique active item numbers operating within the system.*

modular physical automation must be evaluated for the relocation project to absorb future demand peaks.

Table 4.2: Material handling equipment deployed

Equipment Type	Industry Term (Swedish)
Reach Truck	Skjutstativtruck
Roll Container	Rullvagn
Walkie Stacker	Ledstaplare
Pallet Truck	Ledtruck
Roll Cage Picker	Burplocktruck

4.1.2 Items, demand and supply characteristics

The physical properties and demand behavior of items managed at the Sisjön Distribution Centre represent the primary baseline for evaluating warehouse improvements and physical automation technologies.

The primary physical attribute recorded in the database is item volume, measured in cubic decimeters. However, this metric lacks precision because the system limits the number of decimal places when recording volume, rounding errors frequently occur. This lack of precision affects both micro-sized medical items. Furthermore, linear dimensions (length, width, and height) and unit weights are completely absent from the system and around 50% of the active articles in the one-year transactional data have a recorded volume specification. The distribution of these items shows a heavy concentration of small-sized items, with 84% of the catalog categorized as micro or small.

The specific volume ranges are justified by both the physical storage and handling capabilities defined according to Richards (2014):

- **Under 0.1 dm³ (Micro):** This range requires high-density storage solutions, such as bin drawers or highly segmented decking, to maximize cubic space and maintain product security (Richards, 2014).
- **0.1 to 5 dm³ (Small):** This bracket represents individual items or inner packs. As Richards (2014) explains, items of this size are optimal for traditional static bin shelving, vertical carousels, or high-speed automated channels like A-frames.
- **5 to 25 dm³ (Medium):** This category captures medium-sized products or split-cases that fit within standard warehouse bins or gravity-fed carton flow live storage racks.
- **25 to 75 dm³ (Large):** This range targets full shipping cartons and large full-case items. Operationally, this threshold closely aligns with the maximum volumetric capacities of standard automated warehouse donor totes, which Richards (2014) defines as measuring 600x400x250 mm (equivalent to exactly 60 dm³).
- **Over 75 dm³ (Bulky):** This category includes heavy or oversized items that exceed container boundaries. These items require mechanized handling via forklift trucks for storage in wide adjustable pallet racking or direct floor bulk storage.

Table 4.3: Distribution of items volume

Volume Category	Volume Range (dm3)	Number of Items	Percentage of Total (%)
Micro	Under 0.1	1,973	27%
Small	0.1 - 5	4,151	57%
Medium	5 - 25	710	10%
Large	25 - 75	300	5%
Bulky	Over 75	62	1%
Total		7,196	100%

While this physical classification creates an unequal numerical split across the product lines, it is operationally valuable.

In addition, some of the stored goods exhibit high packaging complexity, featuring multiple nested layers including individual units, inner packs, and outer supplier cartons. This nested hierarchy causes a unit of measure divergence, where the digital sales unit does not correspond directly to the physical picking unit. Operators are confused about whether a single ordered article represents an individual piece or an entire inner box.

To prevent errors, operators have placed manual, handwritten notes on the shelves to clarify picking quantities. Furthermore, some suppliers deliver mixed cartons containing multiple SKUs that are visually similar, requiring intensive manual sorting and visual inspections during goods receiving before the items can be registered.

There are sterile items in the warehouse that should meet environmental and hygiene requirements. Approximately 2,000 SKUs are sterile items. Sterile items in the picking shelves must be isolated in a dedicated, hygiene-controlled zone (sterile zone) that is currently on an upper floor of the warehouse. The sterile items in bulk are stored in the main zone on the reserve shelves and will be moved to the sterile zone after refill order release. These sterile items experience faster turnover, remaining in the warehouse for an average of two to three weeks, compared to an average of one month for non-sterile items.

The warehouse also manages 70 SKUs of dangerous goods and 50 SKUs requiring temperature-controlled cold storage, both of which impose rigid constraints on physical placement. Additionally, many items, such as needles and catheters of different sizes, are

packaged in nearly identical boxes, which increases picking error risks.

To analyze demand predictability, a coefficient of variation of demand is calculated for each SKU:

Table 4.4: XYZ Demand Variability Classification of Inventory Items

Demand Category	Variability Level	Percentage of Total (%)
X Items	Highly Stable Demand	64.56%
Y Items	Moderate Fluctuation	31.58%
Z Items	Highly Irregular Demand	3.86%

A standard ABC turnover analysis based on a one-year transactional history demonstrates a highly concentrated workload distribution, where a small fraction of the items generates the vast majority of the daily picking activity:

Table 4.5: ABC Classification of Items by Picking frequency

Category	Picking Velocity	Percentage of SKUs	Movement Contribution
Category A	Fast Movers	8.36%	80%
Category B	Medium Movers	20.40%	15%
Category C	Slow Movers	71.24%	5%

Master data inaccuracies are increased by a lack of coordination regarding item substitutions and packaging adjustments by suppliers. When an item is out of stock and a substitute item is introduced, it may feature different physical dimensions and transport pack sizes. However, the WMS voice-picking infrastructure is rarely updated to reflect the substitute's modified unit quantities. For instance, if an item shifts from a 5-pack to a 10-pack configuration, the voice instruction continues to demand the historical count, causing frequent quantity mispicks.

To mitigate these system update failures, warehouse staff place handwritten paper warning notes directly on the storage racks. As it is observed in-site and validated in the interviews, this practice has created visual load on pickers. Additionally, the regional purchasing portal does not clearly display standard box quantities to customers. This lack of transparency

causes clinical units to order irregular quantities (e.g., ordering 11 loose units instead of a full carton of 12), forcing warehouse operators to execute slow piece-picking tasks instead of rapid full-case handling.

In addition, to identify specific co-picking relationships on the shop floor, the transactional data was analyzed using the Association Rule Mining (ARM) which is explained in section 2.3.2. Quantitative assessment. The model was configured with a minimum support of 0.01 and a minimum confidence of 0.10, meaning an item pair must appear together in at least 1% of total warehouse orders to be considered.

To identify co-picking patterns for slotting optimization, table 4.6 presents a focused selection of the item pairs with the highest Lift numbers. We present only the top-ranked pairs to prioritize the strongest product relationships with highest potential efficiency gains. To interpret the table, a Lift number of 24 means those two specific items are 24 times more likely to be ordered together than by random chance.

The distribution center manages inbound material flows from approximately 450 distinct healthcare suppliers. Due to low order volumes driven strictly by localized consumption requirements, VGR is frequently forced to order mixed cartons from these nodes. While these low volumes cannot easily be increased, management has an opportunity to re-evaluate order parameters within the upstream and downstream supply chain. This can be achieved by

Table 4.6 :Item Pairs with Co-Picking Relationships

Item Pair	Lift Number	Item Pair	Lift Number
103909693 & 103909701	24	110193919 & 110193935	16
104580022 & 104558069	23	113884019 & 113884001	16
104580022 & 104554217	21	200010267 & 200010268	13
110193901 & 110193935	19	200010268 & 200010266	13
104558069 & 104554217	18	113615348 & 113615389	12

measuring the total operational handling costs associated with mixed cartons while incorporating future demand growth models. It is noted that certain suppliers or their third-party logistics (3PL) providers consolidate materials efficiently, delivering mixed cartons with high fill rates and stable delivery performance.

However, significant information asymmetry exists between VGR and its supply base regarding consignment data integration. Items are not fully identified during the goods reception registration stage. For example, the current warehouse management system (WMS)

cannot automatically verify whether an arrived item is sterile until operators individually handle the packages. This issue is exacerbated because the technical definition of sterility differs between the VGR perspective and that of its external suppliers. Consequently, floor operators do not rely on supplier package information during inbound sorting.

SKUs are stored in specific shelf locations based on their production batch numbers. This physical organization is necessary because individual product batches have unique expiry dates, and VGR operates under a strict First Expiry, First Out (FEFO) inventory management policy. To support this policy, each unique shelf address is filled only with items sharing the same batch number and expiration timeline. This design prevents operators from accidentally picking items with longer expiry dates before shorter ones, which would cause product waste. It also removes the need for pickers to spend time searching through a mixed shelf.

At VGR, this method results in a fixed number of storage locations for a specific SKU that function as identical item buffers with different expiry dates, a concept locally known as floating storage locations. Although product demand remains highly stable, this configuration introduces three major operational challenges:

- **Slotting complexity:** Floating locations make slotting optimization highly complex because a unique SKU is distributed across multiple picking addresses simultaneously.
- **Sacrificed space utilization:** Cube and shelf space utilization is reduced because a location cannot be replenished or merged until the current batch is entirely depleted.
- **System discrepancies:** Replenishing multiple batches for a single SKU requires frequent labor interventions. Due to internal capacity and resource constraints, these replenishment tasks are sometimes omitted. This creates a discrepancy where an item is physically present in the warehouse reserve zone, but the WMS directs a picker to an empty forward picking location.

Cataloging the physical properties, demand variability (XYZ), velocity classes (ABC), and co-picking relationships reveals the core complexity of VGR's inventory. This data serves two critical functions in the next chapters:

- **Improvements in manual operations:** The missing dimensional data, high-lift product pairs, and floating location challenges provide the direct foundation for proposing Inbound Measurement Gates, Velocity-Based Slotting, and Item Association-Based Slotting.
- **Automation selection:** These item dimensions and stability rates serve as the non-negotiable criteria for the Binary Qualifying Stage, allowing us to immediately disqualify systems that cannot handle fragile, sterile, or small-sized medical consumables.

4.1.3 Material Flow Mapping (MFM)

The current warehouse operations were mapped using Materials Flow Mapping (MFM) as defined by Finnsgård et al. (2011). The scope was from goods receipt to the loading of transport cages, covering all internal handling, transport, administrative and storage activities. Four distinct flows were identified through observations, interviews and transaction data. The flows are designated as **Picking Shelf, Sterile Refill, Sterile and Bulk**.

Every activity in each flow was classified according to the HATS framework: Handling (physical rearrangement of goods), Administration (information processing and confirmation), Transport (movement between locations) and Storage (any waiting point). To provide a visual overview of the material flow structure, each flow has:

- A map with the main geographic stages through which the item passes in the flow. In each location (node), the number of each activity that has been done in that location (H, A, T and S), total number of activities (Sum), and total duration time of all activities in the location (Time: HH:mm:ss) are presented.
- Between each two successive nodes, transport time (HH:mm:ss) is presented on the arrows that show the direction of the flow.
- For locations where a resource is required specifically only to perform an activity in that node, a support (secondary) flow is presented (in blue color) with an arrow that shows the transport time (HH:mm:ss).
- And finally a table to summarise the number of activities and the total recorded time (HH:mm:ss) per category for each flow.

Picking Shelf Flow

This flow handles fast-moving items that are cross-docked directly to a forward pick shelf. At goods receipt, pallets are unloaded by the external driver, who places them with a paper delivery note on the floor and departs. A warehouse operator visually identifies the delivery and attaches a weekday tag on the pallets. Pallets then queue for registration. When space is tight, the operator may relocate pallets to a temporary buffer based on visual judgment.

In this case, the operator unpacks mixed cartons containing items that are often visually similar, checks the order number on a device, and checks the paper receipt against the system. Multiple controls and extra walking may be required because of item variety and packaging similarity. Items are then sorted into trolleys in their designated sections, each section bearing a barcode, the operator scans the section barcode to confirm the sort. Once a trolley is complete, its number is scanned and it waits, sometimes for extended periods to be moved.

A second operator activates a voice-picking device, confirms the trolley transport, and begins a replenishment route. Items are placed on the pick (forward) shelf following FIFO (first-in-first-out) logic, and each replenishment is confirmed by voice. At this point, the item is added to the available inventory. Goods reside on the picking shelf for approximately one month on average before being picked.

Customer orders are received and dispatched in fixed time windows, for instance, a Monday morning delivery requires the order to be placed by the preceding day. Order release priorities are based on order placement time, delivery route, and emergency status. Once an order is released, a picker confirms it and begins picking. A full order is picked by a single operator (except when sterile items are involved, as described later). The picker hears locations via the voice device, visually searches for the item, picks, and confirms by voice. After the last line of the order is picked, the items are transported to the labelling area, where labels are printed and attached. From labelling, the operator moves to the consolidation area, selects a numbered location for a transport cage, and transfers all order lines into that cage.

The cage waits for transport to the loading area. Another operator walks the cage the short distance to the loading area, scanning each package to create a shipment ID. The cage then queues for the external driver, who scans the cage receipt, checks the packages against a device list, and loads the truck for delivery.

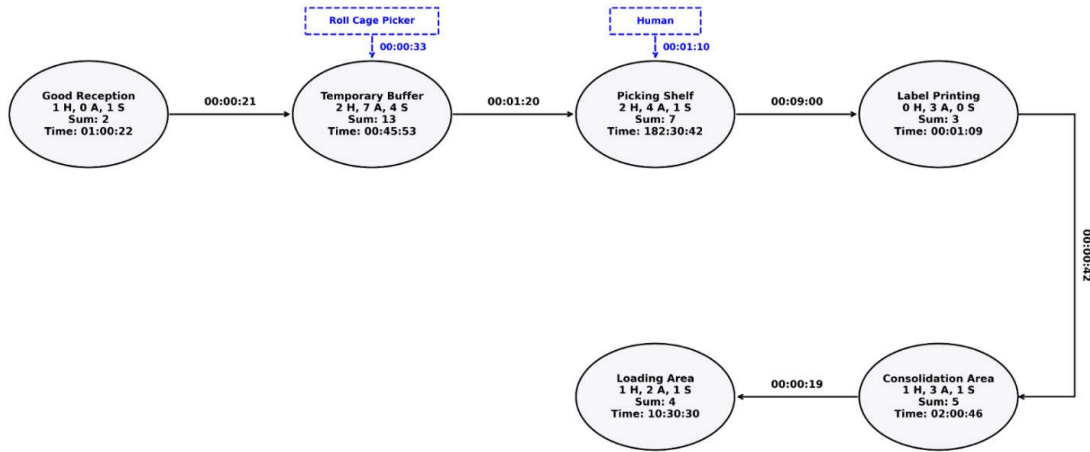


Figure 4.1: Material flow map of the Picking Shelf flow

Table 4.7: HATS Activity distribution for Picking Shelf flow

Activity Category	Count	Total Time
Handling (H)	7	00:32:24
Administration (A)	19	02:38:41
Transport (T)	7	00:13:25
Storage (S)	8	193:38:17
SUM	41	197:02:47

Sterile Refill Flow

Items in this flow arrive as full pallets (bulk) and are registered in goods reception without sorting. Forklifts transport pallets to a reserve shelf. A refill order list is released by the system and confirmed by an operator, who picks the pallet and moves it to the sterile reception area. There the pallet waits to be registered and sorted into trolleys, mirroring the goods-receipt sorting process of the Picking Shelf flow.

