AutoStore performance and the influence of context and configurations

A multiple case study

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Acknowledgments

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Contribution: This thesis has been a complete elaboration between the two authors. Each author has been involved in every part of the process and contributed equally.

Lund, May 2023

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Daniel Lundkvist David Flyrin

This is version 2(2) of our thesis due to the discovery of a minor error in a number in the previous version.

Abstract

Title	*AutoStore performance and the influence of context and configurations*
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Supervisor	Joakim Kembro, Division of Engineering Logistics, Department of Mechanical Engineering Sciences, Lund University. Maximilian Grudeborn, Delivery Director Sweden, Element Logic
Problem description	Multiple cases show that companies can improve performance after implementing an AutoStore system. However, research on optimizing the design and how to successfully control the AutoStore system is limited. Furthermore, studies focusing on optimizing operations around Robot-based Compact Storage and Retrieval Systems (RCSRS) in general, are important for the development of operation efficiency, but are also currently lacking. Today, Element Logic does not have a clear overview of what, and how, contextual factors and configurations are correlated to performance of the AutoStore system.
Purpose	Evaluate what, and how, different contextual factors and configurations affect the performance of the AutoStore system, and how they should be handled to increase performance.
Research Questions	**RQ1**. What contextual factors and configurations are affecting the performance of the AutoStore system? **RQ2**. How do the contextual factors and configurations affect performance of the AutoStore system? **RQ3**. How should the contextual factors and configurations be handled in order to improve the performance of the AutoStore system?
Methodology	Investigation has been using a multiple case study, to locate key differences in ways of working around the AutoStore as well as the influence of different contexts. The multiple case study provided the ability to compare and generalize improvements rather than optimizing one specific case.
Findings	Seven out of eight investigated contextual factors had an influence on the performance to varying degrees, with their corresponding configurations. This thesis resulted in 14 propositions and recommendations for companies using an AutoStore, and sellers of the AutoStore system.
Conclusion	Measures to lower complexity and uncertainty, remove time-consuming activities from ports, and align configurations with contextual factors, are advantageous actions when operating an AutoStore.
Keywords	AutoStore, RCSRS, automated small-parts warehouse, goods-to-person picking, compact storage system, contextual factors, configurations, contingency theory, optimization, performance

Abbreviations and definitions

Abbreviations

AS/RS	Automated Storage and Retrieval System
KPI	Key Performance Indicator
RCSRS	Robot-based Compact Storage and Retrieval System
RMFS	Robotic Mobile Fulfillment System
SKU	Stock Keeping Unit
TOC	Theory of Constraints
WMS	Warehouse Management System

Definitions

AutoStore System	The whole AutoStore System including grid, robots, ports, software, etc.
Bin Presentations/h	A KPI that represents the number of bin-presentations per hour (per port).
Bin Preparation	Percentage of bins on the top layer that have been prepared as the next bin to pick.
Forecasting	Software setting that takes bins “to be picked in the next order release” into account when handling bins.
Order Release	Companies releasing customer orders from the internal system to eManager (for bin preparation).
Pick Strategy	The pick strategy used when choosing the locations to pick bins from.
Pick wave	Contains groups of orders, often used when many orders are similar in for example using the same transportation mode, shipped by the same carrier, or have the same date and time they should be picked.
Queue	A queue includes certain types of orders, for example B2B- or B2C orders.
“Waiting for Bin”	A KPI that represents the amount of seconds the user in a port waits for the AutoStore system to deliver a bin.
“Waiting for User”	A KPI that represents the amount of seconds the AutoStore system waits for a user in a port to be ready for the next bin.

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1. Introduction

Warehousing around the world has in recent times been growing in importance. The increase in e-commerce (Chevalier, 2022), the uncertainties related to the recent pandemic (Monteiro, 2022), and the need of becoming both more responsive and efficient to meet the demands of customers, are some aspects straining on staying competitive in warehouse operations. Customers are demanding a larger variety and accessibility through the internet, and the standards and expectations in delivery times are challenging to keep up with (Andriansyah et al., 2014). These aspects are making it more complex to configure a warehouse that performs well and satisfies all these needs and requirements. Warehouse processes such as put-away and picking are expected to be fast, efficient, and precise. These processes can look very different depending on the context, for example characteristics of the stock keeping unit (SKU), if consolidation is needed for picking, and what the customer expects of the packaging. These aspects require innovative ways of thinking when designing a warehouse in order to stay profitable and relevant. Also, companies are expected to handle impacting events and crises, all while trying to maintain a standard that is already difficult to achieve.

The increasing requirements to meet have led more companies to automate their logistical processes in the hope of improving their performance (Custodio & Machado, 2020). Automation shows a potential gain in throughput (Andriansyah et al. 2014), where automating large parts of picking and put-away processes, can raise accuracy, speed, and compact storing. One of these automated systems is AutoStore, which aims to increase performance by utilizing warehouse space and streamline warehouse operations for its customers. AutoStore is a robot-based compact storage and retrieval system (RCSRS). It stores goods by having them in plastic bins stacked on top of each other in a cubic layout to achieve a high space utilization compared to other storage systems, see Figure 1.1 (Trost et al., 2022; AutoStore, 2023a). Robots traveling on top of the grid, dig up requested bins and deliver them to workstations, also known as ports, where an operator picks products from the bin (AutoStore, 2023b; Element Logic, 2023a). Besides picking, ports are also used for put-away, where operators manually put the products into bins which are then received by the AutoStore system (Element Logic, 2023a).

Figure 1.1. The AutoStore unit, robots, bins and ports (AM Logistic Solution, n.d.).

Although AutoStore comes with a lot of potential, challenges are still present in the transition from a manual to an automated warehouse (Element Logic, 2023b). With a newly implemented AutoStore system, it is expected to achieve a certain performance agreed upon by both seller and customer. The performance is measured with three Key Performance Indicators (KPIs) connected to the AutoStore system, which are explained in Table 1.1 below. The KPIs are part of the contract between the seller and the customer, which also includes specific values of these KPIs that are promised to be achieved with the given AutoStore setup.

Table 1.1. List of KPIs defining performance for AutoStore system with explanations.

KPI:	**Explanation:**
Bin presentations/h (per port)	The amount of bin presentations/h per port (on average).
"Waiting for Bin"	The number of seconds the user in a port waits for the AutoStore system to deliver a bin (on average).
"Waiting for User"	The number of seconds the bin in a port waits for the user to finish the current put-away/pick (on average).

The performance of the AutoStore is affected by different components, where some are more known than others. Kembro and Norrman (2020) discuss "configurations", which is the combination of the operations, design aspects, and resources in a warehouse. With an implemented AutoStore, the configurations around the system can look very different among companies. These configurations can affect the performance, depending on the activities around the put-away- and picking process, together with possible bottlenecks in the processes (Element Logic, 2022a).

Also, companies operate in different contexts in terms of their customers, product characteristics, and order characteristics. These contextual factors can in turn affect the configurations and/or performance of the company.

How are these configurations affected by the contextual factors of the organization? Is the way of working in warehouses limiting to what extent the AutoStore can perform? How well the AutoStore system can perform is heavily affected by the contexts one allows it to operate in, but what these affecting contexts are, and their weight, is yet fairly undiscovered (Element Logic, 2022a).

1.1 Problem formulation

Multiple cases show that companies can improve performance after implementing an AutoStore system. However, the extent of improvement varies significantly depending on how the AutoStore is incorporated into the warehouse operations. Element Logic is a company providing AutoStore solutions to their customers, and is collaborating with us during this thesis. Research on optimizing the design and how to successfully control the AutoStore system is limited (de Koster, 2022). Also, Jaghbeer et al. (2020) recognized the scarcity of empirical research in the field of automation in order picking systems. Furthermore, studies focusing on optimizing operations around RCSRS are important for the development of operation efficiency, but are currently lacking (Ko & Han, 2022).

How organizations choose to implement the AutoStore for their specific operation varies greatly. It is possible to have different configurations, such as different software settings and quantities of ports and robots. The ports themselves can either be used for put-away, picking, or both. Today, Element Logic does not have a clear overview of how contextual factors and configurations are correlated to performance of the AutoStore system (Element Logic, 2022a).

1.2 Purpose of thesis

The purpose of this thesis is: to evaluate what, and how, different contextual factors and configurations affect the performance of the AutoStore system, and how they should be handled to increase performance. An illustration of how contextual factors and configurations are correlated to performance is displayed in Figure 1.2.

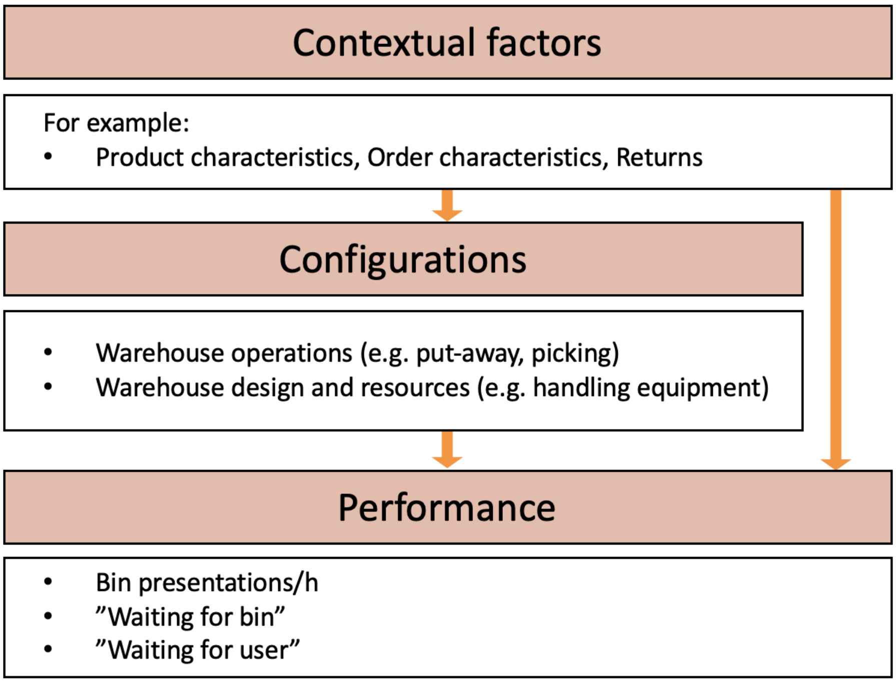

Figure 1.2. Illustration of how contextual factors and configurations are correlated to performance.

After the correlations between contextual factors and configurations in relation to performance are identified, propositions and recommendations will be presented. The recommendations explain how to handle the contextual factors and configurations to increase performance of the AutoStore. This thesis examined the AutoStore systems, contextual factors, and configurations of seven customers of Element Logic within the following industries: Fashion, 3PL, eGrocery, and ePharma.

1.3 Research questions

The research questions below are based on the purpose and aim at structuring the thesis to make sure that the purpose is fulfilled.

RQ1: What contextual factors and configurations are affecting the performance of the AutoStore system?

Element Logic has expressed interest in evaluating what and how contextual factors and configurations affect the performance of the AutoStore system. What are the contextual factors and configurations that are limiting improvement of AutoStore performance?

RQ2: How do the contextual factors and configurations affect performance of the AutoStore system?

The aim was to determine how each contextual factor and configuration directly correlates to the performance of the AutoStore system. Also, how some contextual factors affect the configurations, that in turn affect performance. The initial hypothesis was that some contextual factors and configurations would insignificantly affect performance, while others would heavily affect performance.

RQ3: How should the contextual factors and configurations be handled in order to improve the performance of the AutoStore system?
Seven companies using an AutoStore and operating in different industries will be examined. Therefore, contextual factors and configurations might need to be handled in different ways for each company or industry. Recommendations were created on how the contextual factors and configurations should be handled to improve the performance.

1.4 Focus and delimitations

This thesis is limited to looking at the AutoStore system including the put-away-, storage, and picking operations, as displayed in Figure 1.3. The scope of this thesis starts at put-away when goods have been delivered to the port area, and ends when the goods have been picked and packaged. Examining *all* possible configurations and contextual factors that may affect the output and processes is a complex task and too resource-demanding. Therefore, the scope was defined by identifying key areas through interviews with employees at Element Logic. They provided insights into common problems among their customers.

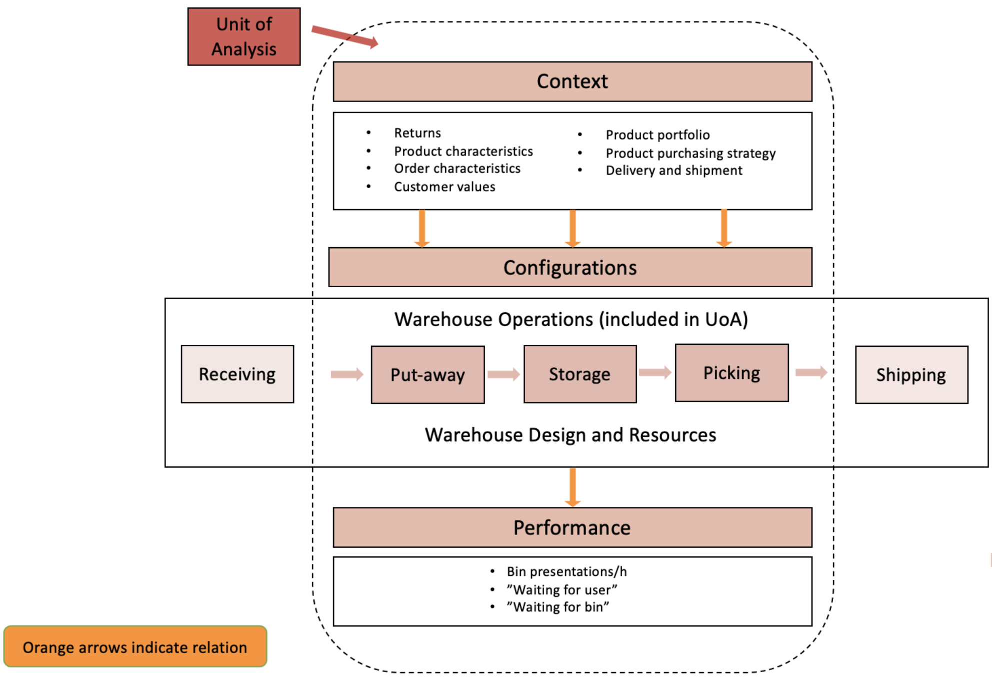

Figure 1.3. Unit of analysis describing the scope of this thesis.

2. Literature review

This chapter covers the researched areas in regards to AutoStore and RCSRSs, and different solutions of automation in warehousing technology. It is divided into two areas; theory & tools for analyzing case companies, and AutoStore research. First theory & tools for analyzing case companies will be presented, and after that the AutoStore research. An overview of the areas and topics included in this literature review are displayed in Figure 2.1.

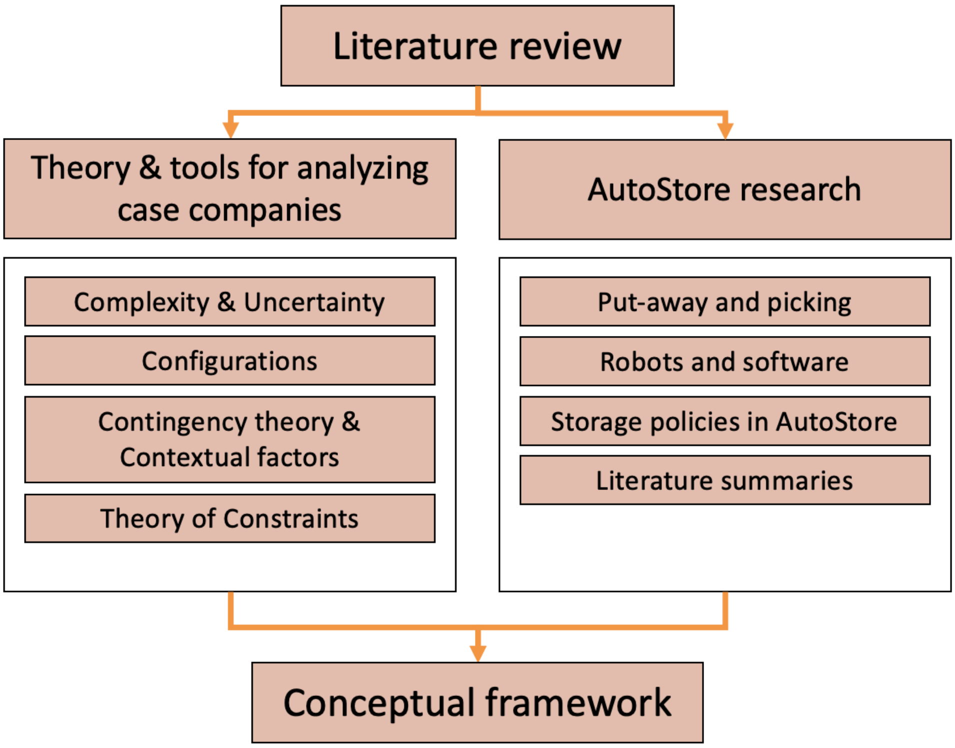

Figure 2.1. Overview of the literature review in this thesis.

Theory & tools for analyzing case companies includes different areas in how warehouse processes can be analyzed, and how complexity and uncertainty affect processes in general. Further, when looking closer on warehouse configurations and contextual factors, the Theory of Constraints (TOC) is applied to effectively identify and analyze bottlenecks, and the reason behind them.

The section of AutoStore research examines existing research made about the AutoStore technology, implementations, and optimization studies revolving automation solutions. It touches upon areas such as algorithm optimization in automated warehousing in general, optimizations in regards to storing and policies of storage, and an overview on RCSRS and similar umbrella terms. These findings are used to locate which areas to examine closer and if researched solutions and optimal ways of working, have made their way into everyday practice.

Utilizing existing research and tools was essential when forming a framework to conduct the study, presented in Section 2.3.

2.1 Theory & tools for analyzing case companies

In this section, literature on theory and tools used to analyze the case companies are presented. All companies were analyzed in terms of complexity and uncertainty from their contextual factors and configurations. Contingency theory was applied to analyze how specific companies align their configurations with its contextual factors to improve performance. Lastly, configurations were assessed by applying Theory of Constraints to locate and handle bottlenecks in processes. This section aims to define and clarify these tools with relevant literature.

2.1.1 Complexity & Uncertainty

Faber et al. (2018) chose complexity and uncertainty as the main warehouse contextual factors, and state that there is consensus between those two factors being important organizational contextual factors in the literature.

"Warehouse complexity refers to the number and variety of items to be handled, the degree of their interaction, and the number, nature, i.e. the technologies used, and variety of processes (including the number and variety of order and order lines and the types of customers) necessary to fulfill the needs and demands of customers and suppliers" (Faber et al., 2002, p.383). When businesses increase their product portfolios as customer demands evolve, they risk adding too much complexity which can tax existing resources (*Unraveling Complexity in Products and Services*, 2006). This was relevant when for example looking at how complex the processes, order characteristics, or product portfolios the companies have, and how that might affect performance.

According to Duncan (1972), uncertainty as a concept has many different definitions in the literature. The definition used in this thesis is inspired by Luce and Raiffa (1957), who defined uncertainty as situations where the probability of the outcome of events is unknown, as opposed to risk situations where each outcome has a known probability. In other words, the less a company knows about the probability, or the less control they have over the outcome of certain events, the higher the uncertainty is.

2.1.2 Configurations

As previously mentioned, Kembro and Norrman (2020) discuss "configurations" related to warehousing, which is a combination of the operations, design aspects, and resources in a warehouse. The operations studied in this thesis include put-away, storage, and picking. Design aspects and resources refer to the physical layout (e.g. Autostore ports and robots), handling equipment (e.g. carton erectors or pick-by-light systems), automation solutions (e.g. conveyors), information systems (e.g. WMS), and labor and activities (e.g. shifts). These resources and design aspects must be considered to manage the warehouse operations effectively and efficiently. These different configurations were important to have in mind when conducting the case company visits. Lastly, the most important configuration goals discussed in literature are to reduce lead time, increase utilization of physical space, reduce material-handling costs, improve safety, and increase total throughput (Kembro & Norrman, 2020). This is interesting since reducing lead time and increasing total throughput are very much connected to the purpose of the thesis.

2.1.3 Contingency theory & Contextual factors

Contingency theory is a theoretical view on organization contingencies (Lawrence & Lorsch, 1967). In essence, the organizational effectiveness results from fitting characteristics of the organization to contingencies that reflect the context of the organization (Donaldson, 2001). The contingency theory has previously been applied in warehousing, (cf. Faber et al., 2018; Kembro & Norrman, 2021). Faber et al. (2018) explored the fit between warehouse management structure and the context in which the warehouse operates, as a significant driver of warehouse performance. The context in which the warehouse operates is further referred to as 'contextual factors'. Contextual factors consider surrounding and internal elements or environments that the examined warehouse is operating in (elaborated in Section 2.3). Their study showed that fitting the warehouse management structure with the warehouse context, leads to a higher performance. In this study contingency theory is applied to contextual factors and configurations, to see how aligning them leads to higher performance. An overview of this is displayed in Figure 2.2.

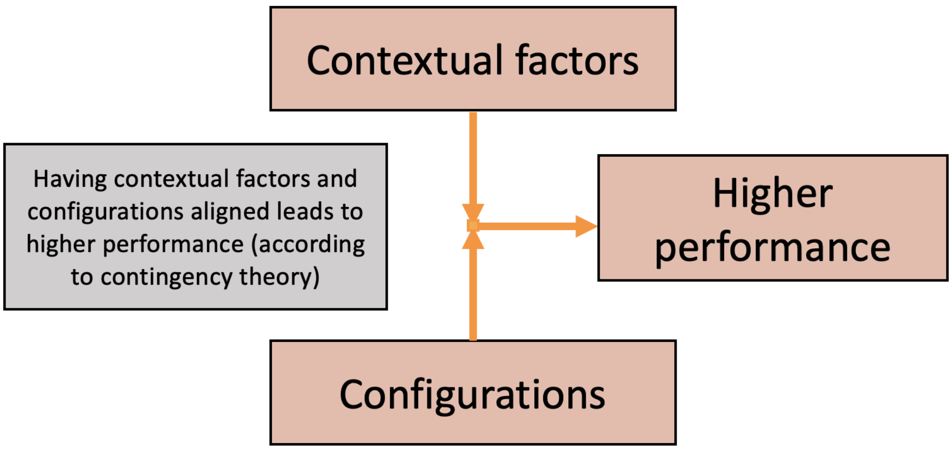

Figure 2.2. Contingency theory on contextual factors and configurations.

As previously mentioned, Faber et al. (2018) chose complexity and uncertainty as the main warehouse contingency factors (contextual factors). Complexity and uncertainty both affect the warehouse management structure, depending on how comprehensive the work that has to be done is (Faber et al., 2018). The more SKUs and the larger variety of SKUs handled in the warehouse, the more differentiated and complex the configurations become (Kembro & Norrman, 2021).

Furthermore, Kembro and Norrman (2021) state that if the goods and packages are standardized, the configurations are more streamlined and integrated. Compared to a retailer with a large variety of SKUs that could need more variation (e.g. different zones, picking methods, and automated solutions). For example, one of the case companies in the study from Kembro and Norrman (2021) had a large number of SKUs with everything from small products to large and bulky goods. Along with this, the company had high requirements on order fulfillment times which lead to three challenges: space, speed and task complexity. To increase speed, there needs to be a fast flow with few handlings, and activities that are similar should be performed as few times as possible. The configurations should also aim to eliminate potential bottlenecks and double handling. To reduce double handling, the decision of when to pack and sort customer orders is getting more important for omnichannel warehouses with variations in packing requirements, delivery times and destinations (Kembro & Norrman, 2021). Lastly, the authors mention the risk of a bottleneck arising in warehouses with large order and material flows. Therefore it was interesting to note how the case company in this thesis handled sorting and packing, as well as the number and variety of SKUs, and the different ways they need to be handled. Overall, complexity and uncertainty were interesting aspects to have in mind before and during the case studies performed in this thesis. Also, how these two aspects correlate to contextual factors and configurations. During the interviews and observations, attention was paid to possible complexity and uncertainty in the configurations.

2.1.4 Theory of Constraints in a warehousing context

Before further exploring the TOC and literature in regards to bottlenecks, clarification must be made on its relation to AutoStore performance. Looking at manual warehousing, there are several measures to take in order to raise effectiveness (i.e. becoming more successful in producing a desired result), and efficiency (i.e. utilizing resources to a greater extent). In the case of AutoStore, the bottleneck is essentially the difference between the system waiting for an operator to put-away/pick, and the operator waiting for the system to present the next bin (Element Logic, 2023c). Depending on which of these two KPIs are highest, gives an indication to where the bottleneck is located and where to start investigating. Examining the relation between TOC and AutoStore, the installed system should perform according to promised performance if its surrounding factors are properly optimized.

The theory of constraints becomes relevant in how manual labor cooperates with automation in many processes, which in this case is relevant for the picking and put-away, where TOC can be used as a tool to manage waste of resources (Naor, et al. 2013). By unsuccessfully integrating the two worlds, bottlenecks in activities may lead to poor utilization of the AutoStore system (Element Logic, 2023a). With the activities around AutoStore mimicking a production line in operations, the analogy of identifying the bottleneck activity becomes interesting to see how it affects the surroundings of the AutoStore and warehouse activities in general. The research around TOC offers well studied tools in how to deal with such challenges (Rahman, 1998) and the theory itself is still one important strategy for companies (Simsit et al., 2014). Some of these tools that have been widely implemented are known as “The Thinking Process” (TP), “The Five Focusing Steps” (5FS), and “Throughput Accounting” (Simsit et al., 2014).

Looking at TP and 5FS, they both are logical approaches in how to optimize operations and eliminate obstacles in processes. Both approaches are extensively used in the industry and each have their own subtools in how to effectively handle constraints. The approaches have steps to identify the constraint, exploiting it, subordinate other processes to it and lastly improve the constraint, before repeating the procedure (Simsit et al., 2014). TP offers subtools to focus on factors preventing the system from functioning optimally, while 5FS offers subtools focusing on the constraints (Simsit et al., 2014).

TOC itself is a useful theory when dealing with process optimization, and was relevant when investigating the bottlenecks at the case companies in relation to AutoStore. By continuously conducting the processes exemplified in TP and 5FS, the processes around the AutoStore would become as optimized as possible. Theoretically, the case company could reach the best-case of all surrounding processes waiting for the system, which is operating at a maximum level without experiencing sub-optimizations. With this theory, TOC becomes a tool to be used when analyzing companies' process lines, where the AutoStore and surrounding activities constitute the central part.

To summarize, the theory and aspects that have been discussed above were used when looking at both the processes and the interaction with AutoStore. Locating where the bottlenecks were constraining the system, and their effects on the performance contributed to the main research questions investigated in this thesis. For example, when observing a case with high "waiting for user", it would indicate that time-consuming steps are dominating the process and the tools of TOC would be applied. If said process is improved and the bottleneck is moved to a scenario of "waiting for bin", it would suggest that the current process is optimized and the scope moves to the system. Analyzing the "waiting for bin", if performance is not at best-case, it becomes the next problem to identify *why* the system is not at best-case speed.

2.2 AutoStore research

In this section, research related to AutoStore or RCSRS in general will be presented. As mentioned in Figure 2.1 above, this section will include the following categories: put-away and picking, robots and software, storage policies, and existing literature summaries. Each subsection includes a description of how the found research was used in this thesis.

2.2.1 Put-away and picking related to AutoStore

In regards to put-away and picking in relation to AutoStore, the aim was to find literature suggesting best practice or studies conducted on how different factors or configurations fit together with the AutoStore or RCSRS in general. It is difficult to find studies focusing on picking and put-away that also integrates RCSRS to some extent (de Koster, 2022). The relevant literature that was found is summarized in Table 2.1 below, including the research area, findings, and how it was used in this thesis.

Table 2.1. Summary of references related to put-away and picking.

Source:	Research area:	Findings:	How it was used in this thesis:
Beckschäfer et al. (2017)	Input- and output policies	Higher efficiency with “empty-bin policy”	Bin configurations, input- and output policies used in case companies was examined
Svensson and Wadsten (2019)	Put-away process in an AutoStore system compared to manual warehousing	The most time-consuming step was transferring pallets with goods to the port, and therefore has the highest potential for improvement.	Examining the processes related to put-away and observations in regards to time-consuming activities.
Tjeerdsma (2019)	AutoStore order processing line redesign	Optimization efforts in the case of PostNL	Look for cases that have implemented similar solutions, or if the generalized recommendations would remove current bottlenecks.
Gallien and Weber (2010)	Pick waves in automated sorters	Optimal waveless picking policy performs equal, or better, than the best policy using waves in all scenarios	Investigate the use of pick waves in empirical findings, if they correlate to similar results for RCSRSs as automated sorters

Beckschäfer et al. (2017) did a simulation study to examine input and output policies for an automated grid-based warehouse system, which the AutoStore system is. By creating a discrete event simulation they could identify optimal settings for the system. The authors examined two policies for input and output from the system, in two cases. In the first case, a bin could only contain one type of product, while in the second case, a bin could contain two types of products, with the help of a divider in the bin. The two policies are called empty retrieval and adding retrieval respectively. The empty retrieval policy makes the system select the next available bin that is completely empty (or has one of the halves completely empty with an existing divider in the bin). The advantage with this policy is that the goods are distributed across in more bins the grid, which increases the likelihood of the goods being closer to the port when they are requested. A disadvantage is the possible lack of empty bins if the system holds many different types of products. For the adding retrieval policy the system seeks a bin that currently contains the same type of product existing in the current order, that also has the enough capacity to store all the existing products plus the amount on the order.

Results show that choosing an empty input policy provided up to 5% higher output efficiency and that dividers in the bin did not result in any significant productivity increase (Beckschäfer et al., 2017). This is due to empty bins being faster to retrieve since they often are located closer to the ports, compared to partially filled bins (for the retrieval policy). For output, the average performance improvement was around 7% when picking from bins that followed the empty retrieval policy. In this setting the bins had no divider and the system had a large number of products stored in it. Beckschäfer et al. (2017) believes this to be because of the orders being satisfied without the need of retrieving multiple bins when numerous units of a product are requested. Compared to, for example, picking from bins with dividers, where a smaller number of each product is stored, that may need multiple bins to satisfy the order. Thus, the bin configurations, as well as input- and output policies used in case companies was something to examine.

A thesis based on a case study performed by Svensson and Wadsten (2019) examined the put-away process in an AutoStore system in contrast to manual warehousing. The results indicated that the most time-consuming step was transferring pallets with goods to the port, and therefore has the highest potential for improvement. Also, suggested future studies in optimization of the whole process around put-away as well as looking at the picking process, would provide a more holistic approach in the manual processes around AutoStore. The findings were used when examining the processes related to put-away and specifically observations in regards to time-consuming activities connected to retrieving the next item to the put-away port.

Research regarding the optimization of order picking lines outside the AutoStore has been made to some extent by Tjeerdsma (2019), who focused on the following question: "How should the AutoStore order processing line be adjusted and redesigned such that the fulfillment center can achieve its target productivity and output rate sustainably?". This investigation is performed by analyzing the Dutch postal service, PostNL. The thesis mainly focuses on a specific example and how the warehouse operations and order picking line of PostNL. Focus was on how it can be optimized rather than general cases, what drivers are resulting in lacking utilization, and to what extent. The scope of the study does not include how put-away into the AutoStore is being made. Results of the study consisted of a list of actions specific for PostNL that would lead to increased performance, based on the outcome of a created simulation model. These recommendations, as stated specific to PostNL, involved offline balancing workload and removing non-value adding process steps, and online dynamic pick to light system in order to balance workload between busy and free stations. Also, to automate packing as an integrated part of the processing line, and compromising the process line in order to minimize distance traveled. Lastly, products were grouped to ensure that no products go through unnecessary steps. These recommendations, if generalized, would still not be able to apply to all facilities and all industries, hence the gap in current research. The study does suggest improvements that could be translated into other industries and warehouses, but since it is a single case study it does not take that aspect into account. However, the results were used in the observations when looking at the layout around the AutoStore, if any cases have implemented similar solutions, or if the generalized recommendations would remove current bottlenecks.

Connected to picking within automated sorters, Gallien and Weber (2010) did a simulation study on the differences in using pick waves or not. Pick waves are often used when many orders are similar in for example using the same transportation mode, shipped by the same carrier, or have the same date and time they should be picked (Gu et al., 2010). Although different technology, pick waves is a recurring setting in the implementation of AutoStore systems and is highly relevant in the aspect of moderating picking in regards to distributor deadlines (Element Logic, 2023d). The insights from industry experts is that adding more waves to the system is also adding constraints, which could possibly impact the performance negatively if not implemented properly (Element Logic, 2023c). Conclusions from Gallien and Weber (2010) share the same perception: that the optimal waveless picking policy performs equal, or better, than the best policy using waves in all scenarios. Thus, the use of pick waves is something to investigate further with empirical findings, if they correlate to similar results for RCSRSs as automated sorters, since it was mentioned by Element Logic as well.

2.2.2 Robots and software

The goal of this section is to cover the progress in both implemented and tested solutions of theory, and identify what the research is focusing on in regards to automation solutions to warehousing in general and to RCSRS. Parts of the research community heavily focus on the algorithms in how the system is operating. The aspect of RCSRS utilizing stacking policies sparks the question of utilizing such policies (Ko & Han 2022; Xue, et al., 2018). The relevant literature that was found is summarized in Table 2.2 below, including the research area, findings, and how it was used in this thesis.

Table 2.2. Summary of references regarding robots and software.

Source:	**Research area:**	**Findings:**	**How it was used in this thesis:**
Xue et al. (2018)	Picking patterns with focus on order batching	Increased efficiency depending on the order picking pattern	Investigate the usage and effects of batch picking
Ko and Han (2022)	Order sequence prioritization in algorithms	Sequencing orders to avoid same bin being needed in multiple ports simultaneously	To understand how the technique is used by eManager when shuffling orders
Trost et al. (2023)	Parameters such as number of robots, grid size, affecting throughput in one port	For a single port system, 13-14 robots theoretical maximum throughput and the smaller grid, better performance by less distance to travel for robots	Corroborate findings in thesis and the need of further research

Batch picking refers to a person picking a group of orders simultaneously (Gu et al., 2010). Xue et al. (2018) focus on the picking patterns together with order batching to minimize the total picking, as well as the traveling time of robots. Results from their studies conclude that picking efficiency can be improved depending on the order picking pattern, as well as prioritizing batching and consolidation of orders differently. As employees from Element Logic stated in interviews, some of their companies use batch picking and some do not. Therefore this was interesting to examine during the case company visits.

Ko and Han (2022) approach RCSRS with the order sequence in focus, since the reshuffling of bins is largely dependent on how the order sequence algorithm is prioritizing the process order. Picking efficiency is hence improved by applying the developed algorithm in the system, to avoid unnecessary and time-consuming reshuffling of bins. A similar algorithm is used in eManager, a software from Element Logic, and is dependent on the amount of orders released into the system at each interval (Element Logic, 2023c).

As recently as May 2023, Trost et al. (2023) released a study where the authors examined how different parameters influence the system behavior of an AutoStore and other RCSRS. The parameters were: number of operating robots, grid size, stack height, and filling degree. Results from simulating show that 13 to 14 robots is a theoretical maximum for a system with one port open. The study is limited to one port, but the findings were interesting to have in mind when analyzing how many robots each company has in relation to ports. Furthermore, Trost et al. (2023) corroborate the lack of existing research on the subject.

There is research on Robotic Mobile Fulfillment Systems (RMFS) in different areas where RCSRS is currently lacking. The order sequencing approach as discussed previously by Ko and Han (2022) is one of the first to look at this problem for RCSRS. According to Ko and Han (2022), robotic sorting systems (Xu, et al. 2022) and RMFS have been investigated through this lens by Valle and Beasley (2021), Boysen et al. (2017), and still continues to be a rather undiscovered area in RCSRS at the end of 2022. Further, Ko and Han (2022) states in regards to order batching and sequencing in conventional AS/RS, Roodbergen and Vis (2009), de Koster et al. (2007), Gu et al. (2010), and Boysen and Stephan (2016) have all done research with much focus on the algorithmic problems in these areas. In regards to the algorithms controlling the robots, Azadeh et al. (2019a) examined the policies in either wait-on-spot or robot recirculation after performing action on a RMFS. Looking at the operating robots, RMFS also has been subject of research looking at battery management, highlighting battery recovery, charging methods in relation to throughput time, and battery swapping strategies (Zou et al., 2017) which yet is not examined on the RCSRS side. Also, other studies from authors active in the field of automation in warehousing, do look into factors such as the configuration of lane depth, the amount and characteristics of picking stations and the amount, but once again with RMFS in focus (Yang et al., 2021).

2.2.3 Storage policies in AutoStore

Both shared and dedicated storage policies were considered as Zou et al. (2018) evaluated storage policies and performance of a RCSRS. Furthermore the authors state that *"the system throughput time is one of the most critical performance measures of an RCSRS"* (Zou et al., 2018, p.4), as the time taken to complete an order reflects the service level of the system. Utilization of workstations and robots are also deemed as important performance measures. In this case, dedicated storage means storing the same type of product in one storage stack, and shared storage meaning multiple types of products are allowed to share one stack. A dedicated storage policy would remove the reshuffling of blocking bins in order to fetch the wanted bin. However, this requires more stacks for products to be stored, especially for companies with large inventory. On the other hand a shared storage policy saves storage space, but increases the retrieval time for robots as they now need to reshuffle bins before fetching the wanted bin. In addition to this, both zoned and random storage were examined in the study. For zoned storage stacks, products with similar turnover are stored together in a zone but randomly assigned within that particular zone, compared to random storage stacks where all products are stored randomly without zones.

Furthermore, Zou et al., (2018) used models to calculate the optimized width-to-length ratio of the system as well as stack height, based on a given number of stored products and storage policy used. In order to validate the analytical models simulations, a real case on an AutoStore system was used. Relative errors show that the system performance can accurately be estimated with the analytical models. Results show that for the RCSRS examined the optimal width-to-length ratio for traveling time was roughly ⅔ for random storage stacks and a bit higher for zoned storage stacks. The dedicated storage policy fits better for a high stack height and exceeds shared storage policy in system throughput time. However, a dedicated storage policy is far more costly compared to shared storage due to the large storage space needed. Therefore, it was relevant to examine what storage policies the case companies have, and how that might affect performance.

