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Exploring Automation Potential: A Case Study of Volvo Penta's Warehouse Operations

Master's thesis in Supply Chain Management

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ABSTRACT

This thesis investigates the feasibility and strategic implications of automating order picking operations at Volvo Penta’s Distribution Centre (VPDC) in Vara, Sweden, within the scope of the company’s VPDC 2.0 development initiative. The focus lies on evaluating four candidate automation technologies, vertical lift modules (VLM), vertical Carousels, horizontal Carousels, and mini-load systems, against the current manual picking solution. These options are assessed across seven performance aspects: throughput, cost, quality, space utilisation, scalability, flexibility, and ergonomics.

To support the evaluation, a multi-method research approach was adopted. This included a literature review, time studies, site visits, historical order data analysis, and unstructured interviews with different stakeholders at various levels within Volvo Penta. The Analytical Hierarchy Process (AHP) was employed to rank the importance of each performance aspect and to compare the suitability of each order picking system based on those performance aspects. Interview insights played a central role in defining criteria relevance. In addition, an association and cluster analysis of historical order data was performed to identify co-picked stock keeping units (SKU) clusters, supporting a data-driven approach to warehouse layout optimisation.

The results reveal that flexibility is the most valued performance aspect at VPDC, followed by quality, scalability, and cost. Although the VLM solution ranked marginally higher overall than the current manual operations, each system excelled in different areas. The findings suggest that a hybrid setup, integrating VLMs for selected high-runner SKU clusters while retaining manual operations for irregular items, may offer the optimal balance of efficiency and adaptability. Key success factors include staged implementation, clear project ownership, super-user training, and risk mitigation through pilot testing and temporary safety stock. Overall, the study demonstrates that automation, when aligned with data insights and operational context, can significantly enhance warehouse performance.

Keywords: Warehouse Automation, Order Picking Systems (OPS), Analytical Hierarchy Process (AHP), Association Analysis, Cluster Analysis, Goods-to-Person (GTP)

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List of Abbreviations

AHP	Analytical Hierarchy Process
AS/RS	Automatic Storage/Retrieval System
GTP	Goods-to-Person
OPS	Order Picking System
SCM	Supply Chain Management
SKU	Stock Keeping Unit
THU	Transport Handling Unit
VLM	Vertical Lift Module
VPDC	Volvo Penta Distribution Centre
WMS	Warehouse Management System

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1. Introduction

This section describes the background and relevance behind the thesis, starting with a historical perspective on logistics and supply chain management and moving into the trend towards warehouse automation. Following this, the purpose and research questions as well as the scope of the research with consideration to delimitations is presented.

1.1 Background

The evolution of logistics and supply chain management (SCM) has been significant throughout the 20th and 21st centuries, reflecting the growing complexity and strategic importance of these disciplines (Southern, 2011). From originally only dealing with transportation in the 1950s, to later combining *physical distribution* and *physical supply* in a more holistic view of the logistics system during the 1960s and 1970s (Southern, 2011). The 1990s marked a shift towards *business logistics*, where cost-saving opportunities and concepts like third-party logistics (3PL), strategic alliances and logistics partnerships emerged (Southern, 2011). Despite these advancements, traditional logistics approaches often lacked coordination with internal functions or external partners (Hou et al., 2017). In response, SCM emerged in the early 21st century, emphasising cross-boundary integration, coordination and collaboration across the entire supply chain (Southern, 2011; Hou et al., 2017).

A crucial component of modern SCM is warehousing, accounting for up to 20% of total logistics cost (Baker & Halim, 2007) and usually fulfilling several essential activities within the logistics function. In their essence, warehouses are dedicated space for storage and handling of materials, with goods receiving, put away, picking and shipping being core activities (Kusrini et al., 2018; Hamberg & Verriet, 2012). One can differentiate between different types of warehouses depending on where in the supply chain they are found, what geographical area they serve and how they are owned. Van den Berg and Zijm (1999) further distinguish between different types of warehouses, for example a distribution warehouse is a warehouse that receives goods from numerous suppliers and delivers them to numerous customers. Modern warehouses usually hold several thousands items from many different suppliers, and in turn supplies a variety of different kinds of customers such as retailers, factories or other warehouses (Hamberg & Verriet, 2012). Each of these customers will have their own set of requirements, for example being able to receive their delivery the next day (Hamberg & Verriet, 2012). The authors further claim that this in turn puts requirements on the operations and performance of the warehouse, which together with an increased difficulty in attracting suitable workforce act as drivers for automating warehouse operations. Baker and Halim (2007) identify further reasons for growing warehouse automation such as a need to accommodate future growth, anticipated cost reduction and service improvement. Reflecting these factors, the global warehouse automation systems market is projected to grow at a compound annual growth rate of 15.7% between 2022 and 2031 (Borasi et al., 2022).

One warehouse activity where automation has been commonly implemented is order picking (Huang et al., 2015). Manual order picking systems (OPS) usually entail a picker walking or travelling with a truck among aisles, locating the correct item and picking and placing it onto some container such as a box or pallet. The picker can be supported by various levels of aids such as barcode scanners, pick-to-light systems or voice picking (Battini et al., 2015a). Lee et al. (2015) also highlight the cognitive aspect of manual order picking, stating that such picking support systems can help decrease both picking times as well as the fluctuation in picking times.

One classification of different OPS distinguishes between human pickers, robot pickers and picker-less, as seen highlighted in Figure 1.1 below. Automation with human pickers is commonly referred to as parts-to-picker or goods-to-person (GTP), which will be the focus in this thesis. This is usually done by so-called automated storage and retrieval systems (AS/RS), where goods are stored and an automatic system brings the required parts to a picking station where human pickers receive them (Huang et al., 2015). Robot picker OPS can be either robot-to-parts, such automated guided vehicles (AGV) carrying and picking the parts, or parts-to-robots where robots perform the actual picking at a picking station (Huang et al., 2015). Pickerless OPS are fully automated, with no human or robot involved in the picking process, such as A-frame dispensers (Huang et al., 2015).