The trolley is then transferred to the sterile zone via an elevator (the sterile zone is on an upper floor). An operator working exclusively in the sterile zone, following its hygiene rules, replenishes the forward shelves using voice guidance and visual search, confirming each placement. Items wait in this zone for 2–3 weeks on average.

When a mixed order containing sterile items is released, pick-start priority is given to the sterile part. The sterile-zone picker first prepares an empty carton, then walks through the zone with a picking trolley, picks and confirms by voice, and after the last pick walks back to the start/end point. Labels are printed with a three-digit number in large font. The picker attaches them to all packages and places the packages on a conveyor that transfers them to the main floor. The conveyor discharges onto a large shared picking shelf in the main zone which has a unique shelf location number registered in the warehouse and system.

Once the last sterile order line is confirmed, the remaining order lines in the main zone are released automatically. This staggered release allows the main-zone picker additional time to start picking while the sterile package is in transit or waiting. The main-zone picker visually identifies the packages by the three-digit label, picks them together with the rest of the order, and proceeds to labeling and consolidation. Thereafter, the process is identical to the Picking Shelf flow.

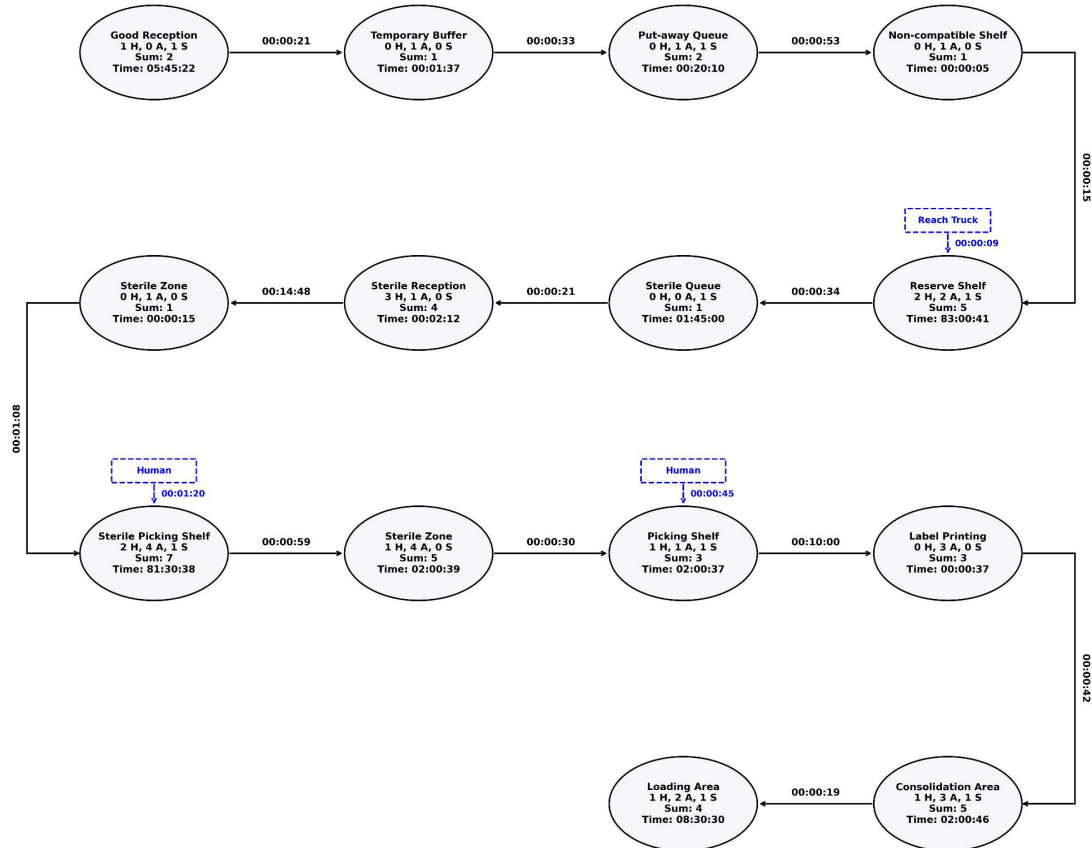


Figure 4.2: Material flow map of the Sterile Refill Flow

Table 4.8: HATS activity distribution for Sterile Refill Flow

Activity Category	Count	Total Time
Handling (H)	12	00:34:30
Administration (A)	24	06:34:39
Transport (T)	16	00:33:37
Storage (S)	8	179:50:00
SUM	60	187:32:46

Sterile Flow

This flow represents sterile items that bypass reserve storage and move directly from goods reception to the sterile zone. They are registered as in the Picking Shelf flow (not in bulk), then transported to a waiting area before sterile reception. From there, the process follows the same steps as the Sterile Refill flow: registration, trolley transport via elevator, replenishment, pick-and-pack in the sterile zone, conveyor transfer to the shared shelf, merging with the main-zone order, and subsequent consolidation and shipping.

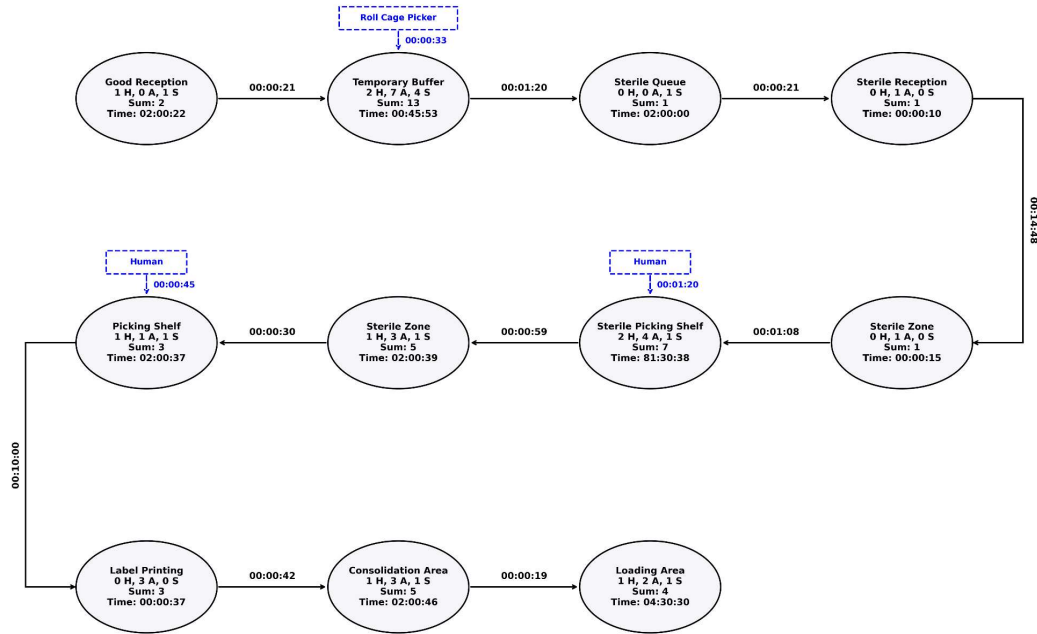


Figure 4.3: Material flow map of the Sterile Flow

Table 4.9: HATS activity distribution for Sterile Flow

Activity Category	Count	Total Time
Handling (H)	9	00:32:45
Administration (A)	25	01:39:25
Transport (T)	13	00:33:06
Storage (S)	11	94:38:17
SUM	58	97:23:33

Bulk Flow

Bulk items arrive on pallets and are registered as in the Picking Shelf flow. They are transferred to the put-away queue, where a reach truck driver scans the receipt. The truck's monitor recommends a system-generated put-away location. However, the process deviates from the intended logic in several important ways, as revealed in interviews:

- Some forklifts lack a monitor, forcing the driver to place pallets in a random location.
- The system holds no dimensional data for pallets, nor does it account for physical infrastructure constraints (e.g., pipes, equipment) that reduce the usable height of some reserve shelves. Consequently, the recommended location may not accommodate the pallet.
- When the pallet does not fit, the driver either requests a new suggestion or, more commonly, places the pallet in an arbitrary compatible location and scans its barcode.

Once the refill order is released, the pallet is moved to a forward picking shelf either in the main zone or the sterile zone, the subsequent steps follow the Shelf Picking or Sterile Refill flow depending on the item's sterility.

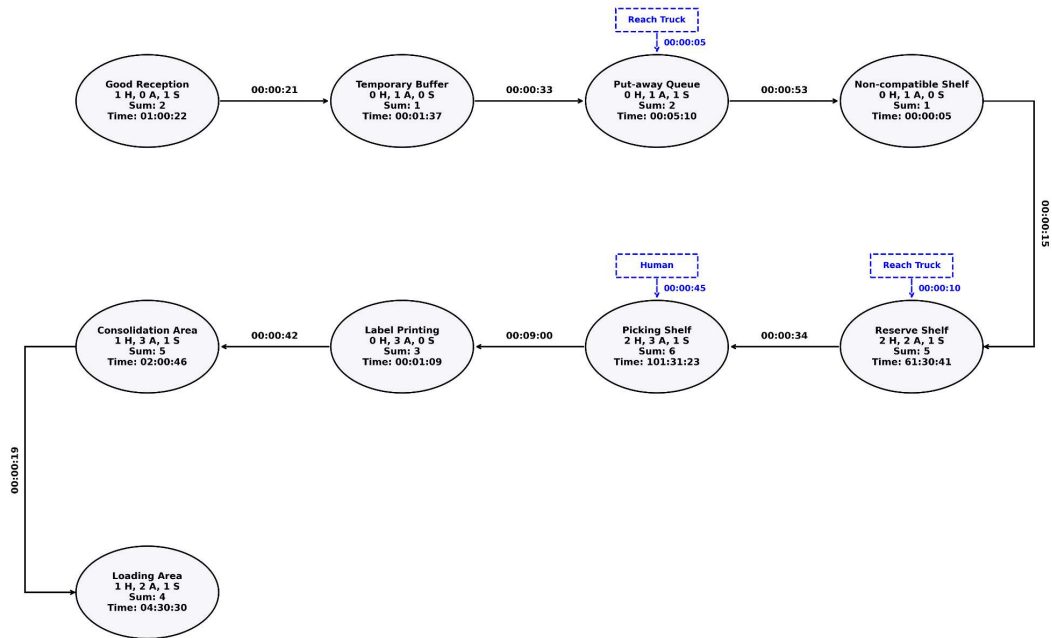


Figure 4.4: Material flow map of the Bulk flow

Table 4.10: HATS activity distribution for the Bulk Flow

Activity Category	Count	Total Time
Handling (H)	7	00:32:50
Administration (A)	16	03:03:53
Transport (T)	11	00:13:37
Storage (S)	6	167:05:00
SUM	40	170:55:20

Summary of MFM results

Table 4.11 provides a comprehensive quantitative summary of the total activity counts and recorded durations for the HATS categories across all four analyzed material flows. Complementing this data, the combined material flow map (see Figure 4.5) provides a visual overview of how these four flows move through the facility layout. By mapping the paths together using distinct colors, the diagram clearly illustrates where different flows share a common route, where they diverge, and which specific locations certain item types bypass. Presenting these summary tools together offers several key benefits for the:

- **Direct comparison:** It allows for an immediate comparison of the operational workloads and time distributions across different warehouse paths.
- **Bottleneck identification:** It highlights major operational bottlenecks, particularly by exposing sections where non-value-adding activities, such as high administrative times, consume a large share of working hours.
- **Improvement prioritization:** It helps quickly identify which material flows contain the highest amounts of waste, establishing clear priorities for where process adjustments are needed most.

This combined dataset serves as an analytical bridge to the upcoming chapters. The time motion tracking and quantified counts within the HATS framework establish the empirical baseline used to diagnose specific operational inefficiencies, removing guesswork regarding where workflows are breaking down. By exposing that administrative activities consume the largest share of working hours across all four material flows, this data directly justifies the improvements in manual processes proposed in this study.

In the performance gap assessment, these precise measurements are utilized to calculate the exact labor hours and order-line capacity that can be recovered by eliminating redundant steps and wastes. This analysis also helps to prioritize the specific improvements that have the greatest impact on key performance metrics. Ultimately, this comprehensive insight provides a holistic view of the manual operations and processes, allowing decision-makers to determine the appropriate scale and scope for physical automation technology implementation.

Table 4.11: HATS activity summary of the four flows

Flow	Activity category								Total No. of Act.	Total Time (working hours)
	Handling		Administration		Transport		Storage			
	Count	Duration	Count	Duration	Count	Duration	Count	Duration		
Shelf Picking	7	0:32:24	19	2:38:41	7	0:13:25	8	193:38:17	41	197:02:47
Sterile	9	0:32:45	25	1:39:25	13	0:33:06	11	94:38:17	58	97:23:33
Sterile Refill	12	0:34:30	24	6:34:39	16	0:33:37	8	179:50:00	60	187:32:46
Bulk	7	0:32:50	16	3:03:53	11	0:13:37	6	167:05:00	40	170:55:20
Total	35	2:12:29	84	13:56:38	47	1:33:45	33	635:11:34		



Figure 4.5: Combined material flow map of the four flows

4.2 Order picking at VGR

Order picking at the Sisjön Distribution Centre is a manual, picker-to-parts operation directed by a voice-picking system integrated in real time with the Warehouse Management System (WMS). Picking tasks are system-driven, meaning the WMS allocates work to operators, who can work across the main picking area or the sterile zone. However, the actual mode of picking shifts depending on order composition, which leads to a blend discrete order picking with a form of sequential zone picking when sterile items are involved.