2.2.4 Literature summaries

Summaries covering the researched areas have been made during the years, in line with the rising popularity in automation within warehousing together with the variety of solutions. René de Koster, Professor of Logistics and Operations Management at School of Management, Erasmus University, has conducted extensive research within warehousing, material handling, behavioral operations and more. Author and editor of eight books, over 230 papers published in books, and journals with over 8700 citations since 2018 (RSM, n.d; Google Scholar, n.d.). In the book "Global Logistics and Supply Chain Strategies for the 2020s", de Koster (2022) contributed with the chapter "Warehousing 2030", discussing current technologies, their development, and some views on the possible future. In this chapter, AutoStore is mentioned together with similar technologies, and is concluded with the statement: *"Surprisingly, little research on how to optimally design or control the system, or when to select such a system, is available. The paper by Zou et al. (2018) is an exception."* (de Koster, 2022, p.249).

The article by Zou et al. (2018) is referring to the same article mentioned in the opening Section of 2.2.3. This conclusion confirms that systems such as the AutoStore, are indeed not widely investigated in the literature. Jaghbeer et al. (2020) performed a literature review of automation in order picking systems, where they recognized the scarcity of empirical research in the field, as most papers use simulation and analytical models. Furthermore, the authors state there is a need for performing case studies and empirical research on automated order picking efficiency in order to understand their performances (Jaghbeer et al., 2020).

2.3 Conceptual framework

The AutoStore research suggests the warehouse configurations can be done and designed in different ways, which might lead to different performance. Based on this and the presented theory and tools, a conceptual framework was made for the data analysis, adapted from Kembro and Norrman (2021) and Eriksson et al. (2019). The framework in Figure 2.3 consists of contextual factors affecting warehouse configurations, which in turn affects performance of the AutoStore system.

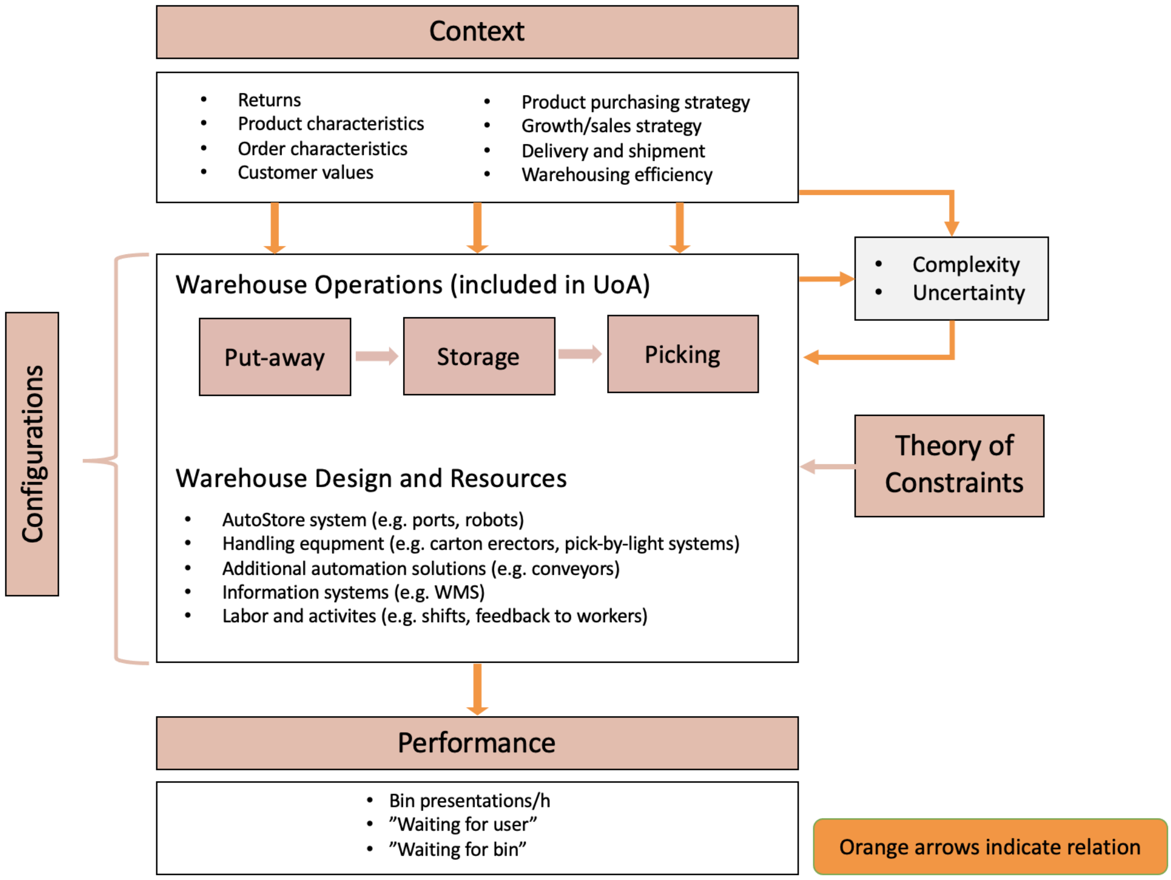

Figure 2.3. Conceptual contingency framework for warehouse configuration, adapted from (Kembro & Norrman, 2021).

As presented in Table 1.1, performance is a combination of three KPIs: bin presentations/h (per port), “waiting for bin”, and “waiting for user”. The number of bin presentations is calculated with the values of “waiting for user” and “waiting for bin”, as in Equation 2.1 below (Element Logic, 2023e).

$$Bin\, presentations/h \;=\; \frac{3600}{\text{"}Waiting\, for\, User\text{"} \;+\; \text{"}Waiting\, for\, Bin\text{"}} \qquad (2.1)$$

Therefore, in order to achieve a high number of bin presentations/h, a company wants low values of “waiting for user” and “waiting for bin”. Since bin presentations/h is calculated this way, efforts in this analysis will be on analyzing the values of "waiting for user" and "waiting for bin", which directly affects the number of bin presentations/h.

The contextual factors were divided into three different levels: external, corporate, and internal. Factors on the external level are to a high extent dependent on the external environment, such as how many customers return their orders and what their order characteristics are. The factors on the corporate level depend on the strategic decisions made by the corporate management, for example the product purchasing strategy. Lastly, factors on the internal level relate to the decisions made internally by the warehouse management. Factors on the external level can influence factors on the corporate level, which in turn can affect factors on the internal level, see Figure 2.4.

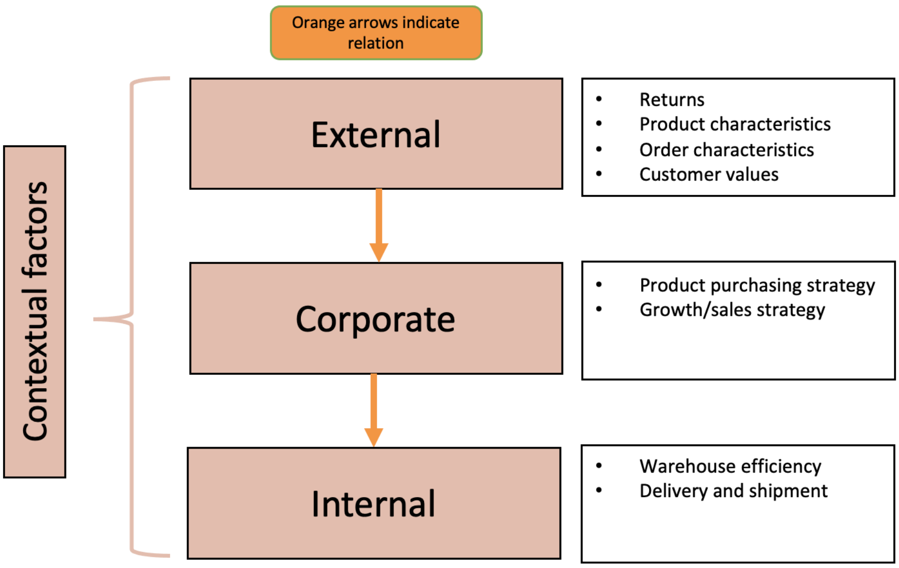

Figure 2.4. Contextual factors are divided into three different levels: external, corporate, and internal.

Contextual factors were based on the work from Kembro and Norrman (2021), as well as from interviews conducted with industry experts at Element Logic. The warehouse operations included in the unit of analysis are as mentioned above, put-away, storage, and picking. Warehouse design and resources are adapted from Kembro and Norrman (2020) to fit a company using an AutoStore. Lastly, it needs to be examined if the configurations are aligned with both the contextual factors and TOC. For example, a contextual factor might affect how the put-away process is done optimally, making it aligned with that contextual factor. However, it also needs to be examined whether the put-away is aligned with TOC, since how the put-away process is done might contradict TOC, and as a result limits performance. Therefore the TOC is applied to the configurations, see Figure 2.3. Complexity and uncertainty were also two aspects that the companies were investigated through. The levels of complexity in terms of variations in processes, orders, and products, as well as the accompanying uncertainty were analyzed, and their resulting effect on performance.

3. Methodology

The purpose of this chapter is to describe the overall methodology to completing our research. The methodology acted as a guide to perform the research required to answer the purpose of this thesis, which is to identify what, and how, different factors affect the performance of the AutoStore system.

Beginning with the research approach used in this thesis, the phenomenon driven research is explained, along with the phenomenon that was studied. Then, the chosen research strategy of case study is presented and discussed. After that the research design is discussed, where the procedure and steps are presented and motivated through literature. How the data collection was done is then presented, which include the data collection protocols and methods used to collect data. Lastly, research quality is discussed, where efforts to counteract bias and strengthen validity are presented together with identified instances where bias might appear.

3.1 Research Approach - Phenomenon Driven Research

Within a scientific practice a phenomenon can be described as a contextual concept that is both an object of explanation, and potential evidence of further scientific claims (Krogh et al., 2012). Phenomenon-driven research (PDR) has an emphasis on "identifying, capturing, documenting and conceptualizing a phenomenon of interest in order to facilitate knowledge creation and advancement, this approach focuses on contributing to knowledge within a field rather than to specific theory." (Schwarz & Stensaker, 2014, p.480). In this way PDR is not confined by specific theory, but rather uses theory to make progress within a field and explain a phenomenon. Eisenhardt and Graebner (2007) state that for PDR the research questions are broadly scoped to give flexibility to the researcher, and the phenomenon is chosen based on importance and lack of existing theory. Due to these mentioned characteristics of PDR, the approach fits the selected phenomenon of the AutoStore system, including put-away, storage, and picking. Furthermore, it suited our broad research questions and the purpose of this thesis. According to Schwarz and Stensaker (2014), a PDR approach needs a comprehensive overview of existing knowledge to motivate the importance of the phenomenon, how it differs from related phenomena, and show the lack of existing theory to sufficiently explain the phenomenon, as presented in Chapter 2. Krogh et al. (2012) state potential challenges in the early stage of a phenomenon, including difficulties for scientists to achieve funding or publish their research on the phenomenon in mainstream journals. These challenges do not affect this master thesis, due to the thesis being published by the university and financed by Element Logic.

To perform relevant and rigorous research on a phenomenon, a research strategy should be used. In PDR strategy there are five activities: distinguishing, exploring, designing, theorizing and synthesizing. However, these activities vary and do not have to be performed in sequence (Krogh et al., 2012). In this thesis, the decision was made to focus on the first two activities, due to lack of research of the phenomenon. The distinguishing activity focuses on distinguishing the key characteristics compared to other existing phenomena. A foundation of PDR is developing different concepts related to the phenomenon and selecting what concepts to study, which allows the phenomenon to be explored. These concepts act as a filter in the data-gathering process. By then gathering information about the phenomenon, the researchers might change their perception of the concepts they earlier developed, which might lead to new data being searched for (Krogh et al., 2012). Furthermore the authors state that "concepts need to be developed around the phenomenon rather than around the theory" (Krogh et al., 2012, p.286). The exploring activity focuses on exploring the phenomenon further, by gathering data related to the concepts describing it. This can be done by collecting primary data unrestrictedly through interviews and secondary data from online sources (Krogh et al., 2012). In our case, concepts were developed based on information from interviews with employees at Element Logic and literature. Data for exploring the phenomenon was collected through interviews, observations and archival data, which will be explained further in the following sections.

3.2 Research Strategy - Case Study

When doing research it is important to dedicate to explicit and formal procedures (Yin, 2014). The author presents five major research methods that can be used depending on the type of research questions, the amount of control a researcher has over events, and if the events are historical or contemporary. The AutoStore system is a relatively new technology and is still being updated. How individual companies should implement this system is missing a standardized template in regards to *their* specific situation. Thus, there is no "one size fits all" and a lot of decision making is individual for each company when designing the environment around the AutoStore. In addition to this, the lack of research regarding this phenomenon motivates the choice of performing a case study, to explore the similarities and differences in using the technology. Also, the literature suggests a case study is preferred as a research method, as the research questions of this thesis are focused on "what" and "how" questions based on contemporary events, that do not require control of behavioral events (Yin, 2014). Ellram (1996) and Voss et al. (2002) further state that a case study is suitable as a research method when examining questions related to "how" and "what".

A case study is "an empirical inquiry that investigates a contemporary phenomenon in depth and within its real-life context, especially when the boundaries between phenomenon and context are not clearly evident" (Yin, 2014, p.16). Advantages of case studies are studying the phenomenon in a natural setting, having the possibility to perform early investigations when the phenomenon is not fully understood, and having a research method that yields rich empirical data (Meredith, 1998; Eisenhardt and Graebner, 2007).

Yin (2014) mentions there are challenges with case studies. For example triangulation of data coming from multiple sources, collecting too much or too little data when the researcher has limited experience of empirical studies, and the importance of using different types of generalizations in the right way. Eisenhardt and Graebner (2007) bring up bias of interview data as a challenge. Furthermore, Voss et al. (2002) mentions challenges of observer bias, case research being time-consuming and using a limited number of cases to draw generalisable conclusions. To mitigate all these challenges it is important to have rigorous and thoughtful research design.

3.3 Research Design

A research design can be described as “the logical sequence that connects the empirical data to a study’s initial research questions and, ultimately, to its conclusions (Yin, 2014, p.28). There are five components of the research design that are particularly important when performing a case study: 1. the research questions, 2. its propositions, 3. the unit of analysis, 4. linking the data to propositions logically, and 5. criteria used when interpreting the findings (Yin, 2014). Developing these components was conducted through a multiple case study. Both single- and multiple case studies would be considered as variations within the same methodological framework, but with different advantages and disadvantages depending on the study. For example, a single case study would be more fitting if the subject at hand is a unique or rare case or an in-depth analysis of the phenomenon is needed, and multiple case studies instead thrive in being more robust at the cost of requiring more resources and time (Yin, 2014).

For this study, a number of companies with an implemented AutoStore were chosen, to examine their specific setup and warehouse design around their AutoStore, thus a multiple case study. This is to gain the comparative element of different solutions, strengthen findings and the correlation between factors, configurations, and performance. In Figure 3.1, the research design for the thesis is presented as an adaptation from the framework used by Yin (2014). In the first steps, the problem was defined and an initial literature review was made in order to investigate the existing research related to the AutoStore. Then, as a continuation of the theory development, information gathering through interviews with industry experts at Element Logic was conducted to better understand the situation. With better understanding, the selection of cases was made, and the data collection protocols were created. With the aid of the data collection protocols, data was collected from each case company through interviews, observations, and archival data. One important factor when conducting a multiple case study is also to reevaluate the theory once data starts to get collected, to avoid distortion or neglecting data to “fit” the original theory (Yin, 2014).

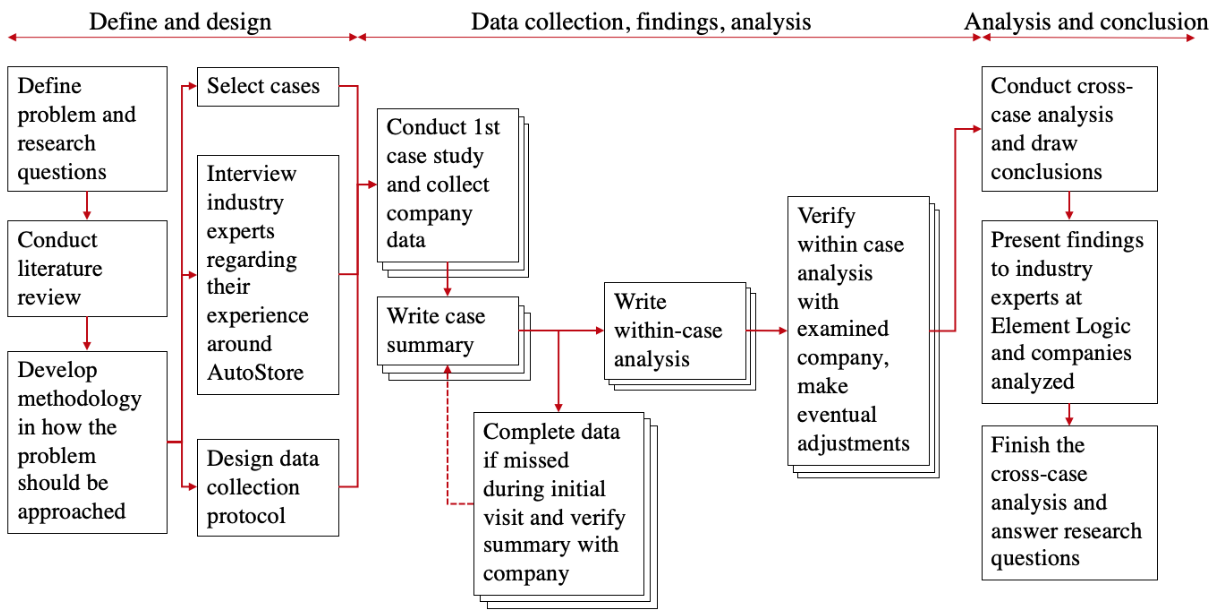

Figure 3.1. The research design for this thesis, adapted from Yin (2014).

3.3.1 Literature Review

Before the research design was done, a literature review (Chapter 2) was performed to gain further knowledge of the field. According to Yin (2014), theory can help immensely with deciding what data to collect when doing a case study. This was done through a series of searches in databases such as LUBSearch, Google Scholar, Web of Science, JSTOR, Elsevier, Emerald and Primo. In LUBSearch, one to three keywords were used with the criteria that they should be included in “title” or “abstract”. For Google Scholar and Web of Science, one sentence including keywords is searched for. Examples of keywords searched for can be found in Appendix A.

In addition to searching for keywords, forward and backwards citation searching was performed on the key literature that was found, in order to find more relevant literature. All these searches were continuously added to an excel document to keep track of them, make a short summary of the relevant key findings and overall make the information gathering process more efficient.

3.3.2 Unit of Analysis

According to Yin (2014), the unit of analysis (UoA) refers to what is being studied, and is used to make sure the case study stays within feasible limits. Furthermore it includes what the immediate topic of the case study is, compared to the context for the case study. When stating a UoA, having specific time boundaries that describe the start and end of the case scope is preferred. All of these aspects will aid in defining the scope of data collection and distinguishing data on the subject from external data (Yin, 2014). The UoA of this thesis is what contextual factors are affecting the configurations, how these factors and configurations are affecting performance, and how these should be handled to improve performance. Also, the operations included in the UoA are put-away, storage, and picking. The UoA is depicted in Figure 1.3.

3.3.3 Case Selection

The goal of selecting cases for this study was to find similarities in implemented technology, but with sharply contrasting characteristics in how the adoption around the AutoStore has been made, to highlight the different outcomes (Voss et al., 2002). Selection of cases were made in cooperation with Element Logic who provided contact information and guidance in arranging meeting opportunities. Element Logic is a company specializing on increasing warehouse performance since 1985, and currently is the largest partner of AutoStore. Besides selling the AutoStore units, Element Logic is supporting their customers with software solutions, expertise, and construction of the AutoStores. The customers are of varying sizes and industries, where Element Logic tailors solutions after desired specifications. The implementations have stretched out through Sweden over 52 sites as of 2022, across different industries such as ecommerce, 3PL and manufacturing. (Element Logic, 2022b).

All companies are customers of Element Logic in Sweden, and hence have an AutoStore sold by Element Logic. Also, the companies are using eManager, a software solution by Element Logic (Element Logic, 2023α), as their integrating software between AutoStore and WMS, and user interface. A total of seven companies were selected and included in analysis, see Figure 3.2. Companies were selected in regards to some sharing characteristics of all being within eCommerce or 3PL, with implemented systems that have gone through some growth since implementation. They all have a degree of complexity in their operations and environment that make them interesting cases to examine, since this complexity and growth have been enforcing different processes to develop. Since it is through Element Logic access to customers has been gained, further selection has been limited.

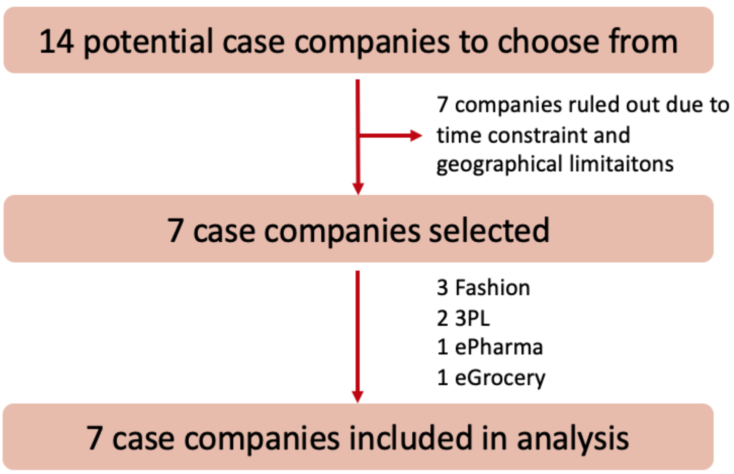

Figure 3.2. Selection of case companies.

3.4 Data Collection

In this section methods of data collection used in this thesis are presented. First, the data collection protocols will be explained. They were created as a preparatory step before being able to conduct the data collection. After that it will be explained how interviews, observations and archival data was used to collect relevant data. An overview of the data collection process in relation to later steps is displayed in Figure 3.3 below.

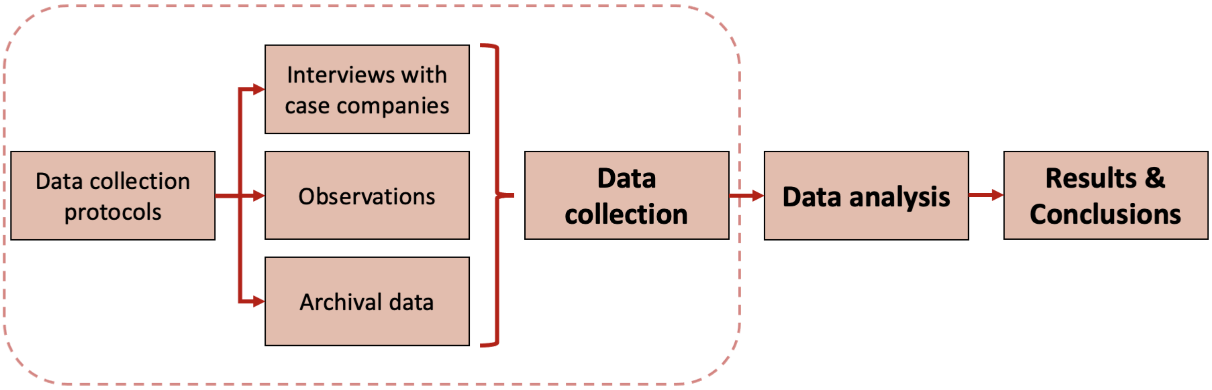

Figure 3.3. Overview of data collection process (circled in red).

3.4.1 Data Collection Protocols

Research protocols are essential for case study research (Voss et al., 2002; Yin, 2014). A well-designed research protocol will enhance the reliability of the case research data and act as a guide for the investigator when collecting data from the cases (Yin, 2014). It includes the information to be collected and questions to ask in the interviews.

A challenge with interviews is the bias of interview data (Eisenhardt & Graebner, 2007). To best mitigate this, a data collection approach that limits bias was used, such as interviewing multiple people that view the phenomenon from different perspectives (Eisenhardt & Graebner, 2007). Before starting with the research, unstructured interviews were used to interview key employees at Element Logic to further understand the AutoStore system, related processes and to gather knowledge when creating the data collection protocol. The employees were from different functions from sales to aftermarket, in order to get a nuanced view on the AutoStore system and what potential factors there are that affect the performance. Since this was in the early stages of knowledge acquisition, the unstructured aspect allowed the advantages of follow-up questions and clarifications to be made (Chauhan, 2022). Also, using unstructured interviews ensured no relevant information was lost due to having predetermined questions and themes.

Information on the interviews are gathered in Table 3.1 below, for example the role of interviewee, duration of interview and what areas were focused on in the interview.

Table 3.1. Unstructured interviews with employees at Element Logic.

Date of interview	Role of interviewee	Years in role / Years in logistics	Duration [mins]	Format	Areas focused on in the interview
19/1 - 23	Service Technician	3 / 5	120	In person	How the AutoStore system works
20/1 - 23	Solution Architect	2 / 10	127	In person	Put-away and picking
20/1 - 23	Solution Architect	6/20	72	In person	How the AutoStore system works, eManager and AutoStore software
23/1 - 23	Aftermarket Director	4 / 11	72	In person	AutoStore optimization
24/1 - 23	System Sales	15 / 22	59	Virtual	Configurations that might affect AutoStore performance
24/1 - 23	Business Developer	3/20	101	In person	AutoStore optimization, configurations that might affect AutoStore performance
24/1 - 23	Product Owner	1 / 7	38	Virtual	AutoStore optimization, integration of IT systems
25/1 - 23	Aftermarket Solution Architect	< 1 / 20	66	In person	AutoStore optimization, configurations that might affect AutoStore performance
25/1 - 23	Sales Director	3 / 18	56	In person	Receiving, put-away, configurations that might affect AutoStore performance
27/1 - 23	Support Director	7 / 15	46	Virtual	AutoStore optimization, configurations that might affect AutoStore performance
30/1 - 23	Head of Software Management	1 / 22	40	Virtual	Configurations that might affect AutoStore performance
20/2 - 23	Logistics Consultant	2 / 3	88	In person	Data analysis and configurations that might affect AutoStore performance

The first interview was a visit to an AutoStore, and acted as an educational opportunity to get first-hand experience and observations of the technology to be investigated in the thesis. Together with the expertise of the experienced Service Technician, explanations in how the system is operating and their daily challenges acted as a foundation in the knowledge gathering process of interviews with Element Logic's employees (Element Logic, 2023a). All interviewed employees are either in executive positions within their function, have relevant experience in the field, or have directly dealt with problems of optimization and initiatives aligning with the purpose of the thesis. The number of years each interviewee has worked in their role and with logistics was collected (displayed in Table 3.1). The interviews were either held in person or in a virtual format. All interviews were recorded and transcribed to make sure all given information was used, and to reduce observer bias as stated by Voss et al. (2002).

After these interviews, we created two separate data collection protocols. The questions were generated from the literature review and the knowledge gathered from interviews with key employees at Element Logic. Both protocols can be found in Appendix B. One protocol was sent to the case companies 2-3 days prior to the visits to give them time to prepare for the questions. This one was more compact and included the main questions to be asked during the interview. The second one was more comprehensive and was used during the interview to make sure all important information was collected. According to Kallio et al. (2016), questions that are well-formulated are participant-oriented, single-faceted, clearly worded, open-ended, and not leading. Furthermore, in order to get descriptive answers, questions can be started with words like who, where, what, when, how or why.

The used data collection protocols follow a logical order and have the following main themes in sequence: put-away, the AutoStore unit configurations, and picking. Every theme starts with a broader question that is followed up by more detailed questions, as mentioned by Kallio et al. (2016). Before using the data collection protocol to analyze the case companies it was pilot tested by three employees at Element Logic with knowledge of the areas. The pilot testing was used to get feedback on the interview questions, which is a mentioned technique by Kallio et al. (2016). This confirmed the relevance and coverage of the questions and also gave feedback on potential reformulations that needed to be done.

3.4.2 Interviews with case companies

Interviews were also held with a person from a managerial- and/or AutoStore focused position at each case company, that has the knowledge of the processes related to AutoStore. These interviews were structured interviews and held with the second data collection protocol. One of us was responsible for leading the interview and asking questions, while the other one took notes. After each company visit, the audio recording of the interview was listened to, while reading the notes taken and comparing them to the audio. This was done to make sure that all the information from the interview was collected and categorized into the data collection protocol. In Table 3.2 information about the interviews can be viewed, for example company, role of interviewee and years of experience.

Table 3.2. Interviews with employees at the case companies.

Company:	Industry:	Date of interview	Role of interviewee	Years in role / Years in logistics	Duration [mins]	Format
F1	Fashion	1/3 - 23	Site Manager (and three colleagues)	<1 / 16	65	In person
F2	Fashion	13/3 -23	Site Manager & Head of Fulfillment	5 / 7.5 & 3 / 11	110	In person
F3	Fashion	20/3 -23	SuperUser	1.5 / 1.5	66	In person
3PL1	3PL	28/2 - 23	Operations Manager	3 / 8	98	In person
3PL2	3PL	22/3 -23	SuperUser	<1 / 7	26	In person
E1	ePharma	23/2 - 23	Group Manager	1 / 1	74	In person
E2	eGrocery	24/2 - 23	Warehouse Optimization Manager	1.5 / 10	77	In person

3.4.3 Observations

In addition to using interviews, observations can be used as a means to collect data. Observations were used in the case company warehouses to collect data on the processes. This was done after the interview had been held, to confirm they actually do as they stated in the interview. If any observations conflicted with things stated in the interview, these were followed up and confirmed. An advantage with observations is that they do not rely on people's perception of what they do, compared to interviews (Denscombe, 2010).

According to Denscombe (2010) there are two types of observation research; systematic observation and participant observation. For this thesis, systematic observations were used as it is an efficient, reliable and systematic way of collecting observer data compared to participant observation. We used an observation schedule as a list of items similar to a checklist, to make sure we monitored the items, and made a record of them when they occurred. Also, Denscombe (2010) states that an observation schedule should be used to record data systematically, produce consistent data and pay attention to the same activities. The observation schedule for the company visits of this thesis is included in Appendix C. For the put-away process observations were divided into three categories: when goods arrive at the port-area, at the put-away station and when the operator is putting the goods into bins. For the picking process the observations were divided into the following three categories: initiating the picking station, at the picking station, and after the picking station. Furthermore there was a general category containing observations on equipment, where ports are located, bottlenecks or waiting times in the processes. One of us was responsible for taking notes of the observations, while both of us observed and made sure all relevant observations were written down.

Denscombe (2010) mentions a few challenges with systematic observations. First, the observation schedule often is decontextualizing the things being observed. Therefore background information was collected to help explain the events observed, and to understand the collected data. This was done the same time as the observations, through questions to the person escorting us around the warehouse at each case company. Second, the researchers should minimize disruptions of the natural setting by having an unobtrusive positioning and avoiding interactions with the people being observed. The person escorting us through the warehouse enabled this, as they could answer any possible questions that might arise during the observations. If any observations differ from the information given in the interview, it is important to challenge the issue and use other data sources to clarify the information. Voss et al. (2002) state the importance of checking the data and getting feedback from the case companies. After the observations had been done at each case company and the case summary had been written, the summary was sent to the company for verification.

3.4.4 Archival Data

Besides interviews and observations, collecting and examining archival data was made to further strengthen the validity of the analysis (Voss et al., 2002). By triangulating all methods around the phenomenon, the goal was to use the archival data in comparison with collected data in interviews and observation. This is to be able to find corresponding differences in characteristics, with the difference in numerical historical data of performance. It is important to avoid bias (Yin, 2014), and thus, the observations and interviews can investigate if the data has been possibly manipulated. Data should then be obtained and treated equally, as well as represent the same operations in order to be comparable.

The data was collected from seven case companies, including both KPIs and descriptive data of the AutoStore system of each customer. The idea behind collecting descriptive data was to include it in the data analysis, to examine whether there are any patterns between performance (the KPIs) and the descriptive data. These KPIs are also defined by Element Logic together with the customers, making the definition unified (Element Logic, 2023d).

Data and from what source it was collected from is found in Appendix D. Each month the customers gets a report from Element Logic presenting the AutoStore performance of the past month. For the analysis, KPIs from two months were combined to calculate the average numbers, to reduce the probability to include any temporary extreme cases in the numbers. Ideally would be to use data over a longer period of time, but as data from the AutoStore is only stored in the system for short periods before being overwritten, no more data was available.

3.5 Data Analysis

When performing data analysis, Miles et al. (2019) mentions three main activities to use: data condensation, data display, and drawing and verifying conclusions. Data condensation refers to selecting, simplifying and transforming raw data. Data display is the process of displaying and organizing the data, to enable conclusions to be drawn from it. Lastly, conclusion-drawing and verification is about extracting meaning from the displayed data through different methods. For example by identifying patterns or regularities in the data.

Section 3.5.1 and 3.5.2 begins with explaining how the within-case analysis and cross-case analysis was performed, and the techniques and tactics used for data analysis. Lastly, Section 3.5.3, 3.5.4, and 3.6 describe how the conclusions were drawn, verified, and tested for robustness, plausibility and validity.

3.5.1 Within-Case Analysis

Miles et al. (2019) state that data condensation can be done through a number of methods, for example coding, generating categories and writing analytic memos. Since the interview notes and audio recording had been compared to make sure all data was collected and categorized, using coding as a method for all the collected interview data was deemed not necessary. When creating the data collection protocol, the different questions were divided into categories, in an effort to make the data collection from interviews and observations as categorized and uniform as possible between the multiple cases.

Analytic memoing was used throughout the data collection all the way to final reporting, especially during both the interviews and observations. The memos were written in the data collection protocol but marked with a distinctive color to separate the data collected from thoughts. Miles et al. (2019) mention analytic memoing as a fast way of capturing thoughts that occur when for example collecting or analyzing the data.

For the within-case analysis all the collected data was already in the format of a table due to the design of the data collection protocol, with questions in the left column and notes in the right column. After the data condensation and data display, the first conclusions could be drawn. Arranging data in a table makes it easy to view and enables detailed analysis (Miles et al., 2019).

3.5.2 Cross-Case Analysis

After each within-case analysis was done for all the case companies, a cross-case analysis was performed. Tables and graphics, as Miles et al. (2019) discusses, were used to display the data from the individual cases together, and enabled us to compare cases when doing the cross-case analysis. For example a figure that mapped out the entire processes for put-away and picking for each case company was made, which made it easier to compare the processes and how that relates to their performance. The decision was made to have one table including data from all categories and all case companies, which would largely reflect the setup of each company and how they are performing in the most common KPIs. This table could not include all the collected data, since this would be too overwhelming and hard to analyze. Therefore all the data deemed most important and best reflect how the case companies are performing and doing their processes, was included in this table. In addition to this, several more tables were made that included all the collected data within each category, which enabled a deeper analysis of the data within each category. The techniques and tactics for drawing meaning from displayed data during the cross-case analysis are further explained in the following section.

3.5.3 Techniques & Tactics for Data Analysis

Yin (2014) presents four analytic techniques that can be used for both within-case- and cross-case analysis: pattern matching, explanation building, time-series analysis, and logic models. Out of these techniques, pattern matching was used for the cross-case analysis. In addition to this, the author mentions one technique specifically for cross-case analysis, which is called cross-case synthesis. Cross-case synthesis involves displaying the data from individual cases in tables with different categories, and was used in this thesis. Since the data from the individual cases are displayed together, it was easier to analyze, compare the data and draw conclusions. After the conclusions were drawn in the cross-case analysis, the conclusions had to be verified and tested.

Miles et al. (2019) discuss 13 specific tactics for drawing meaning from displayed data, of these were 9 tactics used. All the techniques and tactics used in this thesis for the within-case analyses and cross-case analysis are presented in Table 3.3 below.

Table 3.3. The techniques and tactics used for analyzing data.

Technique /Tactic:	**Used in within-case analysis:**	**Used in cross-case analysis:**	**How it was used in this thesis:**	**Source:**
Seeing plausibility	X	X	Intuition that arose during interviews, observations, and data analysis guided us to further examine it with other tactics (e.g. if a certain configuration affects performance more or less).	Miles et al. (2019)
Clustering	X	X	Categories were formed both in the data collection protocol and for the data analysis in tables.	Miles et al. (2019)
Counting	X	X	The collected data that were quantifiable, were displayed in numbers. This was to quickly see and compare in large batches of data.	Miles et al. (2019)
Partitioning Variables	X	X	The KPIs were calculated for both the put-away and picking ports, instead of combining them. This was to more easily identify differences that might not have been spotted otherwise.	Miles et al. (2019)
Factoring	X	X	Processes done by the operator at the ports were divided into smaller individual tasks, which was later used in the cross-case analysis for comparison	Miles et al. (2019)

			between the companies.	
Noting the relations between variables	X	X	In the within-case analyses, the framework in Figure 2.3 was used to identify relations between variables. In the cross-case analysis the relationships between different KPIs are presented, and how they are correlated.	Miles et al. (2019)
Pattern Matching, Noting Patterns & Themes		X	Comparing our predictions with the patterns apparent in the data. Also identifying recurring patterns of data in the cross-case analysis.	Yin (2014), Miles et al. (2019)
Making contrasts, compariso ns		X	Besides numbers representing high or low numbers, conditional formatting was used for numbers in the cross-case analysis. This was to easily make comparisons and identify max and min values.	Miles et al. (2019)
Finding mediating variables		X	When the correlation between two variables A and B that should be correlated was not easily identified, we tried to look for other variables that could affect the correlation between A and B. This was done throughout the cross-case analysis.	Miles et al. (2019)
Cross-case synthesis		X	For example displaying the data from the different companies in tables according to different defined categories, which was done in the cross-case analysis.	Yin (2014)

3.5.4 Verifying Conclusions & Quality of Data

Miles et al. (2019) present 13 tactics for verifying data quality and confirming the findings. The 11 tactics used in this thesis are included in Table 3.4 below, along with how they were used.

Table 3.4. Tactics for verifying data quality and confirming findings (Miles et al., 2019).