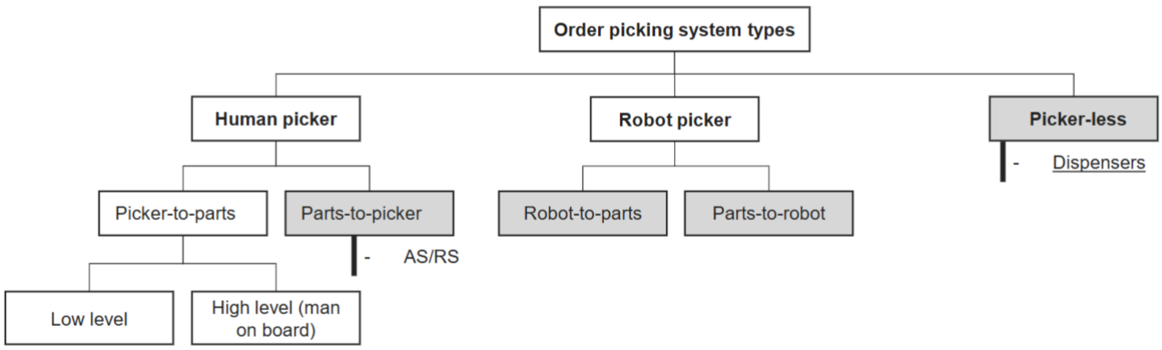

Figure 1.1. Classification of different OPS systems (Jaghbeer et al., 2020).

This thesis focuses on the company Volvo Penta, part of the Volvo Group, a Swedish marine and industrial engine manufacturer with a global logistics presence with manufacturing plants as well as distribution centres in Europe, North and South America and Asia. The current setup includes a central distribution warehouse, named Volvo Penta Distribution Centre (VPDC), adjacent to a supplying factory as well as a nearby 3PL facility. These warehouses receive supplies from multiple global production and distribution sites, and together serve a significant portion of Volvo Penta's global customer base.

At present, the setup at VPDC is considered inefficient, with a scattered footprint that includes multiple external storage facilities and temporary solutions such as rental tents. These tents are used for various purposes, such as additional storage of both packaging and production materials, as well as loading and unloading. Some tents are kept at constant temperature and humidity as per requirements of storing certain products. As such, these factors contribute to redundant processes, underutilised spaces in certain areas and an undercapacity in others, and operational inefficiencies at the VPDC site. To address these challenges, Volvo Penta is exploring ways to optimise its logistics operations both by consolidating parts of their warehouse operations and by improving flows, reducing waste and implementing smarter, more sustainable solutions. The new warehouse project is being called Volvo Penta Distribution Centre 2.0 (VPDC 2.0). Aligned with broader industry trends emphasising automation, this thesis will examine the potential for automation of order picking activities within VPDC 2.0. The thesis will evaluate four candidate automation technologies, vertical lift modules (VLM), vertical carousel modules, horizontal carousel modules and mini-loads as well as the current manual system in the seven performance categories of throughput, cost, quality, space utilisation, scalability, flexibility and ergonomics. To further explore potential solutions to various operational inefficiencies, an association- and cluster analysis to find items usually being picked together will be conducted, which in turn, through optimised item storage allocation, could lead to higher efficiencies in order picking.

1.2 Purpose and Research Questions

The purpose of this thesis is to explore the feasibility and implications of exploiting automation technology within order picking at Volvo Penta's distribution site in Vara, Sweden. Recent studies have addressed similar decisions. Novara (2020) used a multiple-criteria decision tool to select storage systems for a spare parts distribution centre and found throughput and space utilisation to be decisive aspects. Döllinger and Larsson (2016) compared VLM and carousel options for a small parts OPS, recommending VLM:s as a supplement to manual shelving. Johansson and Persson (2023) built a best practice framework for warehouse automation and argued that throughput capacity and picking accuracy are baseline qualifiers before other aspects are considered. All three studies focus on contexts with higher volumes and stronger space pressure than those at VPDC. By focusing on a more uncertain environment with more limited daily throughput, this thesis seeks to fill that gap. With this purpose in mind, the following four research questions have been developed together with short motives.

Which performance aspects matter most can vary by site as seen by the above discussed studies. Thus, a similar priority list should first be developed in order to support a decision on automating or not. The seven performance aspects analysed in this thesis are listed above in section 1.1.

RQ1. *Which performance aspects are most critical in a decision to implement automation of order picking at Volvo Penta's future warehouse operations?*

When the most critical criteria are determined, the different alternatives can be evaluated using a multiple-criteria analysis. The four candidate automation technologies of this thesis are listed above in section 1.1.

RQ2*. Considering those performance aspects, which option among the four candidate automation technologies and the existing manual OPS is the most suitable for order picking in Volvo Penta's future warehouse operations?*

A decision regarding implementing automated OPS would also need to consider risks and challenges, which are covered through the third research question.

RQ3*. What risks and challenges should be addressed to ensure successful implementation?*

Further, through research of automation technologies, and through Volvo Penta's main use of manual systems at the moment, there is proven to be a large complexity in the implementation of such technologies. To build upon RQ2, and give insights on how Volvo Penta could, if choosing to implement automation technologies, apply and optimize the warehouse operations through data-based item allocation strategies, the following RQ was constructed.

RQ4*. What insights can be derived from historical order data through association and cluster analysis to enhance item allocation strategies in automated order picking systems?*

1.3 Scope and delimitations

This thesis examines the feasibility of partially automating the order picking at Volvo Penta's future warehouse operations in Vara (VPDC 2.0). The focus is on evaluating available automated solutions for the order picking and kitting process, as well as future proofing the warehouse for a possible increase in stock keeping units (SKU:s). Other aspects, such as other warehouse activities, inventory management and broader supply chain integration, are outside the scope.

This thesis further only focuses on a specific set of automation technologies due to others either being too expensive, highly technical, or not in alignment with Volvo Penta's requirements and expectations. The technologies the thesis will focus on are VLM, horizontal carousel modules, vertical carousel modules and mini-loads.