Picking execution

For orders consisting entirely of non-sterile items, discrete order picking is used: one operator picks all order lines in a single, continuous route. The operator does not batch or consolidate multiple orders; one order is completed before the next is started. The picture changes when an order contains sterile items. Because sterile goods must be processed in a separate, hygiene-controlled zone on the upper floor, a sequential zone logic is applied. The sterile-zone picker handles all sterile lines first. Only after the last sterile pick is confirmed by voice does the system release the remaining non-sterile lines to a picker in the main zone. This staggered release is functionally a form of sequential zone picking, where the handover between zones is mediated by a conveyor and a shared shelf location in the main picking area. The sterile zone itself achieves higher productivity than the main zone, a fact attributed to shorter internal travel distances, smaller shelf sizes, smaller number of SKUs compared to the main picking area.

While picking is system-directed, several activities, notably goods reception handling and sterile reception processing, are assigned manually. This split between automated task allocation for core picking and manual assignment for support tasks creates a dependency on human coordination at the boundaries of the system, a potential source of delay and inconsistency. The workforce operates on a single-shift pattern. Overtime accounts for around 16 % of total working hours, indicating that the current staffing level cannot absorb the required throughput within standard hours.

Orders are not continuously released. A fixed-window logic governs both order acceptance and dispatch: a hospital requiring Monday delivery must place its order by the preceding Tuesday. The release sequence is then prioritised according to order receipt time, delivery address and route, and any emergency status. The presence of emergency orders significantly affects load consolidation. Out of 12,284 transport routes recorded in one year, 1,489, around 12%, carried only a single order number. While some of these single order routes may represent genuine emergencies.

The voice system announces the next storage location, and the picker walks to the indicated shelf. At the point of picking, no shelf barcode scan is performed in any flow, the picker visually locates the item, picks it, and confirms the action by voice. The only scan-based location verification occurs during replenishment in the Bulk flow, where the operator scans the picking shelf barcode before placing items onto the forward shelf. In the Shelf Picking, Sterile, and Sterile Refill flows, voice confirmation alone serves as the control point, with no automated verification that the correct shelf has been reached before an item is retrieved. This means that, for the majority of picking activity, the system relies entirely on the picker

following the voice instruction and confirming afterward. Even where the scan does occur, both that scan and the subsequent voice confirmation remain dependent on human execution, a picker could scan the right shelf and still place the wrong item if items are visually similar.

In the sterile zone, picking tours are shaped by the fixed position of the exit conveyor, which is located in the middle of the picking aisles. Regardless of where the tour begins, it must end at this conveyor, where the picker prints labels, attaches them to the packages, and sends the goods down to the main floor. This means that the pick path in the sterile zone is not a pure return route, but rather a traversal route that terminates at a fixed infrastructure point. The design eliminates the need for the picker to walk back to a distant start point, contributing to the zone's higher productivity.

Packaging and shipping preparation processes are highly fragmented due to a total lack of container-level traceability. The warehouse does not have standardized picking totes or barcoded plastic bins. Instead, operators must find, choose and handle cardboard boxes of different dimensions to collect picked orders. This introduces major time waste, as operators frequently pack items only to realize the carton is not transport-safe, forcing them to unpack and repeat the sequence with alternative boxes.

Furthermore, scanning actions during fulfillment only register the overall transport cage ID, rather than linking specific SKUs to individual boxes. If a clinical unit reports missing items, the WMS cannot mathematically verify whether the items were packed or not. Because there is no internal trace data to check, VGR ships them out a second time at a loss. This operational blindspot indicates that the official outbound picking accuracy rate (99.65%) only represents visible customer complaints. Management acknowledges a substantial unrecorded error rate, specifically regarding over-deliveries where extra products are sent accidentally but never reported back by the receiving medical facilities.

Currently, the distribution center handles internal traffic flows effectively, and no critical floor congestion is observed around the consolidation area (depot). This lack of congestion is directly related to the current single-order picking method. Under this operational policy, warehouse pickers collect items for only one customer order at a time. The transaction data shows that customer orders at VGR have an average of 16 order lines and a median of 6 order lines. This structure helps distribute picking activities across different storage aisles over time, which prevents heavy traffic from gathering at the consolidation zone.

However, introducing slotting optimization methods could create new layout challenges. Because operators drive trolleys to pick, optimizing the product locations based on demand velocity would likely concentrate picking tasks. This concentration is expected to create congested areas around the consolidation area. To address this risk, the feasibility of combining slotting optimization with alternative picking methods was discussed with VGR management team. They stated that it is possible to implement both batch picking and slotting optimization together. Combining these two methods could improve picking efficiency while managing potential traffic bottlenecks around the depot.

The facility has previously explored changes to its picking methods. VGR conducted a trial to test batch picking on the shop floor, but the project was ultimately unsuccessful. The field findings indicate that this failure was not caused by physical congestion or layout constraints. Instead, the trial failed due to system limitations, as the existing warehouse management

software and voice-picking system could not support batch picking processes. Consequently, implementing a combined batch picking and optimized slotting strategy will require updates to the warehouse system capabilities.

Overall, this operational overview explains the step-by-step methods pickers use on the floor, the workflow patterns between the main and sterile zones, and software blocks. Describing how the facility lacks barcode verification on the racks (relying only on voice confirmation) and has zero container traceability explains why the warehouse suffers from silent information drift. This links to the proposals for standardized reusable containers in the analysis chapter.

Furthermore, detailing how sterile items require a traversal route terminating at a middle exit conveyor provides a clear picture of layout boundaries , linking directly to the proposal to consolidate inbound registration.

Most importantly, explaining that the previous manual batch-picking trial failed because of software system limitations, rather than physical floor congestion or layout constraints , mathematically proves that VGR can successfully implement batch picking once the system capabilities are updated.

Picking productivity

The manual, picker-to-parts operation currently runs on a single-shift schedule. Prior process optimizations successfully increased internal picking output from a historical average of 220 order lines per person-day to the current baseline of 325 lines. This performance growth was achieved through two primary interventions:

- Delivering direct, structured performance feedback to individual operators.
- Restructuring permission settings within the WMS to eliminate selective order selection, thereby preventing operators from choosing shorter or less complex picking lists.

To control floor congestion and mitigate safety risks associated with picking vehicles, management enforces a strict staffing ceiling of 29 operators on the floor at any single time. This workforce density cap limits the total standard manual capacity of the facility to approximately 9,400 order lines per day. However, actual daily customer demand regularly fluctuates beyond this limit, causing a heavy reliance on overtime. Overtime hours account for roughly 16% of the total working hours in the facility.

At the operational volume level (number of order lines picked), transactional records over a one-year period reveal the following parameters for daily picking activity:

- **Mean daily volume:** 8,500
- **Minimum daily volume:** 4,500
- **Maximum daily volume:** 19,400
- **Standard deviation:** 1,750

At the individual order level, customer orders contain a mean of 16 order lines, with a median value of 6 order lines per order.

The warehouse is divided into different picking environments, which display significant differences in speed and time requirements per picked line. The sterile zone is a specialized, hygiene-controlled area located on an upper floor, while the main picking shelf zone is located on the ground floor. The quantitative distribution of picking productivity across these areas is outlined in the table 4.12.

Furthermore, the processing workload is not distributed evenly throughout the day (hourly) or the week (daily). One-year transactional tracking displays a distinct pulsed workload pattern, showing variations in total order lines picked in one year across specific working hours and weekdays.

Table 4.12: Summary of statistics for picker productivity and zonal cycle times

Performance metric*	Sterile zone	Picking shelf zone	Total facility
Picker line rate (Lines/Hour)			
Mean $\pm$ SD **	61 $\pm$ 10	35 $\pm$ 9	-
Range (Min–Max)	45–85	11–62	-
Overall zone picking rate (Lines/Hour)	62	38	41
Average cycle time per order line (Seconds)	-		
Individual picker	60	103	-
Zone total	58	95	88

**SD: Standard deviation

*Note: Individual metrics represent the average performance of a single operator, while zone metrics show the total throughput of the area as a complete operational system. This difference in data aggregation explains why individual worker rates do not match overall zone efficiency.

For example, if Picker A works 4 hours at 50 lines/hour (200 lines) and Picker B works 1 hour at 20 lines/hour (20 lines):

- Individual Mean: $(50 + 20) / 2 = 35$ lines/hour (a simple average of their speeds)
- Zone Throughput: $220/5 = 44$ lines/hour (a weighted average of total output)

The graph visualizes the hourly pickload (starting from just before 6 AM to 6 PM) on different weekdays which have different colors. It illustrates the hourly pickload across

weekdays, from Monday (dark blue), then Tuesday (light green), Wednesday (yellow), Thursday (red), Friday (light blue) and Saturday (dark green).

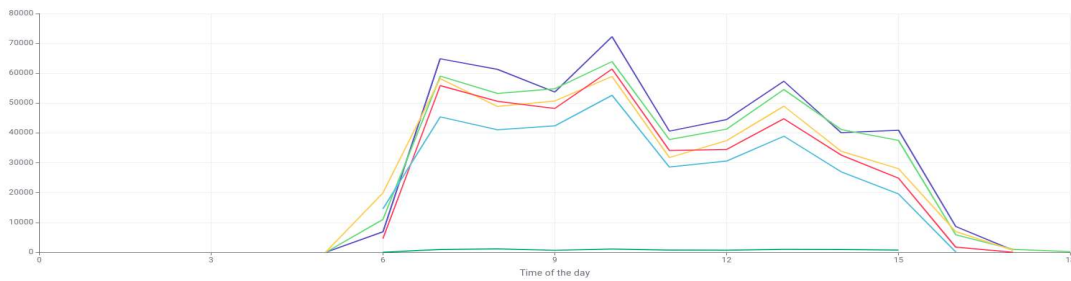


Figure 4.6: Distribution of order lines picked by hour and weekday

Time-motion tracking with the help of MFM method and direct observations identify multiple non-value-adding physical and systemic factors that lower picking speeds and increase travel times:

A. Centralized labeling area: Upon completing a picklist, operators are structurally required to walk to a single centralized terminal. At this station, they manually attach the labels to each package. This routing step creates an operational bottleneck, adding 9 to 10 minutes of non-value-adding transport and administrative time to each picking tour.

B. Lack of standardized materials handling containers: The warehouse does not use standardized picking totes or bins. Operators spend active picking time searching for cardboard boxes to collect and contain their picked items. This introduces sorting delays and in some cases results in re-packing work so items can safely fit into transport cages.

C. Narrow aisle traffic: Racking corridors are wide enough to handle two-way reach truck travel but one-way movement is ruled for manual roll cage pickers. Reach trucks operate under a taxi dispatch policy and can turn around inside the aisles, whereas roll cage pickers operate on a strict S-shape routing policy and cannot turn around. Mixing heavy mechanical reach trucks with manual pickers inside these narrow corridors may result in traffic congestion and lower picking speed.

D. Voice-picking software failures: The system relies entirely on voice-picking headsets linked to the WMS. The software is calibrated strictly to the voice pattern of the individual assigned picker. If an operator's voice alters slightly due to illness, or if the background noise level on the warehouse floor rises, the headset fails to register verbal confirmation commands, causing process delays.

E. Unit of Measure (UoM) identification: Some items are densely nested across individual units, inner packs, and outer supplier cartons. The system's lack of precise data creates confusion for pickers regarding whether a specific line requires a single unit or an entire inner box. Operators rely on hand-written paper notes taped to the shelf edges to clarify true pick quantities, which creates visual and cognitive fatigue.

F. Information drift from substitutions: When a primary product is out of stock, suppliers may deliver a substitute item with alternative box quantities or physical dimensions. The voice-picking data architecture is rarely updated with these physical changes and continues to

read out the historical count instructions. This forces pickers to rely on memory and habit, slowing down verification speeds and increasing picking errors.

G. WMS space allocation: The WMS contains no dimensional data for pallets and lacks measurements for structural ceilings, such as overhead infrastructures. The system may direct replenishment drivers to reserve locations where the pallet cannot physically fit. Drivers are forced to search for alternative spots or leave pallets in random locations, which directly bypasses slotting logic and may increase travel times during subsequent replenishment and picking operations.

Overall, this subsection has provided the time measurements, hourly workloads, and zonal speed differences across the warehouse. The specific line rates and the daily demand variations establish the mathematical baseline used to evaluate capacity gaps. Quantifying specific process wastes, such as the centralized labeling detour, allows the analysis to calculate the exact number of productive labor hours that can be recovered by moving to decentralized mobile printing. Finally, showing that the current operator ceiling caps standard capacity at 9,400 lines and forces a heavy reliance on an overtime rate that can justify the selection of physical automation technologies to decouple total throughput from human labor constraints.

Picking accuracy

Outbound quality is monitored through customer complaints. This indicates an accuracy rate of 99.65%, meaning 0.35% of order lines receive item- or quantity-wise complaints. However, these figures only capture errors that reach the customer and are subsequently reported. The warehouse does not track internal rework loops or errors caught and corrected before shipment, leaving the true first-time-right accuracy unexplained. Missing items and missing quantities account for more than 50% of all reported outbound defects.

Although the baseline error rates seem low, the trend line for picking errors per 10,000 picks indicates a steady upward path over time, implying that quality issues will escalate significantly if unaddressed.

Furthermore, an audit of the warehouse database reveals that inventory discrepancies and quality failures are highly concentrated among specific items. The absolute variance between system records and physical stocks (calculated as system inventory minus reported inventory by the operators) indicates major recording errors (see table 4.14).

When a warehouse operator finds an incorrect stock level at a picking shelf, they report the discrepancy verbally using their voice-picking headset. Although every storage location has a long, unique address code containing the zone, area, and specific shelf, to simplify the data collection and analysis only a three-digit Area Code that represents a group of several successive picking shelves is considered when calculating the picking errors per area.