Tactic:	**Used for:**	**How it was used in this thesis:**
Triangulating	Data quality	Triangulation by method: In this thesis interviews, observations and documents were used to triangulate the findings. There was also a triangulation by data types: qualitative texts from interviews, audio recordings from interviews, and quantitative data from documents.
Weighing the evidence	Data quality	Information from interviewees that had more experience of the AutoStore and the related processes were seen as more valid. Also, analytic memos were written in the field notes regarding data quality issues. For example if the interviewee said or appeared not sure of their answer, this was noted (and triangulated with information from documents and other people at the company). In addition to this, the validity of results was commented on after each within-case analysis.
Checking the meaning of outliers	Testing a conclusion about a pattern	The outliers identified during the analysis were looked into further. For example in the cross-case analysis certain outliers appeared when comparing the performance. Then other correlated data was further

		analyzed to understand the meaning of the outlier.
Using extreme cases	Testing a conclusion about a pattern	Extreme cases were used the same way as other outliers. Trying to understand the meaning of it by looking at other data, or using it to support a conclusion about a pattern.
Following up surprises	Testing a conclusion about a pattern	Empirical findings that surprised us were further looked into. For example, when a configuration/process was done a certain way that surprised us, the pros and cons of doing the process that way were analyzed and discussed.
Looking for negative evidence	Testing a conclusion about a pattern	When trying to test a conclusion about a pattern, negative evidence was looked for that could disconfirm that pattern. This suggests the drawn conclusions are true (when negative evidence was actively looked for but not found).
Making if-then tests	Testing explanations	If-then tests were used during discussions in the analysis. This was to test the explanations to make sure they were logical and reasonable. Especially for explanations on how different configurations would eventually lead to affect any of the performance KPIs.
Ruling out spurious relations	Testing explanations	As mentioned under “Using extreme cases”, other correlated data was looked at when a relationship between two or more variables seemed to be falsely attributed. This was especially done in the cross-case analysis where several patterns and explanations were examined. If proof was found that relations were falsely attributed, this was clearly stated in the analysis.
Replicating a finding	Testing explanations	Replicating was performed as data from observations, audio recordings from interviews, and qualitative text from interviews, was collected. Additionally, when patterns were found in the within-case or cross-case display, it was tracked in all cases to investigate if the pattern was repeated.
Checking out rival explanations	Testing explanations	This was especially done in the cross-case analysis, when multiple patterns were examined in the collected data. When an explanation became increasingly more compelling with more varied sources of evidence, that explanation was chosen.
Getting feedback from participants	Testing explanations	This was done by sending the within-case summary and analysis to each case company for verification. Also, employees at Element Logic gave feedback on the analysis, to confirm there were no conflicting or illogical explanations in the analysis.

3.6 Quality of Research

For the thesis method, five criteria were used to evaluate the research quality; construct validity, internal validity, external validity, reliability (Yin, 2014; Gibbert et al., 2008), and objectivity (Miles et al., 2019). These criteria were considered in order to limit bias and make the study as valid as possible, as been recommended within case study tactics (Yin, 2014). Similar criteria are listed in other literature such as Miles et al. (2019), and share similar descriptions. The goal with the quality of research is to provide transparency and make sure that the findings are properly supported by an extensive and rigorous research methodology. These are summarized in Table 3.5 below.

Table 3.5. Case Study Tactics for Design Tests, modified version inspired by Yin (2014) and Miles et al. (2019).

Tests:	**Case Study Tactic:**	**Phase of research in which tactic occurs:**
Construct validity	❖ Use multiple sources of evidence ❖ Have key informants review draft case study report	Data collection Composition
Internal validity	❖ Do pattern matching ❖ Address rival explanations ❖ Use logic models ❖ Triangulation of methods	Data analysis Data analysis Data analysis Data analysis
External validity	❖ Use theory in single-case studies ❖ Use replication logic in multiple-case studies	Research design Research design
Reliability	❖ Use case study protocol ❖ Develop case study database	Data analysis Data analysis
Objectivity (Miles et al., 2019)	❖ Evaluate and assess the possibility of researcher bias ❖ Construct a transparent and explicitly detailed method	Data analysis Research design

3.6.1 Construct Validity

The construct validity concerns the possibility that the research lacks a “sufficiently operational set of measures and that ‘subjective’ judgments are used to collect the data” (Yin, 2014, p.41). To counteract this, as stated in Table 3.5, proper use of multiple sources of evidence, and reviewing the case study reports through selected key people can be made. Therefore, the use of multiple sources such as observations on-site, gathered raw data, and interviews, are efforts taken through the cases. The two tests needed for this to be fulfilled is to properly define the problem in specific concepts, together with identifying operational measures (Yin, 2014). For this thesis, the definition of performance becomes the center issue, together with suitable KPIs to measure performance, as provided in Table 1.1. Also, as depicted in Figure 3.1, after completing the within-case and cross-case analysis, the findings were presented to the industry experts at Element Logic for input, and within-case presented to analyzed companies respectively.

3.6.2 Internal Validity

The internal validity becomes important in this thesis, since the research questions circle around finding correlations between unknown factors and AutoStore performance. Internal validity concerns the possible gap of knowledge if the thesis would conclude that factor *x* leads to result *y*, while unknowingly overlooking factor *z*, which affects *y* (Yin, 2014). Internal validity concerns if the findings and conclusions make sense, and that efforts should be taken to make sure that the conclusions are indeed logical and accurate. In this thesis, said efforts to reach internal validity, or credibility (Miles et al., 2019), are the triangulation of methods, the verification of within-case, and cross-case analysis with Element Logic and companies (Miles et al., 2019), together with using logic models and pattern matching (Yin, 2014). Triangulation of data both collected through observations, interviews, and collected from databases, increases the credibility if all data sources indicate similar findings. By conducting the verifications, the probability of non-logical reasoning or missed elements to surface are greater. Industry experts at Element Logic are regularly conducting improvement workshops with their customers to identify similar patterns of performance-decreasing factors, and their input therefore becomes valuable. Since the risk of interference occurring during processes not directly observable, measures of caution, verifying methods and findings were taken. These are for example instances where the AutoStore algorithm's decision making is not observable, or situations where poor computer hardware can be a limiting factor when interacting with a user, causing long loading times.

3.6.3 External Validity

External validity considers how transferable, or generalizable the findings are, how well they fit in another context (Miles et al., 2019). In the case of this thesis, the generalizability boils down to different contexts of AutoStore use. Being comprehensive in the development of methodology and description of the setting, was one of the efforts taken in order to make the method applicable to the general case. Other efforts to reach external validity are suggested as using a diverse sample group to increase the applicability, explicitly state eventual limits in generalizing the approach, and having findings agreed upon from readers being consistent with their own experience (Miles et al., 2019). The selected cases are between a range of businesses and encourages the broader applicability over a variety of cases, which ensures it being more transferable. Lastly, by reviewing the draft of the within-case and the cross case analysis with both the companies examined, as well as key people at Element Logic, the findings should be sharing characteristics that correspond to their perception working with these questions.

3.6.4 Reliability

To conduct a reliable study, the data collection procedure should be able to be repeated, by anyone, and result in the same findings (Yin, 2014). The study should have been conducted with care, transparency, and consistently in its method (Miles et al., 2019). Here, the case study protocol comes in with its importance. By making the steps of the method as operational and documented as possible, it raises the possibility of reaching the same results.

This, together with the extensive data collection protocol and how it was developed, the collection of interview data shares the same expectations. Since the interviews with case companies were in a semi-structured format, it allowed for further clarification questions to fully understand the processes. With the provided categorization of answers, and comprehensive interview questions covering the processes, the goal was to fully cover each process, and answer what the interview table suggests the interview should cover. We as researchers ensured to have clearly specified roles throughout the data gathering process, one taking notes about the answers and recording, while the other leads the interview. Also, clearly defined research questions and concrete definitions of performance hinder different outcomes based on misunderstandings. By explicitly defining the parameters examined, it lowers the risk of getting a different result because of other parameters being considered as chosen or left unsaid.

3.6.5 Objectivity

Objectivity refers to remaining objective/neutral and keeping the biases to a minimum during the process, and being transparent and explicitly highlighting areas where inevitable bias may be appearing (Miles et al., 2019). Neither of the two researchers have any form of previous connection to the companies nor to Element Logic. However, the project is influenced by the presence of Element Logic since the thesis idea first was initialized from their part, as something in need of investigation. The project is also funded by Element Logic, and the researchers are being compensated for conducting this research. This can act as a driver of "need to reach results", since the expectations and hopes from Element Logic are to have concrete results after this thesis. The case could be that no clear factor can unanimously be the cause of increasing or decreasing performance, and the fact that the funders expect results, that conclusion would subconsciously be undesired from the researchers' part. Also, the case companies are customers of Element Logic and decided from their part, limiting the researchers influence in selection of cases. However, a broader selection of companies were presented initially, and were narrowed down by the researchers in cooperation with Element Logic's knowledge about their customers and the geographical location of customers. This to make the company visits flexible and doable considering the limited time of this thesis. Being thorough and in detail describing the procedure of the case analysis together with the data collection protocol, reduces the risk of being subjective (Miles et al., 2019). Keeping the research process as operational and properly documented as possible, with a continuous evaluation on instances where internal or external biases can occur, are also measures that have been taken in order to counter subjectivity.

4. Empirical findings - Case summaries

This chapter summarizes the empirical studies with descriptions of the case companies and their main operations, along with a process map for put-away and picking. As previously mentioned, the data was gathered through interviews, observations, and archival data from Element Logic. As earlier explained, the case companies are all customers of Element Logic and have an AutoStore unit installed with varying size and purposes. Some elements are the same for every company, such as the usage of conveyors from picking ports and using shared storage policy (mentioned in Section 2.2.3). Thus, these aspects have been excluded from the scope. Furthermore, all companies are using the same integrating software eManager, provided by Element Logic.

During the thesis, the data was gathered in three different tables to maintain an overview: descriptive data, put-away data, and picking data. Examples of descriptive data are the number of ports, robots, order lines per day that the company has. Both the put-away- and picking tables included data relevant for each process. These three tables are found in Appendix E.

4.1 Company F1 (Fashion 1)

4.1.1 Company description and warehouse conditions

Company F1 operates a warehouse for selling clothes B2C through their website, a third party company, and B2B. They have had their AutoStore for around one year since they went live, which stores 21K unique SKU types of their total assortment of 22K.

Besides the majority of clothes stored in AutoStore (~95%), they sell shoes and some additional items in the smaller furniture category not stored in the AutoStore. The warehouse consists of an AutoStore, a buffer zone, and an oversize zone. The buffer zone represents roughly 65% of all receiving goods and refills the AutoStore once refill tasks are being triggered by the WMS. When goods are received in the warehouse, The WMS informs the operators how much of the arrived goods that should be loaded into the AutoStore, and how much should be put in the buffer zone. In total the AutoStore has 15 ports, with four ports dedicated for put-away and 11 dedicated for picking. These ports are open and closed dynamically depending on how much work there is to do in put-away or picking. Over the examined time period, the number of robots per average open ports are 11,7 robots/port. The release of order to eManager is mostly handled automatically, but manual order release for specific markets occurs. There is an upper limit of order that they release at a time, to prevent too many orders being released at once. Regarding giving the robots more time to prepare bins, the operators at F1 have breaks at the same times during the day when workload is high, otherwise they do not have breaks at the same time. They are utilizing the forecasting function that increases possibilities for preparation of bins in exchange for robot capacity. It is a software setting that takes bins “to be picked in the next order release” into account when handling bins. For example, if a specific bin is to be retrieved in the next pick wave, the robots will try to keep that bin on the top layer. This essentially causes more activities for the robots to conduct.

For put-away, the goods arrive in sealed cartons on pallets that need to be opened for put-away. Prior to this, the goods have been sorted based on SKU type, as well as counted. The returns however, arrive in larger cartons with mixed SKUs, already quality checked and packaged externally, ready to be put in. F1 has two guidelines for put-away: In the season between spring and summer all SKUs up to 20L are stored in AutoStore, while in the season between autumn and winter all SKUs up to 30L are stored in AutoStore. F1 regulates how many different bins a product should be put-away in, to make sure there is availability of certain products in the AutoStore. This is done by using parameters in their WMS.

For picking there are four different queues, which are: Normal, Consolidation, B2B, and Third party. They prioritize the third party company reseller in the beginning of the shift due to earlier shipping. However, no pick waves are used to handle the different shipment schedules. When choosing what bin to pick the product from, the robots apply the First In First Out-principle (FIFO) as pick strategy. The picking method used by the operators is single order picking, which means batch picking is not used. Order consolidation and B2B queues are both picked from dedicated ports, to ease the preparations needed in terms of equipment. Same logic follows by the put-away of returns, with a dedicated port working in the queue that only has the ⅛ bins, to avoid unnecessary queue changes in the port. Performance according to the company is how many pcs/h they are doing for put-away and picking, as well as how many bin presentations/h they are achieving.

4.1.2 Warehouse configurations and process map

The warehouse operation process maps, as depicted in Figure 4.1 and 4.2 below, contain the different steps and measures taken in the put-away and picking process around AutoStore. With a high volume of returns, put-away processes are parallel with two flows, one being returns and the other regular put-away from buffer or inbound. The picking processes are mainly structured in two setups as well, B2C revolving around the conveyor, and B2B and consolidation working with consolidation carts.

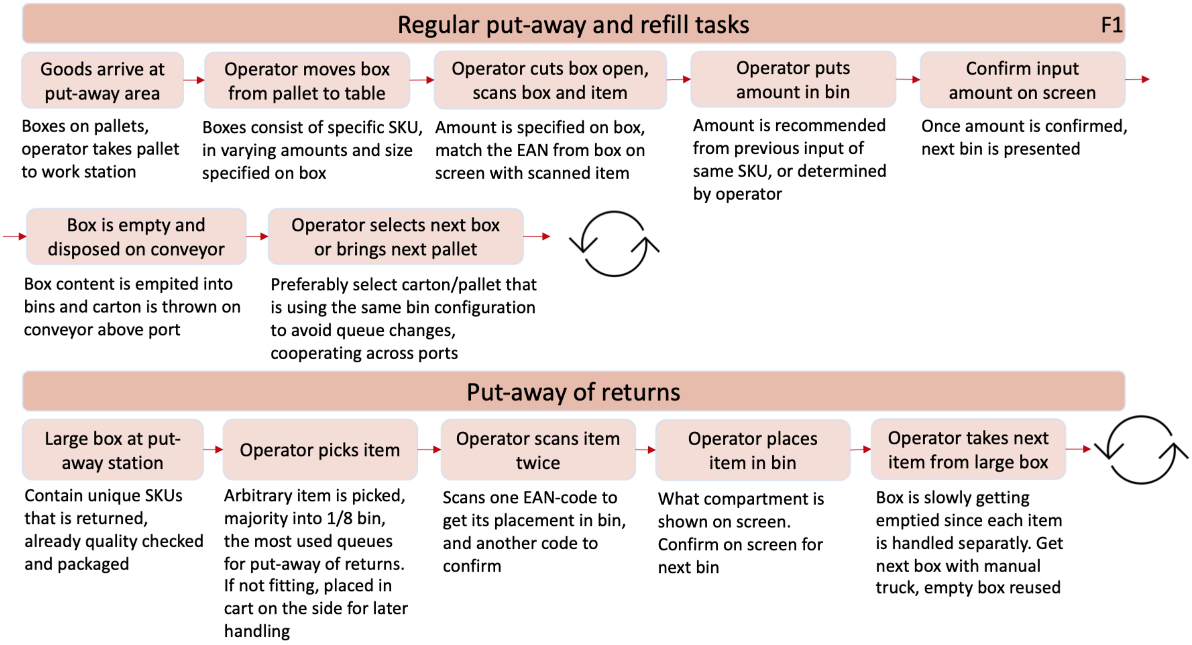

Figure 4.1. Put-away processes for company F1. Circulating arrows means the process is repeated.

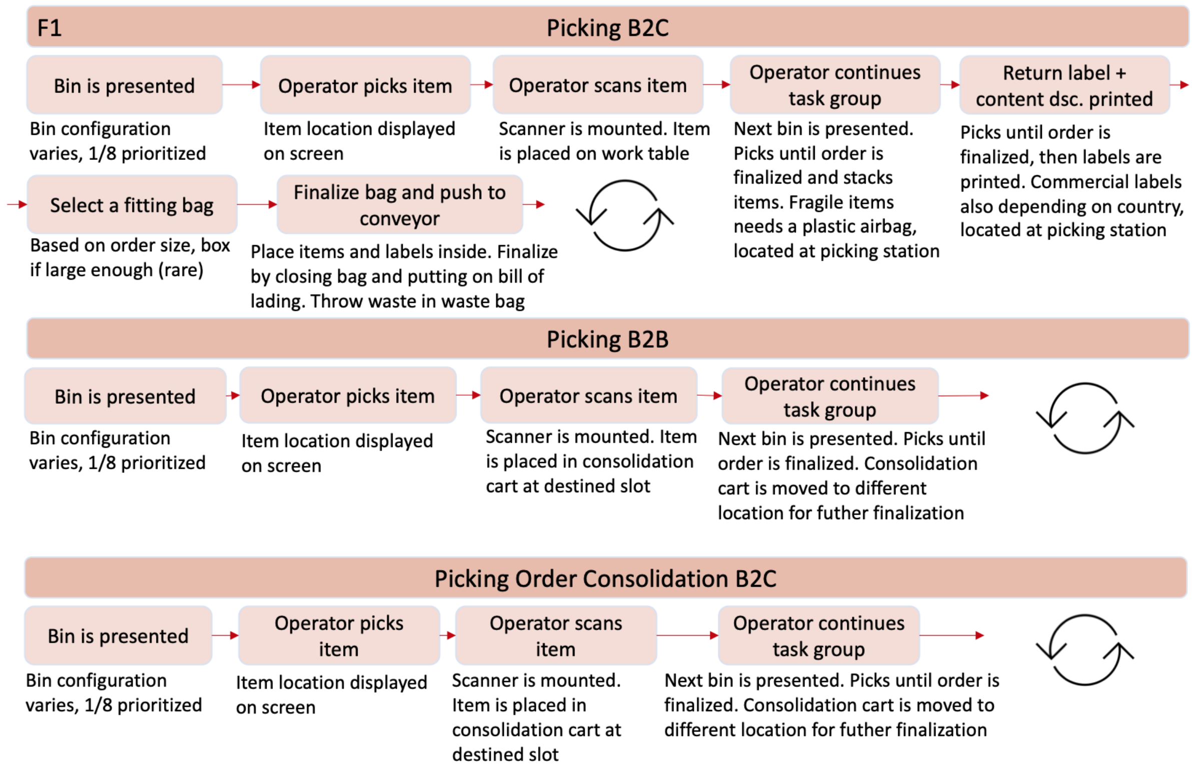

Figure 4.2. Picking processes for company F1. Circulating arrows means the process is repeated.

4.2 Company F2 (Fashion 2)

4.2.1 Company description and warehouse conditions

Company F2 is selling clothes for B2C e-commerce through their own website, as well as a smaller B2B flow. They have had their AutoStore for between two and three years since they went live, which store 97K unique SKU types of their total assortment of 102K. Around 95% of all their SKUs can be stored in the AutoStore, while the rest have to be stored in the oversize zone. Approximately 70% of all incoming goods are stored in the AutoStore and the rest in the buffer zone, but if the goods consist of campaign products, or products expected to sell fast, 100% of inbound is directed to the AutoStore. When stock levels are low, the WMS triggers refill tasks for the AutoStore. In total the AutoStore has 30 ports, 7 dedicated for put-away and 18 for picking that are opened and closed dynamically depending on the workload. Over the examined time period, the number of robots per average open ports are 10,2 robots/port. The order release to eManager is handled manually, where an upper limit of orders they release at a time exists to prevent too many orders being released at a time. During high workloads, all operators at the AutoStore have breaks at the same time during the day, to give the robots time to prepare bins on the top layer. Lastly, the forecasting function for the robots is utilized.

For put-away, the goods arrive in sealed cartons on pallets that need to be opened for put-away. Additionally, all the units need to be counted by the operator at the port, before putting them into a bin. Prior to arriving at the port, the goods have been sorted after SKU type. However, returns are arriving in large cartons with mixed SKUs, but have been sorted according to what bin-configuration they fit in and quality checked externally prior to being sent to the warehouse in Sweden. The priority almost all of the time is to put as many units into the bin as possible, to maximize the fill rate in the bin. However, if there is a sale coming up, then they occasionally put the units into different bins to make them more available across the AutoStore unit. Other guidelines for put-away include not putting too many bigger products that can expand into the bins, to prevent them from causing a stop in the AutoStore.

For picking there are four different queues, which are: AutoStore, Consolidation, Express, and B2B. The picking method used is single order, and their pick strategy is to select up to 5 locations ordered by lowest quantity (not FIFO). If this strategy fails to allocate the necessary quantity, a FIFO strategy is applied for the rest of the quantity. Two ports are dedicated to only work from the Consolidation queue. Between 3-4 pick waves are utilized, which are changed depending on the season. Performance according to the company is mainly how many pcs/h and bin presentations/h they are doing for put-away and picking, as well as the time spent “waiting for user” and “waiting for bin”. Lastly, they make their own reports where they track errors that have occurred, to work towards identifying and preventing these in the future.

4.2.2 Warehouse configurations and process map

In Figure 4.3 and 4.4 below, the different steps and measures taken in the put-away and picking processes around AutoStore are depicted. With an extremely high volume of returns, put-away processes are parallel with two flows, one being returns and the other regular put-away from buffer or inbound. The picking processes are mainly structured in two setups as well, B2C revolving around the conveyor, and B2B and consolidation working with consolidation carts.

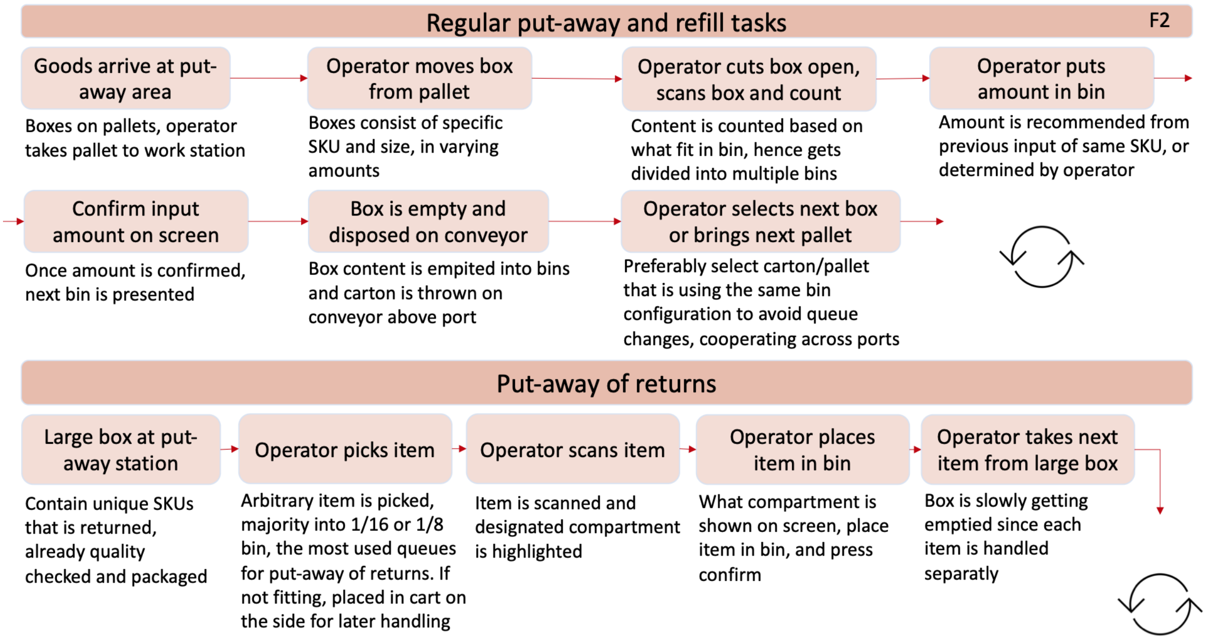

Figure 4.3. Put-away processes for company F2. Circulating arrows means the process is repeated.

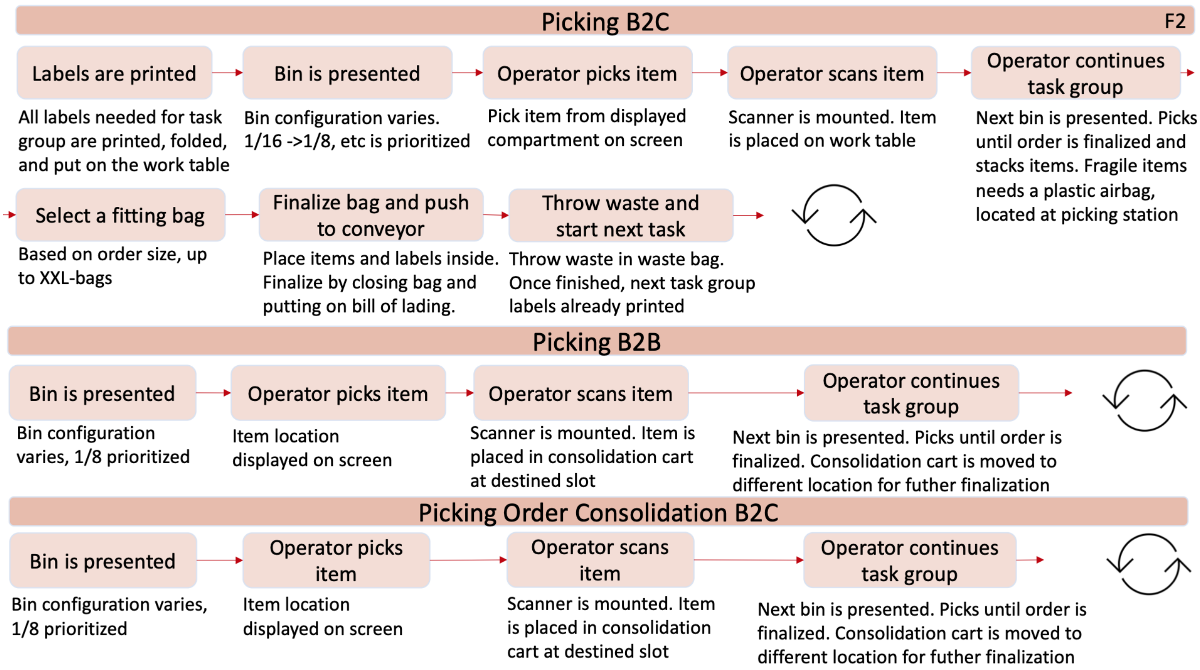

Figure 4.4. Picking processes for company F2. Circulating arrows mean the process is repeated.

4.3 Company F3 (Fashion 3)

4.3.1 Company description and warehouse conditions

Company F3 sells clothes and shoes B2C through their website, a third party company, and B2B. The company has had their AutoStore between one and two years, which store 29K unique SKU types of their total assortment of 49K. Approximately 60% of their SKUs are stored in the AutoStore, while oversize goods, men's clothes, and flammable goods are stored outside AutoStore in zones with manual picking. When goods are received in the warehouse, The WMS informs the operators how much of the arrived goods that should be loaded into the AutoStore, and how much should be put in the buffer zone. In total the AutoStore has 23 ports, 5 dedicated for put-away and 18 for picking. Ports are open and closed dynamically depending on the workload in put-away or picking. Over the examined time period, the number of robots per average open ports are 16,7 robots/port. The release of orders to eManager is mostly handled automatically, but manual order release occurs occasionally. They have an upper limit of orders that they release at a time, to prevent too many orders being released at once. To give the AutoStore robots time to prepare bins on the top layer, all operators at the AutoStore have breaks at the same time during the day. Lastly, the forecasting function that increases possibilities for preparation of bins in exchange for robot capacity is not used.

For put-away, the goods arrive in already opened cartons stacked on pallets, ready for put-away. Before the goods were put into cartons, they were sorted according to SKU type. In addition to this, the goods have been counted, so the operator at the port does not need to count the goods. The operator simply needs to scan the EAN-code on the carton, put the goods into the bin, and confirm on the screen. The priority almost all of the time is to put as many units into the bin as possible, to maximize the fill rate in the bin. However, if there is a sale coming up, then they occasionally put the units into different bins to make them more available across the AutoStore unit. Otherwise, no clear guidelines exist for the put-away process, except the training each operator receives during their first days of work. Returns are quality checked externally prior to being sent to the warehouse in Sweden. They are delivered to the warehouse in larger mixed boxes, ready to be put into the AutoStore. Usually the operator put-away returns into the AutoStore when there is less work to do.

For picking there are four different queues, which are: AutoStore, Consolidation, Express, and Other (where B2B is picked from). The picking method is single order, which means they do not use batch picking. The team leader informs each operator what queue should be picked from. Their picking strategy is FIFO and picking from the bins that have the smallest number of units, to free up more bins. Performance according to the company is mainly how many pcs/h they are doing for put-away and picking. The team leader gives feedback to the operators on how many picks they have done and what the goal of the day is. This is done both during the morning meetings and throughout the day. The queue named “Other” which includes picking B2B is only picked from certain operators, not by all operators. Consolidation are conducted at dedicated ports, but apart from that, any of the other queues can be worked on from any port. 10 pick waves are used, which are based on what freight company is responsible for shipping (which picks up all orders at a certain time), if the order has standard or express shipping, and if consolidation is needed to complete the order.

4.3.2 Warehouse configurations and process map

In Figure 4.5 and 4.6 below, the different steps and measures taken in the put-away and picking processes around AutoStore are depicted. With a high volume of returns, put-away processes are parallel with two flows, one being returns and the other regular put-away from buffer or inbound. The picking processes are mainly structured in two setups as well, B2C revolving around the conveyor, and B2B and consolidation working with consolidation carts.

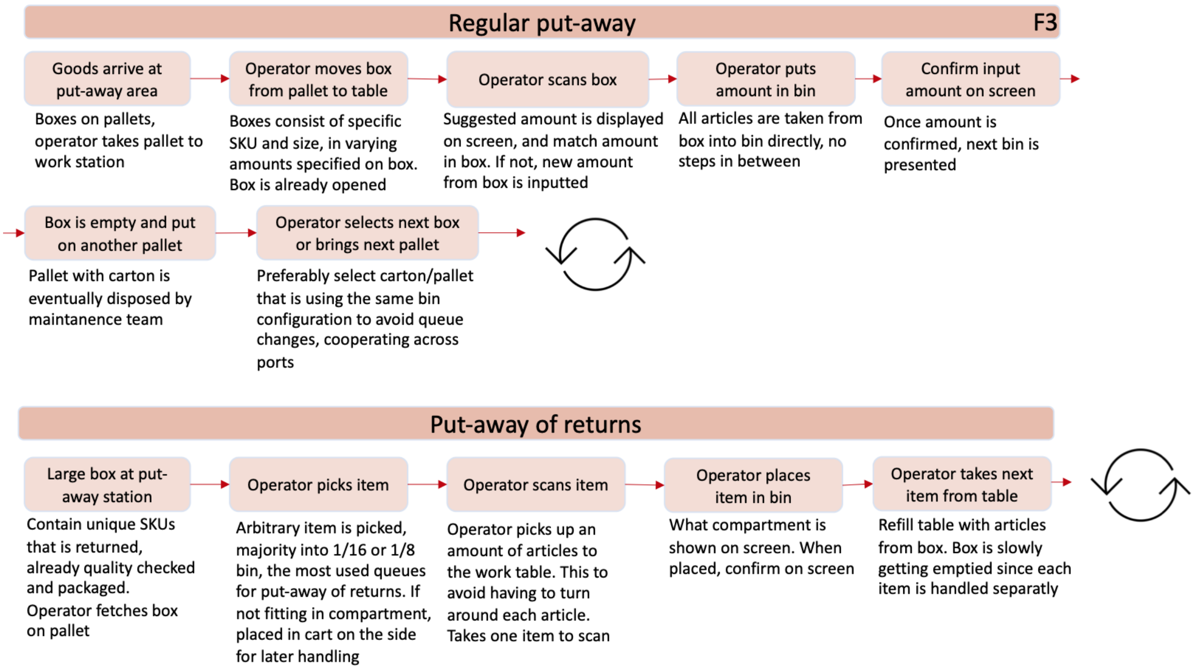

Figure 4.5. Put-away processes for company F3. Circulating arrows means the process is repeated.

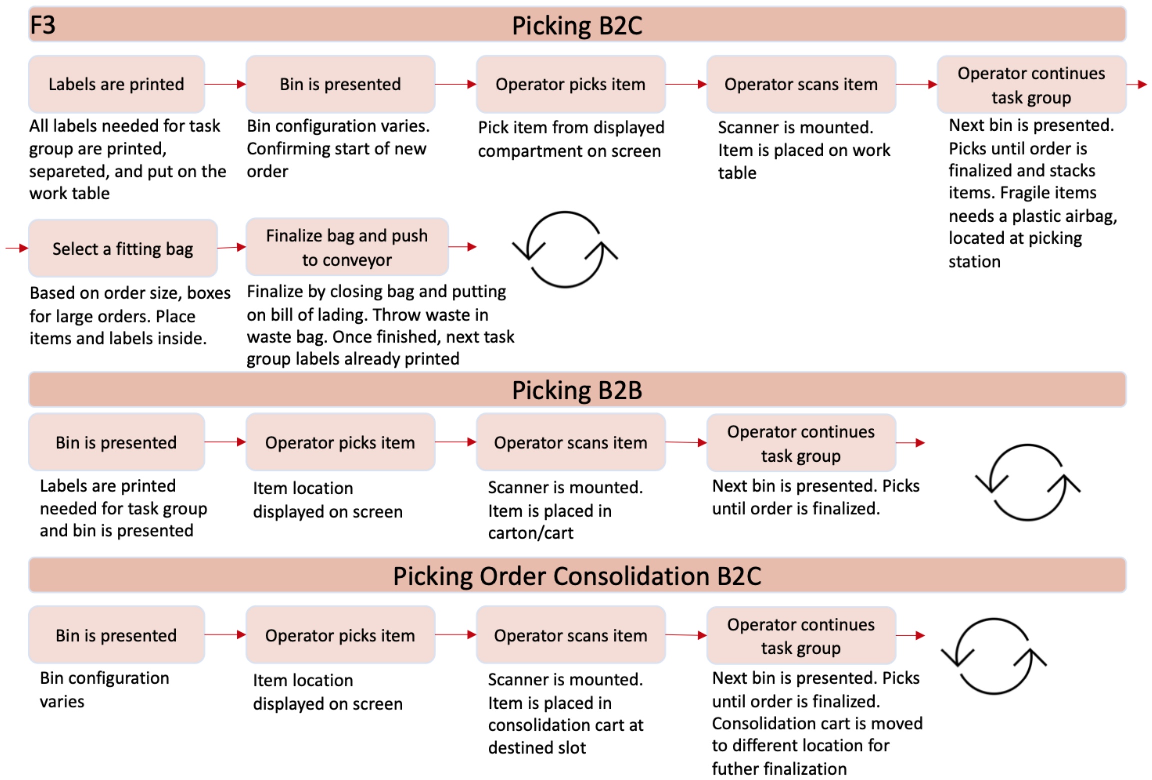

Figure 4.6. Picking processes for company F3. Circulating arrows means the process is repeated.

4.4 Company 3PL1 (3rd Party Logistics)

4.4.1 Company description and warehouse conditions

Company 3PL1 is a company that provides 3PL services for different brands, with fashion companies being some of them. The examined unit provides warehousing operations for a premium clothing brand, who heavily influence their way of conducting operations, as stated in the interview. They handle the receiving, put-away, storage, picking, packing and shipping of these products to both B2C and B2B. The company has had their AutoStore for between two and three years, which store 22K unique SKU types of their total assortment of 27K. In total the AutoStore has 9 ports, 3 dedicated for put-away and 6 for picking. They strive to have all ports active at all times and usually do not open or close ports dynamically. However, during lower workloads usually one person changes from put-away or picking to working with inventory checks. Over the examined time period, the number of robots per average open ports are 11,3 robots/port. Order release to eManager is done manually every day. They have an upper limit of orders that they release at a time, to prevent too many orders being released at once. Regarding giving the robots more time to prepare bins, the operators at 3PL1 do not have breaks at the same times during the day. Lastly, the forecasting function for the robots is utilized.

For put-away, the goods arrive in already opened cartons on a manual conveyor, already sorted by SKU type and size. However, the goods are not counted prior to arriving at the port, which means that the operator performing the put-away has to count the products before putting them into the bin. The priority all of the time is to put as many units into the bin as possible, to maximize the fill rate in the bin. Returns are quality checked in the warehouse, then ready for put-away.

For picking there are four different queues, which are: B2C, B2B, B2C Consolidation and Moveout. Regarding feedback to operators, there is a board that displays how many pieces all operators have picked so far during that day and how many pieces they will pick for the customer. The picking method is single order, which means batch picking is not used. Their picking strategy for the robots is to pick the bins according to FIFO. The company does not use any pick waves when picking. Company 3PL1 does not have any specific ports for only put-away or picking, but rather use the ports for either put-away or picking sporadically.

4.4.2 Warehouse configurations and process map

In Figure 4.7 and 4.8 below, the different steps and measures taken in the put-away and picking processes around AutoStore are depicted. With returns not being that prevalent, there is mainly one process linked with put-away, and a temporary flow once returns are stacking up. The picking processes are mainly structured in two setups. The B2C flow has value-adding steps after order is finished, and therefore, the packing of order is moved to another station by carts. B2B revolving around the conveyor and larger quantities of the same SKU in boxes instead, and consolidation working with consolidation carts.

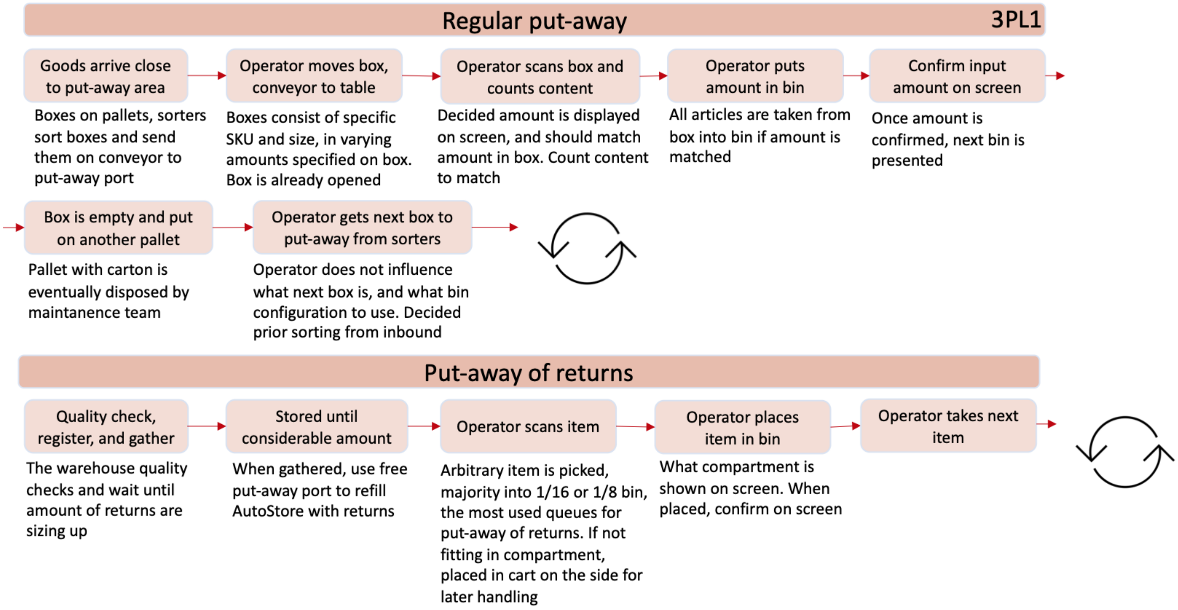

Figure 4.7. Put-away processes for company 3PL1. Circulating arrows means the process is repeated.