The thesis is limited to Volvo Penta's operations in Vara and does not cover other Volvo Penta or Volvo Group sites. While automation trends are considered, findings are specific to this context and may not be fully generalisable.

2. Methodology

The following section describes the combination of qualitative and quantitative data collection techniques that were used to answer the research questions. A combination of literature reviews, interviews, gathered internal Volvo-data, site visits and time studies have been utilised to explore the feasibility and implications of implementing automation technologies in order picking.

2.1 Data collection

The data collection involved literature reviews, interviews, site visits and quantitative data collection to ensure a comprehensive understanding. Literature provides context, interviews offer personal insights, site visits reveal current practices and quantitative data identifies trends and insights.

2.1.1 Literature review

Building upon previous research is of essence in any academic research (Snyder, 2019). Snyder (2019) presents two relevant literature review techniques, systematic literature review and semi-systematic review. A systematic literature review is mostly used when pure quantitative data and predefined criteria should be applied. A semi-structured review is more applicable when researching topics across multiple disciplines with varying methodologies, synthesising the most relevant research findings. For this thesis, a semi-systematic review was applied, given that the different research questions apply to several different practices such as warehousing design, picking performance aspects and automation technology which have been studied from multiple perspectives such as engineering, logistics and business. Literature insights have been found through various academic articles, conference papers and books, primarily searched on Google Scholar, Chalmers Library and Scopus. The literature review served several purposes. Initially, a comprehensive understanding of the subject was sought in order to inform and guide the rest of the work. This included for example best practices and key decision factors in order picking. Further, the literature was used to scan what automation technologies are available and applicable in this specific context, as well as how they worked, their comparative benefits and drawbacks. The literature review also aided in formulating a theoretical framework based on specific performance aspects in order picking. Literature reviewed also supported the analysis by suggesting best practices and insights into which data analysis tools and techniques to use. Finally, RQ3 is answered by applying a literature review of risks and challenges in OPS automation in the context of Volvo Penta and VPDC.

2.1.2 Interviews

Mathers et al. (2000) argue that interviews are an important data collection technique and that they can be in a range of totally unstructured where no questions are determined beforehand to fully structured where the questions are set and the possible answers given are limited.

To gain early insight and build an understanding of the project, unstructured interviews were used. In this format no fixed list of questions is imposed and the discussion develops freely around broad themes linked to the research aim, allowing unexpected issues to emerge (Mathers et al., 2000). Such open dialogue is especially useful at the exploration stage because interviewees can steer the conversation toward the aspects they see as most critical. This flexibility helped build a holistic picture of VPDC’s current operations and its VPDC 2.0 vision.

To further strengthen the research method, conducting interviews with the appropriate people is of great importance. To gain a representative and correct view of the project the respondents have to be carefully selected. To achieve this, Mathers et al. (2000) argue that neither the type of interviewee nor the number of interviews can be specified in advance but that there is a need to change course as more data is gathered and further research is done. Mathers et al. (2000) argue that the snowballing technique is appropriate to use at the end of each interview. The technique involves asking the interviewee if there are other people in the organisation or outside that they think are relevant to what have been discussed throughout the interview. By using this technique throughout the project, it guided the thesis to relevant people and propelled the subject to the best interviewees. The positions of the respective respondents can be viewed below in table 2.1.

Table 2.1. List of current positions of interview respondents.

Organisation	Position	Respondent
Volvo Penta	Manager of the VPDC 2.0 project	1
Volvo Penta	Logistics Specialist	2
VPDC	Operative Manager	3
VPDC	Order Picking Manager	4
VPDC	Warehouse Operator A	5
VPDC	Warehouse Operator B	6

Initially, the interviews conducted were with the manager of the VPDC 2.0 project, a logistics specialist involved in the same project and the operative manager of VPDC. Continuous interviews with the interviewees mentioned above were conducted throughout the project. Operative staff at VPDC were also interviewed. The initial interviews for the project followed an unstructured approach. Due to the large scale and uncertainty of the project at the start, to gain a view of how different respondents see the project and what they believe is important to look at and to research was of importance. To gain a varied view of how different respondents see and want to approach the subject, people at different decision levels were interviewed, with different roles in the company to achieve a wider range of experience and views. This ensured a comprehensive view of the situation at hand and to be able to have more data to work with. RQ1 could directly be answered through the interview with the logistics specialist, and also partially RQ2.

2.1.3 Site visits

Using site visits as a data gathering technique is according to Lawrenz et al. (2003) greatly valuable. Due to the large operations conducted by Volvo Penta in Vara and the sheer extensiveness of data given by Volvo Penta it is crucial to gain real-life perspective. Lawrenz et al. (2003) further develop on the importance of site visits to determine the current state of operations to see where improvements and changes could be done, which is highly relevant for the project. Lawrenz et al. (2003) also state that more approaches to the methodology of a project could be valuable to the different perspectives this could result in, which in turn can increase the complexity and depth of the analysis.

Lawrenz et al. (2003) also bring up the drawbacks of site visits and the limited time the researchers may have to conduct their investigations. This will however throughout the project be counteracted by continuous visits to both the site and the headquarters of Volvo Penta and a continuous dialogue with responsible people will be maintained.

The main value for this thesis was to observe the current state of the site to gain insight into current operations and to provide a baseline for which potential automation technologies can be compared against. Four visits to the Vara site were conducted during the thesis, initially to observe the current processes and the layout. The following visits were focused on gathering specific quantitative data of the order picking activities and also to interview different people working at VPDC.

During the visits, a short study was conducted on the picking process time to map the current throughput performance as a baseline, measuring lead time per picked order line and the time spent on various activities during order picking, for example travelling between SKU locations and searching for items. This was done by following the order picker throughout their picking route with a stopwatch. An initial trial was done to understand the picking process and the usual route, without timing. A total of 12 orders were timed. The different activities performed during the picking were noted separately, including setup, travel, search, pick and other.