The correction rate per area shows how manual inventory corrections are distributed across different warehouse locations. This metric is calculated by dividing the number of reported corrections per area by the total number of quantities picked in that area that has been also

Table 4.13: Customer complaints by issue category

Issue Category	Total Count	Percentage of Complaints (%)
Missing Item	765	27.90%
Missing Quantity	714	26.04%
Wrong Item - Return	536	19.55%
Extra Items - Return	320	11.67%
Physical Damage	205	7.47%
Extra Items - Keep	100	3.65%
Missing Parcel	51	1.86%
Wrong Item - Keep	31	1.13%
Complete Order Missing	20	0.73%

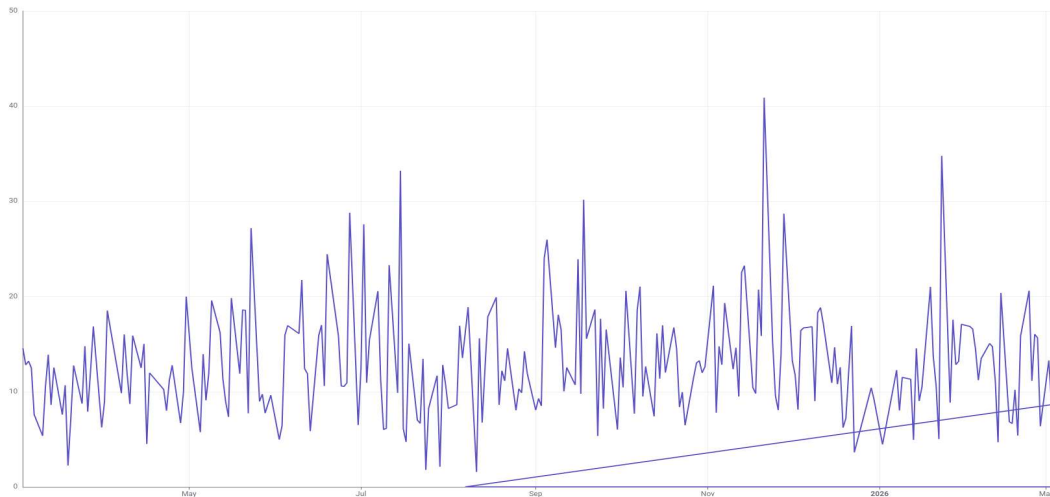


Figure 4.7: Distribution of picking errors per 10,000 picks over one year time period

Table 4.14: Top 10 items with largest inventory discrepancies

Rank	Item Number	Sum of Discrepancy Magnitude	Rank	Item Number	Sum of Discrepancy Magnitude
1	114002975	134,001,124	6	200000987	1,812,917
2	109825190	6,249,517	7	106124738	1,292,635
3	114002967	5,923,048	8	200012896	1,237,843
4	200003157	5,234,368	9	105228456	1,190,464
5	112498480	4,337,243	10	200004565	1,129,296

normalized per 10,000 picks to allow a comparison between areas with different operational volumes. The rate is calculated by matching daily picking volumes against manual inventory corrections in specific areas (with specific Area Codes). The data shows that some highly active areas remain stable despite high volume, while other specific ones show higher error rates. To easily see how different area codes appear in the different columns in rankings (total picks, total corrections, and error rate), the cells are highlighted with different colours, each colour presenting one area code. Area codes with no background color are not repeated in other top 20 rankings in terms of: total number of picks, total number of corrections and normalized error rate.

Quantity-related errors per item metric identifies specific items that are more frequently counted or picked by mistakes. The metric is calculated by combining external customer quantity complaints with internal inventory discrepancy magnitudes for each individual item number.

Overall, this subsection mapped out the critical locations, items, and category of quality errors using both internal data corrections and external complaints. Exposing that missing items and missing quantities make up more than 50% of customer complaints proves that quality issues are concentrated rather than random. Pinpointing the exact high-error zones (like Area 713) and specific items (like 200010130) allows the analysis to target improvements in manual operations precisely where they are needed. Additionally, showing the steady upward path of the error trend line over a one-year period can provide the mathematical justification for selecting picking accuracy as the single most critical factor (Best) in the BWM model.

Table 4.15: Inventory correction rates by area

Rank	Area code	Total picks	Area code	Number of corrections	Area code	Total picks	Number of corrections	Error Rate
1	417	136,807	614	728	713	10,214	130	127.276
2	615	112,895	610	414	515	1,248	14	112.179
3	611	111,904	417	366	614	67,721	728	107.5
4	411	102,173	612	354	717	5,576	59	105.811
5	612	92,164	613	322	746	1,375	14	101.818
6	416	88,637	411	292	511	3,372	34	100.83
7	610	88,274	615	287	718	5,670	51	89.947
8	415	68,897	611	243	322	19,077	150	78.629
9	614	67,721	415	221	729	6,457	47	72.789
10	613	62,201	416	209	419	6,661	47	70.56
11	208	59,962	724	160	723	10,270	70	68.16
12	412	56,508	322	150	315	6,351	40	62.982
13	414	45,158	414	147	510	656	4	60.976
14	410	41,335	208	141	337	4,331	26	60.032
15	336	38,159	716	135	724	27,284	160	58.642
16	335	38,156	713	130	209	3,452	20	57.937
17	716	29,782	413	100	512	523	3	57.361
18	420	29,567	727	100	413	18,842	100	53.073
19	334	28,174	326	96	316	7,697	40	51.968
20	319	27,608	327	96	613	62,201	322	51.768

Table 4.16: Items with highest combined complaint and discrepancy rates

Rank	Item number	Total picks	Total errors	Normalized error rate
1	200010130	521	176	3,359
2	114002967	1,861	567	3,036
3	200010143	170	32	1,824
4	114002959	266	37	1,353
5	102799459	106	14	1,226
6	102776820	21	2	952
7	106124837	871	81	918
8	200013543	28	3	714
9	200013750	412	30	704
10	200009470	46	4	652

4.3 Inventory control and capacity planning

Inventory control at the Sisjön facility relies on manual processes and reactive adjustments. System discrepancies propagate silently because voice-picking uses verbal confirmations rather than physical scans at the shelf, meaning the WMS remains unaware of physical inventory variances. However, when the picker cannot pick the order quantity, he/she can either report the correction through voice by telling the correct in-stock number or skip the order line.

Replenishment scheduling is constrained by manual confirmation rules. Although the WMS generates a replenishment list when sterile items reach their re-order point, an operator must manually confirm and initiate the task. During peak periods or holiday weekends, this manual confirmation step often leads to backlogs.

Furthermore, because the system lacks pallet dimension data and physical height measurements, forklift operators frequently bypass WMS suggestions. This results in random pallet placement and random put-away routines that might deviate from ABC/XYZ slotting principles.

The current warehouse has height constraints, utilizing only three shelf levels in the main picking zone: the lowest level is used for manual picking, while the upper two are reserved for reach-truck-driven stock. The height of some upper shelves varies due to ceiling installations and pipes. Additionally, the physical layout is split across two levels connected by a small elevator, which is highly inefficient for material flow. While low-frequency items are stored on the lower level, operators may transport pallets via public outdoor roads to avoid the elevator bottleneck, when it is out of service.

Material flows within the inbound and replenishment pathways are characterized by excessive manual handling and several administrative steps. Under the current process design, incoming goods are handled by up to six different operators between receipt and final storage placement. This setup requires multiple manual counts and separate barcode registration entries at both the primary reception loading dock and the intermediate storage zone interfaces.

Inventory level accuracy at the Sisjön facility is evaluated through manual cycle counts executed at individual shelf locations. This counting process is performed periodically to generate a warehouse snapshot that is compared against system records. A storage location is recorded as accurate only if the physical count matches the system inventory itemwise and quantitywise. If any discrepancy is identified, the location is marked as inaccurate, regardless of the physical quantity difference or the economic value of the variance. The final accuracy KPI represents the percentage of completely accurate locations relative to the total number of location addresses. The current metric stands at approximately 80%, meaning that 2 out of every 10 storage locations contain volumes that deviate from the WMS records.

Operational control is also limited by an inability to steer the upstream supply chain. Warehouse management emphasizes that core process improvements and data integrity can only be maintained when the supply chain is under control and data flow is synchronized between the different supply nodes.

Overall, the 80% inventory accuracy baseline established a need for manual and structural re-engineering. Specifically, these findings justify the proposal for Two-Level Manual Picking to safely double active forward-picking slots and reduce the frequency of replenishment trips. In the Gap Analysis, this data defines the specific accuracy and storage gaps that must be closed to meet the organization's 99.9% strategic target and the high-density requirements of the inventory reserve law, shaping the selection critical factors in the automation selection step.

5. Analysis

This chapter uses the empirical findings from Chapter 4 to diagnose the root causes of VGR's current performance gaps and to develop a path toward the new distribution centre. The analysis is organised in four steps. First, the diagnose summarises the key operational inefficiencies and quality issues. Second, a set of improvements in manual processes and operations are proposed to address waste and errors. Third, a gap analysis quantifies the difference between current and target performance, showing that the improvements in the manual setting alone are sufficient to meet VGR's stated targets of 99% inventory accuracy and 10,000 order lines per day (without overtime). Finally, based on the remaining strategic gaps (higher accuracy, future volume growth, and the 2027 inventory reserve law), physical automation technologies are evaluated using the qualifying-comparable factors decision-making framework adapted from Johansson and Persson (2023).

5.1 Diagnose

Process inefficiencies dominate. Material Flow Mapping (MFM) reveals that Administration (A) activities account for the majority of activity counts across all flows. In the Shelf Picking flow, 19 A out of 41 activities consume over 2.5 hours, indicating that information handling and not physical movement, is the primary factor on throughput. Non-value-adding wastes include: centralised label printing, which adds 9–10 minutes of travel per picking tour, two-step sterile registration, which doubles administrative work for 2,000 sterile SKUs, and a redundant second scan for shipment ID generation. Together, these inefficiencies directly limit daily capacity to approximately 9,400 order lines (capped by a workforce ceiling of 29 operators).

Quality and accuracy fall below targets. Inventory accuracy stands at only 80%, below the 99.9%+ target for a reliable warehouse operation. Operators visually confirm items, leading to frequent mispicks of visually similar medical products, such as needles and catheters with nearly identical packaging. Unit-of-measure confusion further compounds errors, forcing handwritten notes on shelves. Customer complaints are dominated by missing items (27.9%) and missing quantities (26.0%), together accounting for more than half of all reported complaints. Moreover, the picking error rate per 10,000 picks shows a steady upward trend over the one-year transactional period, indicating that quality is deteriorating, not stabilising.

Throughput capacity falls short of the 10,000 lines/day target. The current ceiling of 9,400 lines is imposed by the combination of a fixed workforce limit (29 operators) and accumulated non-value-adding activities. On peak days, the facility cannot absorb the required volume within standard shift hours, forcing overtime. The workload pattern,

unevenly distributed across weekdays and hours, further strains capacity, creating periods of congestion.

5.2 Improvement suggestions for the manual operations

The following thirteen improvements in manual operations target the non-value-adding activities and were derived from an initial list of solutions that we developed based on process improvements found from the Material Flow Mapping. For instance, when an inefficient process step was identified, we reshaped the flow to eliminate redundant tasks, with the aim to boost both productivity and quality within the operations. Where applicable, we cross-referenced specific proposals with academic research papers to provide a theoretical justification and argue what performance results could be expected from their implementation. This compiled list was then reviewed in discussion with the warehouse manager team at Sisjön Distribution Center, who provided direct confirmation on the practical feasibility and operational viability of each suggestion. Requiring minimal capital investment, these suggestions aim to raise inventory accuracy and increase daily throughput.

5.2.1 Proactive goods arrival registration and measurement gates

Proactive goods arrival registration refers to registering incoming deliveries as soon as possible upon arrival at the inbound gate rather than waiting for an operator to visually identify the goods later during sorting. This process is initiated by a scan of the carrier's transport label when unloading, which serves as a digital arrival signal within the warehouse system. In the current process, registration begins only after an operator physically notices a pallet in the reception area and manually attaches a weekday tag, this reactive approach creates delays, reception floor clutter, and postponed inventory updates that can lead to stock outs in downstream operations.

Measurement gates are physical sizing frames (measuring height, width, and depth) installed at the goods-reception dock for inbound pallets. Pallets pass through these standardized frames during unloading to assign a Size Code (e.g., A, B, C) in the WMS. The system then directs the driver to a storage location that matches those specific dimensions. This eliminates the current problem where dimensions are missing from the WMS, forcing reach truck drivers into trial-and-error transport when the system suggests a location that physically cannot fit a bulky item.

Productivity. Proactive registration reduces the number of times each incoming unit is handled. Under the current process, pallets are unloaded to the goods receipt floor, later moved to a temporary buffer to create space, and then moved again to the sorting area before final put-away. Each of these moves represents a Handling (H) activity in the HATS framework (Finnsgrård et al., 2011). Registering arrivals at the dock door eliminates redundant handling because goods can be directed straight to sorting without intermediate relocation. Faster registration also updates the WMS in real time, enabling automatic notification of sorting personnel. When operators are notified rather than having to discover arrivals, waiting time between goods arrival and task initiation is eliminated, and effective work hours become productive output.

Dimensional gates further improve productivity by ending the trial-and-error put-away that currently consumes driver time. Without dimension data, the WMS often suggests a location where a pallet cannot fit. Drivers must then search for a feasible shelf location to place the pallet, bypassing slotting logic and increasing travel time. Dimensional gates provide more accurate size data at receipt, allowing the WMS to assign a correctly sized location immediately. Drivers go directly to the right spot without searching or making multiple attempts, reducing Transport (T) and Handling (H) activities. For VGR, where the workforce ceiling of 29 operators limits daily throughput to approximately 9,400 order lines, productivity gains from both improvements translate directly into higher daily capacity without requiring additional staff.