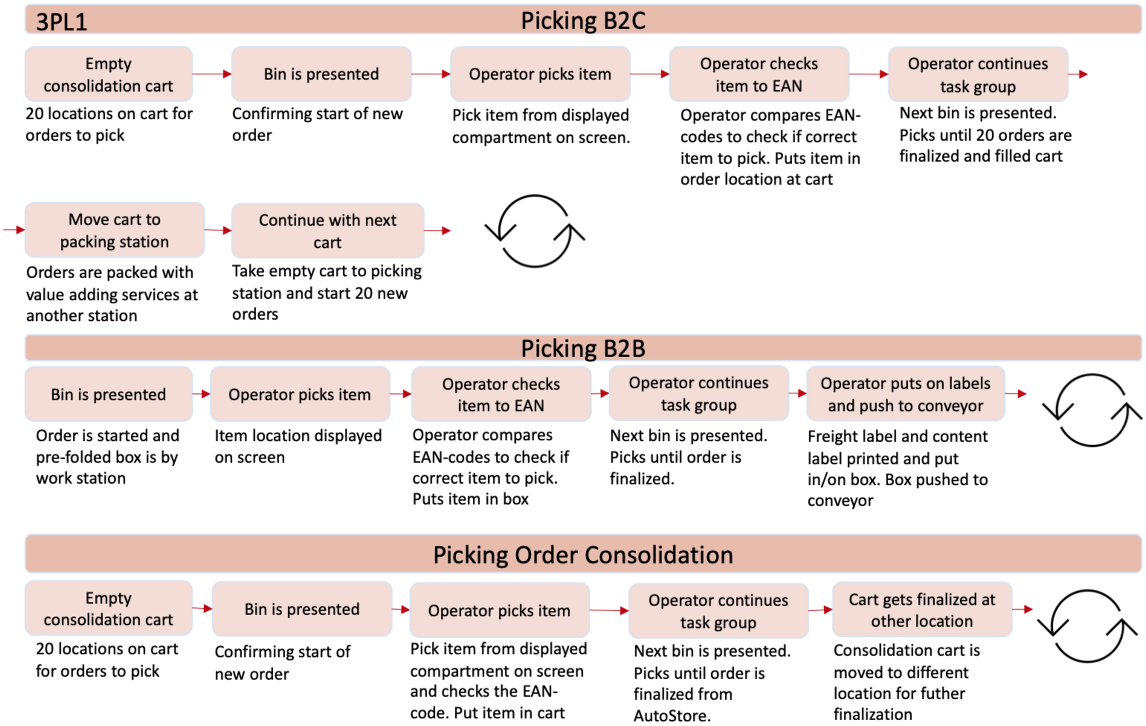

Figure 4.8. Picking processes for company 3PL1. Circulating arrows means the process is repeated.

4.5 Company 3PL2 (3rd Party Logistics)

4.5.1 Company description and warehouse conditions

Company 3PL2 is a company that provides 3PL services for different brands, with fashion companies being some of them. They handle the receiving, put-away, storage, picking, packing and shipping of these products to both B2C and B2B. The company has had their AutoStore for less than a year, which stores 13K unique SKU types of their total assortment of 14K. How many of the total SKUs are stored in the AutoStore depends, but up to 92% of their SKUs fit in the AutoStore, while the rest are stored in the oversize zone. In total the AutoStore has 13 ports, 2 dedicated for put-away and 11 for picking. The ports are open and closed dynamically depending on the workload in put-away or picking. Over the examined time period, the number of robots per average open ports are 13,4 robots/port. B2B orders are released automatically to eManager, while B2C orders are released manually. They have an upper limit of orders that they release at a time, to prevent too many orders being released at once. Regarding giving the robots more time to prepare bins, the operators at 3PL2 do not have breaks at the same times during the day. Lastly, the forecasting function that increases possibilities for preparation of bins in exchange for robot capacity is not used.

For put-away, the goods arrive in sealed cartons on pallets that need to be opened for put-away. Some of the goods come sorted, for example cartons sorted by SKU type on pallets, while other cartons include multiple different SKU types. Prior to arriving at the port-area, the goods have been counted, so the operator at the port does not need to count the goods. The priority all of the time is to put as many units into the bin as possible, to maximize the fill rate in the bin. Besides this, the guidelines for put-away is not to press down products into the bin, to avoid them expanding later on which could cause stops. Returns are quality checked at the warehouse, and put in baskets which are transported to the port-area for put-away. Generally returns have a low priority compared to put-away of new goods. 3PL2 has by the time of the visit recently acquired a new customer, causing high priority on put-away in several ports.

For picking there are four different queues, which are: AutoStore, Consolidation, Express, Other. The picking methods used are single order and batch picking (for B2B using pick by light). The team leader together with the SuperUser decides what queue should be picked from and what ports should be open or not. The pick strategy for robots is to select the bin with the lowest quantity to pick from. If the quantity in this bin is lower than the necessary quantity, the strategy is select from the 7 locations with the smallest quantities. Lastly, if the total quantity in these 7 bins is lower than the remaining quantity that is needed, a FIFO strategy is applied for the remaining quantity. 12 pick waves are used, which are based on what freight company is responsible for shipping (which picks up all orders at a certain time), if the order has standard or express shipping, and if consolidation is needed to complete the order. Performance according to the company is mainly how many pcs/h they are doing for put-away and picking. In addition to this, it is making few errors and making sure the work pace is fast enough to satisfy the orders and goals.

4.5.2 Warehouse configurations and process map

In Figure 4.9 and 4.10 below, the different steps and measures taken in the put-away and picking processes around AutoStore are depicted. With returns not being that prevalent, there is mainly one process linked with put-away, and a temporary flow once returns are stacking up. The picking processes are mainly structured in two setups. The B2C flow covers several different brands and thus packages, and otherwise sent further on conveyor. B2B is often in larger quantities in boxes instead, and dealt with by batch picking with pick-by-light. Larger amounts of the same SKU that is going to B2B is not put into the AutoStore to begin with, and is instead stored in their original boxes on pallets to be shipped directly. Consolidation working as the B2C is, but with a different label put onto the bag. Once the bag is identified later, it gets sorted and placed in a shelf for later completion.

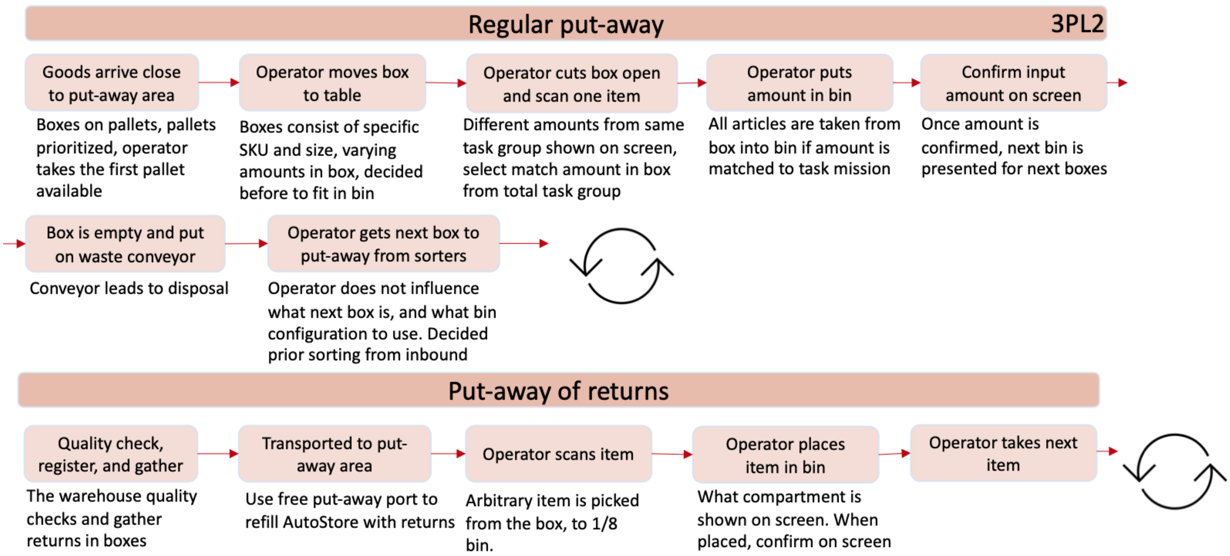

Figure 4.9. Put-away processes for company 3PL2. Circulating arrows mean the process is repeated.

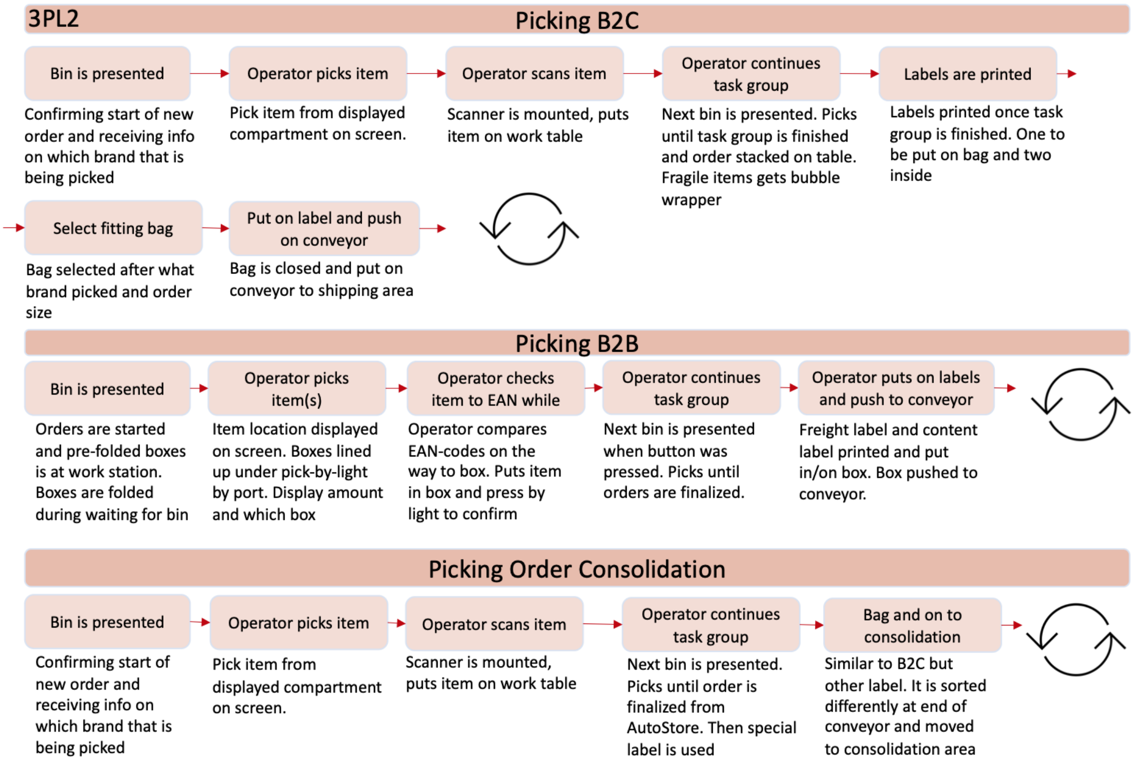

Figure 4.10. Picking processes for company 3PL2. Circulating arrows means the process is repeated.

4.6 Company E1 (ePharma)

4.6.1 Company description and warehouse conditions

Company E1 is a company selling mainly pharmaceutical products B2C through their website. The company has had their AutoStore for less than a year since they went live, which store 13K unique SKU types of their total assortment of 42K. Approximately 30% of their SKUs are stored in the AutoStore, while the rest are stored in the oversize, buffer, A-Frame or Pick By Light zone. According to the company, the primary advantage the AutoStore has for them is compact storage, but the high picking speeds that can be achieved is a plus. In total they have 11 ports, which includes 7 put-away ports not supplied by Element Logic, and 4 picking ports supplied by Element Logic. Three of the picking ports are equipped with an automatic robot arm performing the picking, supplied by Element Logic. Ports are open and closed dynamically depending on the workload in picking, and one port is frequently used to pick specific items when it is not found in the other zones of the warehouse. Company E1 has a software called "Router" which dynamically changes the number of robots dedicated to each port depending on workload. According to employees at Element Logic, this software is more efficient distributing the robot capacity depending on workload, compared to the "Planner"-software which does not do that (Element Logic, 2023f). Their order release to eManager is handled automatically and very frequently. To give the AutoStore robots time to prepare bins on the top layer, all operators at the AutoStore have breaks at the same time during the day. Lastly, the forecasting function is not used.

For put-away, the goods arrive in sealed cartons or packages stacked on pallets, which need to be opened before put-away. Some goods arrive in cartons or packages, automatically sorted after SKU type, while some cartons or packages are not sorted and include multiple different SKU types. The products are not counted, so the operator at the port needs to count them and confirm the quantity on the screen. No prioritization is done when performing the put-away regarding filling the bins to the maximum capacity or distributing them across multiple bins. Goods are filled arbitrarily into bins as fast as possible. The guidelines for put-away is not putting any products that can leak liquid or break easily in the AutoStore, which is instead stored in the oversize zone.

For picking there are two different queues, which are: Normal and Robot. As previously mentioned, three ports are equipped with automatic robot arms which pick from the queue named “Robot”, while the “Normal” queue is picked from the remaining port. Their picking strategy for the robots is to pick the bins according to FIFO. The company does not use any pick waves, however, the ready times for orders are inherited from the WMS.

4.6.2 Warehouse configurations and process map

In Figure 4.11 and 4.12 below, the different steps and measures taken in the put-away and picking processes around AutoStore are depicted. With no returns to be put into AutoStore again, there is mainly one process linked with put-away. The picking processes are mainly in two setups, the robot flow and human flow. The robot is picking 24/7 and picks orders suitable for the robot. All other products are being picked by a human instead. It is essentially designed as a process line similar in production, where orders are completed at different parts in the warehouse. Thus, the AutoStore picking is not reflecting the total picking or orders of the business.

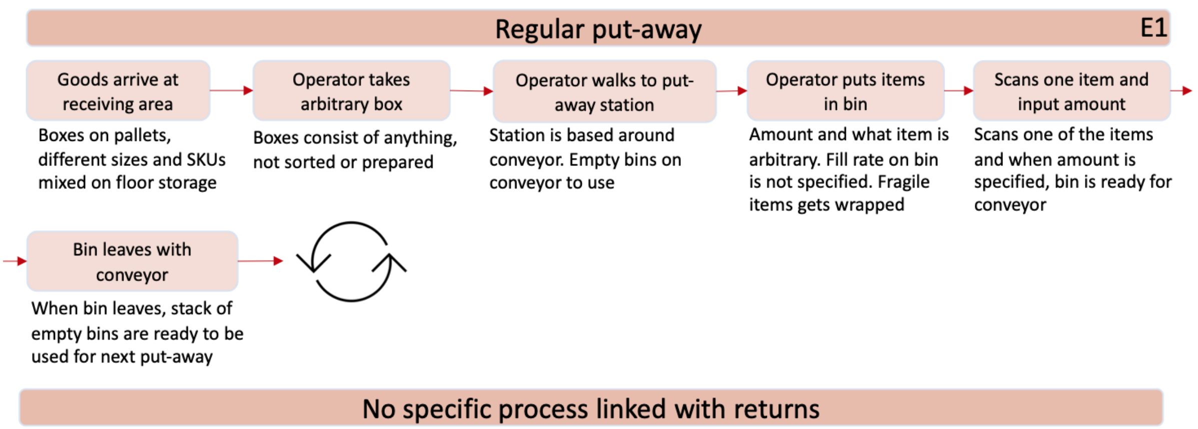

Figure 4.11. Put-away process for company E1. Circulating arrows mean the process is repeated.

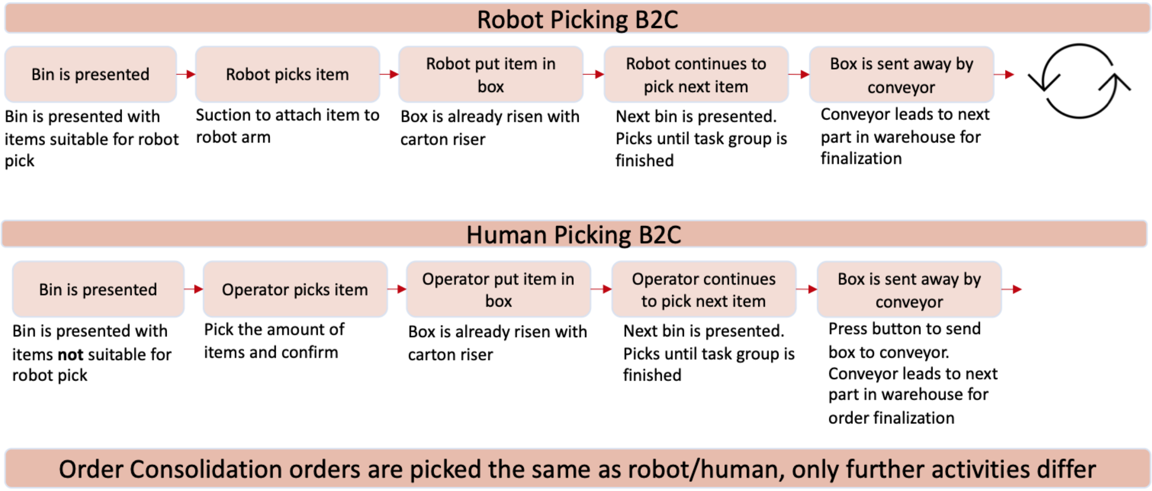

Figure 4.12. Picking processes for company E1. Circulating arrows mean the process is repeated.

4.7 Company E2 (eGrocery)

4.7.1 Company description and warehouse conditions

Company E2 mainly sells groceries B2C through their website. The company has had their AutoStore for between one and two years. They have made a strategic decision only to purchase goods to their warehouse that can fit into the AutoStore, which means 100% of their SKUs are stored in the AutoStore. In the WMS refill tasks are triggered when stock levels in the AutoStore become low, which are refilled with goods from the buffer zone. In total the AutoStore has 34 ports, 9 dedicated for put-away, 24 for picking, and one for adjusting stock levels. The company is sometimes opening or closing ports dynamically depending on the workload in put-away or picking. But in most cases the decision is instead taken to cancel the upcoming workshift, to balance out the workload. Order release to eManager is handled automatically. They have an upper limit of orders that they release at a time, to prevent too many orders being released at once. Company E2 uses the software called “Router”, which dynamically changes the number of robots dedicated to each port depending on workload. To give the AutoStore robots time to prepare bins on the top layer, all operators at the AutoStore have breaks at the same time during the day. Lastly, the forecasting function is not used.

For put-away, the goods mostly arrive in sealed cartons or packages stacked on pallets, which need to be opened before put-away. Occasionally some cartons or packages arriving at the port-area are already opened, making it easier to put-away. Before the goods were put into cartons they were sorted after SKU type, and glass products were wrapped for protection. The goods have often been counted, which means the operator at the port needs to count the products occasionally before putting them into a bin. The company is prioritizing availability in many bins, and are therefore putting products into multiple different bins. Because of E2 often having heavy or relatively storing large volume SKUs in the AutoStore, goods are naturally distributed into different bins. For low weight and low volume goods, the team leader distributes information on how those products should be put-away into different bins. Otherwise, no guidelines for put-away exists since 100% of their SKUs go into the AutoStore. The company has less than 1% returns which they donate, and therefore does not have to transfer into the AutoStore again.

For picking there is only one queue which is called "Picking". Batch picking is the only picking method used, and the operators pick 6 orders at the same time. Their picking strategy for the robots is to pick the bins according to FIFO. Since 100% of their SKUs go into the AutoStore, no consolidation picking is needed. The company does not use any pick waves for picking. Performance according to the company is mainly bin presentations/h and the "batch effect", which reflects how many bins the robots have to receive to fulfill the orders.

4.7.2 Warehouse configurations and process map

In Figure 4.13 and 4.14 below, the different steps and measures taken in the put-away and picking processes around AutoStore are depicted. With no returns, there is mainly one process linked with put-away. The picking process is also standardized with batch picking and no other process for different conditions. No order consolidation since there is nothing picked outside the AutoStore, and B2B would not be managed differently from B2C. One unique constraint in the system is that heavier items are being presented first, regardless of the bin's proximity to the port. Pick-by-light was not functioning by the time of observing, hence the temporary solution of scanning when picked.

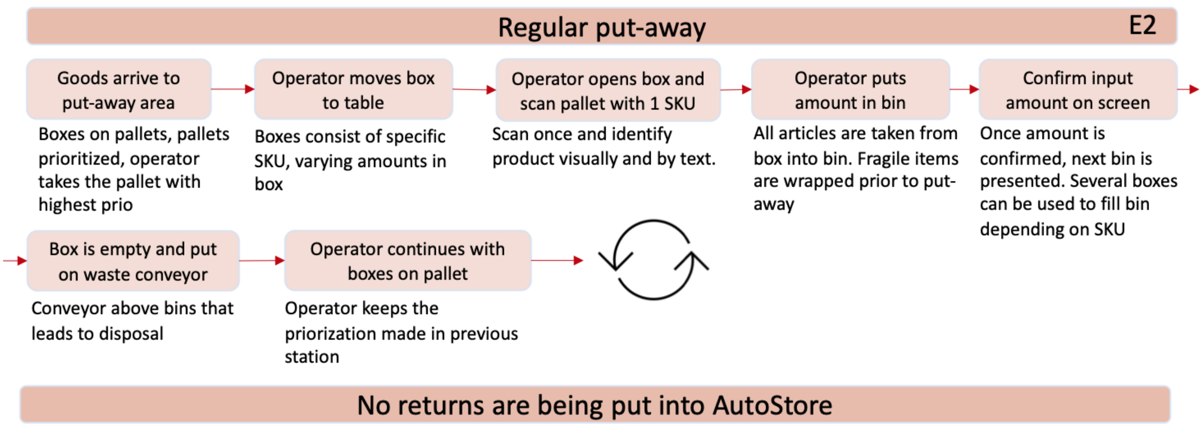

Figure 4.13. Put-away process for company E2. Circulating arrows mean the process is repeated.

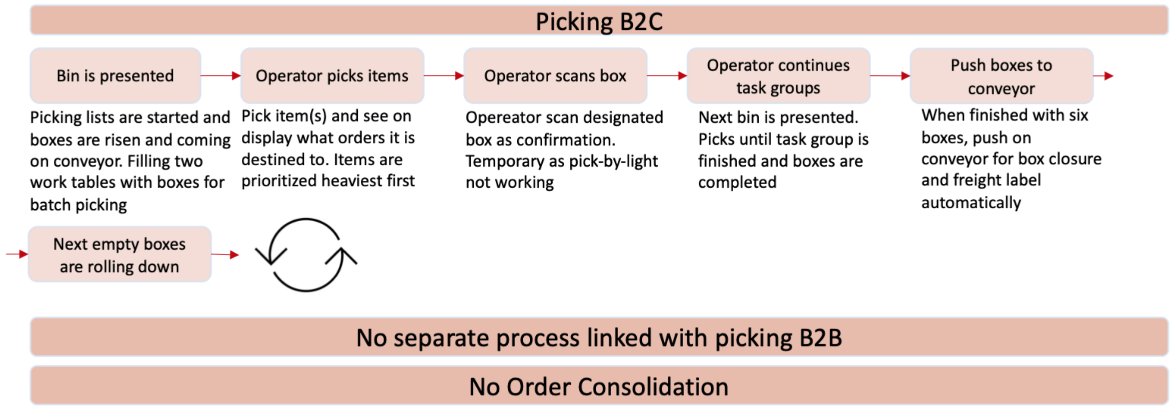

Figure 4.14. Picking process for company E2. Circulating arrows mean the process is repeated.

5. Analysis & Discussion

For the analysis, each case has been analyzed by itself, and then compared in the cross-case analysis. The within-case analyses are in-depth examining the configurations around the AutoStore in correlation to the case's contextual factors, as presented in the framework in Figure 2.3. As previously mentioned in Section 2.3, the contextual factors are divided into three different levels; External, Corporate, and Internal. These are determined as factors which the company can not necessarily change easily and therefore rather optimize their warehouse configurations instead. These configurations are inevitably affected by aspects such as potential constraints, product characteristics, customer value, and more. Further, alignment between contextual factors and configurations according to contingency theory was examined in-depth for each company. When the alignment had been established, the configurations were also evaluated from a perspective of process optimization according to TOC.

Complexity refers to the number and variety of items, orders, and processes. Uncertainty refers to the control a company has over the outcome of certain events (e.g. high variation of orders leading to higher uncertainty). Both contextual factors and configurations were investigated in terms of their complexity and uncertainty, and how they affect performance.

Summarized, in order to answer the RQs, contextual factors and their influence on warehouse configurations were analyzed through the lens of TOC to identify time-consuming tasks and/or configurations to improve performance. The contextual factors and configurations were also examined in terms of their complexity and uncertainty. This was done on case-level and finally comparatively between cases to identify what contextual factors that are affecting performance, regardless if the configurations are aligned or not.

5.1 Within-Case Analyses

For each case there is a table which is based on the contingency framework presented in Figure 2.3 and the categorization of contextual factors in Figure 2.4. All within-case analyses are based on the process maps of each company in empirical findings presented in Chapter 4. The case summaries are meant to provide complete description of configuration elements and how they are structured, and are further analyzed in each section below.

All respective tables are connected to each level of contextual factors, where each factor is being divided into lower levels followed by which configuration it affects. How the configurations are affected are then described, along with how it might affect performance through complexity and uncertainty, TOC, or both. All results are being examined in terms of their validity, as previously discussed in Section 3.6. Results where validity is lacking, was investigated further on *why* data might be compromised and considered during the within- and cross-case analysis.

5.1.1 Company F1

External contextual factors

Starting with the external contextual factors, the identified ones are: returns, product and order characteristics, and customer values. These are displayed in Table 5.1a below.

Table 5.1a. External contextual factors, the configurations affected and how it might affect performance.

Contextual Factors: External context			**Configuration elements mainly affected (operations, design, and resources)**			**How configuration might affect performance**
Returns	Number of returns	→	Put-away, Picking	20% returns (approx.).	→	Increased complexity
		→	Picking	Pick Strategy: Pick from bins with lowest quantity	→	More robot resources used
Product characteristics	Product portfolio	→	Put-away, Picking, Packing	Number of SKU types: 22,000. Leading to additional processes with items not fitting AutoStore. 4 different bin-configurations	→ →	Increased complexity and uncertainty Increased complexity
	Fragility	→	Picking	A few products need to be wrapped/ put in an extra package for protection (when picking the products).	→	Less efficient picking
	Oversize	→	Put-away, Storage, Picking	The 5% (of 22,000 SKUs) are handled manually outside AutoStore.	→	Increased complexity
Order characteristics	SKUs included in order	→	Picking, Packing	Consolidation is required (avg. 5% of total pcs picked in consolidation)	→	Increased complexity
	Order Volume	→	Put-away, Picking, Storage	Opening/closing ports (depending on workload). Synchronized breaks for preparation of bins (only during high workloads, otherwise they do not).	→ →	Robot resources used more efficiently Time for robot charging and preparation
		→	Order Release	Has an upper limit of orders they release at a time.	→	Decreased uncertainty
Customer values	Speed, Quality (few errors)	→	Put-away, Picking, Packing	Operator does not count at port	→	More efficient put-away

The number of returns affects both the put-away and picking operations. At company F1, returns arrive in large boxes with mixed SKUs, that are put-away in one compartment at a time (often in bins with 16 compartments). They have approximately 20% returns, which leads to an increased complexity, as that adds to the process diversity, in other words another process to handle. As the returns are put-away one unit at a time compared to normal goods, this process is necessary due to the contextual factor but less efficient in terms of TOC.

Product characteristics factors such as product portfolio, fragility, special handling or oversize affects the configurations. Company F1 has 22,000 SKUs and 4 different bin configurations for their products (1, ½, ¼, ⅛) leading to increased complexity and uncertainty. The variety and number of SKUs affects packing as company F1 has different sizes for boxes and bags. The operator therefore has to know what size that will fit the products in the current order being picked, and choose the right size. Regarding fragility, F1 has a few products that need to be wrapped or put in an extra package for protection. It is done when picking the products, which leads to a less efficient picking process. Therefore, this is not aligned with TOC as a time-consuming operation is done at the port, contributing to a potential bottleneck. 95% of their SKUs (22,000 total) are stored in the AutoStore, only 5% not stored in AutoStore. The 5% has to be put-away, stored and picked manually. This means a higher process diversity, and therefore complexity, compared to only put-away and pick goods that are stored in the AutoStore. What SKUs in the majority of times are included in the orders also affect if consolidation is needed or not, adding to the process diversity and complexity.

F1 handles around 7,000 order lines per day. Depending on the workload (which is dependent on order volume) they close ports if there are too many open, and vice versa. Closing ports when there are too many open compared to the workload frees up robots (Element Logic, 2023g). The robots can also work more efficiently to provide the open ports with bins, since robots otherwise will try to supply all open ports with bins (Element Logic, 2023g). This leads to the robot resources being used more efficiently, as they can optimize the retrieval of bins to fewer ports (Element Logic, 2023g). In addition to this, the synchronized breaks they have for the operators during high workloads leads to more time for robots to charge and prepare bins. However, this is only done during high workloads which means most of the time robots have less time for preparing and charging, compared to having synchronized breaks all the time. These two configurations are aligned with TOC as they contribute to more efficient put-away- and picking processes, and strive to reduce possible bottlenecks at the ports.

For order release F1 has a maximum limit of orders they release at a time, which decreases the uncertainty as company F1 can make sure they have more control over the outcome regarding preparation of bins. If too many orders are released at once, for example orders that are due to be picked further ahead in time, the robots might start preparing those bins (Element Logic, 2023h). This is aligned with TOC as this contributes to a more efficient picking process when bins need to be retrieved. Lastly, when performing put-away the operators at the port do not need to count the units, which leads to a more efficient put-away process and also aligns with TOC.

Corporate contextual factors

For the case of F1, the only correlation between corporate contextual factors and configuration could be identified in growth/sales strategy, depicted in Table 5.1b.

Table 5.1b. Corporate contextual factors, the configurations affected and how it might affect performance.

Contextual Factors: Corporate context			**Configuration elements mainly affected (operations, design, and resources)**			**How configuration might affect performance**
Product purchasing strategy	Product portfolio	→	Put-away, Storage, Picking, Packing	Purchasing items in furniture category not stored in AutoStore	→	Increased complexity
Growth/sales strategy		→	Picking, Packing	Operators putting discount-leaflets in package	→	Less efficient picking and packing

Operators have to finish each order by selecting the correct discount-leaflet for the corresponding order. Which leaflet to select can be different depending on who the customer is or what current campaign that is running. Thus, it leads to less efficient picking and packing since it is an additional activity that has to be conducted, not aligned with TOC.

Internal warehouse contextual factors

For the internal warehouse context, the factors of Delivery and shipment and general warehouse efficiency are being analyzed, depicted in Table 5.1c.

Table 5.1c. Internal warehouse contextual factors, the configurations affected and how it might affect performance.

Contextual Factors: Internal warehouse context			**Configuration elements mainly affected (operations, design, and resources)**			**How configuration might affect performance**
Delivery and shipment	Number of different shippers	→	Picking	The company does not use any pick waves	→	Reduces complexity
Warehouse efficiency	-	→	Put-away, Picking, Packing	Conveyor for carton disposal	→	Less time-consuming tasks performed at port.
				Some cartons needs to be quick-folded (not like regular folding and sealing with tape)	→	Slightly less efficient picking
				Goods arrive sorted by SKU type to the port	→	More efficient put-away

				Shipping label printed after order is finished	→	Less efficient picking and packing
				Forecasting-function for robots is used	→	Increasing bin preparation

With pick waves enabled, robots prepare bins and pick orders for the current pick wave (Element Logic, 2023c). Having more pick waves therefore adds constraints to the algorithm which might affect its ability to optimize the tasks to be done. Company F1 does not use any pick waves, which reduces complexity in processes and for the AutoStore in its preparations of bins.

Regarding warehouse efficiency, there is a conveyor just above the port used for carton disposal when performing the put-away, instead of operators having to handle the waste. This leads to less time-consuming tasks being performed at the port, and thus aligns with TOC. The operators occasionally collaborate during put-away: if a SKU on the pallet fits another bin configuration than currently being used, the operator can give the products to the operator in the nearby port with that bin configuration, to avoid switching queue. Boxes used for picking and packaging need to be prepared, but not folded and sealed with tape as regular boxes due to the design. The design saves time for the operator, but it is still a time-consuming task contributing to a slightly less efficient picking- and packing process. When picking and packing, the shipping label is printed after the order is finished, which leads to less efficient picking- and packing processes, and does not align with TOC. The forecasting-function for robots is used, increasing the bin preparation and aligning with TOC (but might lower the lifespan of robots).

Validity of results

In the case of F1 we conclude that the results are valid. The main interviewee (Site Manager) was a person with interest and knowledge about the AutoStore. In addition to this, three other employees attended the interview to confirm or add anything to the answers from the Site Manager. The observations and the interview were both depicting the same picture of the business and its operations. When observing the processes in real time, multiple examples were all operating the same way through a variety of products and stations.

5.1.2 Company F2

External contextual factors

Starting with the external contextual factors, the identified ones are returns, product and order characteristics, and customer values, depicted in Table 5.2a.

Table 5.2a. External contextual factors, the configurations affected and how it might affect performance.

Contextual Factor: External context			Configuration elements mainly affected (operations, design, and resources)			How configuration might affect performance
Returns	Number of returns	→	Put-away, Picking	High amount of returns.	→	Increased complexity
		→	Picking	Pick Strategy: Pick from bins with lowest quantity, otherwise pick according to FIFO for rest quantity.	→	More robot resources used
Product characteristics	Product portfolio	→	Sorting, Put-away, Picking, Packing	Very high number of SKU types (102,000).	→	Increased complexity
				5 different bin-configurations	→	Increased complexity
	Fragility	→	Picking	A few products need to be wrapped/ put in an extra package for protection (when picking the products).	→	Less efficient picking.
	Oversize	→	Put-away, Storage, Picking	The 5% (of 102,000 SKUs) are picked manually outside AutoStore.	→	Increased complexity
Order characteristics	SKUs included in order	→	Picking, Packing	Consolidation is required (5% SKUs stored outside AutoStore)	→	Increased Complexity
	Order Volume	→	Put-away, Picking, Storage	Opening/closing ports (depending on workload).	→	Robot resources used more efficiently
				Synchronized breaks for preparation of bins (only during high workloads, otherwise they do not).	→	Time for robot charging and preparation
		→	Order Release, Picking	Has an upper limit of orders they release at a time.	→	Decreased uncertainty
Customer values	Speed, Quality	→	Put-away, Picking, Packing	Operator counts goods at the port as a double check	→	Less efficient put-away

The number of returns affects both the put-away and picking operations. At company F2, returns arrive in large boxes with mixed SKUs, that are put-away in one compartment at a time (often in bins with 16 or 8 compartments). They have high amounts of returns, which leads to an increased complexity, as that adds to the process diversity, in other words another process to handle. As the returns are put-away one unit at a time compared to normal goods, this process is necessary due to the contextual factor but less efficient in terms of TOC.

Product characteristics factors such as product portfolio, fragility, special handling or oversize affects the configurations. Company F2 has 102,000 SKUs and 5 different bin configurations for their products (1, ½, ¼, ⅛, 1/16) leading to increased complexity. The variety and number of SKUs affects packing as company F2 has different sizes for boxes and bags. The operator therefore has to know what size that will fit the products in the current order being picked, and choose the right size. Regarding fragility, F2 has a few products that need to be wrapped or put in an extra package for protection. It is done when picking the products, which leads to a less efficient picking process. Therefore, this is not aligned with TOC as a time-consuming operation is done at the port, contributing to a potential bottleneck. Regarding special handling or guidelines, company F2 stores some bigger products that can expand in the AutoStore, but is cautious putting too many units in one bin. As stated by both Jaghbeer (2019) and multiple employees at Element Logic (Element Logic, 2023i) storing these kinds of products in the AutoStore might lead to stops as it can cause robots to get stuck in the products when moving over the bins.

95% of their SKUs (102,000 total) are stored in the AutoStore, only 5% not stored in AutoStore. The 5% has to be put-away, stored and picked manually. This means a higher process diversity, and therefore complexity, compared to only put-away and pick goods that are stored in the AutoStore. What SKUs in the majority of times are included in the orders also affect if consolidation is needed or not, adding to the process diversity and complexity.

F2 handles around 60,000 pcs per day. Depending on the workload (which is dependent on order volume) they close ports if there are too many open, and vice versa. According to (Element Logic, 2023g) closing ports when there are too many open compared to the workload frees up robots. The robots can also work more efficiently to provide the open ports with bins, since robots otherwise will try to supply all open ports with bins (Element Logic, 2023g). This leads to the robot resources being used more efficiently, as they can optimize the retrieval of bins to fewer ports (Element Logic, 2023g). In addition to this, the synchronized breaks they have for the operators during high workloads leads to more time for robots to charge and prepare bins. However, this is only done during high workloads which means most of the time robots have less time for preparing and charging, compared to having synchronized breaks all the time. These two configurations are aligned with TOC as they contribute to more efficient put-away- and picking processes, and strive to reduce possible bottlenecks at the ports.

For order release F2 has a maximum limit of orders they manually release at a time, which decreases the uncertainty as company F2 can make sure they have more control over the outcome regarding preparation of bins. If too many orders are released at once, for example orders that are due to be picked more further ahead in time, the robots might start preparing those bins. This is aligned with TOC as this contributes to a more efficient picking process when bins need to be retrieved. However, when performing put-away the operators at the port need to count the units, which leads to a less efficient put-away process and also does not align with TOC.

Corporate contextual factors

For the case of F2, the only correlation between corporate contextual factors and configuration could be identified in growth/sales strategy, depicted in Table 5.2b.

Table 5.2b. Corporate contextual factors, the configurations affected and how it might affect performance.

Contextual Factors: Corporate context			Configuration elements mainly affected (operations, design, and resources)			How configuration might affect performance
Product purchasing strategy	Product portfolio	→	Put-away, Storage, Picking, Packing	High number of SKUs	→	Increased uncertainty and complexity
Growth/sales strategy		→	Picking, Packing	Operators putting discount-leaflets in package (occasionally)	→	Less efficient picking and packing

Operators have to occasionally finish each order by selecting the correct discount-leaflet for the corresponding order. Which leaflet to select can be different depending on who the customer is or what current campaign that is running. Thus, it leads to less efficient picking and packing since it is an additional activity that has to be conducted, not aligned with TOC. However, it is performed in periods and not standard procedure.