2.1.4 Quantitative data

Rana et al. (2021) state that using quantitative data is essential to help make predictions, test causal associations and to establish relationships among variables. To make use of quantitative data it is important to ensure that the data is correct and that it is relevant to answer the research questions provided and to interpret and analyse this data correctly. To ensure this, constant contact with people at Volvo Penta was held with weekly discussions about the research work. Three main data extractions were made from Volvo Penta's database to provide knowledge for the thesis, these were:

- A list of all SKU:s in VPDC with corresponding dimensions and picking frequencies was obtained. The list was used to filter out items with a weight larger than 25 kg, and to ensure that items in the orders analysed only contained items from VPDC and not other parts of the warehouse. This data set was also used to match item numbers with item descriptions.
- Data containing previous orders from 2022-2024, including for example item numbers, order numbers and weight of items. Such large amounts of data was required to ensure that data used in the analysis computed to non-causal relationships

between items. The data was used to find correlation between which items were picked the same orders.
- A list of which kits went into production and which were directly transported into the VPDC warehouse since only the kits moving directly to VPDC were considered. This list was later used to filter out kits which were above 25 kg and outside of the scope of the thesis.

2.2 Data analysis

Data analysis is a vital part of any research, whether it being qualitative or quantitative. It helps structuring and reaching meaningful insights about the research conducted (Dibekulu, 2020). The following section will describe the methods used to analyse the gathered qualitative and quantitative data, and how it will be synthesised to answer the research questions.

2.2.1 Analytical Hierarchy Process

Analytical Hierarchy Process (AHP) is a multiple-criteria decision making tool (Vaidya & Kumar, 2006), based on the principle that experience and knowledge of people are at least as valuable as data when making decisions (Vargas, 1990). One of the many previous applications of AHP is as a tool for planning and selecting a best alternative among several alternatives (Vaidya & Kumar, 2006). In this thesis, AHP is used to answer RQ1 and RQ2, first by identifying the most important performance aspects of the VPDC order picking and further by comparing the different candidate automation technologies in the context of Volvo Penta and VPDC.

Multiple performance criteria are important when evaluating automation technologies, for example quality, throughput and cost. AHP allows decision-makers to incorporate all such criteria, synthesising them into a single ranking of alternatives. Nydick and Hill (1992) describe the different steps of the method:

1. Define the overall goal, identify the evaluation criteria and list the decision alternatives. In this thesis, the goal is to identify the most suitable OPS at VPDC. The evaluation criteria in this thesis are Throughput, Cost, Quality, Space Utilisation, Scalability, Flexibility and Ergonomics and these will be described further in section 3.3. The alternatives are the different automation technologies as well as the current manual OPS, described further in section 3.4.
2. The decision-makers conduct pairwise comparisons of the criteria to determine their relative importance in achieving the goal. These comparisons are made using a standardised scale ranging from 1-9, seen in table 2.2. For instance, if criterion A is compared to criterion B, and it is determined that A is moderately more important than B, this results in a value of 3 in this specific comparison. The reciprocal value is assigned in the reverse comparison. In the example, that would mean that B receives a value of ⅓ when compared to A. Once all criteria have been compared to all others, the values are entered into a square matrix. A filled matrix is given below in table 2.3,

to exemplify how a complete criteria matrix with three evaluation criteria could look like.

3. The next step is to derive weights for each criterion, representing their priority. This is done by first calculating the sum for each column, and then dividing each matrix value by its column sum to yield a normalised, adjusted matrix. The weights for each criterion are then given by the average value of each row. Table 2.4 gives an example of how an adjusted matrix could look like.
4. The alternatives are then compared pairwise with respect to each individual criterion, using the same 1-9 scale. This results in one comparison matrix and one adjusted matrix per criterion, with which one can calculate a weight how well each alternative performs in each decision criteria.
5. The weights representing the relative importance of each criteria are combined with the respective weights of the alternatives to compute a final composite score for each alternative. This is typically done using a weighted sum model, allowing for a complete ranking of the alternatives.

Table 2.2. The standard scale of AHP. Intermediate even values provide additional levels of discrimination.

Verbal preference level	**Numerical Rating**
Extremely preferred	9
Very strongly preferred	7
Strongly preferred	5
Moderately preferred	3
Equally preferred	1

Table 2.3. Example AHP matrix with three criteria.

	Criterion A	Criterion B	Criterion C
Criterion A	1	3	7
Criterion B	1/3	1	4
Criterion C	1/7	1/4	1
Column Totals	*31/21*	*17/4*	*12*

Table 2.4. Example adjusted AHP matrix with three criteria.

	Criterion A	Criterion B	Criterion C	*Row Average (weight)*
Criterion A	21/31	12/17	7/12	*0.656*
Criterion B	7/31	4/17	1/3	*0.265*
Criterion C	3/31	1/17	1/12	*0.080*

In this thesis, the pairwise comparisons of the decision criteria were determined by a logistics specialist at Volvo Penta. They were given a questionnaire with all the comparisons. The pairwise comparisons of the alternatives were determined by the authors based on literature findings and the discussion in section 5.2.

2.2.2 Association analysis

Battini et al. (2016) provide insight that through simulation, analysis and AI-learning, as well as previous data retrieved on which items normally are picked together, and which items that are mostly picked, the system can achieve an optimal storing pattern for components. Resulting in a reduced amount of moving for the automation technologies and reduced moving for the picker, while also reducing idle waiting time, since two or more components that are usually picked together can be placed in the same place.

Kotu and Deshpande (2019) explain that the core essence of association analysis is to measure the strength of co-occurrence between different items. The goal of the analysis is to find patterns in the data through easily understandable rules. An example that Kotu and Deshpande (2019) bring up and one of the easiest and most recognisable usages of association analysis is in supermarkets and online shopping where a customer who buys item A, usually also purchases item B. If the store recognises these patterns, it will therefore either place these items close to each other, bundle price the items, or optimise store layout. The application for online shopping is often at check-out, where customers will receive a message similar to “Other customers who bought item A also bought item B”.