Quality. Under the current process, arrived goods can wait for several days in the goods receipt area before being registered and sorted. In logistics literature, this creates a costly 'dock-to-stock' information lag (Bartholdi & Hackman, 2019). During this waiting period, customers may place orders for items that are physically present but digitally invisible within the WMS. Because the system reports zero stock, these orders are left unfulfilled, creating artificial stockouts that directly impair order fulfillment and picking quality (De Koster et al., 2007). Proactive registration prevents this by eliminating this information latency, ensuring that stock is visible as soon as it crosses the gate so that order allocation is consistently based on complete and accurate stock positions.

5.2.2 Scheduled delivery time windows

Scheduled delivery time windows refer to assigning specific arrival slots for healthcare suppliers, rather than accepting deliveries throughout the day. The purpose is to coordinate supplier arrivals to level the daily inbound workload.

Productivity: The lack of an inbound scheduling system destabilizes labor productivity by forcing operators into reactive, non-value-adding material handling. Because suppliers currently arrive throughout the day without prior notification, the facility faces unpredictable traffic peaks that overwhelm the limited reception area. To handle this congestion, operators are forced to repeatedly relocate pallets to temporary buffer zones. Within the MFM analysis, each of these forced movements is recorded as an unnecessary Handling (H) activity, a form of process waste that actively drains operational capacity and must be eliminated to protect throughput.

Quality. Scheduled delivery windows improve inbound quality by reducing the likelihood of sorting errors that occur when operators are under severe time pressure during peak congestion (Grosse et al., 2020). When the reception area is overwhelmed, operators are forced to rush through sorting and registration to clear physical space for the next arrival. Under this operational stress, the misidentification of visually similar medical items becomes highly probable.

When deliveries are strictly scheduled, the goods reception zone can effectively level and balance the daily workload (Boysen et al., 2010). This stabilization leads to accurate handling of goods and a significantly faster transfer of items to picking shelves. Accelerating this put-away velocity ensures that incoming items reach fulfillment zones before they can be

ordered by customers, effectively eliminating the risk of missed picks caused by temporary, artificial stockouts on the shelves (Bartholdi & Hackman, 2019).

5.2.3 Decentralized/mobile label printing

Decentralized or mobile label printing refers to moving label printers from a central station to pickers' trolleys or end-of-aisle locations. The purpose is to enable label printing closer to the point of picking, eliminating unnecessary travel to a centralized printer. In the current process at VGR, after completing a picklist, operators must walk to a single centralized labeling terminal where they manually attach labels to each package

Productivity. In the current process at VGR, after completing a picklist, operators must walk to a single centralized labeling terminal where they manually attach labels to each package. The MFM data identifies this Transport to Labeling step as a major time sink, often taking 9–10 minutes per flow. This forced travel creates inefficiency by interrupting picking tours and adding non-value-adding transport time.

Mobile printing eliminates this travel waste entirely. When printers are mounted on trolleys or placed at aisle ends, operators can print and apply labels at the point of picking without detouring to a central station.

5.2.4 Automatic shipment ID generation

Automatic Shipment ID generation refers to reconfiguring the Warehouse Management System (WMS) to generate shipment numbers automatically upon final pick confirmation, rather than requiring operators to manually scan every package a second time in the consolidation area. The purpose is to eliminate redundant scanning and data entry by using existing picking data to trigger ID generation as soon as an order is closed in the system.

Productivity. In the current process at VGR, after items are picked and labeled, operators must transport them to the consolidation area where they perform a second round of manual scanning on every package just to create a shipment ID. Within the HATS framework used in Material Flow Mapping (MFM), this activity is classified as an “Administration (A)” task, an information management activity that does not physically move goods or add direct value to the product. When the WMS automatically generates shipment numbers upon pick confirmation, this redundant administration activity is eliminated entirely.

5.2.5 Elimination of multiple sterile item registration

Elimination of redundant sterile registration refers to consolidating the two-step registration process for sterile items into a single entry point. Currently, sterile items are registered once at the main goods reception and again when they arrive at the sterile zone. The improvement transfers arrival data directly to the sterile zone replenishment list upon the first scan at goods reception, eliminating the duplicate registration step.

Productivity. In the current process at VGR, sterile items follow a fragmented registration path. When a pallet of sterile goods arrives at the main reception, it is registered and sorted into trolleys. The trolley is then transported via elevator to the sterile zone on the upper floor. Upon arrival at the sterile zone, the same items are registered a second time before replenishment can begin.

Within the HATS framework used in Material Flow Mapping (MFM), each registration is classified as an “Administration (A)” activity, information management that does not physically move goods or add direct value. The two-step registration means that every sterile item is handled twice by the WMS: once when it enters the building, and again when it enters the sterile zone. When the first scan at goods reception automatically transfers arrival data to the sterile zone replenishment list, the second registration step is eliminated entirely. Operators in the sterile zone no longer need to re-register items that have already been recorded in the system. They can begin replenishment immediately upon receiving the trolley, using data already captured at the main reception. This converts administrative time into productive handling time, reducing the total cycle time for sterile items from arrival to shelf availability.

5.2.6 Velocity-based and item association-based slotting

Velocity-based slotting refers to relocating high-frequency items to shelf locations positioned closer to the consolidation area. The purpose is to reduce travel distances for the most active SKUs. The method relies on regular ABC analysis to identify fast-movers (the 8% of items that generate 80% of picking activity) and permanently assign them to the most ergonomic and accessible storage positions.

Association-based item grouping stores frequently co-picked items in adjacent or nearby shelf slots. This reduces total walking distance per order by keeping related healthcare supplies in the same zone. The method uses transactional Lift scores (where Lift > 1 indicates a significant statistical relationship) to identify co-picked pairs and slot them together.

Based on the high-lift item pairs identified in the empirical findings, these highly correlated products should be assigned to storage slots in close physical proximity (Li et al., 2021). Placing these associated items in adjacent forward-picking locations allows a single operator to retrieve both items in immediate succession during a picking tour. Within the HATS framework, this arrangement directly minimizes transport, shortens picking travel times, and maximizes the manual throughput capacity.

Productivity. Within the HATS framework, the majority of picking time in a manual system is classified as Transport (T), transporting between locations. Velocity-based slotting directly reduces both by placing fast-movers in positions that minimise travel distance and physical strain. The MFM analysis of VGR’s current flows shows that Transport accounts for a large portion of cycle time. Because fast-movers are not systematically positioned near the consolidation area pickers spend excessive time moving across the warehouse. By moving the top 8% of SKUs to closer locations, closer to the consolidation area, pickers can complete the majority of their tours in a shorter travel time. VGR works with this to some extent but they don't manage it regularly. However, VGR management points out a current limitation of this approach under their existing single-order picking method:

“It leads to congestion by the consolidation area due to more traffic close by.” Because all orders are picked one at a time, multiple pickers converge on the same high-density zone near the consolidation area, creating bottlenecks. The proposed solution is not to abandon slotting but to combine it with batch picking (see Improvement Suggestion 8). Batch picking allows one operator to collect items for several orders in a single tour, distributing the flow through the fast-mover zone more evenly and reducing peak congestion. When velocity-based slotting is implemented together with batch picking, the travel distance reduction is retained while the congestion risk is mitigated.

5.2.7 Two-level manual picking

Two-level manual picking refers to expanding the active picking shelf from the current single shelf level to the second shelf level (Level 2) using specialised manual equipment. At present, only the lowest shelf level is used for forward picking; the two upper levels serve as reserve storage. The improvement introduces roll containers with integrated, collapsible staircases or battery-powered height-adjustable platforms, allowing pickers to safely reach Level 2 items by hand. This effectively increases the number of forward-picking SKUs and reduces replenishment frequency.

Productivity. In the current VGR configuration, the majority of the vertical shelf capacity is reserved for bulk storage, accessible only by reach trucks. Every time a forward shelf runs empty, a replenishment task must be executed, a reach-truck driver retrieves a pallet from reserve, transports it to the picking aisle, and places the items onto the forward shelf. Within the HATS framework, each replenishment generates Handling (H) (moving items from pallet to shelf) . By making Level 2 accessible to pickers, the need for replenishment is reduced. With more forward positions, the same picking volume can be sustained with a smaller number of replenishment trips. The time currently spent on reach-truck handling, pallet retrieval, and shelf restocking is converted into productive picking time.

5.2.8 Batch picking

Batch picking, also known as sort-while-pick, refers to transitioning from single-order picking to picking multiple orders simultaneously. A picker carries a roll container with several separated compartments, totes, or bins, each assigned to a specific customer order. The voice-directed system instructs the picker which item to pick and into which compartment to place it. This method eliminates the need for a secondary sorting step at the consolidation area because items are sorted by order already during the picking tour.

Productivity. The current VGR process follows discrete order picking, one operator picks one order at a time, completes it, and then starts the next. Cluster batch picking fundamentally changes this by allowing one tour through the warehouse to fulfil several orders at once. When one operator collects items for multiple orders in a single tour, the travel distance per order drops. Research has shown that batching orders can save more than 35 % of picker energy expenditure and more than 70 % of transport distance (Ma et al., 2026). More generally, order batching groups multiple orders for picking, aiming to minimise trips and enhance overall efficiency and productivity. Furthermore, because the items are already sorted into order-specific compartments during the pick, there is no need for a separate sorting

operation after the tour, saving both time and floor space in the consolidation area. In the HATS framework, cluster batch picking reduces Transport (T) travel distances.

5.2.9 Dynamic zone picking

Dynamic zone picking is a self-balancing order picking method where zone boundaries are not fixed but shift dynamically in response to real-time workload. The method sequences pickers from slowest to fastest along the pick path, when the fastest (last) picker finishes an order, they walk back to take over the work of the person behind them, who in turn moves back to the next person. This creates a continuously adjusting flow that eliminates waiting and starvation.

Productivity. In traditional fixed-zone picking, each operator is confined to a predetermined section, creating two productivity losses: blocking (a picker waits because the next zone is still busy) and starving (a picker has no work because the previous zone has not finished). Zone order picking systems are particularly vulnerable to these delays. By applying workload balancing, studies have achieved an average reduction of 27.65% compared to random batching strategies (Park & Hong, 2025). Workload balancing can minimise blocking and starving delays and maximise order picking productivity.

Dynamic zoning logic operates through multi-factor optimization algorithms that continuously evaluate order volumes, demand patterns, picker locations, and storage density to generate zone reconfiguration recommendations. Industry implementations report substantial improvements in walk path reduction, faster order cycle completion, and pick density enhancement (Challagundla, 2026).

5.2.10 Picking from shipping cartons

Picking from shipping cartons, also known as the pick-window method, means leaving items in their original shipping cartons and cutting pick windows or holes in the carton for access instead of fully unpacking the contents onto forward shelves. The carton itself becomes the storage container, and pickers retrieve items directly through the opening. This approach eliminates the non-value-adding step of transferring individual items from shipping cartons to storage totes or shelves.

Productivity. Within the HATS framework, full unpacking is classified as a non-value-adding Handling (H) activity, it moves items from one container to another without progressing the order toward the customer. At VGR, suppliers often deliver mixed cartons containing multiple SKUs with similar packaging. The current process requires operators to unpack these cartons entirely, sort the contents, and place each item onto a picking shelf. This consumes significant labour time without adding value.

The pick-window method eliminates this Handling step entirely. When a carton arrives, operators simply cut a standardized opening (or use a pre-cut window from the supplier) and place the whole carton directly into the picking location. Replenishment becomes a matter of swapping an empty carton for a full one, rather than individually placing dozens of items.

5.2.11 Standardized reusable containers

Standardized reusable containers refer to replacing cardboard cartons of various sizes with a system of standardized plastic bins in a few fixed dimensions. These bins are used for all picking tours, from goods reception to the consolidation area. The bins can be pre-labeled (e.g., with barcodes), eliminating the need to print and attach new labels for each order. After use, the bins are returned, washed, dried, and reused.

Productivity. In the current VGR process, operators spend a significant amount of time handling empty cardboard cartons. They must search for a suitable size, fold or assemble the carton, and then prepare it for picking. After picking, the cartons are often thrown away, generating waste and requiring additional handling for disposal. Within the HATS framework, these activities are classified as non-value-adding Handling (H), they do not move goods closer to the customer.

Standardized reusable bins eliminate this waste. Bins are always available in a few fixed sizes, so operators do not waste time searching for the right carton. Because the bins are rigid and stackable, they can be stored compactly when not in use. The pre-labeled bins also eliminate the need to print and apply new shipping labels for every order, a separate Administration (A) step that currently consumes operator time at the labeling station. When a bin is empty, it is simply returned to a collection point, and made ready for the next tour. This creates a flow that increases productive picking hours.

5.2.12 Carton flow racks with adjustable guide rails

An industrial carton flow rack with adjustable guide rails is a storage system designed to optimize order picking for cartons, boxes, or plastic totes. Instead of flat shelving, the system uses inclined shelves with roller or wheel beds to automate internal material flow. Modern systems use toolless adjustable guide rails that allow operators to quickly change lane widths to match the dimensions of incoming inventory, improving horizontal storage density. Based on VGR's input, these adjustable guide rails can also function as shelf dividers, separating different batches of the same SKU by expiration date, thereby supporting First-Expired-First-Out (FEFO) discipline without adding manual sorting work.

Productivity: Transitioning from traditional static shelving to carton flow racks directly targets travel time, which literature establishes as the primary non-value-adding waste in manual order picking (De Koster et al., 2007). The current VGR process uses static shelving, which forces pickers to search for the right carton. In contrast, carton flow racks concentrate the picking area, automatically bringing the next item forward via gravity and eliminating unnecessary walking and searching paths (Bartholdi & Hackman, 2019). By keeping the picking area consistently replenished and improving SKU density, the system minimizes operator movement, allowing workers to focus on value-adding fulfillment activities (Tompkins et al., 2010).