Internal warehouse contextual factors

For the internal warehouse context, the factors of Delivery and shipment and general Warehouse efficiency are being analyzed, depicted in Table 5.2c.

Table 5.2c. Internal warehouse contextual factors, the configurations affected and how it might affect performance.

Contextual Factor: Internal warehouse context			Configuration elements mainly affected (operations, design, and resources)			How configuration might affect performance
Delivery and shipment	Number of different shippers	→	Picking	3-4 pick waves are used	→	Increases complexity
Warehous e efficiency	-	→	Put-away, Picking, Packing	Conveyor for carton disposal Some cartons (very few) needs to be folded manually (and some also sealed with tape) Goods arrive to the port	→ → →	Less time-consuming tasks performed at port. Less efficient picking and packing More efficient put-away

				sorted by SKU type		
				Sealed cartons arrive to put-away port - cartons need to be opened	→	Less efficient put-away
				Shipping label printed before order is finished	→	More efficient picking and packing
				Forecasting-function for robots is used	→	Increasing bin preparation (but might lower life span of robots)

With pick waves enabled, robots prepare bins and pick orders for the current pick wave (Element Logic, 2023c). Having more pick waves therefore adds constraints to the algorithm which might affect its ability to optimize the tasks to be done. Company F2 uses 3-4 pick waves, which increases complexity in processes and for the AutoStore in its preparations of bins.

Regarding warehouse efficiency, there is a conveyor just above the port used for carton disposal when performing the put-away, instead of operators having to handle the waste. This leads to less time-consuming tasks being performed at the port, and thus aligns with TOC. The operators occasionally collaborate during put-away: if a SKU on the pallet fits another bin configuration than currently being used, the operator can give the products to the operator in the nearby port with that bin configuration, to avoid switching queue. Some boxes used for picking and packaging need to be folded and sealed which is still a time-consuming task contributing to a slightly less efficient picking- and packing process. When picking and packing, the shipping label is printed before the order is finished, which leads to more efficient picking- and packing processes, and aligns with TOC. The forecasting-function for robots is used, increasing the bin preparation and aligning with TOC (but might lower the lifespan of robots).

Validity of results

In the case of F2 we conclude that the results are valid. The main interviewees (Site Manager and Head of Fulfillment) are two people that have knowledge about the warehouse in general and operations around the AutoStore. The observations and the interview were both depicting the same picture of the business and its operations. When observing the processes in real time, multiple examples were all operating the same way through a variety of products and stations.

5.1.3 Company F3

External contextual factors

Starting with the external contextual factors, the identified ones are returns, product and order characteristics, and customer values, depicted in Table 5.3a.

Table 5.3a. External contextual factors, the configurations affected and how it might affect performance.

Contextual Factor: External context			**Configuration elements mainly affected (operations, design, and resources)**			**How configuration might affect performance**
Returns	Number of returns	→	Put-away, Picking	30% returns (approx.)	→	Increased complexity
		→	Picking	Pick Strategy: FIFO	→	More robot resources used
Product characteristics	Product portfolio	→	Sorting, Put-away, Picking, Packing	Many SKU types (49,000) Large amount not stored in AutoStore (40%) 5 different bin configurations	→ → →	Increased complexity and uncertainty Increased complexity Increased complexity
	Fragility	→	Picking	A few products need to be wrapped/ put in an extra package for protection (when picking the products).	→	Less efficient picking with extra steps by port
	Oversize	→	Put-away, Storage, Picking	Oversize, men's articles and hanging are stored outside	→	Increased complexity
Order characteristics	SKUs included in order	→	Picking, Packing	Consolidation (40% SKUs stored outside AutoStore) Men's clothes outside AutoStore	→ →	Increased complexity Increased complexity
	Order Volume	→	Put-away, Picking, Storage	Opening/closing ports (depending on workload). Synchronized breaks during afternoon	→ →	More efficient robot management Robots can prepare or charge
		→	Order Release	Has an upper limit of orders they release at a time and release automatically and manually	→	Decreased uncertainty
Customer values	Speed, Quality (few errors)	→	Put-away, Picking, Packing	No counting or sorting of goods at the port	→	More efficient put-away

The number of returns affects both the put-away and picking activities. In the case of F3, returns arrive in large boxes with mixed SKUs, and are to be inserted into the AutoStore. Although they are quality checked and prepared for put-away at an external location, returns are prevalent to an extent needing a specific process to handle. Thus, returns increase complexity in put-away by requiring a separate process. Besides, conducting put-away one piece at a time is a more time-consuming task than regular flow of put-away, with more articles inserted per presentation, leading to inefficiency. F3 does follow the picking strategy of FIFO, and therefore constraints the system in that aspect. Since returns are inserted on single-item-basis in compartments of 1 SKU, it increases the availability of random items.

Product characteristics factors such as product portfolio, fragility, special handling or oversize affects the configurations. F3 has 49,000 SKUs and 5 different bin configurations for their products in whole bins, ½, ¼, ⅛, and 1/16, leading to increased complexity. The amount of SKU types also leads to increased uncertainty in handling the increased variety.
The variety and number of SKUs further affect packing as F3 has different sizes for bags. The operator therefore has to know what size that will fit the products in the current order being picked, and choose a sufficient size, adding a decision-making element to the process. F3 has a few products that need to be wrapped or put in an extra package for protection. It is done when picking the products, which leads to a less efficient picking process for those orders. Thus, an additional time-consuming activity by the picking port does not align with TOC.

Regarding special handling and guidelines, a considerable amount of SKUs are stored outside the AutoStore. The complexity increases as all processes have to be compatible with consolidation, even men's clothing that are ordered through a different website but are consolidated before shipping, also surfaces when examining SKUs per order.

Continuing on order characteristics, F3 regulates the order volume by opening and closing ports depending on what is needed, as well as assisting the timed order release with manual releases, as well automatic releases at a certain volume of orders in the system. These are all measures to mitigate uncertainty and keep a steady flow of orders to prepare and pick in the AutoStore. Also, during the afternoon when preparation levels usually start to go lower (Element Logic, 2023a), there is a synchronized break to let the preparation level and/or battery levels increase. Thus, robots are rather optimizing to supply open ports than sub-optimizing if volumes are too low, and also do get the possibility to charge and/or prepare bins. With higher levels of preparation, picking has the possibility to be more efficient, aligning with the TOC.

Corporate contextual factors
For the case of F3, the correlation between corporate contextual factors and configuration could be identified in product purchasing strategy and growth/sales strategy, depicted in Table 5.3b.

Table 5.3b. Corporate contextual factors, the configurations affected and how it might affect performance.

Contextual Factors: Corporate context			Configuration elements mainly affected (operations, design, and resources)			How configuration might affect performance
Product purchasing strategy	Product portfolio	→	Put-away, Storage, Picking, Packing	High number of SKUs	→	Decreased uncertainty and complexity
Growth/sales strategy	-	→	Picking, Packing	Operators putting discount-leaflets in package	→	Less efficient in picking

Operators have to finish each order by selecting the correct discount-leaflet for the corresponding order. Which leaflet to select can be different depending on who the customer is or what current campaign that is running. Thus, it leads to less efficient picking and packing since it is an additional activity that has to be conducted, not aligned with TOC.

Internal warehouse contextual factors

For the internal warehouse context, the factors of Delivery and shipment and general warehouse efficiency are being analyzed, depicted in Table 5.3c.

Table 5.3c. Internal warehouse contextual factors, the configurations affected and how it might affect performance.

Contextual Factor: Internal warehouse context			Configuration elements mainly affected (operations, design, and resources)			How configuration might affect performance
Delivery and shipment	Number of different shippers	→	Picking	10 pick waves are used	→	Increases complexity
Warehouse efficiency	-	→	Put-away, Picking, Packing	Some processes are limited to specific operator	→	Increase complexity
				Manual for carton disposal but not operator that throws used carton	→	Little less time-consuming tasks performed at port
				Opened cartons arrive to put-away port, ready for put-away	→	More efficient put-away
				Goods arrive sorted by SKU type to the port	→	More efficient put-away
				Shipping label printed when order is started	→	More efficient picking and packing

With the setup of distributors and shippers used by F3, it is handled by using 10 different pick waves. By limiting the system with further constraints on what to prepare and when, the complexity increases and re-prepares orders before the next pick wave. Further forcing the system to rearrange the top grid comprises the already prepared bins before they are being picked, thus re-shuffling bins again, not optimized risking a bottleneck in waiting for the next bin.

In regards to warehouse efficiency and optimizing the processes according to TOC, F3 does take a number of efforts. For starters, goods arrive at the put-away port already sorted, counted, and with boxes already open, allowing operators to focus on put-away and removing time-consuming activities otherwise performed by the port. However, carton is being disposed of by the operator once a box is empty, but activity does only include to gather by station and emptied by a service team, only compromising the put-away to an extent. Also, one of the picking queues is only used by specific operators, increasing complexity by introducing limitations. Later by the picking, there are instances of larger orders to be packed in boxes. If these order sizes are occurring, the operator has to prepare a box by folding and raising the box, as well as sealing, all time-consuming activities in these cases, not aligned with TOC. Lastly, all labels needed for sending the order are being printed at the start of the order, which is aligned with TOC. By the time the operator is finished picking, the labels are prepared, removing potentially waiting for printing from the process.

Validity of results

For F3, we conclude that the results are valid. The interview was with two people involved in both the daily operations as well as maintaining a balance in the AutoStore with a rather mature installation. The observations were corresponding to what had been discussed in the interviews, with several instances of confirmation. There was time for questions to both operators and the interviewees that accompanied through the warehouse, clearing any misunderstandings and observing processes in real time. Also, F3 has been keen to answer follow-up questions frequently to further depict their operations accurately.

5.1.4 Company 3PL1

External contextual factors

Starting with the external contextual factors, the identified ones are returns, product and order characteristics, and customer values, depicted in Table 5.4a.

Table 5.4a. External contextual factors, the configurations affected and how it might affect performance.

Contextual Factor: External context			**Configuration elements mainly affected (operations, design, and resources)**			**How configuration might affect performance**
Returns	Number of returns	→	Put-away	15% returns (approx.). Do not have a dedicated port for returns.	→	Increased complexity
		→	Picking	Pick Strategy: FIFO	→	More robot resources used
Product characteristics	Product portfolio	→	Sorting, Put-away, Picking, Packing	Using 4 bin configuration	→	Increased complexity
				27,000 number of SKU types	→	Increased complexity and uncertainty
	Fragility	→	Sorting, Put-away or Picking	Fragile items uncommon	→	Decreased complexity
	Special handling	→	Put-away, Picking	Premium packing station after picking	→	Decreased complexity in port and more efficient
	Oversize	→	Put-away, Storage, Picking	Oversized products stored outside AutoStore	→	Increased complexity
Order characteristics	SKUs included in order	→	Picking, Packing	Picking and packing dependent on queue rather than SKU	→	Decreased the complexity in picking and packing
				Consolidation orders and B2C are handled the same way	→	Reduced complexity in B2C & Consolidation
	Order Volume	→	Put-away, Picking, Storage	Opening/closing ports (depending on workload)	→	More efficient robot management
				Do not use the AutoStore for everything	→	Less dependency on AutoStore, but risk inefficiency by using less efficient picking methods
		→	Order Release	Has an upper limit of orders they release at a time and release manually	→	Decreased and increased uncertainty
Customer values	Speed, Quality (few errors)	→	Put-away, Picking, Packing	Premium packing at other station	→	More efficient picking
				Sorting stations prior to put-away	→	More efficient put-away
				Labels are printed after finished pick	→	Less efficient picking

Beginning with returns, 3PL1 does have returns to be inserted into the AutoStore, but to a limited degree. The flow of returns is not enough to have a dedicated port for this specific process, and is instead gathered up. When returns have been gathered and checked in a substantial amount, put-away is conducted in one of the standard ports during calmer periods. Thus, the process of inserting returns is existing, but does not necessarily interfere with port being used to a normal flow instead. However, the AutoStore instead needs to prepare ⅛ bins to a port which is normally used for other configurations. Looking at the product characteristics, they manage the stock of a clothing brand, with products both fitting the AutoStore and not. With products in other parts of the warehouse, the complexity of consolidation surfaces and demands a specific process to manage. Also, having parallel storing and handling of oversize products raises complexity in general. The number of SKU types raises complexity in handling and furthermore in accurately forecasting demand and managing a wider catalog. Specific SKUs also have different volume, making capacity and usage of bins to look very different, with instances of larger products filling the bin with only 1-2 SKUs. The bin itself also has 4 different configurations, with different SKUs suitable for different configurations. This increases the complexity of the system with added variations and restrictions, but also raises the availability of SKUs in smaller amounts. Further, the SKUs are rarely fragile, saving special handling time for wrapping or similar. The SKUs are though considered to be a premium product to a very wide extent, requiring premium packaging for the B2C flow in picking. Instead of packing by the port, finished orders are transported to a packing station, removing a very time-consuming activity from the port, relocating the bottleneck elsewhere. In put-away, time-consuming activities such as opening boxes, sorting, and counting have been moved to stations prior to the port, removing time-consuming tasks, as well as the decision of what to prioritize.

Continuing with the order characteristics, orders do consist of things needing consolidation, and not. However, the B2C flow and the consolidation flow are two very similar processes, due to the need for premium packaging, leading to reduced complexity in processes. Instead of having activities linked to the SKU variety, it rather differs depending on the queue, decreasing complexity in terms of special handling. Regarding order volume, the orders released into the system are manually regulated, to lower uncertainty in the system and allow for preparations accordingly together with allocation of open ports and/or queues. In the case of large quantity orders, within B2B, the picking can instead of picking items from the AutoStore, be directly picked on pallet not yet inserted into the AutoStore. When dealing with large enough volume, time-consuming activities through the AutoStore and the resources to handle these are removed completely. Besides the AutoStore, all activities do not revolve around the AutoStore, thus less dependency on the AutoStore and its performance. Though, the AutoStore is an efficient technology for picking, and not utilizing it leads to inefficiency. Uniquely for 3PL1 is the customer value of premium that heavily affects the processes related to B2C. As mentioned in the previous section, each piece picked directly from the customer is supposed to be packaged in a more extensive process, a process that has been removed from the port. By both removing a time-consuming activity and standardizing two processes is aligned with TOC and to lower the complexity by the picking ports.

Corporate contextual factors

For the case of 3PL1, the only correlation between corporate contextual factors and configuration could be identified in Product purchasing strategy, with no use of discount-leaflets, as depicted in Table 5.4b.

Table 5.4b. Corporate contextual factors, the configurations affected and how it might affect performance.

Contextual Factors: Corporate context			**Configuration elements mainly affected (operations, design, and resources)**			**How configuration might affect performance**
Product purchasing strategy	Product portfolio	→	Put-away, Storage, Picking, Packing	3PL dependent on its client	→	Increases complexity and uncertainty
Growth/ sales strategy	-	→	Picking, Packing	No discount-leaflets in package	→	More efficient in picking

Further on with looking at the purchasing strategy, the company being a 3PL and limited to the desires of their customers (the company the 3PL service is provided to), the complexity and uncertainty increases with an additional decision maker and party to consider. 3PL1 stated in the interview that since they are busy fulfilling the desires and demands of their customers, they do not prioritize using AutoStore in an optimized way. The amount of different SKUs also raises complexity and uncertainty in how much to keep in stock and how to design the processes needed to handle certain SKUs and orders.

Internal warehouse contextual factors

For the internal warehouse context, the factors of Delivery and shipment and general Warehouse efficiency are being analyzed, depicted in Table 5.4c.

Table 5.4c. Internal warehouse contextual factors, the configurations affected and how it might affect performance.

Contextual Factors: Internal warehouse context			**Configuration elements mainly affected (operations, design, and resources)**			**How configuration might affect performance**
Delivery and shipment	Number of different shippers	→	Picking	The company does not use any pick waves	→	Reduces the complexity of when orders have to be picked and thus allowing the system to optimize after less constraints
Warehouse efficiency	-	→	Put-away, Picking, Packing	Removing time-consuming activities from port, such as packaging, sorting, opening and counting	→	More efficient processes by port

				Labels printed after picking is finished Forecasting-function for robots is used	→ →	Less efficient by picking station Increasing bin preparation

For delivery and shipment, the amount of distributors or shipping companies and their agreements with 3PL1 allows them to operate their AutoStore without the use of pick waves. No pick waves leads to decreased complexity in processes and for the AutoStore in its preparations of bins. As mentioned previously, there are several activities in the processes that have been removed or altered in the favor of higher throughput. From the put-away process with sorting, counting and opening of boxes, to the picking process of moving the packaging activity. In the picking process, the step och label printing is once the order is finished instead of before or during, potentially adding seconds to wait for print, thus slightly lowering the efficiency. Looking into the AutoStore, the forecasting function is used, further allowing the robots to prepare more bins by extending the horizon of orders to be picked later.

Validity of results

We conclude that the results are fairly valid, but only after measures of internal validation, such as triangulation, addressing rival explanations, and using logical models. Some information was contradicting itself at first, but after further investigation, consensus was reached. Some parts of the observation were compromised due to the workload being very low by the time of visit, as all existing practices mentioned by 3PL1 during the interview were not matching the observations. To be specific, low volume of put-away was conducted by the time of visit, and thus the counting was performed by the port instead of earlier. However, the setup and configurations were still aligning with the described process, which would support the existence of such a design of counting/sorting/opening prior to port. Further, some questions were answered after the visit in complementary e-mails that could not be answered during the interview due to missing knowledge regarding specific settings and KPIs. Regarding data, some further investigations had to be made together with additional questions for the case companies, and input from Element Logic. In the end, faulty data was excluded and consideration was taken to the used data.

5.1.5 Company 3PL2

External contextual factors

Starting with the external contextual factors, the identified ones are returns, product and order characteristics, and customer values, depicted in Table 5.5a.

Table 5.5a. External contextual factors, the configurations affected and how it might affect performance.

Contextual Factor: External context			Configuration elements mainly affected (operations, design, and resources)			How configuration might affect performance
Returns	Number of returns	→	Put-away, Picking	10% returns (approx.).	→	Increased complexity
		→	Picking	Pick Strategy: Pick from bins with lowest quantity, otherwise pick according to FIFO for rest quantity.	→	More robot resources used
Product characteristics	Product portfolio	→	Sorting, Put-away, Picking, Packing	The variety and number of SKUs (14,000). 2 different bin-configurations	→ →	Increased complexity Increased complexity
	Fragility	→	Picking	A few products need to be wrapped/ put in an extra package for protection (when picking the products).	→	Less efficient picking.
	Oversize	→	Put-away, Storage, Picking	The 8+% (of 14,000 SKUs) are picked manually outside AutoStore. Storing cartons/pallets with larger quantities of a product outside AutoStore can be beneficial for large B2B orders	→ →	Increased complexity More efficient picking
Order characteristics	SKUs included in order	→	Picking, Packing	Consolidation is required (8+% SKUs stored outside AutoStore) Uses batch picking (and single order picking)	→ →	Increased Complexity Less robot resources used
	Order Volume	→	Put-away, Picking, Storage (Ports and Robots)	Opening/closing ports (depending on workload). No synchronized breaks for preparation of bins.	→ →	Robot resources used more efficiently Less time for robot charging and bin preparation
	Size per Order	→	Order Release	Has no upper limit of orders they release at a time.	→	Increases uncertainty
Customer values	Speed, Quality (few errors)	→	Put-away, Picking, Packing	No counting of goods at the port	→	More efficient put-away

Starting with the external contextual factors, the number of returns affects both the put-away and picking operations. Company 3PL2 has approximately 10% returns, which leads to an increased complexity, as that adds to the process diversity, in other words another process to handle. As the returns are put-away one unit at a time compared to normal goods, this process is necessary due to the contextual factor but less efficient in terms of TOC. Product characteristics factors such as product portfolio, fragility, special handling or oversize affects the configurations. Company 3PL2 has 14,000 SKUs and 2 different bin configurations for their products (1, ⅛) leading to increased complexity. The variety and number of SKUs affects packing as company 3PL2 has different sizes for boxes and bags. The operator therefore has to know what size that will fit the products in the current order being picked, and choose the right size. Regarding fragility, 3PL2 has a few products that need to be wrapped or put in an extra package for protection. It is done when picking the products, which leads to a less efficient picking process. Therefore, this is not aligned with TOC as a time-consuming operation is done at the port, contributing to a potential bottleneck.

Maximum 92% of their SKUs (14,000 total) are stored in the AutoStore depending on demand, which means 8+% are not stored in AutoStore. The 8% has to be put-away, stored and picked manually. This means a higher process diversity, and therefore complexity, compared to only put-away and pick goods that are stored in the AutoStore. What SKUs in the majority of times are included in the orders also affect if consolidation is needed or not, adding to the process diversity and complexity. However, for large B2B orders 3PL2 picks from cartons or pallets containing larger quantities, which leads to a more efficient picking process, and aligns with TOC. In addition to this batch picking is used for B2B, which leads to less robot resources being used and is aligned with TOC.

3PL2 handles around 6,000 order lines per day. Depending on the workload (which is dependent on order volume) they close ports if there are too many open, and vice versa. Closing ports when there are too many open compared to the workload frees up robots (Element Logic, 2023g). The robots can also work more efficiently to provide the open ports with bins, since robots otherwise will try to supply all open ports with bins (Element Logic, 2023g). This leads to the robot resources being used more efficiently, as they can optimize the retrieval of bins to fewer ports (Element Logic, 2023g). This is aligned with TOC as it contributes to a more efficient picking process. 3PL2 has no synchronized breaks for operators, which leads to robots getting time to charge and prepare bins, which is not aligned with TOC since the picking process becomes more time-consuming.

For order release 3PL2 has no maximum limit of orders they release at a time, which increases the uncertainty as company 3PL2 have less control over the outcome regarding preparation of bins. If too many orders are released at once, for example orders that are due to be picked more further ahead in time, the robots might start preparing those bins. This is not aligned with TOC as this contributes to a less efficient picking process. Lastly, when performing put-away the operators at the port do not need to count the units, which leads to a more efficient put-away process and also aligns with TOC.

Corporate contextual factors

For the case of 3PL2, the correlation between corporate contextual factors and configuration could be identified in Product purchasing strategy and Growth/sales strategy, depicted in Table 5.5b.

Table 5.5b. Corporate contextual factors, the configurations affected and how it might affect performance.

Contextual Factors: Corporate context			**Configuration elements mainly affected (operations, design, and resources)**			**How configuration might affect performance**
Product purchasing strategy	Product portfolio	→	Put-away, Storage, Picking, Packing	As a 3PL they are not in control of the product portfolio. Have different products and processes for each customer	→ →	Increases uncertainty and complexity Increases complexity
Growth/sales strategy		→	Picking, Packing	Operators putting discount-leaflets in some boxes	→	Less efficient picking and packing

Looking at the purchasing strategy, the company being a 3PL and limited to the desires of its client, the complexity and uncertainty increases with an additional decision maker and party to consider. Another driver of uncertainty and complexity that was observed is the acquiring of new customers. New customers would increase the need of queues, and put strain on inputting sufficient stock of the new customer parallel with daily operations. The amount of different SKUs also raises complexity and uncertainty in how much to keep in stock and how to design the processes needed to handle certain SKUs and orders. Operators have to finish each order by selecting the correct discount-leaflet for the corresponding order. Which leaflet to select can be different depending on who the customer is or what current campaign that is running. Thus, it leads to less efficient picking and packing since it is an additional activity that has to be conducted, not aligned with TOC.

Internal warehouse contextual factors

For the internal warehouse context, the factors of Delivery and shipment and general Warehouse efficiency are being analyzed, depicted in Table 5.5c.

Table 5.5c. Internal warehouse contextual factors, the configurations affected and how it might affect performance.

Contextual Factors: Internal warehouse context			**Configuration elements mainly affected (operations, design, and resources)**			**How configuration might affect performance**
Delivery and shipment	Number of different shippers	→	Picking	12 pick waves are used	→	Increases complexity
Warehouse efficiency	-	→	Put-away, Picking, Packing	Conveyor for carton disposal	→	Less time-consuming tasks performed at port
				Some cartons needs to be manually folded and sealed, and some quick-folded manually (and some also sealed with tape)	→	Less efficient picking and packing
				Sealed cartons arrive to put-away port - cartons need to be opened	→	Less efficient put-away
				Some goods arrive sorted by SKU type, while some cartons do not.	→	Both less & more efficient put-away
				Shipping label printed after order is finished	→	Less efficient picking and packing

With pick waves enabled, robots prepare bins and pick orders for the current pick wave (Element Logic, 2023c). Having more pick waves therefore adds constraints to the algorithm which will affect its ability to optimize the tasks to be done. Company 3PL2 uses 12 pick waves, which increases complexity in processes and for the AutoStore in its preparations of bins. As the system has worse conditions to optimize the processes, this contributes to less efficient processes, and therefore does not align with TOC.

Regarding warehouse efficiency, there is a conveyor just above the port used for carton disposal when performing the put-away, instead of operators having to handle the waste. This leads to less time-consuming tasks being performed at the port, and thus aligns with TOC. The operators occasionally collaborate during put-away: if a SKU on the pallet fits another bin configuration than currently being used, the operator can give the products to the operator in the nearby port with that bin configuration, to avoid switching queue. Some boxes used for picking and packaging need to be folded and sealed with tape, and some need to be prepared (but not folded and sealed with tape as regular boxes due to the design). The design saves time for the operator, but the two tasks are time-consuming contributing to a less efficient picking- and packing process. When picking and packing, the shipping label is printed after the order is finished, which leads to less efficient picking- and packing processes, and does not align with TOC.

As part of their growth strategy, operators put discount-leaflets in some of the packages. This is a time-consuming task as the operator both has to make sure they have the leaflets in the different languages available at the port and put in the leaflet in the package. Therefore the picking- and packing process is less efficient, and not aligned with TOC.

Validity of results

In the case of 3PL2 we conclude that the results are valid. The main interviewee (Super User) was a person with knowledge about the AutoStore and mainly responsible for its performance. The observations and the interview were both depicting the same picture of the business and its operations. When observing the processes in real time, multiple examples were all operating the same way through a variety of products and stations.

5.1.6 Company E1

External contextual factors

Starting with the external contextual factors, the identified ones are returns, product and order characteristics, and customer values, depicted in Table 5.6a.

Table 5.6a. External contextual factors, the configurations affected and how it might affect performance.

Contextual Factor: External context			**Configuration elements mainly affected (operations, design, and resources)**			**How configuration might affect performance**
Returns	Number of returns	→	Put-away	No returns are put into the AutoStore	→	Reduced complexity
Product characteristics	Product portfolio	→	Sorting, Put-away, Picking, Packing	Only use whole bins (1 bin configuration) High number of SKU type (42,000) Large and small items Items too big for AutoStore	→ → → →	Reduced complexity Raised complexity and demand uncertainty Inefficiency can occur Raised complexity
	Fragility	→	Sorting, Put-away or Picking	Wrapping items by port, no sorting previously	→	Raised complexity and time-consuming by port
	Special handling	→	Put-away	No directions in suggested capacity, leading to unused space in bins	→	Less efficient
	Oversize	→	Put-away, Storage, Picking	Oversized products stored outside AutoStore	→	Raised complexity
Order characteristics	SKUs included in order	→	Picking, Packing	"Process line" through warehouse with rather standardized processes Multiple storage locations for	→ →	Reduces the complexity in picking and packing Raised complexity but

				same type of SKU		increased availability
	Order Volume	→	Put-away, Picking, Storage (Ports and Robots)	Mainly robot pick from AutoStore 24/7 Other automation solutions in warehouse to spread the load of volume	→ →	Flexibility in times of high order volumes Less dependency on AutoStore, but risk inefficiency by using less efficient picking methods
	Size per Order	→	Order Release	Has no upper limit of orders they release at a time (but very frequent order release)	→	Increased uncertainty
Customer values	Speed, Quality (few errors)	→	Put-away, Picking, Packing	Customers are valuing speed but the AutoStore is primarily utilized for its efficient storage Mainly put-away in the AutoStore is not optimized for speed	→ →	Inefficiency in terms of speed Inefficiency in terms of speed

To start with, we look at the external context, such as returns, product and order characteristics, and customer values. Returns are not prevalent in terms of e-Pharma, although they do get some. These are received at the warehouse where they are quality checked, and if still sellable, not inserted into the AutoStore. Articles are instead placed at another storing location within the warehouse, since the majority of SKU types are accessible at multiple locations. This is also the reason behind the single item pick usage, as the items get lost in the other zones, AutoStore acts as a “finder”. Using the AutoStore as a “finder”, compromises the preparation levels, as the prepared bins get reshuffled when a specific bin is being appended. Absence of returns into the AutoStore leads to more standardized put-away and lowering complexity. With one less process connecting to put-away enables faster handling than the common one-piece handling per returned item in small compartments. According to Beckschäfer et al. (2017) the use of only whole bins decreases the complexity in the system and possibly lowers the amount of bins needed to complete orders. Because of the product portfolio, SKUs are being stored outside the AutoStore leading to complexity in finalizing orders. This is mitigated by standardizing the route for orders through the warehouse similar to a process line, regardless of its content.

Continuing with product characteristics, some SKUs are fragile, and need to be wrapped or taped to some extent before shipping. E1 has chosen to have tools by the put-away port, for operators to finalize before inserting into the bin, increasing the time needed to put-away some SKUs successfully. It is up to the operator to decide what item to prioritize, without any guidelines on what to select or the capacity of said item, leading to the AutoStore not necessarily being filled with prioritized items nor bins being filled properly. The process of selecting the next item to insert is therefore time-consuming and haphazard, and items that could be stored more efficiently in the AutoStore, is instead taking up floor storage by the put-away area or in other storage locations of the warehouse. Thus, keeping decisions and activities by the port to be executed by operators does not align with the ideas of TOC.

Order characteristics such as size, SKU range, and in general order volume influence the configurations as well. In regards to order volume, E1 divides the labor of picking onto several different technologies of picking, making the strain on AutoStore reduced. Besides this, two of their picking ports are operated by robotic arms, allowing picking to occur 24/7. Also, by having constant picking, the system does not get the same chance to recover, leading to preparation levels as well as battery capacity and levels being compromised.

Further looking at the customer value prioritized is speed, that orders are being sent from the warehouse in a proximity from when customer places order. The usage of the AutoStore is not utilized for the potential speed, but rather for its compact storage. Considering the automated and streamlined design of the warehouse, this does not necessarily impose an issue, since many orders are consolidated through various stations. However, the low utilization of capacity, the time-consuming put-away process, and the need for every order to traverse multiple stations do not match with the aim of higher speed.

Corporate contextual factors

For the case of E1, the only correlation between corporate contextual factors and configuration could be identified in Product purchasing strategy, depicted in Table 5.6b.

Table 5.6b. Corporate contextual factors, the configurations affected and how it might affect performance.

Contextual Factors: Corporate context			**Configuration elements mainly affected (operations, design, and resources)**			**How configuration might affect performance**
Product purchasing strategy	Product portfolio	→	Put-away, Storage, Picking, Packing	Product portfolio is not actively taking AutoStore into account, hence multiple storage locations	→	Raises complexity
				High amounts of different SKU types	→	Raises complexity

Still looking at the product portfolio, the purchasing strategy to fulfill their customers needs has resulted in a broad variety of SKUs. Since they vary in size and category, stretching to an assortment not only focusing on pharmaceuticals, the complexity increases. E1 has a relatively high amount of SKU types and besides the added complexity, the demand uncertainty increases as well. As previously mentioned, the configurations in the warehouse to accommodate for this variety, rather focuses on alternatives than fully relying on the AutoStore, which limits the total impact of not fully utilizing the AutoStore technology. The procurement of items not fitting in the AutoStore bins adds complexity with the need of oversize storage and order consolidation. Although, as stated, this does not affect the picking in AutoStore, since the picking methods of both human and robot pick are very standardized and do not get affected by what happens later down the process line.

Internal warehouse contextual factors

For the internal warehouse context, the factors of Delivery and shipment and general Warehouse efficiency are being analyzed, depicted in Table 5.5c.

Table 5.6c. Internal warehouse contextual factors, the configurations affected and how it might affect performance.

Contextual Factors: Internal warehouse context			**Configuration elements mainly affected (operations, design, and resources)**			**How configuration might affect performance**
Delivery and shipment	Number of different shippers	→	Picking	The company does not use any pick waves	→	Reduces the complexity of when orders have to be picked and thus allowing the system to optimize after less constraints
Warehouse efficiency	-	→	Put-away, Picking, Packing	Carton risers, conveyors, but still time-consuming activities by put-away	→	Both adding time and removing time around ports

When it comes to delivery and shipment, the amount of distributors or shipping companies and their agreements with E2 allows them to operate their AutoStore without the use of pick waves. No pick waves leads to decreased complexity in processes and for the AutoStore in its preparations of bins.

As with the warehouse efficiency, processes around picking are aimed to be as quick as possible and operate around the clock. Aligned with the ideas of TOC, configurations in the case of E1 are carton risers and sealing, robot picking, and no label printing by the AutoStore picking port. The box is directly connected to the conveyor, and is sent away with the press of a button. Thus, the configurations by the picking port are heavily leaned towards speed and not being time-consuming. The put-away is however not aligned with a lot of activities performed by the operator, lack of guidelines in capacity, and prioritization. However, no data is available on the put-away performance since those ports are not supplied by Element Logic.

Validity of Results

In the case of E1 we conclude that the results are rather valid in terms of picking. The interviewee was not necessarily responsible for AutoStore configurations nor the warehouse design in general. Since definitions were not discussed prior to the interview, some misunderstandings in questions and/or answers occurred during the interview. Also, the researchers did possibly influence the interviewee by providing definitions that had to be cleared during the interview. However, this was mitigated by fully unfolding any unclear subjects, as well as once again questioned during the observations, where the possibility of witnessing examples made the results more valid.

The observations were conducted thoroughly throughout the warehouse in order to fully understand the processes, considering the misunderstanding in the interview. E1 also has a lot of other processes not directly linked to the AutoStore. Therefore it was critical to examine the other processes to achieve a holistic view and understand the role of the AutoStore in the warehouse. As previously mentioned, data on put-away performance was non-existent as the ports are not supplied by Element Logic, meaning no analysis of the put-away KPIs could be conducted. Lastly, some information regarding the amount of SKU types that are stored in the AutoStore was not correct, since the total types of SKUs were 68% higher than existing bin locations. Once this error was noticed, data was changed to the correct value after discussions with Element Logic.

5.1.7 Company E2

External contextual factors

The external context focuses on areas such as returns, product and order characteristics, as well as customer values, depicted in Table 5.7a.

Table 5.7a. External contextual factors, the configurations affected and how it might affect performance.

Contextual Factor: External context			**Configuration elements mainly affected (operations, design, and resources)**			**How configuration might affect performance**
Returns	Number of returns	→	Put-away	No returns are put into the AutoStore	→	Decreased complexity
Product characteristics	Product portfolio	→	Sorting, Put-away, Picking, Packing	All products fit in whole bins and in AutoStore	→	Decreased complexity
				Low number of SKU type	→	Decreased complexity and uncertainty
				Large and small items	→	Inefficiency can occur in capacity of bin
	Fragility	→	Sorting, Put-away or Picking	Separate wrapping and sorting station	→	Decreased complexity and standardized processes
	Oversize	→	Put-away, Storage, Picking	No oversize products	→	Decreased complexity
Order characteristics	SKUs included in order	→	Picking, Packing	No consolidation	→	Decreases the complexity in picking and packing
				Only whole bins	→	Reduces complexity
	Order Volume	→	Put-away, Picking, Storage (Ports and Robots)	Aims to rather cancel shifts than closing ports when order volumes are at the lower end	→	Decreased uncertainty and the risk of having too many ports open with not enough orders to supply them with tasks

				Order volume is regulated with the ambition to allow all operators working in the AutoStore to take synchronized breaks.	→	Synchronized breaks allow the system to recover, raises preparation levels and enable charging if needed
	Size per Order	→	Order Release	Has an upper limit of orders they release at a time	→	Decreased uncertainty
Customer values	Speed, Quality (few errors)	→	Put-away, Picking, Packing	Quality of arriving goods is an important factor, and since groceries can vary in shape, weight, and fragility, the system is prioritizing heavier, less fragile items first	→	Raises complexity in picking since the algorithm gets another constraint to follow. This limits the system from taking the optimal routing in terms of digging and distance.
				Occasionally the operator counts the goods at put-away	→	Occasionally less efficient put-away

Returns are a difficult area to deal with groceries since expiration dates will be compromising the item value, as well as the sanitary issues with some products. In favor of the AutoStore, this means that no returns are being processed through the AutoStore and are instead donated or disposed, saving one form of process in put-away and lowering complexity. Eliminating one process of put-away enables standardization in ports and offers faster handling than the common one-piece handling per returned item in small compartments. No returns and the SKU catalog also enables the use of only whole bins, further decreasing the complexity in the system and possibly lowering the amount of bins needed to complete orders.

Further with the product portfolio only using whole bins, there are instances of the SKU's size or weight being a limiting factor in put-away. One example of the extreme case would be bins being full with 2 SKUs not utilizing the full potential of the AutoStore. With only 2 SKUs in the bin the probability of emptying the bin after one single bin presentation is high, depriving the functionality of having a top layer of frequently picked bins.

Continuing with product characteristics, some SKUs are fragile, and need to be wrapped to some extent before shipping. E2 has chosen to have dedicated wrapping stations before put-away, reducing the amount of activities by the put-away- and picking ports. In general by the put-away ports, goods are sorted and prioritized beforehand, transferring the decision making on what goods to choose from the operator to the WMS or previous stations. With already prepared goods, the operator only has to scan the box, put in the correct amount, confirm, and dispose of the carton with the conveyor above the port. Transferring other activities to other parts of the warehouse reduces time spent on activities by the port, aligning with TOC.

Order characteristics such as size, SKU range, and in general order volume influence the configurations as well. In regards to order volume, E2 regulates the order releases in the sense of allowing synchronized breaks for their operators. By letting the AutoStore recover, preparation levels and battery levels increase. Connected to order volume, E2 also rather cancels shifts than closing ports, or operating all ports on lower speed, lowering demand uncertainty by regulating the operations accordingly. Since all SKUs are being stored and picked from the AutoStore, there is no need for consolidation, decreasing complexity. With only whole bins, there is no mix of SKUs in one bin but different compartments, possibly resulting in waiting for a busy bin but another SKU. Multiple SKUs per bin in compartments allows for the risk to "lock" a bin when another operator requests the same bin but another SKU. The same "lock" does occur if enough operators request the same SKU, but often avoided by the system algorithm, rearranging tasks accordingly (Element Logic, 2023c). For these instances, lower complexity and constraints in the system do play an important part for the sake of efficiency (Element Logic, 2023b). One of these constraints that increases complexity, is the customer value of quality, which surfaces in the case of E2 as goods not damaging other goods. The different shape, size, and especially weight of certain products, is a contextual factor that has resulted in E2 introducing the constraint of heavier items being picked first. As stated, this increases complexity for the system to optimize by limiting the system from taking the optimal routing in terms of digging and distance. However, it is crucial in the eyes of E2's customers to receive their goods in non-compromised condition.