Kotu and Deshpande (2019) further explain that an association analysis also can play tricks on the user through false relationships. It is therefore of great importance to filter through these relationships and find “true” co-occurrences in the data as well as strong relationships rather than weak ones. To start an association analysis, previously recorded order data is required (Jukić & Nestorov, 2006). The initial insight gained from the data will be the amount of times each of the item pairs such as {Item A, Item B} as well as {Item B, Item A} have been picked together.

To answer RQ4, an association analysis was conducted, which provided insights into which items in historical order data have a high correlation, meaning which items, one to one, are picked together. Such analysis was done in Power Query rather than Excel to be able to handle the massive amounts of data as well as the complex formulas to handle the complexity of the item pair analysis.

It is important to consider both that item A can be the antecedent of the rule, meaning that when Item A is picked, Item B is also picked $\{Item\ A\} \ -> \ \{Item\ B\}$, as well as the consequent, meaning that when Item B is picked, Item A is also picked $\{Item\ B\} \ -> \ \{Item\ A\}$, which will be necessary to discriminate between in the analysis. Using this information, several factors will determine if the co-occurrence between these items is strong enough to be considered a non-causal relationship.

The three most important values calculated from an association analysis are the support, confidence and lift (Kotu & Deshpande, 2019). Support measures the relative relevance of pick rate to the total orders as shown in the formula below:

$$Support(A) = \frac{Times\ Item\ A\ is\ picked}{Total\ amount\ of\ orders}$$

To showcase this in a example; if Item A is picked 10 times in a total of 20 orders, the support value for Item A would be:

$$Support\ (A) = \frac{10}{20} = 0.5$$

The support value of an item cannot be above a value of 1. Likewise, the co-occurrence of two items can have a support value, Item A and Item B can be picked 5 times together in a total of 20 orders, giving the combination of these items the support value of:

$$Support = \frac{Times\ Item\ A\ and\ B\ is\ picked}{Total\ amount\ of\ orders} = \frac{5}{20} = 0.25$$

The main goal of a support value is to realise if the item, or itemset is worth considering or not in the subsequent association analysis where a minimum threshold for support values will be applied to filter away infrequent itemsets and to consider the most frequent items, or itemsets.

Confidence measures the likelihood of the consequent (Item B) being in the same order as all orders that the antecedent is in (Item A) in the itemset {Item A -> Item B} which provides the reliability of the measure in a relative manner rather than support which gives the absolute number (Kotu & Deshpande, 2019). It will answer the question: “If item A is picked, what is the likelihood of Item B also being picked?”. The formula is as follows:

$$Confidence\ (A \ -> \ B) = \frac{Support\ (A \cup B)}{Support\ (A)}$$

This explains the reason for discriminating the different occasions where Item A can be the antecedent and the consequent in the same itemset, which will result in different values. Such an example can be: Item A has been picked 10 times out of 20 orders, in these 10 orders, Item B has been picked 5 times which will result in a confidence level of:

$$Confidence\ (A \ -> \ B) = \frac{5/20}{10/20} = 0.5$$

Meanwhile, the confidence level for {Item B → Item A} could potentially look different if item B was picked in 15/20 orders, while the combination of the two was picked in 5/20 orders, just like before, since the support of two items will always be the same. This would result in a confidence of:

$$Confidence\ (B\ \ -> A)\ =\ \frac{5/20}{15/20}\ =\ 0.33$$

Lastly, the lift value measures how much more likely two items are to be picked together compared to if they were picked independently (Kotu & Deshpande, 2019). If the lift-value is below 1, the association between the two items is considered negative, if the value is above 1 it is considered a positive association, meaning that the two items are more likely picked together than one by itself. The formula is as follows:

$$Lift\ (A\ \ -> B)\ =\ \frac{Support\ (A \cup B)}{Support\ (A)\ x\ Support\ (B)}$$

The lift value of our previous example of Item A and Item B if the support for Item B was for example 0.33 would therefore be:

$$Lift\ (A\ -> \ B)\ =\ \frac{0.25}{0.5\ x\ 0.33}\ =\ 1.52$$

This indicates a strong association between Item A and Item B, they are therefore picked together more frequently than if their selections would be totally independent.

Before the values for confidence, lift and support are used to filter for item pairs, an ABC-analysis will filter for the most frequently picked items that are of greatest interest due to their volumes. An ABC analysis will categorise the items in three different slots, A, B and C where the items in slot A will consist of 15% of the total amount of items (Lehmusto, 2024; Zhou et al., 2020). Zhou et al. (2020) argue that doing a class based filtering is important to reduce the amount of low-frequency items, and argues that an ABC-analysis is easy and well applicable. These 15% of items should according to the pareto principle amount to a larger proportion of the total picked goods, optimally around 70-80% which will further be considered.

After the association analysis, itemsets might show a high value in support but this does not necessarily mean that it will show high value of confidence or vice versa. Therefore it is important to set a standardised minimum threshold for each of the values, since an itemset with great support, but with very low confidence for example, is not of interest for further analysis (Hikmawati et al., 2021).

The determination of such a threshold for the values generated by the association analysis is almost always an arbitrary task. The thresholds vary in such a great manner depending on for example which market, number of items, size of orders (Hikmawati et al., 2021).

Instead of arbitrarily picking thresholds for such a large warehouse, a combined score of the three values confidence, lift and support will be measured. As previously mentioned, an item pair with high confidence but very low lift for example, is not of interest. Therefore, a combined score derived by multiplying all values and then picking the top 90th percentile of item pairs is of good measure for this thesis.

2.2.3 Cluster analysis

After the association analysis, to further answer RQ4 and insights into which items should be allocated together, a cluster analysis was done to prove which combination of items are most likely to be picked together in an order, and therefore should be placed close to each other.

Chuang et al. (2012) explains that to gain proper use of the insights from the association analysis which only shows item pairs of two items, suggests a cluster analysis for further insights. Rosenwein (1994) explains that a clustering of items is the grouping of items into exclusive subsets where elements in the subset have a high degree of natural association. The cluster analysis is a basis for showing which items have a high correlation in larger clusters than just a single item pair. An example of relevant clusters can be the power cord, power adapter and relevant electrical component, while the items not always create frequently picked item pairs, together make up a frequent order configuration.