Quality: Carton flow racks eliminate several critical sources of picking errors by replacing manual, cognitive tasks with a physically self-enforcing storage design (Tompkins et al., 2010). The natural gravity-fed flow inherently ensures proper FEFO (First-Expired, First-Out)

rotation, positioning older inventory at the pick face first and preventing the costly expiration write-offs associated with overlooked stock (Bartholdi & Hackman, 2019). By physically separating the loading and picking zones, this layout completely removes the requirement for operators to manually search for and verify individual expiry dates under operational time constraints, thereby significantly mitigating cognitive fatigue and reducing mispicks (Grosse et al., 2020).

5.2.13 Pick-by-voice system improvements

The current picking process at VGR is supported by a pick-by-voice system, which provides operators with verbal picking instructions through headsets connected to the warehouse management system. While the technology enables hands-free operation and eliminates the need for paper-based picking lists, several issues were identified during the empirical study that negatively affect warehouse performance.

Observations and interviews revealed recurring system disconnections, delays in communication, and difficulties with voice recognition. These issues force operators to repeat commands and confirmations, resulting in non-value-adding activities and reduced picking efficiency. The study also identified challenges related to outdated product information and packaging configurations within the system, requiring employees to rely on handwritten notes and personal experience to compensate for system shortcomings.

Productivity. To address these issues, improvements to the existing pick-by-voice system are proposed. By reducing communication delays, voice-recognition failures, and system disconnections, operators can spend less time on non-value-adding activities and more time on productive picking tasks, thereby improving picking productivity. The proposed improvements include upgrading headset, communication equipment and improving system stability. Together, these measures aim to improve both inventory accuracy and operational efficiency while reducing disruptions in the picking process.

The primary benefits of improving the existing pick-by-voice system include increased picking efficiency, reduced operator frustration, improved inventory accuracy, and enhanced process reliability. Compared with implementing a completely new picking technology, these improvements can be achieved with relatively limited investments while leveraging the existing warehouse infrastructure and employee familiarity with the system.

5.3 Gap analysis

The gap analysis serves as an analytical bridge within the thesis methodology, connecting the empirical diagnostics of the current manual operations with the technical matching of future physical automation systems. By utilizing the data gathered via MFM and the HATS framework, this section evaluates the operational and strategic discrepancies between the baseline performance at the Sisjön facility and the future requirements of VGR.

The primary objective of this analysis is to determine the extent to which the identified performance gaps can be closed through non-automated process re-engineering, thereby

isolating the remaining strategic requirements that necessitate physical automation infrastructure in the new facility.

5.3.1 Operational and strategic targets

To guide the transition to the new distribution center, VGR management has quantitative performance metrics and qualitative structural constraints. These targets are designed to absorb expanding healthcare logistics volumes while ensuring patient safety through high delivery reliability.

Daily throughput capacity: The central operational target is the capability to process a steady volume of 10,000 order lines per day entirely within standard working hours. The future facility layout must be structurally scaled to handle a projected 40% workload expansion in total order lines to accommodate regional healthcare growth.

Inventory level accuracy: To eliminate stockouts and administrative discrepancies, management mandates a location-based inventory accuracy target of 99.9%.

Structural facility parameters: To house expanded inventory volumes safely, the new building layout requires a clear, unobstructed vertical ceiling height of at least 12 meters.

5.3.2 Current performance vs. targets

The empirical findings indicate that the existing manual process design cannot absorb future volume targets within standard working hours, causing a heavy reliance on operational overtime. The quantitative and qualitative performance gaps between the current baseline and future targets are compiled in the evaluation table (5.1):

Table 5.1: Comparison of current operational performance baselines against future targets.

Performance metric	Current	Target	Gap	Note
Inventory level accuracy	80%	99.9%	-19.9%	Location based
Daily throughput (lines/day)	7,150	10,000	-2,850	16% overtime excluded
Picking accuracy	99.65%	99.8%	-0.15%	Complaint based to total

The qualitative gap in inventory location accuracy highlights a significant operational risk. The current baseline of 80% is driven by internal information drift, where physical stock movements occur without immediate, corresponding updates in the WMS. This variance stems from a total reliance on verbal confirmations through the voice-picking system rather than physical barcode verification at the storage rack. This issue is compounded by a lack of synchronized supplier master data, which leads to unit of measure confusion and unrecorded item packaging substitutions.

The throughput capacity is physically capped by the current process layout. While prior process optimizations successfully increased internal picking output to a baseline of 325 lines per person per day, the strict floor safety ceiling of 29 operators limits standard manual maximum capacity to approximately 9,425 lines per day. Actual daily demand regularly exceeds this threshold, reaching peak volumes of up to 19,400 lines, which forces the facility into frequent overtime operations that account for roughly 16% of total working hours. As diagnosed through MFM, non-value-adding administrative tasks dominate the workflows, characterized by centralized labeling detours, redundant barcode scanning for shipment ID generation, and discrete single-order picking paths that maximize operator transit distances.

5.3.3 Closing the gaps through improvements to manual operations

To evaluate whether improving the processes in the manual operations can bridge the identified operational discrepancies, the thirteen non-automated improvement suggestions developed in Section 5.2 were questioned against the empirical data.

Throughput capacity projections

The MFM time-motion tracking reveals that information handling and administrative detours constitute the primary bottleneck restricting manual material flows. Implementing targeted process changes reclaims substantial labor capacity without capital-intensive hardware investments:

- **Eliminating centralized labeling detours:** Transitioning to decentralized or mobile label printing mounted directly on pickers' trolleys eliminates the 9 to 10-minute transport walk required at the end of every picking tour. Assuming 20 active pickers executing an average of 6 tours per day, this process adjustment recovers 18 to 20 productive labor hours daily. At a standard picker line rate of 40 lines per hour, this change yields an additional 720 order lines per day within standard hours.
- **Automating shipment ID generation:** Reconfiguring the WMS to generate shipment numbers automatically upon final pick confirmation eliminates the redundant administrative second scan at the consolidation area. Across approximately 500 daily orders, saving 12 seconds per order recovers 1.6 labor hours (equals to 64 order lines picking time) daily.
- **Consolidating inbound sterile registration:** Combining the two-step entry process for sterile items into a single entry point at primary goods reception saves approximately 0.5 man-hours (equals to 20 order lines picking time) per day across the 2,000 active sterile SKUs.
- **Implementing batch picking and balanced slotting:** Transitioning from discrete single-order picking to batch picking directly targets the total transport time recorded across warehouse material flows. Because approximately 75% of this transport time is spent traversing active picking routes, applying order batching can reduce transport distances by more than 70% (Ma et al., 2026), effectively freeing up around 50% of total transport time. Focusing specifically on the main zone, where transport averages 14 minutes per tour, fulfilling 500 orders per day saves roughly 58 man-hours daily, which is equivalent to the picking time required for 2,300 order lines. When integrated with velocity-based and association-based slotting, this combined strategy

minimizes travel waste, balances the shop floor workload, and mitigates the probability of localized congestion near the consolidation area.

The mathematical aggregation of these manual capacity gains demonstrates that process re-engineering can elevate the standard manual throughput capacity beyond the 10,000 lines/day target, effectively removing the regular 16% overtime burden.

Inventory accuracy projections

To close the 19.9% inventory accuracy gap, manual operations improvements target the specific zones and items where historical discrepancies are concentrated. Transactional audits show that quality failures are highly localized, with area 713 generating a normalized error rate of 127 corrections per 10,000 picks, and missing items or quantities accounting for over 53% of customer complaints.

- **Standardized reusable containers and carton flow racks:** Implementing rigid, pre-labeled plastic bins and gravity-powered carton flow racks enforces strict physical FEFO discipline, removing the reliance on picker memory and stabilizing location integrity:

By utilizing gravity-fed carton flow racks, the oldest stock is automatically rolled to the front of the picking face. This directly addresses the batch management and inventory control challenges identified in Section 4, where operators were required to manually verify batch numbers and expiration dates during picking activities. This design eliminates the requirement for operators to manually search for or verify specific batch numbers and expiration timelines on the shelves under time constraints. The design eliminates the need for operators to search for or verify specific batches under time constraints, thereby reducing the cognitive effort required during order picking. Consequently, the likelihood of picking errors, such as retrieving items from an incorrect product batch, may be reduced while simultaneously supporting FIFO inventory management.

Furthermore, inventory accuracy can be improved through more structured replenishment processes. The adjustable guide rails inside the carton flow racks function as rigid physical dividers. These dividers allow operators to easily isolate different production batches of the same SKU without adding complex manual sorting tasks. Consequently, replenishment operators can place full batches into designated lanes more consistently. This addresses the mixed shelf storage practices identified in Section 4 and reduces the risk of discrepancies between physical stock locations and WMS records.

The implementation of standardized reusable containers further supports this accuracy by replacing erratic supplier cardboard boxes with uniform plastic bins. These plastic bins can be pre-labeled with unique barcodes to introduce a reliable control mechanism on the shop floor. This barcode-based verification addresses the inventory accuracy challenges identified in Section 4, where the current voice-picking process relies primarily on verbal confirmations rather than physical scans at the storage location. Additionally, fixed-dimension bins reduce uncertainties regarding units of measure and nested packaging configurations. Since items are stored in standardized quantities, operators can more easily identify true pick counts. This reduces reliance on handwritten notes and lowers the risk of unrecorded inventory discrepancies or delivery errors.

Overall, for the majority of the improvements in manual processes, the expected productivity gains are derived directly from the Material Flow Mapping analysis, where eliminating identified non-value-adding activities translates into quantifiable time savings and additional order line capacity. For the remaining suggestions, where direct quantification through MFM was not possible, the expected directional benefits are supported by findings from the reviewed literature, which generally describes positive operational outcomes from similar process changes in comparable warehouse environments. However, estimating the exact final result for inventory accuracy remains difficult, as predicting the precise percentage outcome is challenging when factoring in the compounding effects of future volume increases. Consequently, while a significant upward trend in accuracy is expected, the exact figure cannot be stated with absolute certainty.

5.4 Physical automation technology matching

To ensure a reliable and structured technology matching process, this study implements a multi-criteria decision-making framework adapted from the literature (Johansson & Persson, 2023). This framework establishes a clear separation between binary qualifying factors, which filter out unfeasible technologies based on physical and operational constraints, and weighted comparable factors, which rank the qualified technologies to align with VGR's priorities.

To make the selection more realistic and see if a technology can be qualified only for a specific function, this section also introduces a two-level (dual-tier) approach. This analysis will show how different technologies can be combined in specific warehouse zones instead of just choosing one single system for the whole facility.

5.4.1 Analysis and selection of critical factors

The qualifying and comparable factors were derived through a process combining empirical findings, literature insights, and validation with VGR warehouse management. First, the empirical analysis identified the key operational characteristics and challenges of the Sisjön Distribution Centre, including high SKU diversity, strict accuracy requirements, future preparedness requirements, throughput constraints, and the need to handle a broad range of product types with regulatory requirements. These findings established the operational context that any future automation solution must support.

Second, the warehouse automation literature emphasizes that technology selection should be based on the alignment between operational requirements and technological capabilities rather than solely on technological performance (Roodbergen & Vis, 2009). Previous studies highlight factors such as throughput capacity, storage characteristics, scalability, flexibility, item handling capabilities, and implementation constraints as critical considerations when evaluating warehouse automation technologies (Azadeh et al., 2019).

Finally, the preliminary factors were validated through discussions with VGR management. Feedback from warehouse managers confirmed the importance of handling SKU diversity, maintaining high picking accuracy, supporting future increases in stock levels, enabling phased implementation, and ensuring sufficient flexibility to accommodate changing operational requirements. The stakeholder feedback was used to refine and prioritize the final set of qualifying and comparable factors used in the evaluation framework.

Qualifying factors (Q1–Q4): Qualifying factors function as binary, non-negotiable pass/fail gates. Any technology that fails to meet these threshold criteria is immediately excluded from further evaluation:

Demand profile (Q1): The technology must align with VGR's specific demand characteristics. Even if the demand is quite stable (with around 65% X items), it consists of a high volume of small, low-complexity customer orders (averaging 16 order lines with a median of 6 lines per order), it should also support peak demands and emergency orders.

SKU characteristic and compliance (Q2): The technology must be capable of processing small and medium-sized goods, which comprise the majority of VGR's inventory, while complying with sterile handling standards and dangerous goods regulations.

Operational throughput baseline (Q3): The automated system must support a standard throughput capacity of at least 10,000 order lines per shift, without relying on operator overtime.

Q4: Regulatory and handling constraints (Q4): The system must support handling of regulated products (e.g. sterile, medical, or controlled goods). Furthermore, as VGR's future security and contingency requirements have not yet been fully defined, the selected technology should be sufficiently adaptable to accommodate future preparedness needs. VGR also emphasized that the solution should be implementable within an existing operating warehouse with minimal disruption to ongoing healthcare supply activities, making phased implementation approaches preferable.

Comparable factors (CF1–CF5): Five customized comparable factors are defined specifically to target VGR's performance gaps and requirements:

CF1: Picking accuracy: The physical capability of the system to eliminate mispicks caused by visually similar items or unit-of-measure confusion, facilitating a transition from the current 80% inventory level accuracy to the 99.9% target.

CF2: Storage density: The effectiveness of the technology in space utilization to accommodate the storage mandates of the 2027 inventory reserve law.

CF3: Throughput capacity: The degree to which the system minimizes non-value-adding labor steps to secure a lower picking cycle time.

CF4: Versatility handling: The system's capacity to process diverse shapes, fragile components, and sterile packaging.

CF5: Modularity and scalability: The ease of expanding the system's storage capacity or throughput to support at least the minimum 40% volume expansion without disrupting ongoing warehouse operations.

Weighting of comparable factors via the Best-Worst Method (BWM)

The importance weights assigned to the comparable factors were determined using the

Best-Worst Method (BWM). Rather than being defined by the researchers, the weights were obtained from VGR decision-makers through an assessment process. The purpose was to ensure that the resulting technology evaluation reflected VGR's operational priorities and strategic objectives.

To establish the weights, VGR representatives first identified the most important (best) and least important (worst) comparable factors based on their operational context. Later, pairwise comparisons were conducted following the BWM methodology, where the decision-makers assessed the relative importance of each factor against the selected best and worst factors using a scale ranging from 1 to 6. The resulting comparisons were used to calculate the final factor weights.