Corporate contextual factors

For the case of E2, the major correlation between corporate contextual factors and configuration could be identified in Product purchasing strategy in a manner of significant importance, depicted in Table 5.7b.

Table 5.7b. Corporate contextual factors, the configurations affected and how it might affect performance.

Contextual Factors: Corporate context			**Configuration elements mainly affected (operations, design, and resources)**			**How configuration might affect performance**
Product purchasing strategy	Product portfolio	→	Put-away, Storage, Picking, Packing	Actively not purchasing items not fit for AutoStore, thus eliminating the need of oversize storage and consolidation	→	Reduces complexity in all activities as well as lower uncertainty due to lower statistical variations of outcome in orders
				Very low types of SKUs	→	Reduces complexity

E2 has taken the strategic decision to not purchase items that do not fit the AutoStore in terms of size, eliminating the need of oversize storage and picking, as well as consolidation processes. No consolidation and no oversize handling reduces complexity in all processes. Furthermore, E2 has a relatively low number of SKU types. With lower possible SKUs to order, complexity and uncertainty decreases due to fewer possible order combinations and variations. Connecting to the configuration of only performing batch picking, utilizing each bin presentation to a greater extent. To utilize batch picking, there is a need for orders to be fairly similar to each other as well as low complexity in product catalog.

Internal warehouse contextual factors

For the internal warehouse context, the factors of Delivery and shipment and general Warehouse efficiency are being analyzed, depicted in Table 5.7c.

Table 5.7c. Internal warehouse contextual factors, the configurations affected and how it might affect performance.

Contextual Factors: Internal warehouse context			**Configuration elements mainly affected (operations, design, and resources)**			**How configuration might affect performance**
Delivery and shipment	Number of different shippers	→	Picking	The company does not use any pick waves	→	Reduces the complexity of when orders have to be picked and thus allowing the system to optimize after less constraints
Warehouse efficiency	-	→	Put-away, Picking, Packing	Carton risers, sorting and wrapping stations, conveyors for waste management	→	Remove time-consuming operations from the ports
				Mostly sealed cartons/packages arrive at put-away port - has to be opened.	→	Less efficient put-away

When it comes to delivery and shipment, the amount of distributors or shipping companies and their agreements with E2 allows them to operate their AutoStore without the use of pick waves. No pick waves leads to decreased complexity in processes and for the AutoStore in its preparations of bins.

In regards to warehouse efficiency, processes are aimed to be as quick as possible and minimize "waiting for user" by the port. Configurations in the case of E2, are as mentioned sorting and wrapping stations prior to put-away, conveyor for carton disposal, lowering the time needed by the put-away. The operator does have to fetch the pallet of boxes themselves and occasionally open the boxes, which adds time needed by the port. By the picking stations the operator receives risen boxes and they are sealed through automation later in the process line. Boxes are directly pushed on the conveyor in connection to the work table, eliminating any transport time needed for the picker. The not-functioning pick-by-light system would also remove the use of scanners and confirmation steps after a successful pick, boiling it down to one single button press. Lastly, steps connected to printing shipping labels are not performed by the picker but instead through automation in later stages, further decreasing time-consuming steps needed by the port.

Validity of Results

In the case of E2 we conclude that the results are valid. The interviewee was a person with interest and knowledge about the AutoStore, making the discussions and questions thorough. The observations and the interview were both depicting the same picture of the business and its operations. When observing the processes in real time, multiple examples were all operating the same way through a variety of products and stations. Also, after the company visit, they continuously responded in detail regarding any questions of the processes.

5.2 Cross-Case Analysis

For the cross-case analysis, we compared the gathered data to the performance of each company. As presented in Table 1.1, performance is a combination of three KPIs: Bin presentations/h (per port), “waiting for bin”, and “waiting for user”. The optimal numbers of these KPIs is a high number of bin presentations/h, low numbers on “waiting for bin” and “waiting for user”. In Section 5.2.1, data related to put-away is analyzed and the identified propositions are presented. After that, data and propositions related to picking are presented in Section 5.2.2. Lastly, all the propositions are summarized in Section 5.2.3.

When analyzing data and processes, the information was displayed in larger tables to maintain a holistic approach. Since the performance is dependent on several different factors and configurations, it was important to look at all the aspects before drawing any conclusions. The techniques and tactics mentioned in Table 3.3 and 3.4 were applied on the case company data to identify the contextual factors and configurations that may affect performance, and how. Also, how these are intertwined and related to each other was investigated. The seven examined companies are ranging in their similarities and differences, and in order to compare them justly, considerations to their characteristics have been taken when analyzing the data. Categorization was done to find patterns and contrasts. For example, all fashion companies have identical types of products with some variations, thus, they have been compared more extensively. As presented in the within-case analyses, for example having more bin configurations and a large number of SKUs is leading to increased complexity, which according to Kembro and Norrman (2021) can lead to challenges in speed (i.e. performance) in a warehouse. Uncertainty is also a subject touched on in the within-case, and how it affects the configurations, as well as to what extent activities are performed or placed in regards to TOC. Therefore one of the goals in this cross-case analysis was to evaluate if this complexity and uncertainty seems to have an affect on performance in an AutoStore, and how much. To summarize; complexity, uncertainty, and best practices in terms of TOC are the phenomena used as tools to grade companies.

To more easily follow the analysis to be presented, smaller tables will be displayed that include the data analyzed for each proposition. For the tables in Section 5.2.1 and 5.2.2, a red color means the value is low compared to the other companies, while green represents a comparatively high value. The color formatting only takes the relative values into account. The colors only suggest the relative performance, and does not necessarily indicate poor performance or misaligned processes looking at the company itself. For all the processes with no values to compare (e.g. Figure 5.4), the processes requiring more time at the put-away/picking port are manually marked in red, while the opposite applies for green color. Processes marked with a yellow color means it occasionally leads to more time being spent at the port. The analysis is divided into data and propositions related to “waiting for bin” and “waiting for user”, for both put-away and picking.

Company E1 does not have put-away ports supplied by Element Logic, thus no data is available on the performance of the put-away ports. Also, the lower validity of data of 3PL1, as mentioned in 5.1.4, has been mitigated by analyzing specific ports, looking at maximum values as the average value includes multiple processes.

5.2.1 Put-away

"Waiting for Bin"

For put-away, the "waiting for bin" is the average number of seconds it takes for the robots to retrieve and present a bin to the operator. Since it is for put-away and all the seven companies in this case use empty bins for the put-away process, it is the seconds spent waiting for the robots to retrieve and present an empty bin with the right bin-configuration. The values on "waiting for bin" and the number of bin configurations are displayed in Figure 5.1 below.

Company	F1	F2	F3	3PL1	3PL2	E1	E2
Waiting for Bin	5,6	12,6	6,3	12,3	5,7	N/A	7,7
# of Bin configs.	4	5	5	4	2	1	1

Figure 5.1. "Waiting for bin" [s] and number of bin configuration for each company.

It was examined whether the number of bin-configurations had any clear influences on the time spent "waiting for bin". That is, if the fact that E1 and E2 only have one bin-configuration is leading to a lower "waiting for bin", compared to companies like F2 and F3 that have 5 different bin-configurations. When performing the put-away the operator chooses what bin-configuration they want to put goods into. According to (Element Logic, 2023j) the robots start preparing empty bins with that specific bin-configuration in close proximity to the port, after the bin-configuration has been chosen by the operator. This is to minimize the distance between the bins and the port to achieve a lower "waiting for bin", once the robots need to deliver a new empty bin to the port. With several bin configurations, the complexity rises in terms of having wider variety and more constraint in preparing a specific type of empty bin. The increased complexity does not necessarily affect performance in presented data, as pattern matching did not indicate a clear correlation.

To examine why 3PL1 has such a high value on "waiting for bin" with seemingly small differences, indications were discovered looking at their operations. As previously stated, operations of 3PL1 are heavily determined by their customer. Thus, configurations are decided in line with fulfilling the desires and demands of their customers, and they do not focus on optimizing the configurations related to AutoStore in terms of performance. This explains why their performance on "waiting for bin" is an outlier, which will be considered during the comparative analysis.

Lastly, the correlation between robots per port and the influence on "waiting for bin" was analyzed. The values on "waiting for bin", the size of grid (measured in number of bins), and the number of robots per average open ports are displayed in Figure 5.2.

Company	F1	F2	F3	3PL1	3PL2	E1	E2
Waiting for Bin	5,6	12,6	6,3	12,3	5,7	N/A	7,7
# Robots / avg. open port	11,7	10,2	16,7	11,3	13,4	Router	Router
Bins (K)	60	150	80	40	65	25	88

Figure 5.2. "Waiting for bin" [s], number of robots per avg. open port, and bins for each company.

F2 has the lowest number of robots per port and the highest "waiting for bin". With the exception of the high value on "waiting for bin" for 3PL1 mentioned above, both F1 and 3PL2 have the same amount of robots per port and similar values on grid size, and have more or less identical values on "waiting for bin". F3 has a higher number of robots per port than F1 and 3PL2, but still has a higher "waiting for bin". This can be explained with the increased complexity coming from having 5 bin-configurations, even though the correlation could not be clearly identified in the analysis above. E1 and E2 were excluded from this particular analysis, since they have the "Router"-software that dynamically changes the number of robots dedicated to each port depending on workload.

"Waiting for User"

As previously mentioned, "waiting for user" is how many seconds on average the operator spends on put-away for each bin. Therefore it was relevant to analyze what the operator needs to do when the bin has been presented, and how these things are done for each company. The values on "waiting for user" and bin presentations/h are displayed in Figure 5.3 below.

Company	F1	F2	F3	3PL1	3PL2	E1	E2
Waiting for User	49	89	56	80	72	N/A	38
Bin presentations/h (per port)	66	36	61	40	47	N/A	80

Figure 5.3. "Waiting for user" [s] and bin presentations/h for each company.

When comparing the results in Figure 5.3 we can see that it is the same order as for bin presentations, with E2 having the lowest "waiting for user" followed by F1, F3, 3PL2, 3PL1 and lastly F2.

To analyze what is prepared before and what tasks that are done by the operator at the put-away port, a table was created to achieve an overview. Tasks included in the table are if the cartons are opened, if the goods are sorted by SKU and size, if the operator has to count at the port, and lastly how waste is handled by the port. The data is displayed in Figure 5.4 below.

Company	F1	F2	F3	3PL1	3PL2	E1	E2
Cartons opened/sealed	Sealed	Sealed	Opened	Opened	Sealed	Sealed	Sealed (mostly)
Sorted (SKU)	Yes	Yes	Yes	Yes	Yes & No	No	Yes
Sorted (Size)	No	Yes	Yes	Yes	Yes & No	No	Yes
Counted in advance	Yes	No	Yes	No	Yes	No	Yes & No
Waste disposal	Conveyor	Conveyor	Manually	Manually	Conveyor	Manually	Conveyor

Figure 5.4. Values on cartons opened/sealed, sorted (SKU), sorted (size), counted in advance, and waste disposal for each company.

Looking at the data from F2 and 3PL1, who are the two companies with the highest "waiting for user", both of them count the units at the port instead of in advance. Based on the interviews, double checking does occur to mitigate a faulty item balance being put into the AutoStore. This is an additional time-consuming task to be done at the port, which increases the "waiting for user". However, it must be stated that E2 that has the lowest "waiting for user" also occasionally counts the units in case the quantity is not displayed on the package. The only difference between F3 and 3PL1 is that the goods need to be counted at the port. F3 has a "waiting for user" that is 30% lower than 3PL1, which indicates the influence counting goods at the port has on "waiting for user". Important to point out is that 3PL1 has the lowest average order lines per day, which decreases the need for speed in the operations, something that was also observed during the company visit. As previously mentioned, the data of 3PL1 has a lower validity due to them occasionally performing put-away and picking in the same ports. That leads to the data not reflecting strictly put-away or strictly picking. However, in this case, performing picking in a put-away port only decreases the "waiting for user" since it is on average 4 times lower for picking. Therefore, these compromised numbers do not contradict the discussed example of counting goods at the port leading to a 30% lower "waiting for user", but rather corroborates it.

Proposition 1: Counting goods when performing put-away at the port significantly increases "waiting for user".

By looking at the data over the tasks done by the port and the performance, no clear pattern could be identified on whether opening cartons before they arrive to the put-away ports leads to any significant improvement in “waiting for user”. This was also the case with sorting the SKUs after type and size prior to the goods arriving at the port, and using a conveyor for handling waste. For example, E2 who has the lowest “waiting for user” also most often open sealed cartons or packages at the port, which does not corroborate the hypothesis that having sealed cartons arriving at the port leads to a lower “waiting for user”. However, opening the sealed cartons at the port is de facto an additional time-consuming task which does not align with TOC. The data indicates that this task is not dominant in comparison with other preparatory tasks (e.g. counting at the port). This is also the case for using a conveyor to handle the waste, in comparison to it being handled manually by other employees not operating the port. Regarding sorting, no clear comparison between companies could be done since all companies were sorting to some extent, with the exception of E1 that also had no data on put-away performance. However, non quantifiable data in terms of observations by the put-away ports, indicated that sorting by the port was a time-consuming task.

From conducting the observations at the warehouses, it was noticed that put-away of returns can take a long time, compared to filling the bin with only one type of SKU. For example, picking up, folding and placing 16 or 8 units of returns in one compartment each, compared to placing a pile of 16 units of the same SKU into the bin at once. Data on “waiting for user”, returns, number of bin configurations, if cartons arrive opened or sealed, and if goods are counted in advance are displayed in Figure 5.5 below.

Company	F1	F2	F3	3PL1	3PL2	E1	E2
Waiting for User	49	89	56	80	72	N/A	38
Returns (into AutoStore)	20%	Highest	30%	15%	10%	0%	0%
# of Bin configs.	4	5	5	4	2	1	1
Cartons opened/sealed	Sealed	Sealed	Opened	Opened	Sealed	Sealed	Sealed (mostly)
Counted in advance	Yes	No	Yes	No	Yes	No	Yes & No

Figure 5.5. “Waiting for user” [s], returns [%], bin configurations, if cartons arrive opened/sealed, and if goods are counted in advance for each company.

What stands out for F2 compared to the other companies is their very high “waiting for user”, very high share of returns and having 5 bin-configurations (including the 16 compartment bin). In addition to this they have to open the sealed cartons at the port as well as count all units before being able to put-away the units in the bin. These could be the main contributions to their high “waiting for user”. F3 has approximately 40% lower “waiting for user” compared to F2, and lower returns than F2 (30%). On top of this, F3 also has already opened cartons arriving to the port and does not need to count the units before put-away, which lowers time needed for put-away and therefore also lowers the “waiting for user”. F1 has 20% returns and an even lower “waiting for user” than F2 and F3. 3PL1 has 15% returns but a relatively high “waiting for user”, which does not follow the hypothesis that low returns equates to a low “waiting for user”. However, operators at 3PL1 also need to count the units at the port which could be a main contribution to the higher “waiting for user”. Lastly, E2 that has 0% returns into AutoStore but mostly has to open cartons at the port and occasionally also count the units, has the lowest “waiting for user” of all companies. Based on the analysis above one proposition was made.

> **Proposition 2:** The amount of returns significantly affects “waiting for user”. The put-away process related to returns is more time-consuming compared to the put-away of non-returns.

5.2.2 Picking

“Waiting for bin”

Data on “waiting for bin” and if synchronized breaks are used are displayed in Figure 5.6 below.

Company	F1	F2	F3	3PL1	3PL2	E1	E2
Waiting for bin	5,2	7,8	5,7	7,0	6,3	8,9	5,6
Synchronized breaks	Yes (only during high workloads)	Yes (only during high workloads)	Yes (only during evening)	No	No	No	Yes

Figure 5.6. “Waiting for bin” [s] and if synchronized breaks are used, for each company.

Regarding “waiting for bin” E1 has a high value that is 58,9% higher in comparison to E2. Further examining E1 and E2, several differences started to appear. The 24/7 operation of E1 and absence of synchronized breaks are resulting in less time for the system to recover and prepare bins and thus lowering the time spent for robots acquiring the next bin (Element Logic, 2023j; Element Logic, 2023a). Also, from the observations of E1, there is a lot of unused storage space in the bins due to the nature of their put-away processes, making the bins empty at a faster rate than necessary. This lessens the utilization of having frequently picked bins that stay on the top of the grid, and increasing the need of retrieving another bin containing the wanted item.

> **Proposition 3:** Picking long hours without breaks does not let the system regain preparation levels together with robots not having the opportunity to recharge properly, increasing “waiting for bin”.

Data on “waiting for bin”, dig depth, the size of grid (measured in number of bins), and number of SKU types stored in AutoStore are displayed in Figure 5.7 below.

Company	F1	F2	F3	3PL1	3PL2	E1	E2
Waiting for bin	5,2	7,8	5,7	7,0	6,3	8,9	5,6
Dig depth	1,91	2,05	3,04	2,75	1,66	3,51	1,37
Bins (K)	60	150	80	40	65	25	88
# SKU types in AS (K)	21	97	29	22	13	13	2

Figure 5.7. "Waiting for bin" [s], dig depth, bins, and number of SKU types stored in AutoStore for each company.

Reflecting on the usage of synchronized breaks in correlation to the considerably higher dig, a lot of multiple handling of bins in terms of reshuffling is occurring in the case of E1. E1 does not use synchronized breaks and has a dig depth that is 156% higher than E2. However, the system of E2 is 3,5 times larger than E1, and at the same time, E2 stores 6,5 times less SKU types in the AutoStore. Thus, the lower complexity of assortment and the ability to spread their different SKUs, raise availability of standard items. Therefore, E2 is lowering their dig depth and by that also their "waiting for bin". As stated, E1 frequently uses one port as a single item pick port, causing prepared items to be reshuffled since operators override the algorithm to access a specific item, compromising the preparation. Also, operators can not see where the bins containing sought after items are located, thus unable to select the easiest bin to retrieve. The same effect is seen at 3PL1, where ports are used for different processes and opened and closed sporadically, which causes the same type of reshuffling of prepared items (Element Logic, 2023j).

> **Proposition 4:** Using the AutoStore to find and pick single items, compromises already prepared bins, and causes multiple handling and unnecessary reshuffling of bins.

Data on "waiting for bin", number of queues, and average bin preparation throughout the period is displayed in Figure 5.8 below.

Company	F1	F2	F3	3PL1	3PL2	E1	E2
Waiting for bin	5,2	7,8	5,7	7,0	6,3	8,9	5,6
# of queues	4	4	4	4	4	2	1
Avg. bin preparation	99,1	91,9	95,3	90,2	98,7	65,3	87

Figure 5.8. "Waiting for bin" [s], number of queues, and average bin preparation [%], for each company.

Also, E2 uses 1 queue, and E1 uses 2 queues, further limiting E1's ability to prepare with an additional constraint on the already smaller grid. Preparation of the top grid is divided between queues which leads to the fraction of preparation per queue gets used up faster (Element Logic, 2023e). For example, having five queues with 20% dedicated area each for preparation, can be used up faster if all ports pick in one queue, causing unprepared picks. Unprepared picks result in increased uncertainty in terms of bin location, thus leading to higher dig depth and higher "waiting for bin". In the case of E2 specifically, the lower preparation level does not indicate any substantial negative impact on the "waiting for bin". The finding was further investigated, and after discussions with employees at Element Logic together with examining their data, the lower complexity in terms of SKU variety increases the availability of items. Since E2 only uses 1 queue the preparation area is not divided. As data suggests, the lower preparation of E2 is therefore an outlier in terms of not affecting dig depth and "waiting for bin".

> **Proposition 5:** The number of queues corresponds to how the preparation area is divided between the queues, increasing the probability to pick unprepared goods by using up the dedicated prepared bins faster.

When analyzing the "waiting for bin" and average preparation of bins in Figure 5.8, E2 stands out. They have the second lowest average bin preparation, but still achieve the second lowest "waiting for bin". As stated by Kembro and Norrman (2021), more SKUs and SKU variety increases complexity. When comparing E2 to the other case companies, the SKU variety is uniquely low. With the very low SKU variety of E2 (displayed in Figure 5.7), items are more standardized and widely available. This mitigates a higher dig depth due to the lower complexity in SKU variety, even if an unprepared pick has to be made. Thus, the following proposition was made.

> **Proposition 6:** High SKU variety further increases the necessity of high levels of preparation to achieve lower levels of "waiting for bin".

When investigating the "waiting for bin", besides letting the system rest or not in terms of breaks and 24/7 picking, order release structure affects the preparation levels. Each time orders are released into the system, they are initially considered as unprepared unless they are on top of the grid, thus lowering preparation levels instantly until robots have prepared them (Element Logic, 2023j). Data on "waiting for bin", average bin preparation, how order release is handled, along with the average, minimum, and maximum tasks released during the period are displayed in Figure 5.9 below.

Company	F1	F2	F3	3PL1	3PL2	E1	E2
Waiting for bin	5,2	7,8	5,7	7,0	6,3	8,9	5,6
Avg. bin preparation	99,1	91,9	95,3	90,2	98,7	65,3	87
Order release	Automatically (mostly)	Manually	Automatically (mostly)	Manually	Automatically (B2B) Manually (B2C)	Automatically	Automatically
# of order releases	2375	3447	2683	1159	2008	7453	2945
Avg. tasks per release	81	332	158	85	76	45	561
Max. released tasks	2603	6617	2899	3071	4685	1506	25231
Min. released tasks	1	1	1	1	1	1	1
Picking Method	Single order	Single order	Single order	Single order	Single order and Batch picking (for B2B)	Single order	Batch picking

Figure 5.9. "Waiting for bin" [s], average bin preparation [%], order release, number of orders released along with avg., max., and min. tasks released. Displayed for each company.

In terms of order release, both E1 and E2 are conducted automatically but with very different structures. Analyzing the data on E1 and E2 in terms of bin preparation and order release shows that a more frequent order release of small amounts leads to lower average preparation levels during working hours. However, as stated above E1 is picking 24/7 which affects the preparation levels.

Automatic order release does not equal higher preparation but rather the structure of the releases and how well they align with current operation schedule. By continuously releasing orders and not having any breaks for the system, it does not get the opportunity to prepare to higher levels, as the data suggests, aligning with experienced technician's hypothesis (Element Logic, 2023a). Consistently, companies with an order release structure dependent on the operations, as well as automatically rather than manual, were performing better in terms of "waiting for bin". Higher levels of preparation were the results of mindful breaks and order release structure. Both 3PL2 and E2 are using batch picking. As stated in the interview with 3PL2, batch picking free up robots for preparation while the picker is conducting multiple picks from the bin already presented. In relation to the picking schedule, orders that are being released will be prepared. If no picks are to be made in the specific queue, the preparation area is being unnecessarily occupied (Element Logic, 2023j). Therefore, order release in relation to picking schedule should be considered.

> **Proposition 7:** Order release structure needs to be configured to align with the daily operations of the case company. Parameters to consider are timing, frequency, size, and to which queue in relation to picking schedule.

Focusing on the fashion companies, the amount of robots per average open port, is suggested by data to play an essential role in keeping "waiting for bin" low despite higher levels of complexity. By comparing contextual factors and configurations, some substantial differences can be seen that contribute to complexity and/or uncertainty. Data on "waiting for bin", number of robots per open port, pick waves, bin configurations, SKUs stored in AutoStore, and how orders are released are displayed in Figure 5.10.

Company	F1	F2	F3	3PL1	3PL2	E1	E2
Waiting for bin	5,2	7,8	5,7	7,0	6,3	8,9	5,6
# robots / open port	11,7	10,2	16,7	11,3	13,4	Router	Router
# pick waves	0	3,5	10	0	12	0	0
# of bin configs.	4	5	5	4	2	1	1
# SKU types in AS (K)	21	97	29	22	13	13	2
Order release	Automatically (mostly)	Manually	Automatically (mostly)	Manually	Automatically (B2B) Manually (B2C)	Automatically	Automatically

Figure 5.10. "Waiting for bin" [s], number of robots per open port, pick waves, bin configurations, SKU types stored in AutoStore, and how orders are released.

Comparing F1 to F2, F2 has a longer time spent "waiting for bin" corresponding to an increase of 50% from F1. Examining deeper, the underlying factors resulting in the increase could be connected to complexity in terms of using pick waves, amount of bin configurations, SKU variety, and manual order release structure. Including F3 in the comparison, F3 shares similarities in terms of using pick waves, amount of bin configurations, as well as a rather high SKU variety. The dig depth of F3 is even higher than F2 even if the order release structure of F3 is automatic and aligns with their operations. However, the essential difference besides order release structure, is having a greater amount of robots per average port open. Therefore, despite added complexity to a similar degree as F2, they manage to maintain rather similar values of waiting for bin as F1.

Data on bin presentations/h (per port), dig depth, if forecasting is used or not, and pick strategy is displayed in Figure 5.11 below. The "/" indicates the next strategy that is applied if the quantity could not be satisfied with the current strategy.

Company	F1	F2	F3	3PL1	3PL2	E1	E2
Bin presentations/h (per port)	149	148	165	117	183	162	256
Dig depth	1,91	2,05	3,04	2,75	1,66	3,51	1,37
Forecasting	Yes	Yes	No	Yes	No	No	No
Pick strategy	Lowest quantity (no max)	Lowest quantity (max 5) / FIFO	FIFO	FIFO	Lowest quantity (max 1) / Lowest quantity (max 7) / FIFO	FIFO	FIFO

Figure 5.11. Bin presentation/h (per port), dig depth, forecasting, and pick strategy for each company. The "/" indicates the next strategy that is applied if the quantity could not be satisfied with the current strategy.

Configurations of F3 compared to F1 and F2 differ in terms of more robots per port, not utilizing forecasting, and FIFO picking instead of focusing on "half-empty" bins. Although the level of preparation is in between F1 and F2, the dig depth is substantially higher, but mitigated with the higher rates of robots since the waiting for bin still is comparable. Thus, in the case of F3 and F1, the difference on robots per port open is 40% higher on average, compensating for higher complexity in terms of waiting for bin, as suggested by data. To handle the complexity, companies can either increase the number of robots in the system, or close redundant ports that are open without full capacity used. According to employees at Element Logic, closing ports increases the robot resources per open port (Element Logic 2023g). Therefore, if the same number of picks can be completed with fewer open ports, a higher efficiency can be achieved due to a higher number of robots per open port (Trost et al., 2023). If a higher number of total picks is necessary, more robots are needed in the system to supply open ports sufficiently (not to a degree where too many robots block each other (Trost et al., 2023)).

> **Proposition 8:** By having an increased number of robots per open port, complexity can be mitigated and despite a higher dig depth, the system can deliver a lower level of "waiting for bin".

According to conclusions by Gallien and Weber (2010), waveless picking performs equal or better than best policy pick waves in automated sorters. Conclusions are also supported from experience among employees at Element Logic, who state that pick waves add constraints to the system. It thereby increases the complexity and can also affect the preparation of bins (Element Logic, 2023c). However, no correlation on pick waves and worse performance is seen in the data and comparison, suggesting that other contextual factors and configurations affect the performance to a greater extent. As discussed in the meeting with Element Logic regarding findings (2023j), the explanation might be that orders are fairly similar regardless of carrier, not causing too much unnecessary reshuffling. For example, including 3PL1 and 3PL2 in the comparison since they also have products within fashion. 3PL1 does not constrain the system with pick waves while 3PL2 has 12 (displayed in Figure 5.10). However, 3PL2 has 56% higher bin presentations/h per port in comparison to 3PL1 (displayed in Figure 5.11), and roughly 30% higher than F1 and F2. Thus, no pattern could be found in investigated cases. Furthermore, the correlation between pick strategy and "waiting for bin" in picking was examined. According to employees at Element Logic, the pick strategy can affect the numbers of orders completed per hour when picking orders with high amounts per order line, often occurring in the B2B flow (Element Logic, 2023j). Having a pick strategy that prioritizes picking from bins with the lowest quantity can lead to a lot of bins having to be retrieved to fulfill the needed amount. Said strategy leads to robot resources being used to prepare or retrieve the bins, taking up preparation area (Element Logic, 2023j), leading to less orders being prepared. However, if it is one or several orders taking up the preparation area does not interfere with "waiting for bin", but instead lowers the amount of orders completed per hour, since multiple bins need to be presented to fulfill the order instead of one. Examining data confirms that there is no correlation between pick strategy and "waiting for bin".

When looking at the usage of forecasting (displayed in Figure 5.11), it closely follows the order release structure, and does not indicate worse or better performance by itself according to data. The utilization of the forecasting function varies from company to company. Examining the function itself, it can raise preparation levels and lower "waiting for bin" if there are orders to forecast and enough time for the robots to take action (Element Logic, 2023e). If there are no orders to forecast, the function becomes redundant (Element Logic, 2023e). Therefore, looking at the companies would suggest that F1 has aligned its automatic order release structure with forecasting, since their preparation levels are the highest. On the contrary, the other companies using forecasting both have manual order release structure, and also lower levels of preparation. If it is manual or not, does not necessarily equal poor alignment with forecasting, but for the function to be utilized, it has to match the order release time and size.

> **Proposition 9:** To fully utilize the functionality of forecasting, a sufficient order backlog must exist and order release structure must be aligned to raise preparation levels.

In the case of having dedicated ports for specific types of processes, the data suggests along with interviews with Element Logic (Element Logic, 2023j) that bin preparation levels get affected by the switching process. If put-away is conducted in a specific port, empty bins will be prepared around that port, until the port is eventually used for picking instead. Regardless if the switch is happening after hours since last operation, empty bins around the put-away port will now be placed elsewhere, hence the *unnecessary preparation* (Element Logic, 2023j). Due to contextual factors of being dependent on the customer, this is occurring in the case of 3PL1 and 3PL2 to a noticeable extent. When investigating specific port data, it is fluctuating to a greater degree because several types of operations are being conducted in port.

Proposition 10: Switching between operations in ports rather than having dedicated ones causes unused preparation, and multiple handling of bins.

Data on average and maximum bin presentations/h (per port) along with the picking method is displayed in Figure 5.12 below.

Company	F1	F2	F3	3PL1	3PL2	E1	E2
Bin presentations/h/ (per port)	149	148	165	117	183	162	256
Max. bin presentations/h (per port)	265	284	279	245	357	326	384
Picking Method	Single order	Single order	Single order	Single order	Single order and Batch picking (B2B)	Single order	Batch picking

Figure 5.12. Average bin presentation/h, max. bin presentations/h, and picking method for each company.

Two of the examined companies were using batch picking , which according to data and the interview with 3PL2 positively affects “waiting for bin”, since it relieves some of the robot resources and utilizes the current bin to a larger extent with less multiple handling. This is because for each item to be picked for each order, the bin will spin away 120° and back again, counting as a bin presentation with minimal time spent “waiting for bin”. Instead of displaying the total amount to be picked to all orders and which these orders are, the system will present desired amount and location one at a time (Element Logic, 2023e). Since the spin does count as a bin presentation, the value of bin presentations can appear to be inflated, but rather display the efficiency of utilizing batch picking if possible. When comparing maximum bin presentations/h within the fashion- and 3PL companies, 3PL2 is substantially higher than the second highest, F2, with a 25,7% increase. The average bin presentations/h at 3PL2 is 10,9% higher than the second highest, F3. Comparing 3PL2 with E2, the latter has a more standardized assortment and a more optimized picking process in terms of TOC, and the difference is noticeable by 39,9% more bin presentations/h on average.

Proposition 11: If possible to utilize batch picking, it can greatly improve maximum and average performance as well as relieving robot resources. It allows operators to utilize each bin presented to a greater extent and spend less time “waiting for bin”.

"Waiting for User"

The picking processes of the companies were examined in terms of their activities conducted by the port, such as scanning, procedure after pick, selection of package, carton rising, wrapping fragile items, packing, discount-leaflets, and label printing. Data on this along with the "waiting for user" for each company is displayed in Figure 5.13.

Company	F1	F2	F3	3PL1	3PL2	E1	E2
Waiting for user	19,0	16,9	17,0	24,0	14,0	14,0	8,3
Procedure after pick	Scan	Scan	Scan	Scan & compare product EAN	Pick-by-ligt & compare EAN / Scan	No scan	Scan box
Bag/box selection	Manually by port	Manually by port	Manually by port	B2B: Manually by port B2C: Later station	Manually by port	Automatically	Automatically
Raise & seal cartons	Quick-fold (low freq.)	Manually (low freq.)	No boxes	Manually	Manually & Quick-fold	Automatically	Automatically
Wrapping	Yes (low freq.)	Yes (low freq.)	Yes (low freq.)	No	No	No	Yes (low freq.)
Packing by port	Yes	Yes	Yes	Yes & No	Yes	No	No
Discount-leafets in package	Yes	Yes (occasionally)	Yes	No	Yes	No	No
Label printing	After	Before	Before	After	After	Later	Later

Figure 5.13. "Waiting for user" [s] and activities related to picking at the port, for each company.

Looking at the three companies with the lowest average "waiting for user", 3PL2 and E1 share the same value, and E2 has the lowest value of 40% less than the other two (. Comparing E2 and E1, they both share many characteristics in terms of their equipment regarding carton risers, sealing and no labels to handle in the picking process. The most noticeable differences in processes are mainly the use of a robotic arm to pick in the case of E1, and that E2 utilizes batch picking instead of single order pick (displayed in Figure 5.12). From observations, the robotic arm has the advantage of not needing breaks and getting tired, but a disadvantage in its ability to recognize and actually pick objects. The human hand appeared to be more accurate during observations, something that is confirmed in gathered data with a higher amount of bin presentations/h caused by a lower "waiting for user" in the human port. Diving deeper into the data from E1, comparing robotic and human queues, the human on average out-performs the robot in terms of speed, further confirming the observations. However, the picking processes of humans are very similar between E1 and E2 in terms of activities conducted by the port. There is no clear indication of why E1 would need such an increase in time per pick by the human user, and analyzing the maximum values for the period confirms that the "waiting for user" has potential to be substantially shorter. Comparing E2 with 3PL2, the processes look very different, despite both using batch picking. 3PL2 has their fastest process in the B2B queue, since it is utilizing batch picking as well as pick-by-light. In terms of activities, comparing the standardized one queue process of E2, with 3PL2, there are some differences in their most similar process. E2 has everything regarding cartons and labels automated, removing said processes from the picking operator. These processes regarding packing is something 3PL2 does manually, which is the most prominent difference in terms of activities.

> **Proposition 12:** Keep as few activities as possible by the picking port for the greatest decrease in "waiting for user", increasing bin presentations/h. Time spent "waiting for user" rooted in manual activities is responsible for a substantial amount of the total time per bin presentation. Optimize activities in terms of TOC to lower "waiting for user" significantly.

One specific difference that was significant when doing pattern matching, was the label printing. Looking at E1 and E2, no label printing is conducted at all, which further simplifies the picking process and lowers "waiting for user". Comparing F1 and F2, the "waiting for user" is consistently higher for F1 than F2 with many similarities in terms of configurations. F1 has 12,6% increased time by the port for each pick, with the most noticeable difference in configuration being printing of labels to be included in each package. F1 prints the labels once the order has been completed, while F2 at the start of the order. The activities by port are comparable from interviews and observations with label printing being the only configuration differing, which is not connected to any specific contextual factor. Involving F3, looking at their configurations, they also print by the start of the order, with similar values of "waiting for user" as F2. Thus, data suggests that if label printing is conducted after instead of before pick is finished it would result in an increase of 12,6% in time taken to finish each pick, assuming the operators perform the other picking activities at the same speed. Printing labels before or during the picking is aligned with TOC and would remove a time-consuming activity of waiting.

> **Proposition 13:** Conduct any sort of label printing at the start of the order rather than when it is finished to lower the time "waiting for user".

Data on "waiting for user", total number of SKU types, % and number of SKU types stored in AutoStore for each company is displayed in Figure 5.14.

Company	F1	F2	F3	3PL1	3PL2	E1	E2
Waiting for user	19,0	16,9	17,0	24,0	14,0	14,0	8,3
Total # SKU types (K)	22	102	49	27	14	42	2
% of total SKU types in AS	95%	95%	60%	83%	92%	30%	100%
# SKU types in AS (K)	21	97	29	22	13	13	2

Figure 5.14. "Waiting for user" [s], total number of SKU types, % and number of SKU types stored in AutoStore, for each company.

For all companies except E1 and E2, there are several types of processes connected to the picking due to a variety of SKUs and orders. E1 has a similar type of process regardless of human or robot pick, and what SKUs to later be included in the order. E2 has chosen its SKU variety carefully with consideration of the AutoStore, and eliminated the need for any type of other storage, handling, or consolidation of orders. This decision is taken early on in the design phase, and influences other design decisions as well as determines how the warehouse will be operated. This highlights the importance of overlooking the amount of SKU types a company has prior to acquiring and designing their AutoStore system (and warehouse overall), if conditions for high performance want to be achieved. As previously stated by Kembro and Norrman (2021) and *Unraveling Complexity in Products and Services* (2006), increased complexity uses up resources to a greater extent with the need of varied configurations to maintain functional operations. Applying this to E2, it is the case company with least complexity and uncertainty compared with all others, and also the one with highest performance. Both contextual factors as well as configurations favor the AutoStore, which is reflected in their performance, and the standardization of processes allow for further optimization and less variation.

> **Proposition 14:** Lowered complexity in terms of SKU and order variety, configurations outside and inside the AutoStore, is resulting in higher performance. When acquiring and having an AutoStore, the complexity and uncertainty have to be taken into consideration to determine if the variety is advantageous.

5.2.3 Summary of propositions

To conclude, Table 5.8, 5.9 and 5.10 below summarizes all propositions from the cross-case analysis. The tables are divided into each category they focus on. In order the tables include propositions for “waiting for user” in put-away, followed by “waiting for bin” in picking, and lastly “waiting for user” in picking.

Table 5.8. List of propositions focusing on “waiting for user” in put-away.

Proposition | Description | Cases corroborating the proposition		
1	Counting goods when performing put-away at the port significantly increases “waiting for user”.	F2 and 3PL1 vs rest
2	The amount of returns significantly affects “waiting for user”. The put-away process related to returns is more time-consuming compared to the put-away of non-returns.	F1, F2, F3, E2

These propositions mainly apply TOC in terms of activities by port, where counting goods by the port has been identified as the most time-consuming task. The contextual factor causing the parallel process of put-away of returns, is the amount of returns, also affecting the “waiting for user”.

Table 5.9. List of propositions focusing on “waiting for bin” in picking.