Zhou et al. (2020) argue that research regarding cluster analysis and using big data for storage allocation in a warehouse is rare in practice due to the fact that good data is hard to come by. Research has therefore used random simulated data. While Zhou et al. (2020) further develop their algorithm to include other variables into the cluster analysis, such as the favorable rate, support for cash on delivery and availability of free shipping, this thesis will not consider similar variables.

Rosenwein (1994) explains that cluster analysis is especially efficient to use when the demand for items is relatively stationary over a longer period of time (3-6 months) and would only need iteration when that period is expired.

A basic clustering algorithm was developed in Python, with the intent of creating clusters of between 2-9 items that all have a high correlation, meaning they have a strong history of being picked together, reflecting real-world picking behavior. Using the association analysis count and the combined score of the confidence, lift and support, the cluster analysis can provide great insights into how items should be placed in a warehouse to reduce the overall travelling distance to complete orders, reducing the fulfilment time of orders and improving efficiency (Zhou et al., 2020).

3. Context and Literature Foundations

In this section, relevant literature and prior research related to order picking, performance aspects, warehouse design and automation solutions will be presented. The literature review will also help contextualise the challenges and opportunities of automating order picking at Volvo Penta’s distribution centre. This section will further provide a basis for the feasibility of automation solutions for Volvo Penta’s operations.

3.1 Order picking

Order picking is defined as the process of retrieving items from their dedicated warehouse storage location in accordance to customer orders. The most common system is a manual picker-to-parts system (De Koster et al., 2007), in which a warehouse operator moves along aisles and picks items corresponding to a customer order (Dallari et al., 2009). The picking can be either low-level, in which only the locations accessible from the ground level are picked from, or high-level where the higher locations can be picked from as well with the aid of lifting trucks. Depending on what sort of OPS is used, pick confirmation is performed in different ways. In its simplest form, a paper list is ticked each time an item is picked. Other variants can include confirming the item by scanning a barcode or entering a confirmation number into a computer system (Battini et al., 2015a). It is considered one of the most time-consuming activities within the warehouse, accounting for up to 50% of total activities in a warehouse, making it an important lever for efficiency increase (Anđelković & Radosavljević, 2018; Hompel & Schmidt, 2007; De Koster et al., 2007; Tompkins et al., 2003). The sub-activities of order picking can be divided into travelling (55%), searching (15%), extracting (10%) and paperwork (20%) (Anđelković & Radosavljević, 2018). Anđelković and Radosavljević (2018) discuss automating the process, however eliminating people totally in the warehouse for order picking is an extremely hard task and requires large investments. However, implementing equipment and adequate technology can greatly increase the efficiency of warehouse order picking.

Kitting as it applies in this case is viewed as a sub-process of order picking. Kitting is described by (Bottin et al., 2021) as the process of consolidating a number of components into a singular standardised unit which is then sold to customers or supplied to production. According to Simões (2023) there are several other parts of the kitting process than just placing the parts in a kit container, such as counting or weighing the specific items. This would make sure the correct items are placed within the kit, quality and service level would therefore theoretically increase due to less errors.

3.2 Warehouse design

There are several aspects of a warehouse that influence the performance of order picking, including layout design, picking routes and storage allocation policies (De Koster et al., 2007). Often, these factors influence each other, for example, a certain layout may only be optimal when combined with a specific storage allocation policy and routing policy (De Koster et al., 2007). This section will introduce some warehouse design aspects that are relevant for this thesis, including zoning policies, storage allocation policies as well as batching.

Zoning refers to dividing up the warehouse in different areas or zones, where separate policies may be applied and separate pickers may operate (De Koster et al., 2007). Item locations can be decided differently depending on certain properties, for example weight, frequency of use or temperature requirements (De Koster et al., 2007). Order picking can then either be progressive, where orders are picked sequentially in their respective zones and handed over to the next zone, or in parallel (synchronised) where an order is picked in multiple zones simultaneously. The latter requires that the order is split initially, and then consolidated again afterwards (Baudin, 2004; De Koster et al., 2007). De Koster et al. (2007) describe some advantages with implementing zones such as the respective picking area becomes smaller and the picker may become more familiar with it, leading to reduced congestion and increased productivity. Petersen (2002) means that further aspects also impact the travel distance and therefore the travel time within a zone, including the zone shape, average order length and storage assignment policy. Jane and Laih (2005) also discuss the possibility of co-assigning items that regularly appear together in orders in the same zone, as to further improve the performance. However, one issue that must be addressed in progressive zoning is that of workload balance, or risk impacting the order throughput negatively (De Koster et al., 2007).

Another important policy relates to the storage locations of items. Several different assignment policies have been previously discussed in literature, but a main distinction is that between static assignment and dynamic assignment. With static assignment, items have a dedicated fixed location in the warehouse where they are always stored and picked from (De Koster et al., 2007). An advantage with this is that items can be strategically located according to their properties. For example heavy items may be stored early in the picking route in order to end up on the bottom of the pallet, or items with a higher frequency may be stored closer to the depot so that pickers don't have to travel as far (De Koster et al., 2007). Another aspect is that pickers can more easily learn where items are located, which can reduce picking times (De Koster et al., 2007). However, a fixed allocation also brings drawbacks. For example, the location must always be reserved even if the item is out of stock, and it must be sized according to the maximum quantity (De Koster et al., 2007). Thus, this often results in a lower space utilisation (De Koster et al., 2007). An alternative is dynamic assignment, where the location can change depending on some rule. The simplest version is random allocation, either determined by a warehouse management system (WMS) or "closest open location" (De Koster et al., 2007). Such policies usually have the effect of better space utilisation, however the travel time may increase instead (De Koster et al., 2007). Thus, it can be viewed as a trade off. One option is to apply different policies in different zones, for example the "class based storage" makes use of different zones depending on some classification of items such as high frequency items (De Koster et al., 2007). Different zones house different classes of items, but within each zone the assignment can be more or less random, thus gaining advantages from both methods (De Koster et al., 2007). Higher space utilisation within each zone, and higher productivity as pickers more seldom have to visit zones further back (De Koster et al., 2007).