The prioritization reflected VGR's specific requirements as a healthcare logistics provider. Picking accuracy was identified as the most critical factor because errors in healthcare logistics can have serious consequences for service quality and patient supply. Furthermore, the ability to handle SKU diversity, varying demand patterns, and changes in product mix was considered highly important, since the order profile includes both high- and low-frequency items and requires flexibility in daily operations. Storage density was ranked lower because high space efficiency does not create sufficient value if the system cannot support the actual order profile.

At the same time, throughput was considered more important than storage density, because the warehouse must still be able to handle the required order volumes efficiently. VGR also highlighted the importance of modular, scalable, and stepwise implementable solutions that can be introduced gradually without disrupting ongoing operations. This was especially important because a highly automated warehouse would be difficult to implement in the current organizational context, where a phased or hybrid approach was considered more realistic than a fully automated solution. Consequently, the calculated weights represent VGR's preferences and priorities rather than the researchers' subjective judgement. Solving this optimization model yields the mathematically consistent weights presented in table 5.2.

The resulting consistency indicator (ξ) is 0.0390. For five criteria with a maximum preference of $a_{BW}=6$, the Consistency Index (CI) is 3.00 and the Consistency Ratio (CR) is calculated as:

$$CR = \frac{\xi}{CI} = \frac{0.0390}{3} = 0.0130$$

Since the CR value is close to zero (well below the standard 0.10 threshold), it indicates an exceptionally high level of consistency in the pairwise comparisons, validating the reliability of the weights.

5.4.2 Warehouse physical automation selection framework

With the criteria weights established, the multi-stage matching framework is implemented to evaluate the candidate technologies.

Binary qualifying results

All technologies were evaluated against the four qualifying factors (Q1–Q4). The qualifying factors represent minimum operational requirements that must be satisfied for a technology to be considered feasible within VGR's warehouse environment. A technology was qualified only if it demonstrated the ability to support all qualifying factors. Technologies that failed to

Table 5.2: BWM Pairwise Comparison Vectors and Derived Weights

Criteria code	Comparable factor	Best to others vector	Others to worst vector	Optimized weight
CF1	Picking accuracy	1	6	0.4286
CF2	Versatility handling	2	4	0.2338
CF3	Throughput capacity	3	3	0.1558
CF4	Modularity and scalability	4	2	0.1169
CF5	Storage density	6	1	0.0649

satisfy one or more qualifying factors, or where significant operational limitations were identified, were excluded from the comparative evaluation.

Traditional crane-based AS/RS: *Disqualified.* Although crane-based systems provide high storage density and efficient pallet handling, they are primarily designed for standardized pallet flows and offer limited flexibility when handling VGR's diverse SKU portfolio and changing operational requirements. Furthermore, the system structure makes phased implementation and future adaptation difficult, reducing alignment with VGR's demand profile and item characteristics (Q1 and Q2).

A-frame automated dispensing systems: *Disqualified.* A-Frame systems are designed for standardized pharmaceutical packaging and high-volume dispensing of uniform products. They cannot effectively accommodate VGR's wide range of product dimensions, packaging types, and medical consumables, making them unsuitable for the warehouse's SKU diversity and handling requirements (Q2 and Q4).

Carousel-based AS/RSs: *Disqualified.* Carousel systems provide efficient storage for slower-moving inventories but offer limited throughput capacity and scalability. Consequently, they are unlikely to support VGR's current throughput baseline and future

growth requirements while maintaining sufficient operational flexibility (Q1 and Q3).

VLMs: *Disqualified.* VLMs provide high storage density and proper inventory control but are constrained by a single-extractor mechanism that limits throughput performance. As a result, they are more suitable for slower-moving inventories than for VGR's high-volume and variable order fulfillment operations (Q3).

Pallet shuttle systems: *Disqualified.* Pallet shuttle systems are designed primarily for deep-lane pallet storage and reserve inventory management. While they can support bulk storage requirements, for example for the reserve inventories at VGR, they cannot independently perform the piece-picking activities required to satisfy VGR's demand profile and SKU characteristics (Q2 and Q3).

Cube-based AS/RSs: *Qualified.* Cube-Based AS/RS systems are highly compatible with VGR's small- and medium-sized product profile and provide excellent storage density while utilizing the available building height efficiently. Furthermore, throughput can be increased through additional robots, enabling the system to accommodate future demand growth and preparedness requirements (Q1, Q2, Q3 and Q4).

Shuttle-based storage and retrieval systems (AVS/RS and multi-shuttles): *Qualified.* Shuttle-based systems provide high throughput capacity, support a broad range of tote and carton sizes, and offer strong scalability through the addition of shuttles and lifts. These characteristics make them well suited to VGR's demand profile, SKU diversity, and future growth requirements (Q1, Q2, Q3 and Q4).

AMR / RMFS: *Qualified.* RMFS solutions provide a highly flexible and modular automation approach capable of handling diverse product portfolios and changing operational requirements. The fleet-based design enables gradual system expansion and supports both current throughput requirements and future growth, while maintaining a high degree of adaptability to evolving warehouse operations (Q1, Q2, Q3 and Q4).

Weighted comparison and technology selection

The three qualified technologies, Cube-Based AS/RS, Shuttle-Based AS/RS, and AMRs/RMFS, are scored on a scale from 1 (poor) to 10 (excellent) across each comparable factor based on their performance capabilities and suitability for VGR's operational requirements. The scoring reflects both the technology characteristics identified in the literature review and the feedback provided by VGR's Process Manager and Department Manager. The performance scoring matrix and final weighted scores for the three qualified technologies are presented in table 5.3.

Analysis of technology performance and matching

The multi-criteria result reveals that AMRs/RMFS achieve the highest performance score of 8.49, followed by Shuttle-Based AS/RS (8.39), and Cube-Based AS/RS (8.13). Each technology has distinct operational advantages that match specific requirements within VGR's warehouse.

Cube-based AS/RS for small-to-medium items: This technology is highly suitable for VGR's small-to-medium item profile and performs particularly well in relation to picking accuracy and storage density. By utilizing the available building height efficiently, Cube-Based AS/RS provides dense storage for a large number of items while supporting a high level of inventory control. This makes the technology well suited for items that require compact storage and reliable retrieval. However, its lower performance in versatility handling means that it is less flexible than AMR-based solutions when it comes to diverse product types.

Table 5.3: Performance scoring matrix and weighted total scores

Comparable factor	Weight (w_j)	Cube-based AS/RS		Shuttle-based AS/RS		AMR / RMFS	
		Score (P_j)	Weighted score	Score (P_j)	Weighted score	Score (P_j)	Weighted score
CF1: Picking accuracy	0.4286	9	3.8574	9	3.8574	8	3.4288
CF2: Versatility handling	0.2338	6	1.4028	7	1.6366	9	2.1042
CF3: Throughput capacity	0.1558	9	1.4022	10	1.5580	9	1.4022
CF4: Modularity and scalability	0.1169	7	0.8183	7	0.8183	10	1.1690
CF5: Storage density	0.0649	10	0.6490	8	0.5192	6	0.3894
Total Weighted score (S)	1.0000	—	8.1297	—	8.3895	—	8.4936

Shuttle-based AS/RS (AVS/RS & multi-shuttles) for high throughput: Shuttle-based systems achieve the highest throughput capacity score. Their ability to separate horizontal and vertical movement allows multiple shuttles to operate simultaneously, which supports high transaction volumes and reduces cycle times. This makes the technology particularly suitable for VGR's need to handle peak demand and maintain high operational capacity. Shuttle-based systems also perform well in picking accuracy, but they are slightly less flexible than AMRs and somewhat less space-efficient than Cube-Based AS/RS.

AMRs / RMFS for flexible goods-to-person flow: AMRs are the strongest match for VGR's need for versatility handling and modular scalability. By delivering inventory pods directly to stationary workstations, AMRs reduce operator travel time and support a more flexible and adaptable warehouse design. This makes the technology particularly attractive in a setting with high SKU diversity, changing packaging requirements, and a preference for phased implementation. AMRs also allow VGR to expand capacity gradually by adding more robots or pods as operational needs increase.

The case for dual-tier qualification

This study adds a deeper step to the evaluation process to see if a technology can be qualified for a specific area or function in the warehouse. The standard framework uses a strict pass or fail rule for the whole warehouse. However, a single type of technology may not handle an entire facility that manages more than 14,000 active items with very different physical needs. Instead of completely excluding the options that failed the first filter, this section looks at whether some technologies can work well as smaller solutions in specific warehouse areas or functions. This approach ensures we do not miss helpful solutions just because they do not fit the entire warehouse operations and zones. To achieve this, the technologies were evaluated on two distinct levels:

- Tier 1: Standalone facility-wide qualification: Evaluating if a technology can independently manage all material flows and SKUs across the entire facility.
- Tier 2: Zonal or complementary qualification: Evaluating if a technology can handle a part of material flows and storages within the warehouse, even if it cannot support the entire facility operations.

This dual-tier logic clarifies the importance of separating tote-based shuttle systems from pallet shuttle systems in Chapter 3. If combined into a single shuttle-based system category, the technology would technically pass the tier 1 qualification because the tote-based systems can process piece-picking demands. However, combining them would lead to inaccurate scores in our evaluation matrix. A single category would force a single, compromised score for Versatility Handling and Storage Density, masking the operational reality that pallet shuttles provide deep-lane density for bulk unit loads but zero piece-picking capability.

Separating these categories allows to recommend the right technology for the right warehouse zone. While tote-based shuttle systems qualify for high throughput piece-picking areas, pallet shuttle systems are qualified as a tier 2 zonal solution dedicated to VGR's bulk deep stock zone. Similarly, VLMs are rescued from complete elimination. While a single VLM cannot support the total daily facility throughput due to mechanical extractor limits, it represents the optimal tier 2 solution to house the slow-moving category C SKUs.

In conclusion, the analysis shows that the future distribution center is unlikely to rely on only one single technology. Instead, a hybrid technology solution is proposed as a highly promising direction, combining different systems to match the specific needs of each warehouse zone. This combination should not be viewed as a final, absolute recommendation, nor is it a random collection of technologies. Instead, it represents a promising conceptual example that is supported to some extent by the empirical findings of this study.

The primary support for this suggestion is that the warehouse consists of several distinct zones and manages a wide variety of items with different physical and operational requirements. For example, fast moving items require high picking accuracy and rapid throughput, whereas bulk reserve stock requires high density storage and efficient pallet handling and slow moving items require compact, space efficient storing. To show how these requirements can be matched with specific technologies, a potential hybrid combination is outlined in table 5.4.

Table 5.4: A potential hybrid combination of different technologies

Warehouse area	Items	Suggested technology	Expected operational benefit
Main piece picking	Fast moving and small	AMR / RMFS or a Cube-based ASRS	Maintains high picking accuracy and minimizes operator travel time
Bulk storage	Deep reserve stock	Pallet shuttle systems	Maximizes storage density and ensures safe and efficient pallet handling
Slow moving	Category C	VLMS	Floor space utilization

Because of the shallow analytical scope, it is not possible to be completely certain whether a primary qualified technology actually needs complementary technologies to achieve VGR's goals, or if it could succeed on its own. This uncertainty is partly due to gaps in the available master data, such as missing weight and dimension specifications and partly because of insufficient level of details in technical specifications when evaluating several warehouse physical automation technologies based on selected research.

For these reasons, the suggested hybrid setup should be interpreted as a promising conceptual design rather than a final, definitive plan. It demonstrates how different systems can work together to solve the unique challenges of different warehouse zones, providing a structured foundation for future detailed plans.

6. Discussion

This chapter discusses the main findings of the study in relation to the research aim and the empirical analysis of VGR's warehouse operations. The discussion reflects on the suitability of the proposed improvement measures and automation technologies, as well as the operational risks, sustainability aspects, and limitations associated with the recommendations. It also considers how the findings may be generalized to similar healthcare logistics environments and what they contribute to the field of warehouse process improvement and automation selection.

6.1 Evaluation of technology ranking and matching

The technology matching results should be interpreted as a structured decision support outcome rather than as an exact and fixed ranking. The scoring of the qualified technologies was based on VGR's contextual assessment of how each technology would perform in the Sisjön environment, rather than on theoretical maximum performance. VGR's Department Manager explicitly noted that the scores were intended to reflect expected performance in their operational context, and that flexibility, variation handling, and stepwise implementation were more important than maximizing storage density.

This introduces a degree of uncertainty into the ranking, since the final result depends on expert judgment and on the selected weights of the comparable factors. Small changes in the weights or in the technology scores could therefore affect the ordering of the top-ranked alternatives. In particular, Cube-Based AS/RS scores highest on storage density, while AMRs/RMFS score highest on versatility and modularity. This means that the final ranking is sensitive to how strongly VGR prioritizes density versus flexibility. Because VGR emphasized that a stepwise or hybrid automation approach is more realistic than a fully automated solution, the ranking should be viewed as indicating the most suitable technology directions rather than a single definitive winner.

Overall, the ranking appears reasonably robust in direction. The small score differences between the three qualified technologies indicate that a different weighting emphasis could shift their relative order. For that reason, the results are best interpreted as a context-dependent ranking that supports the recommendation of a hybrid automation strategy rather than a single stand-alone technology.

6.2 Operational risks and challenges

While the proposed improvement initiatives offer significant potential to enhance warehouse performance, their implementation is associated with several operational risks and challenges. Both improvements in manual operations and physical automation solutions introduce uncertainties that may affect implementation success and long-term performance. Improvements in manual processes are largely dependent on human behavior and organizational commitment, whereas automation technologies introduce technical, and integration related risks. Therefore, it is important to consider these challenges when evaluating the feasibility and expected benefits of the proposed solutions.

6.2.1 Challenges in improvement suggestions for manual operations

The proposed manual operation improvements rely on employee compliance. Activities such as pallet labeling, structured delivery scheduling, and revised picking procedures require employees to follow standardized work methods. Consequently, human errors, resistance to change, and insufficient training may reduce the effectiveness of the proposed improvements (Bortolini et al., 2018).