Proposition | Description | Cases corroborating the proposition		
3	Picking long hours without breaks does not let the system regain preparation levels together with robots not having the opportunity to recharge properly, increasing “waiting for bin”.	E1, E2
4	Using the AutoStore to find and pick single items, compromises already prepared bins, and causes multiple handling and unnecessary reshuffling of bins.	3PL1, E1, E2
5	The number of queues corresponds to how the preparation area is divided between the queues, increasing the probability to pick unprepared goods by using up the dedicated prepared bins faster.	E1, E2
6	High SKU variety further increases the necessity of high levels of preparation to achieve lower levels of “waiting for bin”.	E2 vs rest
7	Order release structure needs to be configured to align with the daily operations of the case company. Parameters to consider are timing, frequency, size, and to which queue in relation to picking schedule.	3PL2, E1, E2
8	By having an increased number of robots per open port, complexity can be mitigated and despite a higher dig depth, the system can deliver a lower level of “waiting for bin”.	F1, F2, F3
9	To fully utilize the functionality of forecasting, a sufficient order backlog must exist and order release structure must be aligned to raise preparation levels.	F1, F2, F3, 3PL1, 3PL2, E1, E2
10	Switching between operations in ports rather than having dedicated ones causes unused preparation, and multiple handling of bins.	3PL1, 3PL2, vs rest
11	If possible to utilize batch picking, it can greatly improve maximum and average performance as well as relieving robot resources. It allows operators to utilize each bin presented to a greater extent and spend less time “waiting for bin”.	3PL2, E2 vs rest

The displayed propositions above focus on the AutoStore system itself with its ability to retrieve the next bin. They mainly focus on configurations to allow the AutoStore to prepare bins, or not operate in an inefficient way. Inefficiency mainly surfaces in terms of unused preparation, not giving the system an opportunity to prepare, or simply making it difficult for the system to keep up with preparation levels.

Table 5.10. List of propositions focusing on “waiting for user” in picking.

Proposition | Description | Cases corroborating the proposition		
12	Keep as few activities as possible by the picking port for the greatest decrease in “waiting for user”, increasing bin presentations/h. Time spent “waiting for user” rooted in manual activities is responsible for a substantial amount of the total time per bin presentation. Optimize activities in terms of TOC to lower “waiting for user” significantly.	F1, F2, F3, 3PL2, E1, E2
13	Conduct any sort of label printing at the start of the order rather than when it is finished to lower the time “waiting for user”.	F1, F2, F3, E1, E2
14	Lowered complexity in terms of SKU and order variety, configurations outside and inside the AutoStore, is resulting in higher performance. When acquiring and having an	E1, E2 vs rest

	AutoStore, the complexity and uncertainty have to be taken into consideration to determine if the variety is advantageous.	

These propositions focus on the TOC in terms of picking, and look at the processes related to picking. As number 13 suggests, label printing has been identified as a time-consuming step where the operator waits for the printer without being able to further advance the order finalization. Besides this, due to the large variance in “waiting for user” among all companies suggest that minimizing activities performed by port has the most potential of decreasing time, and thus increasing bin presentations/h. Not only keeping the processes efficient, but also keeping the process standardized and not having multiple slower processes due to SKU variety, which also increases the need of more queues, which in turn as suggested by number 5 in Table 5.9, further decreases performance.

All propositions were further used when returning to the research questions and are used to form general recommendations that all case companies can benefit from. Some propositions are applicable to the organization as a whole and intertwined with other propositions, while others are more specific. The contextual factors that affect performance and the corresponding configurations are displayed in Figure 5.15 below, along with the propositions connected to each configuration. Also, the groupings and connections to “waiting for user” and “waiting for bin” respectively are displayed.

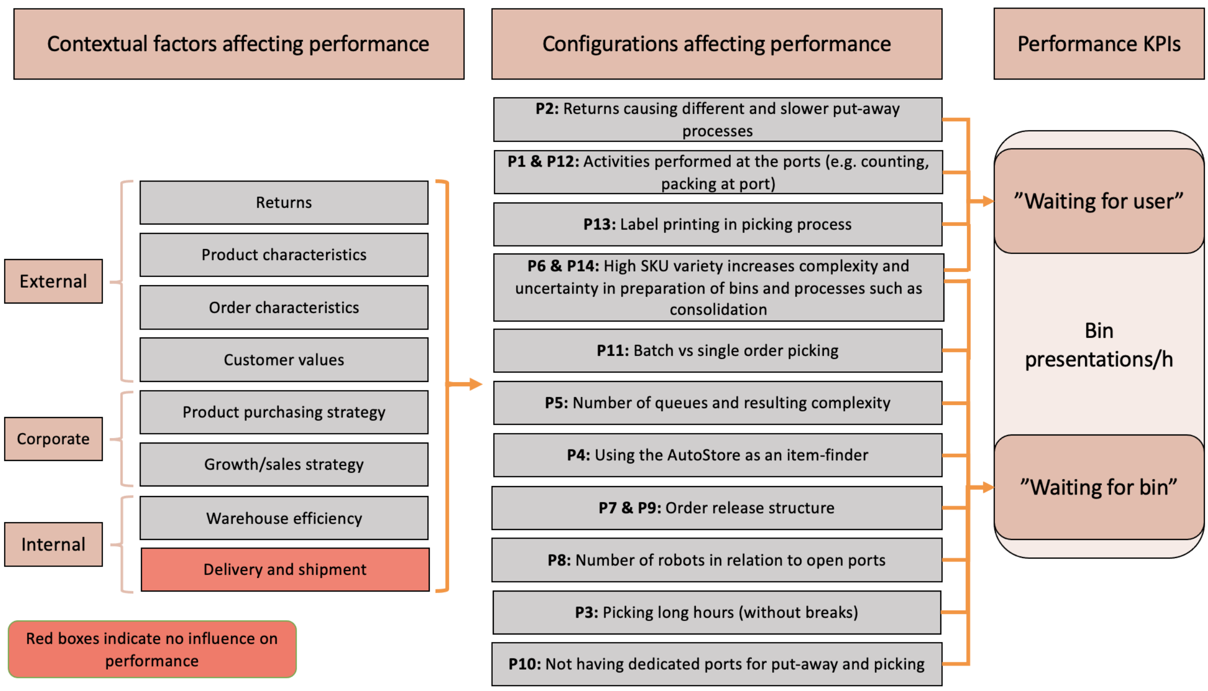

Figure 5.15. Contextual factors and propositions connected to configurations affecting performance.

The only contextual factor that could not link to affecting performance was “Delivery and shipment”, which influence the usage of pick waves. No relation between the usage of pick waves and performance could be seen in data, thus “Delivery and shipment” is not affecting performance. The contextual factors affecting performance directly or through configurations are listed in gray and in many ways intertwined. In Figure 5.15, it can be seen that there are more identified configurations affecting “waiting for bin” than “waiting for user”. However, the relatively few propositions connected to “waiting for user” weigh heavier since it is the area with the largest difference and possibility to improve performance.

5.3 Discussion

In this section, the discussion of findings will be presented along with recommendations on how to improve performance by handling the propositions. The recommendations can either be used by companies having an AutoStore, or by employees at Element Logic designing and implementing AutoStore systems for their customers.

5.3.1 Discussion of findings

How the companies are performing in relation to their complexity and uncertainty are depicted in Figure 5.16 and 5.17, focusing on put-away and picking respectively. The performance is referring to average bin presentations/h and companies are accurately placed in relation to each other in the Y-axis. Their degree of complexity and uncertainty is more difficult to quantify since there are a lot of different aspects to consider and weigh differently. Therefore, the companies are arbitrarily placed in relation to each other. The placements are based on each within-case analysis with aspects such as SKU variety, number of queues, and existence of parallel processes considered. The figures are not meant to depict a specific level of complexity and uncertainty but rather work as an overview to visualize what each company should focus on. The matrix consists of four quadrants, each focusing on a different area, “Optimal for AutoStore”, “Optimized after given conditions”, “Optimize processes”, and “Decrease/mitigate complexity or uncertainty”. The dotted line is an approximated mean of where the companies are placed, suggesting the trend among companies.

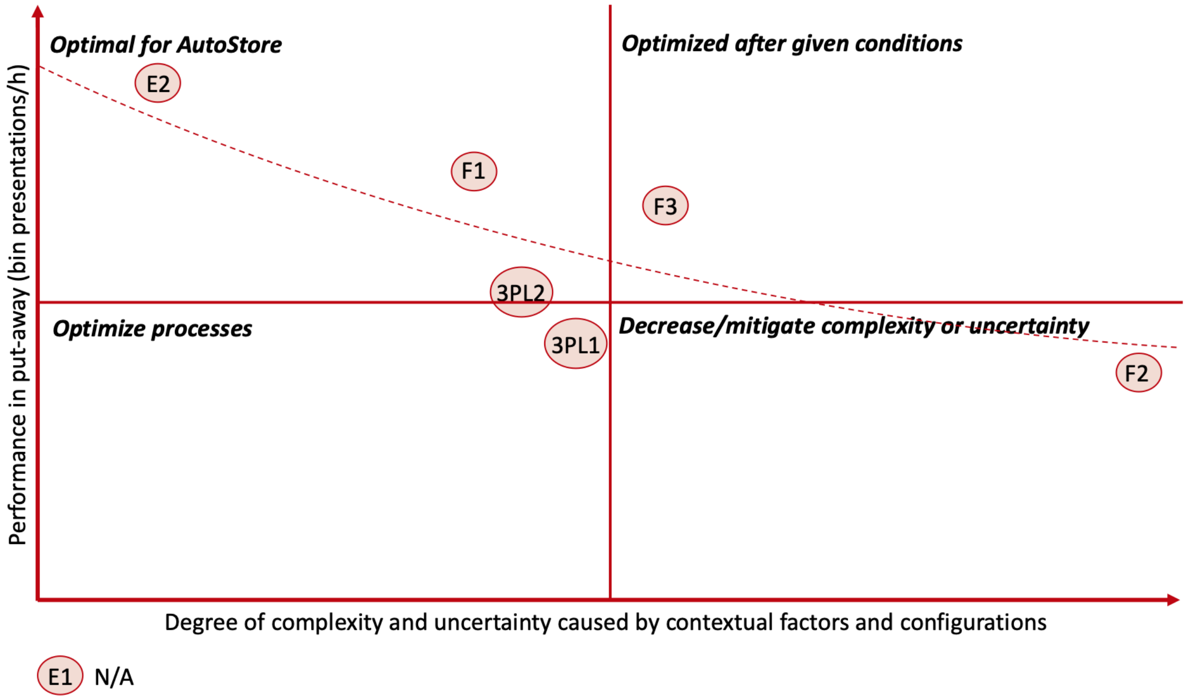

Figure 5.16. Put-away performance and degree of complexity & uncertainty for the different companies.

The put-away process is heavily affected by the amount of returns to be inserted in the AutoStore since each item is being handled separately, and each bin is being filled comparatively slowly. The existence of a slower parallel process caused by returns, would be mitigated by decreasing complexity through minimizing returns. Moving to the left in the figure, allowing higher performance through standardization and process optimization. Returns are mentioned as a contextual factor and are considered difficult to change from the warehouse’s perspective. To further decrease this level of complexity, the return policy/strategy has to be overseen by the company. Also, not counting goods by the port as suggested by proposition would be an example of applying TOC on process, removing time-consuming activity, moving for example F2 upwards along the Y-axis.

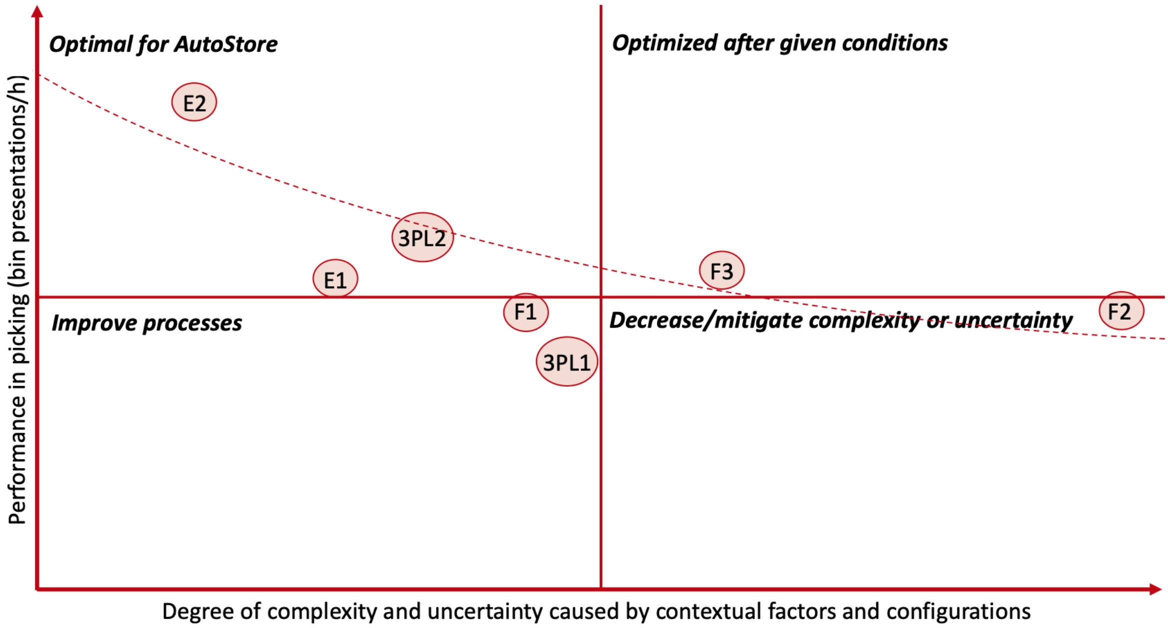

Figure 5.17. Picking performance and degree of complexity & uncertainty for the different companies.

Looking at picking, the quadrant of "Optimal for AutoStore" would suggest companies that have lower levels of complexity that are manageable, and already have configurations accordingly. To further improve performance, their focus should be on optimizing processes in terms of applying TOC, and removing time-consuming activities from the picking port. This focus is shared with the quadrant below, "Improve processes". Companies in this quadrant also have manageable levels of complexity, but still have a lot to gain by standardization and process optimization. To take an example, F1 could move label printing to during the pick instead of after the order is finished. 3PL1 has a high "waiting for user" suggesting inefficient processes by the port. However, the validity of the data is heavily affected by frequent switches of operations in port, and average picking data is compromised by put-away performance negatively.

Companies in the lower right quadrant, "Decrease/mitigate complexity or uncertainty", should focus on aligning their configurations with their contextual factors. This is done according to contingency theory to improve performance by lowering complexity and uncertainty. Alignment has for example moved F3 upwards, since their configurations and contextual factors are aligned to a greater extent. F3 has mitigated some of its complexity through more robot resources per average open port, and lowering the uncertainty through order release automation according to their operations. Company F3 is in the last quadrant, "Optimized after given conditions", which suggests the company has taken measures to deal with complexity or uncertainty. This by either mitigating it which has moved them upwards, or by decreasing it that has moved them to the left, further allowing process standardization and optimization.

Continuing with contingency theory and how warehousing performance is affected by whether or not contextual factors and configurations are aligned, offers interesting insights. The case of each company aligning their factors and configurations to improve performance, does not necessarily indicate that the factor and resulting configuration is optimal in relation to AutoStore. For example, F2 did have the highest amounts of returns as a contextual factor, with an aligned corresponding put-away process. In its individual case it leads to an increased performance according to contingency theory. However, according to the cross-case analysis, alignment does not equal a *relatively* high performance. In the within-case analysis, configurations could result in as good performance as the contextual factors allow. However, when compared to other cases, the contextual factor itself can be the reason behind lacking performance. Thus, as with the example of F2 and returns, the greatest improvement would rather be to lower the amount of returns, rather than focusing on aligning configurations with the context.

One interesting finding regarding pick strategy was comparing fashion companies and their strategy to either prioritize picking returns, or not. The setting is not necessarily strictly to pick returns, but rather to pick from bins with lowest quantity, to clear bins for future put-away. Looking at B2B, it is common for orders to be larger in terms of size and amount per SKU. Applying said picking strategy would then mean that for example, an order with 15 pieces of a desired SKU, could result in 15 separate bin presentations to fulfill the order line. This is true assuming no bin location limit exists on the picking strategy and there is only a single piece per bin. Instead the same order line could be completed in one or two bin presentations if not prioritizing low quantity bins, depending on the SKU characteristics. This does not affect performance in any way based on our analysis, but greatly decreases the number of orders completed. It could potentially affect the preparation levels depending on order release structure in terms of upper limits, but it has not been investigated in this thesis.

In Figure 5.18 below, a comparison between performance and years since implementing the AutoStore is illustrated.

Company	F1	F2	F3	3PL1	3PL2	E1	E2
Years since Go-live	1-2	2-3	1-2	2-3	<1	<1	1-2
Waiting for user (picking)	19,0	16,9	17,0	24,0	14,0	14,0	8,3
Waiting for bin (picking)	5,2	7,8	5,7	7,0	6,3	8,9	5,6
Bin presentations/h (picking)	149	148	165	117	183	162	256
Waiting for user (put-away)	49	89	56	80	72	N/A	38
Waiting for Bin (put-away)	5,6	12,6	6,3	12,3	5,7	N/A	7,7
Bin presentations/h (put-away)	66	36	61	40	47	N/A	80

Figure 5.18. Picking performance and degree of complexity & uncertainty for the different companies.

The aspect of how long each company has had their AutoStore did not show any pattern in more mature systems would have comparably high performance. Maturity might increase the probability of optimizing processes in line with context and locating bottlenecks, but it is not essentially considered to be a contextual factor or configuration.

5.3.2 Recommendations to handle propositions

The recommendations are added on to the propositions presented earlier in Table 5.8, 5.9 and 5.10. These can be found in the right column of Table 5.11, 5.12 and 5.13 below. Certain recommendations need to be elaborated on, which is presented after each table.

Table 5.11. List of recommendations for the propositions focusing on "waiting for user" in put-away.

Proposition | Description		**Recommendations**
1	Counting goods when performing put-away at the port significantly increases "waiting for user".	Count goods in advance (not by port)
2	The amount of returns significantly affects "waiting for user". The put-away process related to returns is more time-consuming compared to the put-away of non-returns.	Oversee return policy/strategy

As for proposition 1, goods should be counted in advance and not when performing the put-away at the port. For some of the observed companies, the goods arrived at the warehouse already counted with an EAN-code which the port operator scans when performing put-away. Other companies counted at a station prior to put-away, to avoid counting at the port. The recommendation for proposition 2 is to oversee the return policy/strategy of the company. Is the current return policy/strategy economically beneficial when comparing the increased sales as a result of easy and cheap returns, with the decreased performance in put-away? This is especially aimed at companies with a high amount of returns.

Table 5.12. List of recommendations for the propositions focusing on “waiting for bin” in picking.

Proposition | Description		**Recommendations**
3	Picking long hours without breaks does not let the system regain preparation levels together with robots not having the opportunity to recharge properly, increasing “waiting for bin”.	Implement synchronized breaks to let system regain preparation
4	Using the AutoStore to find and pick single items, compromises already prepared bins, and causes multiple handling and unnecessary reshuffling of bins.	Avoid using the AutoStore to find and pick single items. Evaluate why this is done today to identify the root cause.
5	The number of queues corresponds to how the preparation area is divided between the queues, increasing the probability to pick unprepared goods by using up the dedicated prepared bins faster.	Keep number of queues to a minimum
6	High SKU variety further increases the necessity of high levels of preparation to achieve lower levels of “waiting for bin”.	Oversee SKU variety and examine whether all existing SKUs are economically beneficial
7	Order release structure needs to be configured to align with the daily operations of the case company. Parameters to consider are timing, frequency, size, and to which queue in relation to picking schedule.	Align order release to order structure and daily operations
8	By having an increased number of robots per port, complexity can be mitigated and despite a higher dig depth, the system can deliver a lower level of “waiting for bin”.	If complexity is inevitable, oversee amount of robots per open port
9	To fully utilize the functionality of forecasting, a sufficient order backlog must exist and order release structure must be aligned to raise preparation levels.	If forecasting is to be used, oversee order characteristics and order release structure
10	Switching between operations in ports rather than having dedicated ones causes unused preparation, and multiple handling of bins.	Avoid switching between put-away and picking in the same ports
11	If possible to utilize batch picking, it can greatly improve maximum and average performance as well as relieving robot resources. It allows operators to utilize each bin presented to a greater extent and spend less time “waiting for bin”.	Oversee possibility to implement batch picking

For proposition 3, companies should implement synchronized breaks to let the system regain preparation, which facilitates for the system to achieve a lower “waiting for bin”. The recommendation is especially aimed at companies that have a high SKU variety as stated in proposition 6, since a higher preparation then is required to accomplish a lower “waiting for bin”. Regarding proposition 4, it should be avoided to use the AutoStore to find and pick single items. If this is done frequently today, the suggestion is to do a root cause analysis on why the AutoStore needs to be used this way. Observations and interviews at a case company confirmed that the AutoStore is used in this way as a consequence of having unorganized manual shelves. If the person picking from the manual shelves could not find the item that was searched for, the person used the AutoStore to find and pick the item from (assuming it also is stored in the AutoStore). The recommendation for proposition 6 is to oversee SKU variety and examine whether all existing SKUs are economically beneficial. As stated in the proposition, the higher variety of SKUs demands a higher level of preparation to achieve a lower "waiting for bin". Companies need to analyze whether the variety of SKUs is more economically beneficial for them, as "waiting for bin" might be higher if preparation levels also are lower. For proposition 11, the recommendation is to oversee the possibility to implement batch picking. According to employees at Element Logic, there are several conditions that need to be fulfilled to make batch picking work, such as specific order characteristics. However, having the performance increase in mind can act as a reminder for companies to every now and then oversee the possibility to implement batch picking.

Table 5.13. List of recommendations for the propositions focusing on "waiting for user" in picking.

Proposition | Description		**Recommendations**
12	Keep as few activities as possible by the picking port for the greatest decrease in "waiting for user", increasing bin presentations/h. Time spent "waiting for user" is rooted in manual activities responsible for a substantial amount of the total time per bin presentation.	Keep time-consuming activities at the port to a minimum (such as packing, selection of bag/carton), by applying TOC.
13	Conduct any sort of label printing at the start of the order rather than when it is finished to lower the time "waiting for user".	Print labels at the start of the order
14	Lowered complexity in terms of SKU and order variety, configurations outside and inside the AutoStore, is resulting in higher performance.	Oversee SKU variety and correlating processes (e.g. consolidation).

For proposition 14, the recommendation is to oversee SKU variety and correlating processes, such as consolidation. As discussed above, the SKU variety affects performance in different ways. Order variety is hard to control, as a company cannot control what their customers order from their website. However, the company can control what SKUs and the variety they offer to their customers. This not only applies to companies with an existing AutoStore, but also companies planning on acquiring an AutoStore for their warehouse. The complexity and uncertainty of the SKU variety have to be taken into consideration, to determine if the SKU variety is more advantageous than the lower performance that comes with it.

To summarize, Figure 5.19 below is an illustration of where the specific propositions are in relation to the AutoStore and analyzed processes.

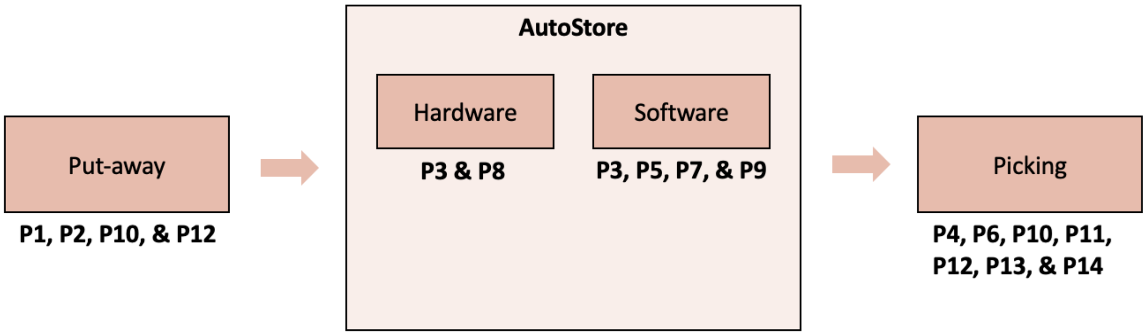

Figure 5.19. Overview of propositions in relation to AutoStore and processes.

Further, propositions and the corresponding recommendation are summarized in Table 5.14.

Table 5.14. Summary of recommendations (Tables 5.11, 5.12, 5.13 consolidated).

Proposition | Corresponding recommendation	
P1	Count goods in advance (not by port)
P2	Oversee return policy/strategy
P3	Implement synchronized breaks to let system regain preparation
P4	Avoid using the AutoStore to find and pick single items. Evaluate why this is done today to identify the root cause.
P5	Keep number of queues to a minimum
P6	Oversee SKU variety and examine whether all existing SKUs are economically beneficial
P7	Align order release to order structure and daily operations
P8	If complexity is inevitable, oversee amount of robots per open port
P9	If forecasting is to be used, oversee order characteristics and order release structure
P10	Avoid switching between put-away and picking in the same ports
P11	Oversee possibility to implement batch picking
P12	Keep time-consuming activities at the port to a minimum (such as packing, selection of bag/carton), by applying TOC.
P13	Print labels at the start of the order
P14	Oversee SKU variety and correlating processes (e.g. consolidation).

6. Conclusion

For the conclusion, insights from the analysis and discussion will be used to answer the research questions and the "fulfillment of purpose" of this thesis. After that, the theoretical and practical contributions will be presented. Lastly, limitations in the research as well as areas for future research are discussed.

6.1 Research questions and fulfillment of purpose

All research questions involve the contextual factors of companies and their inevitable effect on warehouse configurations and performance. First, the goal was to find what the driving contextual factors and configurations are and explore how they affect performance. Secondly, when the relevant contextual factors and configurations had been identified, the degree of their influence was analyzed, to enable prioritization and create some perspective of their weight. Lastly, recommendations on how to handle the contextual factors and configurations were presented.

6.1.1 RQ1: What contextual factors and configurations are affecting the performance of the AutoStore system?

The contextual factors and configurations affecting performance are depicted in Figure 6.1. All contextual factors marked in gray are affecting performance either directly or through configurations. Only one contextual factor did not affect performance based on the analysis, which is marked in red in the figure. The configurations are categorized based on if it affects "waiting for user", "waiting for bin", or both.

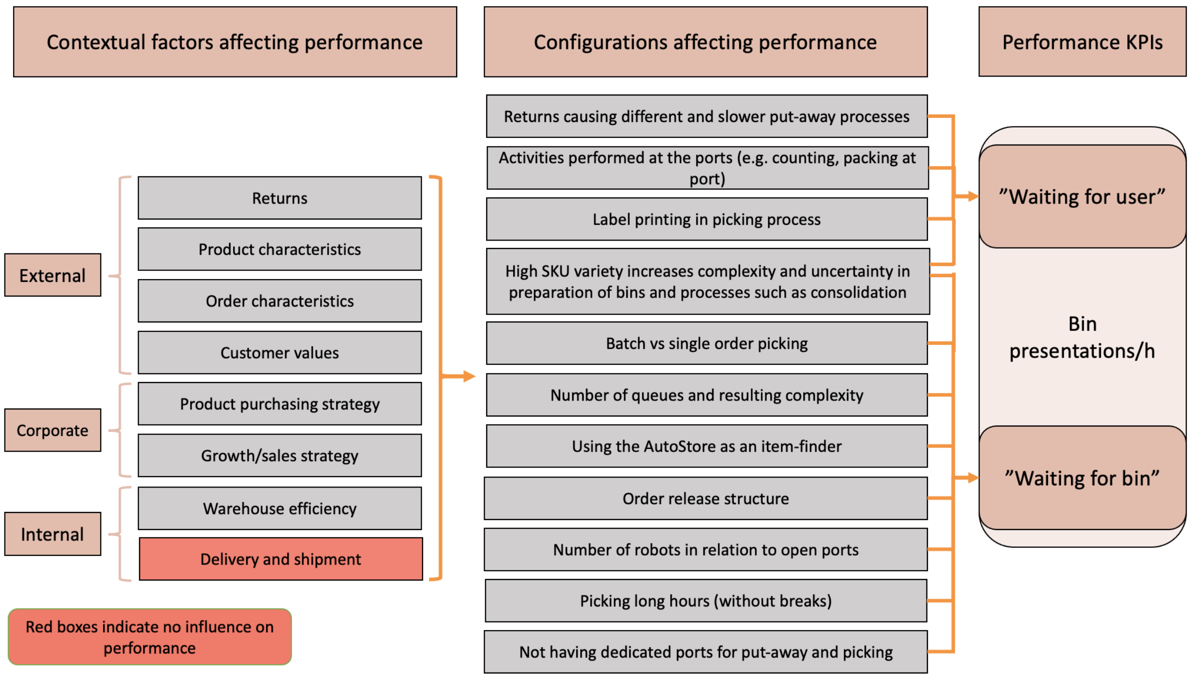

Figure 6.1: The contextual factors connected to configurations affecting performance.

The identified contextual factors and configurations that affect performance are related to the increased complexity and uncertainty and/or inefficient ways of working. The contextual factors from Figure 6.1 are in different ways affecting the configurations that in turn affect performance, with the highlighted exception of “Delivery and shipment”. The configuration that has been examined related to this factor is the usage of pick waves, which did not indicate affecting performance.

In many situations, the contextual factor has a strong connection to its resulting configuration, with clear logical explanations of *why* the configuration is designed that way. However, there are cases where the configuration does not necessarily align with a contextual factor, where the configuration also is changeable, such as label printing. In these cases, it comes down to process optimization by applying TOC.

6.1.2 RQ2: How do the contextual factors and configurations affect performance of the AutoStore system?

The contextual factors and configurations from Figure 6.1 are affecting performance in terms of either increasing or decreasing the time spent “waiting for bin”, “waiting for user”, or both. This was either through the degree of complexity and/or uncertainty or through time-consuming activities by the port in put-away and picking processes. From the analysis, it was found that the time spent “waiting for user” is much higher compared to “waiting for bin”. Not only is it responsible for the longest time taken, but also the greatest variance, hence the part where the most time can be reduced.

The KPI “waiting for user” is correlated with the number of activities as well as variation in the activities, resulting in time-consuming processes. The most common variations are related to packing, or having different parallel processes caused by a wide SKU variety. Having to select which bag/carton to use and waiting for label printing were noticeable differences between companies, highly affecting performance to a great extent. The same goes for time-consuming activities in put-away, where counting the goods at the port leads to a long time spent “waiting for user”. The more activities moved to stations before the port, the faster and easier handling at the port. Double checking does occur, a time-consuming task used to mitigate faulty put-aways such as faulty item balance in exchange for performance. The process of put-away of returns is considerably slower than put-away of non-returns and was identified as greatly affecting the performance since each item has to be put in a separate compartment in the bin.

Overviewing the KPI “waiting for bin”, several contextual factors and configurations are affecting the performance negatively when misaligned with daily operations. Preparation levels were being compromised when interfering with the AutoStore in an unpredictable manner, such as finding single items or switching processes in a specific queue. Also, not letting the AutoStore have breaks interfere with its regaining of preparation levels, where non-stop picking can lead to worse performance rather than more orders picked.

Batch picking was positively leaving more time for the robots to conduct other activities such as preparing or charging, as well as putting less strain on the system. This is because the bin that is retrieved can be used for several consecutive picks/orders, as opposed to retrieving and picking from a new bin for each pick/order. SKU variety along with the consequential order variety played its part by increasing the number of possible bins to prepare and putting further demand on high preparation levels to avoid deeper and time-consuming digging. Lastly, the number of queues also limits the grid in its ability to prepare bins, since heavy picking from a queue quickly uses up the prepared bins dedicated to the queue. This can cause unprepared picks from a queue, leading to a higher "waiting for bin" and thus worse performance. Not aligning what queue to pick from with the bins that have already been prepared was proven to sub-optimize the system, as it simply does not utilize the already prepared bins or the ones being prepared at the moment. Further, aligning the order release structure accordingly is necessary to avoid picking unprepared picks.

6.1.3 RQ3: How should the contextual factors and configurations be handled in order to improve the performance of the AutoStore system?

Based on the created propositions, recommendations were made. The recommendations are listed in Table 6.1 below and aim to handle the contextual factors and configurations that are affecting performance.

Table 6.1. Recommendations based on the propositions from the analysis

Recommendations
Count goods in advance (not by port)
Oversee return policy/strategy
Implement synchronized breaks to let system regain preparation
Avoid using the AutoStore to find and pick single items. Evaluate why this is done today to identify the root cause.
Keep number of queues to a minimum
Oversee SKU variety and examine whether all existing SKUs are economically beneficial
Align order release to order structure and daily operations
If complexity is inevitable, oversee amount of robots per open port
If forecasting is to be used, oversee order characteristics and order release structure
Avoid switching between put-away and picking in the same ports
Oversee possibility to implement batch picking
Keep time-consuming activities at the port to a minimum (such as packing, selection of bag/carton), by applying TOC.
Print labels at the start of the order
Oversee SKU variety and correlating processes (e.g. consolidation).

The recommendations range from small changes in configurations to decrease “waiting for user”, to strategic decisions to decrease complexity in processes. Some of the contextual factors are indeed difficult to simply change but should be considered when operating an AutoStore system. The eventual cost of conducting operations in a certain way might accumulate to a considerable amount, raising some strategic questions, for example regarding product characteristics and customer values.

6.1.4 Fulfillment of purpose

The purpose of this thesis was to evaluate what, and how, different contextual factors and configurations affect the performance of the AutoStore system. RQ1 aims at identifying what contextual factors and configurations affect performance, while RQ2 is focusing on how these contextual factors and configurations affect performance. Lastly, RQ3 looks at recommendations to improve performance connected to the identified contextual factors and configurations.

The conducted analysis to answer these questions started with designing a method based on literature and the influence of industry experts at Element Logic. Protocols in regards to how data should be gathered and analyzed were made before visiting each case company, combining interviews, observations, and data analysis of archival data to get a comprehensive and accurate picture of the case company. A within-case analysis for each company was conducted to identify what their processes look like in terms of Theory of Constraints as well as the alignment of its contextual factors and configurations. The analysis investigated how and what traces of complexity and uncertainty could be found within their operations. After the within-case, a cross-case analysis was made to compare case companies and identify performance-driving contextual factors and configurations and with what magnitude they affect the performance. Finally, the findings from the cross-case analysis were summarized in 14 propositions, with dominant areas in terms of affecting performance. These 14 propositions and recommendations acted as a foundation to answer each research question, thus, fulfilling the purpose of the thesis.

6.2 Theoretical contribution

De Koster (2022) concludes that little research is available on how to optimally design or control an AutoStore system and other RCSRS. Furthermore, Trost et al. (2023) also state the lack of scientific research on AutoStore systems. The scarcity of empirical research on automated picking systems is further recognized by Jaghbeer et al. (2020). Jaghbeer (2019) examined how design and context influence the performance of different robotic parts-to-picker order-picking systems, but not AutoStore specifically. Faber et al. (2018) used contingency theory to explore the fit between warehouse management structure and the context in which the warehouse operates to evaluate how that affects warehouse performance. This study aims to contribute to this gap of research through the empirical case research, and is to our knowledge the first study that examines how contextual factors and configurations affect AutoStore performance. By examining the contextual factors and their relation to configurations and AutoStore performance, this study contributes with a wider perspective rather than looking at details through simulations. Studies have not yet considered outer aspects such as the SKUs stored in the AutoStore, queues and order release structure, and how activities around the port can vary and affect performance. In this thesis, we have created 14 propositions, identifying correlations between contextual factors, configurations, and AutoStore performance. These are listed in Table 5.8, 5.9, 5.10, and focus on put-away, “waiting for bin” in picking, and “waiting for user” in picking respectively.

Gallien and Weber (2010) concluded in their simulation study of automated sorters that the optimal waveless picking policy performs equal, or better than the best policy using waves in all scenarios. That using pick waves in some cases can lead to worse performance has also been mentioned by employees at Element Logic. In this thesis, data did not show any clear relation that using pick waves leads to a lower performance of AutoStore.

Regarding the method used in this thesis, contingency theory was used by Kembro and Norrman (2021), which highlighted the importance of adopting a contingency approach to configuring omnichannel warehouses. This study also contributes to the usage of contingency in warehouses, and further advocates the benefit of applying it to other areas within warehousing. Furthermore, the usage of old theories such as TOC in a modern setting corroborates its continued benefit and relevance. This study applies the way of looking at warehouse operations as a process line and uses TOC to improve its rather streamlined processes. With automation, warehousing is changing, and this study encourages future research to adapt the viewpoint.

6.3 Practical contribution

The goal was to identify the contextual factors and configurations that affect AutoStore performance. Both the propositions and recommendations from this thesis can be applied to every company using an AutoStore or wanting to acquire an AutoStore. They can especially be used by customers of Element Logic since several settings included in the analysis are part of eManager, the software system Element Logic has developed. The recommendations are listed in Table 6.1 above. According to the AutoStore-company, 1150+ AutoStore systems exist worldwide, which would correspond to a lot of savings in terms of time if bin presentations/h increased by only a few percent (AutoStore, n.d.). The findings can also guide customers to further examine and test how these propositions affect their AutoStore system, to pinpoint what areas the company needs to improve in.

Furthermore, the findings can be used by employees at Element Logic when designing the AutoStore system and surrounding processes for new and existing customers. The propositions and recommendations can then be used in combination with other important aspects not included in this report, such as overall warehouse performance. For example, a change might be better for increasing AutoStore performance, but how the decision affects warehouse performance and the other processes in the warehouse still need to be considered before making the final decision. If a certain proposition that affects performance is already known by employees at Element Logic, the findings can act as yet another source that corroborates the relation between that proposition and performance.

6.4 Limitation and future research

Due to the limited period of this thesis as well as limitations in data, some findings were not possible to further explore. As stated, the data used in the analysis is from two months, since data from longer periods was not available. Using data from longer periods would further mitigate extreme cases and season variations. Also, the observations were only a momentary insight into how the companies operate, and do not necessarily reflect the operation as a whole. It would be of interest to see how companies are performing in for example November, during "Black Week", when order volumes are expected to skyrocket. When looking closer at the available data, it could also be compromised by unknown happenings that only the company itself is aware of. Instances where operators deviate from what *should be done,* are not on any level traceable or verifiable, limiting the data analysis that has been conducted. All case companies are using the software supplied by Element Logic, which limits the generalizability for AutoStores using other software systems.

One aspect of the AutoStore performance that has not been investigated, is the human factor. The skills of the operator are very individual and rather different from observations. Not only the operator's general speed in handling but also attention to detail or accuracy in picking and put-away. Incentives for striving to achieve high performance are yet undiscovered. Feedback to operators was slightly examined but was outside the timeframe of this study. Therefore, no clear incentives and initiatives that would encourage higher performance could be identified. Related to the human factor is if higher order volumes per day are affecting the general order and culture of the company. From observations and interviews, a lot of orders and a high workload can occasionally lead to unorganized areas and a higher percentage of faulty activities due to stress. On the contrary, lower levels could instead lead to poor incentives as to why high performance is needed, which might affect the results.