Finally, orders can also either be picked individually or batched together. That means that multiple orders are picked during the same picking tour, and either continuously being kept sorted or sorted at the end of the picking route (De Koster et al., 2007). A prerequisite for order batching is that the orders are relatively small (De Koster et al., 2007). Batching can reduce repeat travel if items from different orders are stored close to each other, so-called proximity batching (De Koster et al., 2007).

3.3 Performance Aspects

Koster et al. (2007) mention that the most common objective for an OPS is to maximise the service level subject to resource constraints, and that the service level in turn is composed of a variety of factors. Further, in their literature review, Staudt et al. (2015) synthesise and present commonly used performance aspects and their definitions used among scholars within a warehouse setting. They categorise these aspects into four dimensions consisting of time, quality, cost and productivity with each dimension being further divided into individual measurements for specific activities, such as receiving time and order picking time as subcategories of the time dimension. Further, other performance aspects are also mentioned in literature such as scalability (Van der Gaast et al., 2019; Li & Li, 2022), flexibility (Beamon, 1999; De Koster et al., 2007) and ergonomics (Grosse et al., 2017). Table 3.1 below presents all individual performance aspects used and their definitions.

Table 3.1. All performance aspects that will be evaluated.

Performance Aspect	Definition
Throughput	Number of order lines per hour per picker.
Cost	Total cost of the OPS.
Quality	Ratio of wrongly picked order lines per time unit.
Space Utilisation	Rate of space occupied by storage.
Scalability	Ability to change volume capacity over time.
Flexibility	Ability to accommodate changes and uncertainties.
Ergonomics	How well work conditions support employee comfort, safety and efficiency.

3.3.1 Throughput

The performance aspect throughput combines the customer-facing speed of an order line and the internal efficiency with which labour is used, and is therefore expressed as order lines per staffed hour. A high throughput implies both short lead times and effective use of operator time, in turn reducing labour cost per order line (De Koster et al., 2007). In manual picker-to-parts systems the greatest impact on throughput is non-value-adding travel, which can account for up 50% of the picking time (Anđelković & Radosavljević, 2018; Hompel & Schmidt, 2007). Tompkins et al., (2003) present a typical distribution of the different components making up manual order picking, as seen in Figure 3.1. Layout design, routing policy, storage assignment and batching all influence that travel portion of the picking time (Chan & Chan, 2011; Jaghbeer et al., 2020). GTP automation raises throughput by eliminating most walking and by preparing the next SKU while the operator works, yet only if the equipment cycle time matches demand (Lee et al., 2015). Literature reports substantial gains when GTP technologies are deployed in settings where manual travel dominates (Finco et al., 2023; Bitterling et al., 2022; Loske, 2022). Loske (2022) also notes that employee learning is faster when working in an automated OPS compared to a manual one due to the access to real time feedback. Lee et al. (2015) investigate how different degrees of automation affect throughput and mean that fully automated systems can be highly efficient, but only if the productivity justifies the fixed inputs. Finally, Litvak and Vlasiou (2010) investigated the relation between the number of carousel units served by a single picker and productivity and found that increasing the number of carousels from one to two greatly increases throughput. This relation is diminishing however, too many carousels starve each unit of labour.

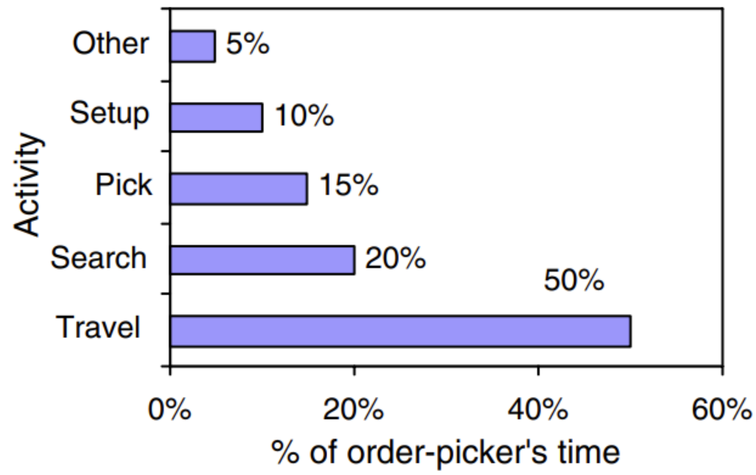

Figure 3.1. Average time distribution of a manual order picking process. (Tompkins et al., 2003)

3.3.2 Cost

Order picking is one of the most cost intensive activities in a warehouse, contributing up to 55% of total operating costs (Đukić et al., 2015). This is due to either being very labour intensive in manual order picking or very capital intensive in automotive picking (Staudt et al., 2015; De Koster et al., 2007). As seen in figure 3.1, time spent travelling and searching are a major part of the picking labour costs in manual picking. Cost savings can also be found in inventory holding, since with certain automation solutions such as VLM height is utilised, items can be stored more densely without impacting their retrievability and thus provide a higher storage efficiency, reducing the need for excessive warehouse space (De Koster, 2018). Simultaneously, in automated OPS these components are usually significantly lower resulting in a more efficient picking activity and lower operational costs per order line (Baker & Halim, 2007; De Koster et al, 2007; Marchet et al., 2014). However, while automation can reduce operational costs, they simultaneously bring increases in other cost areas. Baker and Halim (2007) highlight the fact that high anticipated capital investment is a concern for potential warehouse automation projects. Other operational costs introduced by automation technologies are regular servicing and maintenance of the equipment.