Another challenge concerns sustainability over time. Continuous commitment to standardized procedures requires management support and ongoing performance monitoring. Without regular follow-up, employees may gradually return to previous working practices, reducing the long-term benefits of the improvements (Liker, 2004).

Furthermore, some of the proposed improvements may create new operational challenges if not carefully implemented. For example, VGR management highlighted that velocity-based slotting could increase congestion in areas close to the consolidation zone. Since high-frequency SKUs would be concentrated in a limited area, picker traffic may become more intensive, potentially increasing travel interference, waiting times, and local bottlenecks during peak periods. Therefore, the benefits of reduced travel distances must be balanced against the risk of increased congestion.

Finally, manual operation improvements have limited scalability. As order volumes and inventory levels increase, additional labor resources are typically required to maintain performance. This is because order picking is the most labor- and cost-intensive warehouse activity, accounting for 50–75% of total operating costs and nearly 55% of labor time (De Koster et al., 2007). Consequently, scaling manual operations to meet growing demand can lead to rising operational costs over time.

6.2.2 Physical automation challenges

Although automation technologies such as Cube-based AS/RS systems, AMRs, and pallet shuttle systems offer significant operational benefits, their implementation involves substantial challenges.

One major challenge is the high initial investment required for purchasing equipment, modifying warehouse layouts, and integrating automation with existing information systems (Roodbergen & Vis, 2009). Additionally, integration between automation technologies and warehouse management systems can be technically complex and require significant customization efforts (Roodbergen & Vis, 2009).

Operational reliability represents another challenge. Automated systems depend on software, sensors, communication networks, and mechanical components. Equipment failures, software errors, or power outages can disrupt warehouse operations and create significant downtime if contingency plans are not established (Berglund & Persson, 2025).

Furthermore, automation implementation often requires organizational adaptation. Employees must acquire new technical competencies and learn to work alongside automated systems. Resistance to technological change and uncertainty regarding future job roles may negatively

affect implementation success if change management activities are neglected (Romero et al., 2022).

Automation solutions generally provide less flexibility than manual processes. Changes in product assortment, storage requirements, or operational flows may require costly system modifications after implementation, reducing the organization's ability to adapt rapidly to future changes (Gu et al., 2007)

A further critical challenge concerns the availability and quality of data used as input for process improvement and performance modelling. The master data available at Sisjön contained significant gaps: linear dimensions, weights, and heights were entirely absent from the system, and approximately 50% of active articles lacked a recorded volume specification. Additionally, rounding errors in volume recording and the complete absence of pallet dimensional data reduced the precision of storage capacity estimations and technology dimensioning. Since automation systems rely heavily on precise and structured data inputs, these master data deficiencies may lead to suboptimal system design choices or reduced operational performance after implementation.

6.3 Sustainability aspects of the study

This section focuses on human and social aspects of sustainability regarding warehouse physical automation technology implementation. These social sustainability factors play a critical role in the successful implementation of both improvements in manual processes and automation technologies. The proposed improvements in manual operations require active employee participation and depend heavily on workforce engagement. For instance, Liker (2004) showed that employee involvement in improvement activities is a key success factor in lean implementation and continuous improvement initiatives.

At the same time, the introduction of automation can create concerns regarding job security and changing work responsibilities. Employees may perceive automation as a threat to existing roles, which potentially creates organizational resistance to implementation. Therefore, management should emphasize employee involvement, transparent communication, and skills development throughout the transition process. Rather than replacing employees, physical automation should be viewed as an opportunity to transition workers toward more value-adding activities and process improvement.

Assuming that VGR implements a hybrid warehouse layout that combines partial automation with manual operations, the organization must evaluate the human-centric and organizational changes introduced by physical automation as necessary to ensure long-term sustainability. This evaluation is necessary to align fully with institutional social sustainability directives and to address evolving job profiles and technical skill prerequisites.

Logistics research shows that automated systems are expected to replace 40% to 60% of entry-level warehouse jobs over the next ten years (Garaga, 2025). Specifically, picking roles face the highest displacement at 64.7%, followed by packing at 51.3% and inventory management at 43.8% (Garaga, 2025). Although these global industry trends point toward high worker displacement, the strategy for VGR is fundamentally different due to specific capacity constraints. Because VGR operates under a strict floor density limit of 29 operators,

the primary objective of automation is not headcount reduction. Instead, automation acts as a capacity-enhancing tool to safeguard the existing workforce from extreme workloads, helping them handle high demand and eliminating the current 16% operational overtime rate.

Even though headcounts will remain stable, automation will significantly change daily worker roles. Garaga (2025) explained that regular warehouses allocate 71.4% of roles to manual tasks, while automated warehouses require 63.8% of positions to have technical skills. This shift creates risks for workers who lack technical training or are over 40 years old, as they often face difficulties adapting or finding new employment (Garaga, 2025). To address this risk within the case study environment, VGR's management team needs to evaluate the age and skill profile of their current workforce during transition planning. This evaluation will allow the organization to design targeted training and upskilling programs, ensuring a socially sustainable transition to the automated systems.

To address ergonomic sustainability, when designing the automation phase of warehouse operations, planners must carefully evaluate how human-robot collaboration affects the physical well-being of operators. According to Zhang et al. (2023), integrating autonomous mobile robots and human pickers into a shared hybrid order picking system can significantly reduce the total daily physical workload of employees. Because the automated robots handle the long-distance material transportation and navigation tasks, they directly decrease the total walking distance of the human staff. Consequently, this system design shifts the human role away from travel intensive tasks, allowing workers to spend a higher percentage of their working shift performing direct picking actions.

Despite these operational efficiencies, the reduction in walking time creates distinct ergonomic hazards that require active management. Zhang et al. (2023) observed that because human operators save travel time, they remain inside focused picking zones and handle items at a much higher frequency. This concentration of activities increases the continuous repetition of manual lifts, exposing workers to a higher ergonomic risk for work-related musculoskeletal disorders (MSDs) and physical fatigue.

To ensure operational sustainability and safety during the automation phase, management must implement specific protective strategies:

- **Item weight restrictions:** Operations planners should use lifting guidelines to set strict limits on the maximum weights handled by humans in high-frequency picking areas.
- **Rest allowances:** Introducing structured rest breaks or shorter work rotation cycles within the human team can significantly mitigate repetitive strain injuries without hurting total warehouse throughput.
- **Layout adaptation:** Designing a wide warehouse layout with wider picking aisles provides adequate physical space for parallel human-robot movements, lowering worker stress and delays caused by physical picker blocking.

6.4 Limitations and future research

Several limitations should be considered when interpreting the findings of this study.

First, the research was conducted as a case study within one healthcare logistics organization. While this approach enabled an analysis of operational challenges and improvement opportunities, it limits the generalizability of the findings to other organizational contexts (Yin, 2018).

Second, although the study utilized multiple complementary methods, including process mapping, material flow analysis, interviews, literature review, and a multi-criteria decision-making framework, which strengthened the validity of the findings through methodological triangulation, the proposed solutions were not physically implemented or empirically validated within the organization. Consequently, the expected performance improvements are based on analytical assessments and existing literature rather than direct operational evidence. Therefore, the actual impact of the proposed improvements in manual processes and automation solutions may differ from the outcomes predicted in this study.

Third, several assumptions were made throughout the analysis. The proposed solutions assume that current demand levels and material flows remain relatively stable over time. Furthermore, the evaluation assumes that the suggested automation technologies can be successfully integrated into the existing warehouse infrastructure and information systems. It is also assumed that employees will receive sufficient training and support during implementation. Changes in these conditions may affect the actual performance and feasibility of the proposed solutions.

Future research could focus on implementing and evaluating the recommended solutions in practice to measure their actual impact on warehouse performance. Additional studies could also compare the proposed automation technologies using simulation modelling or cost-benefit analyses. Furthermore, future research could investigate employee perceptions of warehouse automation and explore strategies for managing organizational change during automation implementation.

6.5 Research contribution and generalization of findings

This study helps VGR in two main ways: it suggests economic and customized process improvements and provides a clear, step-by-step way to choose the right warehouse technology without being tied to a specific brand. By fixing current problems and planning for the move to a new building, this work gives VGR quick operational relief and a safer way to make long-term investments.

The main practical contribution is the list of improvements in manual processes. Together, these create a highly efficient, non-automated setup for the new warehouse. These suggestions came directly from mapping the material flows. They target paperwork, transport, and handling wastes that used to slow things down and cause bottlenecks. By moving tasks away from single, central desks and using mobile tools instead, these ideas save a lot of work hours on the shop floor. For example, cutting out extra walking and removing double-checks

directly helps operators pick faster. Saving this time means the warehouse can handle busy periods during normal shifts, reducing the need for expensive overtime.

The manual ideas also improve quality and keep data accurate. They replace quick visual checks with better physical layouts, standard boxes, and set delivery times. This makes picking less tiring for workers and cuts down the delays. Most importantly, by using these manual fixes first, VGR can see what it can achieve without technology. This helps them find the exact gaps only automation can solve, preventing them from buying expensive, overly complex systems they do not actually need.

Along with the manual fixes, our evaluation guide serves as an objective manual for buying new equipment. Instead of just trusting what vendors say or following popular trends, it uses a two-stage decision model. This model bases all technology choices on VGR's actual situation, including their characteristics of products and demand patterns. It filters automation options through strict requirements first, and then scores the remaining choices. This makes sure any chosen system fits the new facility's goals and constraints.

Finally, using the Best-Worst Method (BWM) helps solve conflicting goals in a mathematical way, like balancing the need for more storage space with the need to pick and ship orders quickly.

Even though we focused on a regional healthcare warehouse, other warehouses can easily use the same step-by-step method. By separating the planning steps from specific brands or temporary local issues, we created a general four-phase framework: Diagnose, Improvements in Manual Operations, Gap Assessment, and Technology Matching.

To show how this method works as a general planning template, table 5.5 compares our structured approach against common, less organized buying practices.

Other warehouses can use this four-phase method by simply plugging in their own data, product sizes, and physical and operational constraints. Within this framework, using the HATS categories helps find wastes and operational costs by breaking down all the activities along an item's flow. This is very helpful in strict or complex sectors where different product sizes and flows make the evaluation and assessment complex.

Additionally, using the brand-free matching process gives any future logistics project a clear way to handle conflicting goals, see if problems can be fixed through better manual work alone, or find the exact size and type of automation needed for the long run.

7. Conclusion

This thesis has analyzed the current warehouse operations at VGR's Sisjön Distribution Centre and identified several operational gaps related to productivity, accuracy, storage capacity, and future preparedness requirements. Through site observations, interviews,

Table 5.5: Comparison of traditional logistics procurement and the proposed framework

Evaluation area	Traditional way	Our structured method	Why it generates value
Starting assessment	Relying on personal opinions or casual observations of the floor	Measuring flows using the HATS framework	Creates a standard way to find waste in any warehouse, no matter the industry
What to fix first	Automating current manual work directly, even if it is slow or messy	Making manual work as efficient as possible before buying automation	Finds the true performance limit of manual work and shows exactly where automation is needed
How to filter technologies	Asking vendors for proposals right away with no set rules	Using clear physical and operational gates to filter options	Quickly eliminates systems that cannot fit the building or the product types
Deciding what is important	Guessing priority or using simple tables where every goal is treated the same	Comparing goals in pairs using the Best-Worst Method (BWM)	Uses math to solve conflicting goals in a reliable, logical way
Long-term success	High risk of overspending, technical errors, and buying the wrong system	Choosing technology based on how well it fits the specific context and goals	Keeps choices independent of brands, making the system flexible for the future

transactional and master data analysis, and material flow mapping, the study established a comprehensive understanding of the warehouse's current performance and the challenges associated with the planned relocation to a new facility.

Based on the empirical findings, several improvements in manual processes were developed, focusing on process standardization, slotting strategies, picking methods, and inbound and outbound process improvements. The analysis indicates that these improvements can significantly reduce non-value-adding activities, improve operational efficiency, and increase warehouse performance without requiring major technological investments. However, the gap assessment also demonstrated that improvements in manual processes alone are unlikely to fully satisfy VGR's long-term requirements related to inventory and picking accuracy, throughput capacity, future growth, and preparedness demands.

To address the remaining performance gaps, a range of warehouse automation technologies were evaluated using a structured multi-criteria decision-making framework. The evaluation showed that among others, RMFS/AMRs, shuttle-based AS/RS and cube-based AS/RS met the minimum requirements to operate as standalone, facility-wide solutions. However, each of these technologies has unique trade-offs, meaning no single system is perfect for every operational task. To solve this, a dual-tier qualification analysis was used to evaluate systems at both a facility-wide and zonal level. This step showed that some disqualified technologies in the first-tier qualification filter could still provide value as complementary solutions in specific zones or functions. For example, pallet shuttle systems are suitable for bulk reserve storage, while VLMs are ideal for slow moving SKUs. These findings support the final recommendation to implement a solution, combining different technologies to maximize overall performance.

From a practical perspective, the study provides VGR with a structured and evidence-based foundation for future warehouse design decisions. From a research perspective, the study demonstrates how material flow analysis, warehouse design principles, and multi-criteria decision-making methods can be integrated into a framework for evaluating warehouse improvement initiatives and automation technologies. While the specific recommendations are tailored to VGR's operational context, the methodology and decision-making approach can be generalized beyond healthcare logistics to other warehousing operations facing similar challenges related to growth, efficiency, and automation planning.

Overall, the study concludes that the highest future performance improvements can be achieved through a combination of improved manual processes and carefully selected automation technologies. By combining these approaches, VGR can improve productivity, maintain high service quality, and create a scalable warehouse solution capable of supporting future operational and preparedness requirements.

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DEPARTMENT OF TECHNOLOGY MANAGEMENT AND ECONOMICS
DIVISION OF SUPPLY AND OPERATIONS MANAGEMENT
CHALMERS UNIVERSITY OF TECHNOLOGY

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