Another aspect interesting to further research is to further develop a framework for how companies should design their order release structure based on their unique situation. Each company has its order characteristics and daily warehouse operations. We could only deduce for examined cases whether or not the order release structure was aligned or not. How it optimally should be designed based on certain parameters in the general case, is an interesting subject to examine. Order release structure was one of the configurations that was intertwined with other configurations to a great extent. It is a configuration that is currently designed through trial and error in the case of the examined companies.

The potential of using batch picking heavily depends on contextual factors whether or not it is plausible to implement. Based on interviews with employees at Element Logic, factors such as order characteristics play a huge part in deciding if batch picking is possible to implement or not. Batch picking essentially utilizes the bin to a greater extent when it is present in front of the operator. Based on the potential of using batch picking, a future research area is to examine the potential of storing products that usually are picked together in the same bin (but in different compartments). Family picking and storing accordingly would potentially relieve the system in a similar fashion as batch picking, which would be an interesting topic of future research.

One recurring theme among companies dealing with clothing was the extensive use of plastic bags in B2C. Looking at the companies using automated carton risers and closers, the whole activity of packing is automated and is decreasing the “waiting for user” substantially. Would it be a feasible solution to implement a similar technology for packing goods into plastic bags? Since packing is a time-consuming activity by the port, further investigation on how the solution could be generalized regardless of the SKU characteristics would be of interest to improve picking performance.

Lastly, the findings of this thesis would be interesting to test and implement at the case companies as well as others, to measure how accurately the generalized recommendations perform in other cases.

6.5 Concluding remarks

When first defining the problem and trying to understand the AutoStore, we underestimated the complexity of the AutoStore itself and how everything is connected. Our first definition of factors was considerably more blurry and the destination was unsure. However, by gaining more experience and knowledge about AutoStore, we believe this thesis can act as a tool of guidance when looking at AutoStore performance. Matching the company’s contexts with configurations is a challenging task without prior knowledge about AutoStore and the transition looks very different among companies. Something that has been mentioned since the start, is that the old way of operating a warehouse does not look the same when incorporating substantial amounts of automation, such as the AutoStore. With this thesis, companies will have insights in areas otherwise overlooked, due to the “black box”-nature of AutoStore at first glance. It has been an interesting journey indeed, and the future of automation side-by-side with humans will be interesting to follow.

References

AM Logistic Solutions. (n.d.). *AutoStore - the automatic small parts warehouse*. AM Logistic Solutions. Retrieved May 10, 2023, from https://www.amlogisticsolutions.de/en/autostore/

Andriansyah, R., Etman, L. F. P., Adan, I. J. B. F., & Rooda, J. E. (n.d.). Design and analysis of an automated order-picking workstation. *Journal of Simulation*, *8*(2), 151-163. https://doi-org.ludwig.lub.lu.se/10.1057/jos.2013.24

AutoStore. (2023a). *The Grid - Modular framework*. AutoStore. Retrieved January 26, 2023, from https://www.autostoresystem.com/system/grid

AutoStore. (2023b). *Our Automated Warehouse Robots - Robot R5 and R5+*. AutoStore. Retrieved January 26, 2023, from https://www.autostoresystem.com/system/robots/robot-r5

AutoStore. (n.d.). *About Us*. AutoStore. Retrieved May 10, 2023, from https://www.autostoresystem.com/company

Azadeh, K., Debjit, R., & de Koster, R. (2019b, August 5). Design, Modeling, and Analysis of Vertical Robotic Storage and Retrieval Systems. *Transportation Science*, *53*(5), 1213-1234. https://doi.org/10.1287/trsc.2018.0883

Azadeh, K., de Koster, R., & Roy, D. (2019a, June 28). Robotized and Automated Warehouse Systems: Review and Recent Developments. *Transportation Science*, *53*(6), 1430-1455. https://doi.org/10.1287/trsc.2021.1053

Beckschäfer, M., Malberg, S., Tierney, K., & Weskamp, C. (2017, September 27). Simulating Storage Policies for an Automated Grid-Based Warehouse System. *International Conference on Computational Logistics*, *10572*, 468-482. https://doi-org.ludwig.lub.lu.se/10.1007/978-3-319-68496-3_31

Chauhan, R. S. (2022). Unstructured interviews: are they really all that bad? *Human Resource Development International*, *25*(4), 474-487. https://doi.org/10.1080/13678868.2019.1603019

Chevalier, S. (2022, September 21). *Global retail e-commerce sales 2026*. Statista. Retrieved December 19, 2022, from https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales/

de Koster, R. (2022). Warehousing 2030. In R. Merkert & K. Hoberg (Eds.), *Global Logistics and Supply Chain Strategies for the 2020s: Vital Skills for the Next Generation* (pp. 243-260). Springer International Publishing. https://doi.org/10.1007/978-3-030-95764-3_14

Denscombe, M. (2010). *The Good Research Guide: For Small-scale Social Research Projects*. McGraw-Hill/Open University Press.

Donaldson, L. (2001). *The Contingency Theory of Organizations*. SAGE. https://doi.org/10.4135/9781452229249

Duncan, R. (1972, September). Characteristics of Organizational Environments and Perceived Environmental Uncertainty. *Administrative Science Quarterly*, *17*(3), 313-327. https://doi.org/10.2307/2392145

Eisenhardt, K. M., & Graebner, M. E. (2007, February). Theory Building From Cases: Opportunities And Challenges. *Academy of Management Journal*, *50*(1), 25-32. https://doi.org/10.5465/amj.2007.24160888

Element Logic. (2022b). *Guest lecture: Automation in Warehousing*. Lunds Tekniska Högskola - Course: Warehousing.

Element Logic. (2022a, December 6). *Zoom Meeting* [Meeting with Max Grudeborn, Kristina Medved, Marcus Rasmusson].

Element Logic. (2023e). *eManager*. Element Logic. Retrieved January 26, 2023, from https://www.elementlogic.se/losningar-och-tjanster/mjukvara/emanager/

Element Logic. (2023α). *Mjukvarubaserad lagerautomation*. Element Logic. Retrieved January 26, 2023, from https://www.elementlogic.se/losningar-och-tjanster/mjukvara/

Element Logic. (2023a, January 19). *Interview* [Interview with Mattias Nordengren, Service Technician at Element Logic.]. Ängelholm, Sweden.

Element Logic. (2023i, January 20). *Interview* [Interview with Ann Lundgren, Solution Architect at Element Logic.]. Lund, Sweden.

Element Logic. (2023c, January 20). *Interview* [Interview with Joakim Petersson, Solution Architect at Element Logic.]. Lund, Sweden.

Element Logic. (2023b, January 24). *Interview* [Interview with Eryk Smaga, Business Developer at Element Logic]. Lund, Sweden.

Element Logic. (2023d, January 25). *Interview* [Interview with Fredrik Olsson, AfterMarket Solution Architect at Element Logic.]. Lund, Sweden.

Element Logic. (2023g, January 27). *Interview* [Interview via Teams with Desmond, Support Director at Element Logic]. Sweden.

Element Logic. (2023f, April 11). *E-mail* [E-mail from Marcus Wegestrand, Project Manager at Element Logic].

Element Logic. (2023h, April 26). *Meeting* [Meeting with Bengt Nilsson, Account Manager AfterMarket at Element Logic].

Element Logic. (2023e, May 2). *Meeting regarding findings* [Meeting with Bengt Nilsson, David Olsson, Account Managers, Aftermarket at Element Logic].

Element Logic. (2023j, May 3). *Meeting regarding findings* [Meeting with Fredrik Olsson, Marita Johnsson, Solution Architects, Aftermarket at Element Logic].

Ellram, L. M. (1996). The use of the case study method in logistics research. *Journal of Business Logistics*, *17*(2), 93-138. https://www.proquest.com/openview/c03cb489c3cdeb1ec635a8f4c3b5ff54/1?cbl=36584&pq-origsite=gscholar

Eriksson, E., Norrman, A., & Kembro, J. (2019, June). Contextual adaptation of omni-channel grocery retailers' online fulfilment centres. *International Journal of Retail & Distribution Management*, *47*(12), 1232-1250. https://doi.org/10.1108/IJRDM-08-2018-0182

Faber, N., De Koster, R. B.M., & Smidts, A. (2018). Survival of the fittest: the impact of fit between warehouse management structure and warehouse context on warehouse performance. *International Journal of Production Research*, *56*(1-2), 120-139. https://doi.org/10.1080/00207543.2017.1395489

Faber, N., de Koster, R. B.M., & van de Velde, S. L. (2002). Linking warehouse complexity to warehouse planning and control structure: An exploratory study of the use of warehouse management information systems. *International Journal of Physical Distribution & Logistics Management*, *32*(5), 381-395. https://doi.org/10.1108/09600030210434161

Feldt, J., Kontny, H., & Niemietz, F. (2020). *How disruptive start-ups change the world of warehouse logistics* [Chapters from the Proceedings of the Hamburg International Conference of Logistics (HICL), Institut für Logistik und Unternehmensführung, Technische Universität Hamburg]. http://hdl.handle.net/10419/228916

Gallien, J., & Weber, T. (2010, May). To Wave or Not to Wave? Order Release Policies for Warehouses with an Automated Sorter. *Manufacturing & Service Operations Management*, *12*(4), 547-708. https://doi.org/10.1287/msom.1100.0291

Gibbert, M., Ruigrok, W., & Wicki, B. (2008, September 19). What passes as a rigorous case study? *Strategic Management Journal*, *29*(13), 1465-1474. https://onlinelibrary.wiley.com/doi/abs/10.1002/smj.722

Gu, J., Goetschalckx, M., & McGinnis, L. F. (2010, June 16). Research on warehouse design and performance evaluation: A comprehensive review. *European Journal of Operational Research*, *203*(3), 539-549. https://doi.org/10.1016/j.ejor.2009.07.031

Jaghbeer, Y. (2019). *On the performance of robotic parts-to-picker order picking systems*. Retrieved December 13, 2022, from https://www.proquest.com/openview/218a0c6d8481000855ec809326ef7005/1?cbl=2026366&diss=y&parentSessionId=EiOdmEh%2F90jM4346tYgDpwiUlsVT98Pvf6IX4rwDPAo%3D&pq-origsite=gscholar&accountid=12187

Jaghbeer, Y., Hanson, R., & Johansson, M. I. (2020, July). Automated order picking systems and the links between design and performance: a systematic literature review. *International Journal of Production Research*, *58*(15), 4489-4505. https://doi.org/10.1080/00207543.2020.1788734

Kallio, H., Pietilä, A.-M., & Johnson, M. (2016, May 25). Systematic methodological review: developing a framework for a qualitative semi-structured interview guide. *Journal of Advanced Nursing*, *72*(12), 2954-2965. https://doi.org/10.1111/jan.13031

Kembro, J. H., & Norrman, A. (2020, August 20). Warehouse configuration in omni-channel retailing: a multiple case study. *International Journal of Physical Distribution & Logistics Management*, *50*(5), 509-533. https://doi.org/10.1108/IJPDLM-01-2019-0034

Kembro, J. H., & Norrman, A. (2021, February). Which future path to pick? A contingency approach to omnichanel warehouse configuration. *International Journal of Physical Distribution & Logistics Management*, *51*(1), 48-75.

https://www.emerald.com/insight/content/doi/10.1108/IJPDLM-08-2019-0264/full/html

Ko, D., & Han, J. (2022, October 1). A rollout heuristic algorithm for order sequencing in robotic compact storage and retrieval systems. *Expert Systems with Applications*, *203*, Article 117396. https://doi.org/10.1016/j.eswa.2022.117396.

Krogh, G. v., Rossi-Lamastra, C., & Haefliger, S. (2012, August). Phenomenon-based Research in Management and Organisation Science: When is it Rigorous and Does it Matter? *Long Range Planning*, *45*(4), 277-298. https://doi.org/10.1016/j.lrp.2012.05.001

Lawrence, P. R., & Lorsch, J. W. (1967, June). Differentiation and Integration in Complex Organizations. *Administrative Science Quarterly*, *12*(1), 1-47. https://doi.org/10.2307/2391211

Luce, R. D., & Raiffa, H. (1957). *Games and Decisions*. New York: John Wiley.

Meredith, J. (1998, July). Building operations management theory through case and field research. *Journal of Operations Management*, *16*(4), 441-454. https://www.sciencedirect.com/science/article/pii/S0272696398000230

Miles, M. B., Huberman, A. M., & Saldana, J. (2019). *Qualitative Data Analysis: A Methods Sourcebook*. SAGE Publications.

Monteiro, A. (2022, January 11). *Supply Chain Latest: Covid E-Commerce Boom Sees Warehouse Demand Soar*. Bloomberg.com. Retrieved December 19, 2022, from https://www.bloomberg.com/news/newsletters/2022-01-11/supply-chain-latest-covid-e-commerce-boom-sees-warehouse-demand-soar

Naor, M., Bernardes, E., & Coman, A. (2012, January). Theory of constraints: Is it a theory and a good one? *International Journal of Production Research*, *51*(2), 1-13. https://doi.org/10.1080/00207543.2011.654137

Rahman, S. (1998, April). Theory of constraints: A review of the philosophy and its applications. *International Journal of Operations & Production Management*, *18*(4), 336-355. https://doi.org/10.1108/01443579810199720

Schwarz, G., & Stensaker, I. (2014, September). Time to Take Off the Theoretical Straightjacket and (Re-)Introduce Phenomenon-Driven Research. *The Journal of Applied Behavioural Science*, *50*(4), 478-501. https://doi.org/10.1177/0021886314549919

Şimşit, Z. T., Günay, N. S., & Vayvay, Ö. (2014, September). Theory of Constraints: A Literature Review. *Procedia - Social and Behavioral Sciences*, *150*, 930-936. https://doi.org/10.1016/j.sbspro.2014.09.104

Staudt, F. H., Alpan, G., Mascolo, M. D., & Rodriguez, C. M. T. (2015, April 15). Warehouse performance measurement: a literature review. *International Journal of Production Research*, *53*(18), 5524-5544. Retrieved December 12, 2022, from https://www.tandfonline.com/doi/full/10.1080/00207543.2015.1030466

Svensson, S., & Wadsten, A. (2019, August 16). *Kriterier för automation vid inlagring: Ett beslutsunderlag i valet av artikelplacering*. DiVa. Retrieved December 12, 2022, from https://www.diva-portal.org/smash/record.jsf?pid=diva2%3A1341855&dswid=9480

Thiessen, S. (n.d.). *Boozt expands world's largest AutoStore™*. AutoStore. Retrieved January 26, 2023, from https://www.autostoresystem.com/cases/boozt-installs-worlds-largest-autostore

Tjeerdsma, S. (2019). *Redesign of the AutoStore order processing line*. University of Twente. http://essay.utwente.nl/78822/

Trost, P., Karting, G., & Eder, M. (2023, May 13). Simulation study of RCS/R-systems with several robots serving one picking station. *FME Transactions*, *51*(2), 201-210. https://doi.org/10.5937/fme2302201T

Trost, P., Kartnig, G., & Eder, M. (2022). *Simulation study of Autostore-systems* [Proceedings of the XXIV Inter-national Conference MHCL'22, 2022]. https://www.researchgate.net/profile/Philipp-Trost/publication/366065720_Simulation_study_of_Autostore-systems/links/63904d1211e9f00cda25658b/Simulation-study-of-Autostore-systems.pdf

Unraveling Complexity in Products and Services - Knowledge at Wharton. (2006, February 1). *Knowledge at Wharton*. https://knowledge.wharton.upenn.edu/special-report/unraveling-complexity-in-products-and-services/

Voss, C., Tsikriktsis, N., & Frohlich, M. (2002, February). Case research in operations management. *International Journal of Operations & Production Management*, *22*(2), 195-219. https://doi.org/10.1108/01443570210414329

Wang, Y., Mou, S., & Wu, Y. (2016). Storage assignment optimization in a multi-tier shuttle warehousing system. *Chinese Mechanical Engineering Society*, *29*(2), 421-429. LUBSearch. 10.3901/cjme.2015.1221.152

Xue, F., Dong, T., & Qi, Z. (2018, September 11). An improving clustering algorithm for order batching of e-commerce warehouse system based on logistics robots. *International Journal of Wireless and Mobile Computing*, *15*(1), 10-15. https://doi.org/10.1504/IJWMC.2018.094633

Yin, R. K. (2014). *Case Study Research: Design and Methods*. SAGE Publications.

Zou, B., de Koster, R., & Xu, X. (2018, May 22). Operating policies in robotic compact storage and retrieval systems. *Transportation Science*, *52*(4), 788-811. https://doi.org/10.1287/trsc.2017.0786

Zou, B., Xu, X., Gong, Y., & de Koster, R. (2017). Evaluating battery charging and swapping strategies in a robotic mobile fulfillment system. *European Journal of Operational Research*, *267*(2), 733-753. https://doi.org/10.1016/j.ejor.2017.12.008

Appendix A - Keywords used in literature review

Some of the examples of keywords used in literature review for online databases

Examples of keywords used in literature review:		
"AS/RS"	"Autostore"	"Picking""
"ASRS"	"Compact storage"	"RCS/RS"
"Automated storage"	"CS/RS autostore"	"RCSR" + "AutoStore"
"Autostore conveyor"	"CSRS autostore"	"RCSR" + "cube storage"
"Autostore efficiency"	"Cube storage autostore"	"RCSR" + "cube"
"Autostore parts-to-picker"	"Goods to person"	"RCSRS Autostore"
"Autostore picking efficiency factors"	"Grid storage"	"RCSRS"
"Autostore picking efficiency"	"Grid-based storage system picking"	"Robotic compact storage"
"Autostore picking"	"High-density storage autostore"	“Robotic compact storage and retrieval systems”
"Autostore put-away"	"Live-cube compact storage systems"	

Appendix B - Data collection protocols

Data collection protocol 1 - was sent to the case companies prior to visit

Introduction

Short introduction about us and our project.

About you

Short questions about you, and your relation to logistics and automation.

About the warehouse/business

Here are some questions to get to know your business and an overview of your operations.

1. How many order lines and orders per day?
2. # of SKUs?
3. # of employees in this warehouse?
4. What are your operating hours? i.e. shifts, breaks, etc
5. How was the transition from manual warehousing to automated? What changes did you make in your way of working?
6. What do you and your customers value? (e.g. speed or accuracy?)
7. What is your pareto-distribution and Bin distribution?
    a. Is it something you oversee periodically?
    b. How do you segment your products?
    c. How is your data analytics and training the operators in regards to the ABC of your products?

About your AutoStore

1. How long have you had your AutoStore?
2. How comfortable are you in the usage of the AutoStore?
3. Percentage of SKUs in AutoStore vs total?
4. How long is your avg. buffer of products in your AutoStore last (based on avg. demand and that no replenishment/put-away is performed)?
5. What is performance according to you? What KPIs are you valuing/measuring? How do you follow up on these?
6. Have you increased/upgraded your AutoStore system?
    a. If yes - how many times?
7. Have you had any improvement-workshops?
    a. If yes - how many?
8. What do you usually struggle with in regards to using/operating the AutoStore? i.e. what is the hardest part to make sure that all the operations are running smoothly and efficiently?
    a. Have you identified any bottlenecks?

Put-away

From Receiving to Port-area

How is the goods handled when arriving at the port area?

This refers to for example how and where does it arrive? Is it sorted? Is it unpacked? Do all items go into the AutoStore? Do some go to a buffer storage? Do they all fit in both dimensions and characteristics? How do you deal with returns? These are some examples to understand the goods before they are handled by the put-away operator.

At put-away station

What does the operator have to prepare in order to insert items into bins?

This refers to for example does the operator have to unpack anything? Decide on bin-type? Any preparation needed? What knowledge does the operator have about the goods and its storing? Is waste handled at the port from packaging etc? What training/experience does the operator have? These are some examples to understand the actions the operator has to take in order to perform put-away.

When performing the put-away

How does the operator put goods into bins?

This refers to for example what bin sizes and configurations are used? Do you refill empty and half-empty bins? When are you conducting put-away? How does the operator decide on bin capacity? Any guidelines? Do you mix SKUs in the same bin? How do you maintain a good inventory balance? These are some examples to understand how you work with put-away.

AutoStore

Hardware

How are your robots used?

This refers to for example when and how often are the robots charged? Do they have dedicated time for preparation? When are you performing inventory checks? These are examples to understand the way your robots are working.

Software

How is the software used?

This refers to for example how your WMS integrated is with eManager, what is your storage policy? What does your order release look like? What pick strategies are you using? Forecasting? Pick waves? What are the types and number of queues used? Are they dynamic? How do you, in software, react to trends/sales? These are examples to understand how you are using the software in relation to increasing or adapting performance.

Picking

The picking area

What does the picking stations look like?

This refers to for example how many ports and of what type? Are they all open all the time? How do you pair queue types to ports? These examples are to understand the layout of your picking area.

At picking station

What does the process look like?

This refers to for example what is done with picked items before they are ready to send? Are goods both picked and packaged at the port? What equipment do you have for cartons, labels, etc? How do you consolidate order with SKUs not stored in the AutoStore/another unit (if you have multiple units)? These examples are to understand the process of picking.

After picking station

What happens after the operator has finished packing the order?

This refers to for example how is it transported to the next area? Is the order scanned or labeled before send-off? Are the order picked and sent in batch or one at a time? These examples are to understand what happens with the goods once it has been picked out of the AutoStore.

Employees and training

1. How are the employees trained/onboarded, in relation to AutoStore? (put-away & picking)
2. When are they trained?
3. What does training look like?
4. Who trains them?
5. How many are employed from a staffing company?
6. What is your employee turnover rate?

Data collection protocol 2 - was used during the case company visit

Introduction

1. We are David and Daniel, students from LTH
2. Our master thesis
3. Our method and desired results
4. You will get to see information from the interview to approve
5. All is anonymized and data is manipulated
6. We visit many other companies
7. Plan for the interview:
    a. Start with general questions about you, the warehouse and Autostore
    b. Then go into more specific questions of each area (put-away/AutoStore/picking)
8. **Before starting:**
    a. **Can we record this interview?**

About you

1. Who are you? Name and title	
2. How long have you had this position and within this industry	
3. How long have you been working with AutoStore and automation in warehousing in general?	
4. Responsibilities in your position (short description)?	
5. Contact information for verification of data/information	
a. Email	
b. Phone number	

About the warehouse/business

1. Order lines per day?	
2. # of SKUs?	
3. # of employees?	
4. What are your operating hours? i.e. shifts, breaks, etc	
5. What do you sell and how? (B2B or B2C)	
6. How was the transition from manual warehousing to automated? What changes did you make in your way of working?	
7. What do you and your customers value? (e.g. speed or accuracy?)	
8. What is your pareto-distribution and Bin distribution?	
a. Is it dynamic?	
b. How do you segment your products?	
c. How is your data analytics and training in regards to the ABC?	

About your AutoStore

1. How long have you had your AutoStore?	
2. How comfortable are you in the usage of the Autostore?	
3. Percentage of SKUs in AutoStore vs total	
4. How long is your avg. buffer of products in your AutoStore last (based on avg. demand and that no replenishment/put-away is performed)?	
5. What is performance according to you? What KPIs are you valuing/measuring?	
6. How do you work with follow-up on these KPIs?	
7. Have you increased/upgraded your AutoStore system?	
a. If yes - how many times?	
8. Have you had any improvement-workshops?	
a. If yes - how many?	
9. What do you usually struggle with in regards to using/operating the AutoStore? i.e. what is the hardest part to make sure that all the operations are running smoothly and efficiently	
a. Have you identified any bottlenecks?	

Put-away

From Receiving to Port-area

How is the goods handled when arriving at the port area?

1. How does it arrive? (on a pallet? by truck/conveyor belt?)	
2. Where does it come from?	
3. Is it sorted?	
4. If yes - how?	
5. If no - why not?	
6. Is it packed in cartons or unpacked already?	
7. if yes - how?	
8. if no - why not?	
9. Are all items going into AutoStore? Buffer? Does the product fit?	
10. How do you handle high-frequency products?	
11. Frequency of deliveries to port-area/day?	
12. Time of day for deliveries?	
13. How do you deal with and prioritize returns?	
14. Is the person delivering goods for put-away aware of coming steps	

At put-away station

What does the operator have to prepare in order to insert items into bins?

1. Unpack/pack something?	
2. Does the operator know what goods it should prioritize when performing put-away?	
3. Does the operator know what goods that go into which bin-types?	
4. Does the operator start with preparing goods that fit the same bin-type?	
5. Any form of preparation? (sorting/folding/weighing/labeling/other)	
a. If yes - why?	
6. Handle waste or any other maintenance from unpacking/preparation?	
7. How do you prioritize availability in many bins vs packing compressed?	
8. Is the put-away process individual or are operators standing by the stations cooperating?	
9. How many ports are used for put-away (of each type)?	
a. And when?	
10. Where are the ports used for put-away located?	
11. How many people do you have a dedicated put-away?	
12. How frequently is the put-away performed?	

13. When is the put-away performed? In relation to when the goods are expected to be picked?	
a. At what time of the day?	
14. Who is conducting the put-away?	
a. Experience?	
b. Training?	
c. Knowledge about AutoStore?	

When performing the put-away

How does the operator put goods into bins?

1. How does the operator know what type of bin configuration to choose?	
2. Are the arriving bins completely empty or not?	
3. Is the bin filled according to its capacity?	
4. What does the procedure of deciding the capacity of the bin look like?	
5. What guidelines in put-away are you using? (no products that can expand, etc)	
6. What does the procedure look like going from a finished task to the next one?	
7. On avg, how many SKUs per bin? Any extreme cases?	
8. What/who decides on what SKUs should go into a 1/1 or divided bin? Mixing SKUs?	
9. How do you maintain a good inventory balance in the AutoStore?	
10. Amount of faulty put-aways? (felinlagringar)	

AutoStore system

Hardware

1. Dedicated time for charging the robots?	
a. When do they charge?	
b. Charge frequency?	
c. Avg. charge duration?	
2. Dedicated time for preparation?	
a. In relation to order release time?	
3. When are you scheduling “inventory checks”	

Software

1. What is your storage policy? (dedicated/shared/other)	
2. How do you integrate your IT solutions (e.g WMS) with eManager?	

3. How do you analyze your product data in regards to your pareto-distribution and new articles being introduced?	
4. How do you decide on prioritizing picking from full- or “half-full” bins? Prioritize to empty bins or not?	
5. How do you convert your customer orders to picking lists meant for eManager?	
a. What are your priorities?	
b. What are your thoughts when doing it?	
6. When does order release occur?	
7. Frequency of order releases?	
8. Avg. size of order release?	
9. Avg. # of order lines per order?	
10. What pick strategies are you using?	
11. Avg. Fill rate on bins?	
12. Are you utilizing the high-frequency-function?	
13. Are you utilizing forecasting?	
a. If yes - how?	
b. If no - why not?	
14. Are you utilizing pick waves?	
a. If yes - how?	
b. If no - why not?	
15. Max queue length?	
16. # of queues?	
a. Type of queues? (express/regular/other)	
b. Percentage of ports who picks from each queue? Dynamic?	
c. How do you decide on what queue/pick wave to pick from?	
d. How do you define the type?	
17. How reactive to sales or trends are you in your settings	
18. How often do you change settings?	
a. How? Manually or through Element Logic etc.	
b. Who is authorized and who decides to change settings?	
c. In what areas are you changing the settings the most/least?	

Picking

The picking area

What does the picking station look like?

1. How many ports?	
a. What types?	
a. Are all ports used at all times?	

b. Who decides what ports- and how many ports are active for picking? Is it dynamic?	
c. Do you pair specific port types to specific queue types? (express-queue/other)	

At picking station

What does the process look like?

1. What is done with picked items before “ready to send”? (value-adding services etc.)	
2. In what order are tasks performed? (e.g. Is it allowed to ask for next bin *during* packing or is the task finalized and *then* next bin is demanded)	
3. Are the goods both picked and packaged at the port?	
4. How do you deal with folding & sealing cartons?	
5. How do you work with labeling/printing of labels?	
6. Is the picking process individual or are operators standing by the stations cooperating?	
● If yes - how?	
7. Pick frequency? (picks/port)	
8. Preparing one order at a time or several? (Batch picking vs order picking)	
9. Who is the picker?	
● Experience?	
● Training?	
● Knowledge about AutoStore?	
● When are they trained (peak season, little training etc.)	
10. What time of the day are they picking?	
11. How do you deal with order consolidation?	

After picking station

What happens after the operator has finished packing the order?

1. Any steps in software? (confirming inventory/picks, identifying picked item etc)	
2. What happens with the package/order once finalized?	
3. How is it transported to the next area?	

Employees & Training:

1. How are the employees trained/onboarded, in relation to AutoStore? (put-away & picking)	
2. When are they trained?	
3. What does training look like?	
4. Who trains them?	
5. How many are employed from a staffing company? (share/%)	
6. What is your employee turnover rate?	

Appendix C - Observation schedule

Observation schedule - was used during the case company visit

General Questions

1. Where are the ports for put-away and picking located?	
2. General order/cleanliness in the warehouse?	
3. Find any bottlenecks/waiting times?	
4. Are there any clusters in picking and put-away?	
5. What equipment exists that can aid the processes? e.g. any carton risers & sealers, printing devices.	

Put-away

From Receiving to Port-area

What do the goods like when arriving at the port area?

1. Write down the steps	
2. How does it arrive? (on a pallet? by truck/conveyor belt?)	
3. Where does it come from?	
4. Is it sorted?	
5. Is it packed?	
6. Are all items going into AutoStore? Buffer? Does the product fit?	
7. How do you deal with and prioritize returns?	

At put-away station

What does the operator have to prepare in order to insert items into bins?

1. Write down the steps	
2. Unpack/pack something?	
3. Any form of preparation? (sorting/folding/other)	
• If yes - why?	
4. Handle waste or any other maintenance from unpacking/preparation?	
5. Is the put-away process individual or are operators standing by the stations cooperating?	
6. Where are the ports used for put-away located?	

When performing the put-away

How is the operator putting in goods in bins?

1. Write down the steps	

2. What does the procedure look like going from a finished task to the next one?	

Picking

The picking area

What does the picking area/station look like?

1. Write down the steps	

At picking station

What does the process look like?

1. Write down the steps	
2. What is done with picked items before “ready to send”? (value-adding services etc.)	
3. In what order are tasks performed? (e.g. Is it allowed to ask for next bin *during* packing or is the task finalized and *then* next bin is demanded)	
4. Are the goods both picked and packaged at the port?	
5. How do you deal with folding & sealing cartons?	
6. Is the picking process individual or are operators standing by the stations cooperating?	
● If yes - how?	

After picking station

What happens after the operator has finished packing the order?

1. Any steps in software? (confirming inventory/picks, identifying picked item etc)	
2. What happens with the package/order once finalized?	
3. How is it transported to the next area?	
4. Preparing one order at a time or several? (Batch picking vs order picking)	

Appendix D - Archival data collection

The table below includes the data/KPIs that was collected, from what document/source it was collected, and lastly a brief description of the document/source.

Name of document/ source:	**Description of document/source:**	**Data/KPIs collected:**
SLA-report	Document that includes the monthly values of the three performance KPIs, along with other data. This document is sent to the customer each month.	Bin Presentations/h (per port)
		“Waiting for user”
		“Waiting for bin”
Database at Element Logic	Element Logic has a database where they keep all the information regarding the customers and their AutoStore setups.	Number of bins
		Number of bin configurations
		Number of robots
		Number of ports
		Number of queues
		Number of pick waves
		Pick strategy
		Using forecasting (Yes/No)
		Using the high-frequency-function (Yes/No)
		Using Planner/Router (routing software)
AutoStore Log-files	The AutoStore system logs all the data in separate log-files. These include all the data from the system (only for a short period of time before being overwritten).	Avg. number of ports open (during operating hours)
		Avg. Dig depth
		Avg. bin preparation levels
		Data on order release

Appendix E - Empirical findings

Company	F1	F2	F3	3PL1	3PL2	E1	E2
Years since Go-live	1-2	2-3	1-2	2-3	<1	<1	1-2
Customers	B2C & B2B	B2C & B2B	B2C & B2B	B2C & B2B	B2C & B2B	B2C	B2C & B2B
Average Pcs / Order Lines per day	7,000 order lines	60,000 pcs	36,000 order lines	3,000 order lines	6,000 order lines	9,250 order lines	71,000 order lines
Robots	62	151	127	36	51	35	149
Routing software	Planner	Planner	Planner	Planner	Planner	Router	Router
Bins (K)	60	150	80	40	65	25	88
% in AS / Total SKU types (K)	95% of total / 22	95% of total / 102	60% of total / 49	83% of total / 27	Depends on demand, but up to 92% of total /14	30% of total / 42	100% of total / 2
SKU types in AS (K)	21	97	29	22	13	13	2
Ports dedicated for Put-away / Picking	4 / 11	7 / 23	5 / 18	3 / 6	2 / 11	N/A / 4	9 / 24
Robots/put-away port	2	1.4	3	2	2	N/A	3
Robots/picking port	4	4	4.8	4	4.5	N/A	5
Warehouse Zones (for picking)	AutoStore, Buffer, Oversize	AutoStore, Buffer, Oversize, Hanging goods	AutoStore, Buffer, Oversize, Hanging goods	AutoStore, Buffer, Oversize	AutoStore, Buffer, Oversize	AutoStore, Buffer, Oversize, A-frame, Pick By Light	AutoStore, Buffer
Bin configurations	1, ½, ¼, ⅛	1, ½, ¼, ⅛, 1/16	1, ½, ¼, ⅛, 1/16	1, ½, ¼, ⅛	1, ⅛	1	1
Working dynamically with ports (Yes/No)	Yes, they open or close ports depending on the workload.	Yes, they open or close ports depending on the workload.	Yes, they open or close ports depending on the workload.	Yes, if the workload is low, operators can change to working with inventory checks.	Yes, they open or close ports depending on the workload.	Yes, they open or close ports depending on the workload.	Yes sometimes, but in almost all cases the next shift is cancelled if workload is too low.

Figure E.1: Descriptive data of the companies.

Called	F1	F2	F3	3PL1	3PL2	E1	E2
Bin presentations/h (per port)	66	36	61	40	47	N/A	80
Waiting for user	49	89	56	80	72	N/A	38
Waiting for bin	5,6	12,6	6,3	12,3	5,7	N/A	7,7
How does ithe goods arrive to put-away port?	Sealed cartons arrive on pallets, cartons need to be opened.	Sealed cartons arrive on pallets, cartons need to be opened.	Opened cartons on pallets, ready for put-away.	Opened cartons on a manual conveyor, ready for put-away.	Sealed cartons arrive on pallets, cartons need to be opened.	Sealed cartons/packages arrive on pallets, cartons need to be opened.	Mostly sealed cartons/packages arrive on pallets, which need to be opened. (Occasionally the cartons/packages are already opened).
Goods have been sorted in advance(Yes/No)	Yes. Sorted after SKU type.	Yes. Sorted after SKU type.	Yes. Sorted after SKU type.	Yes. Sorted after SKU type and size.	Yes & No. Some cartons are automatically sorted by SKU type on whole pallets, while other cartons include multiple different SKUs types.	Yes & No. Some SKUs arrive in packages, automatically sorted after SKU types. Some cartons/packages are not sorted.	Yes. Sorted after SKU type. Glass products are wrapped for protection.
Goods counted in advance(Yes/No)	Yes	No (operator counts at the port)	Yes	No (operator counts at the port)	Yes	No (operator counts at the port)	Yes & No (occasionally operator counts at port)
Waste disposal	Conveyor	Conveyor	Manually	Manually	Conveyor	Manually	Conveyor
How do you prioritize availability in many bins vs filling as much as possible?	Prioritizing filling as many units as possible into the same bin.	Prioritizing filling as many units as possible into the same bin. But high-frequency products are put in many different bins.	Prioritizing filling as many units as possible into the same bin. If there is a sale coming up, then they possibly put the product into different bins to make it more available.	Prioritizing filling as many units as possible into the same bin.	Prioritizing filling as many units as possible into the same bin.	No prioritization is done. Goods are filled arbitrarily into bins, as fast as possible (even if that means a low fill rate is achieved).	Prioritizing availability in many bins.
Returns into AutoStore (approx.)	20%	50%	30%	15%	10%	0%	0%

Figure E.2: Put-away performance and descriptive data of the processes.

Called	F1	F2	F3	3PL1	3PL2	E1	E2
Bin presentations/h (per port)	149	148	165	117	183	162	256
Waiting for user	19,0	16,87	17,00	24,0	14,0	14,0	8,3
Waiting for bin	5,2	7,80	5,70	7,0	6,3	8,9	5,6
Queues	4 - Normal, Consolidation, B2B, Third party	4 - Autostore, Consolidation, Express, B2B	4 - Autostore, Consolidation, Express, Other (e.g. B2B)	4 - B2C, B2B, B2C Consolidation, Moveout	4 - AutoStore, Consolidation, Express, Other	2 - Normal, Robot	1 - Picking
Picking Method	Single order	Single order	Single order	Single order	Single order and Batch picking (for B2B)	Single order	Batch picking
Pick Strategies (for robots)	Prioritize locations with the lowest quantity. There are no maximum number of locations considered, this strategy is applied for the whole quantity that needs to be picked.	Select up to 5 locations ordered by lowest quantity (not FIFO). If this strategy fails to allocate the necessary quantity, a FIFO strategy is applied for the rest of the quantity.	Pick according to FIFO.	Pick according to FIFO.	Select 1 location with lowest quantity (not FIFO). If this strategy fails to allocate the necessary quantity, the same thing is done but for up to 7 locations. If this strategy fails to allocate the necessary quantity, a FIFO strategy is applied for the rest of the quantity.	Pick according to FIFO.	Pick according to FIFO.
Pick Waves	Not used	3-4 (changed depending on season)	10	Not used	12	Not used (ready times inherited from WMS)	No
Forecasting	Yes	Yes	No	Yes	No	No	No
Shipping label printed	After	Before	Before	After	After	Later on	Later on
Order release	Automatically (mostly). Has an upper limit of orders they release at a time.	Manually. Has an upper limit of orders they release at a time.	Automatically (mostly). Has an upper limit of orders they release at a time.	Manually. Has an upper limit of orders they release at a time.	Automatically (for B2B), manually (for B2C). Does not have an upper limit of order they release at a time.	Automatically. Does not have an upper limit of order they release at a time.	Automatically. Has an upper limit of orders they release at a time.
Synchronized breaks	Yes (only during high workloads)	Yes (only during high workloads)	Yes (only during evening)	No	No	No	Yes

Figure E.3: Picking performance and descriptive data of the processes.