3.3.3 Quality

The quality dimension for the order picking activity relates to picking accuracy, or more specifically the ratio of number of order lines picked correctly to the total number of order lines picked during the observed time period (Staudt et al., 2015). Battini et al. (2015a) discuss different kinds of picking errors that can occur in manual paperless picking systems and describe them as either *detectable*, which can be intercepted and corrected during the picking, or *propagating*, which are only noticed at the end of a picking tour. The correction of detectable errors makes use of a WMS in which the picker needs to confirm the item picked. If the picker inputs the wrong item information, the WMS will alert the picker. Propagating errors are not immediately detected by the WMS as the picker incorrectly inputs the right item information. Such pick errors lead to increased order picking time due to rework and increased travel time (Grosse et al., 2013). In a completely paper-based picking system, no errors will be detected during the pick tour, as there is no active WMS to detect these. In cases where order picking quality is not sufficient, introducing automation technologies can aid in improving accuracy (Baker & Halim, 2007; Marchet et al., 2015; Đukić et al., 2015). By reducing human involvement, errors that can be attributed to the human factor, such as misreading labelling can be reduced or eliminated (Đukić et al., 2015).

3.3.4 Space Utilisation

An indicator related to productivity is the inventory space utilisation. Benson (2008) defines the storage-capacity ratio as the theoretical cubic capacity of a warehouse, and the storage-utilisation ratio as the actual utilisation of the capacity. Benson (2008) claims that the capacity ratio in manual shelving warehouses usually is between 22% and 27%, and that the storage utilisation is often under 50%. Đukić et al. (2021) confirm this finding, claiming that traditional shelving results in low space utilisation. Inefficient space utilisation can in turn result in cluttered and poorly organised warehouses, further reducing the available storage capacity (Deepika & Vinoline, 2025). Implementing AS/RS is one way to improve the storage space utilisation, as it often makes use of vertical space and denser item slotting, increasing the storage-utilisation ratio (Deepika & Vinoline, 2025; AbdelGawad, 2015; Đukić et al., 2021). One supplier of automation technologies states for example that implementing VLM:s can reduce area requirements by up to 85% (Kardex, n.d.).

3.3.5 Scalability

The performance aspect scalability refers to how difficult or easy it is to change volume capacity over time, both to increase and decrease. Few scientific articles directly discuss scalability of different OPS, though some touch upon it indirectly. Van der Gaast et al. (2019) model sequential zone-picking and show that once labour is balanced across all zones, extra zones (and therefore pickers) add sharply diminishing capacity. Literature on automation offers a more equipment-centred view. A meta-analysis of 41 AS/RS studies finds that throughput capacity scales almost linearly with shuttle count up to a congestion threshold, after which the VLM:s, not the shuttles, become the constraining resource, underscoring that scalability depends on the mix of components rather than any single element (Li & Li, 2022).

Industrial sources give a consistent picture of mini-load crane-based AS/RS scalability. Swisslog (n.d.) calls its mini-load highly scalable and future-proof, noting that extra aisles can be added as demand rises, and SSI Schäfer (n.d.) attributes their mini-load as "easily expanded".

3.3.6 Flexibility

Flexibility as a performance aspect in OPS is generally difficult to measure directly (Staudt et al., 2015) and has been defined in various but similar ways in literature. Beamon (1999) defines it as "the ability to respond to a changing environment", and De Koster et al. (2007) write "the ability to accommodate changes and uncertainties" and argue that short order retrieval times imply a higher flexibility. Further, in the context of automated OPS, flexibility usually refers to "the effort needed for required changes in equipment when adapting to shifts in demand" (Heragu et al., 2011; Cai et al., 2014), and the ability to cope with changes in volume (Azadeh et al., 2017). Such changes can for example be variations in order volume, order profiles, item assortment or fluctuations in labour availability. Azadeh et al. (2017) mean that a high flexibility is essential in environments marked by high variability in demand, but claim that the flexibility of GTP automation has received little attention in literature. However, van Gils et al. (2018) found that in general, a manual OPS outperforms an automated OPS as humans usually react better to such unexpected changes, are more flexible with respect to capacity and can retrieve a large variety of products without needing modifications (van Gils et al., 2018).

3.3.7 Picking Ergonomics

An important factor for the working condition in warehouses is the ergonomics of workers. It is further one of the areas of the UN's sustainability development goals (Swedish UN Association, 2023), number 8.8, to foster the safe working conditions of all.

Human factors cover many aspects relevant for order picking, but due to scope limitations this thesis will focus only on picking ergonomics. Ergonomics in this context will refer to the physical working conditions and their adverse effects on operators. According to Grosse et al. (2017), ergonomics in order picking have received little attention in literature compared to other, more distinct measurements. Jaghbeer (2019) further mentions that there is little work evaluating ergonomics in automated OPS. However, some authors have conducted experiments in which they investigate the ergonomic effects of activities within order picking, both in manual picker-to-parts systems and automated GTP systems. The main ergonomic risks in manual OPS include heavy lifts, long walking distances, awkward picking angles such as above the shoulders or below the knees and large item quantities leading to repetitive work (De Lombaert et al., 2024; Calzavara et al., 2016; Labus & Gajšek; 2018; Feldmann et al., 2019). Further, ergonomic strain mainly depends on the tasks themselves rather than the individual traits of the workers (De Lombaert et al., 2024; Labus & Gajšek; 2018). Therefore, it is important to decrease these ergonomics risks in relation to social sustainability. According to Loske et al. (2021) there is a large connection between logistics and health risks related to ergonomic stress which can in turn further increase the economic and social disadvantages in the long term, both for the individual and also for the company. Loske et al. (2021) also argue for an increase in automated and digitised working systems within logistics to decrease the risk of ergonomic stress and increase the overall living conditions for workers in these areas. Fariolo et al. (2024) further agree with Loske et al. (2021) that companies can make well-informed decisions when adopting automation technologies in OPS systems by understanding the interconnection between automation and social sustainability. The research of Fariolo et al. (2024) also shows that profitability within warehouses does not need to be in contradiction to increasing the social sustainability of workers but can rather work and foster each other.

Battini et al. (2015b) modeled how ergonomics can be measured as both a capacity and cost driver, and showed that it can be quantified directly. For example, poor ergonomics silently erode throughput over time, leading to more frequent and longer breaks (Battini et al., 2015b). Within an automated OPS, some demanding activities can be negated such as long walks, heavy lifts and awkward angles as items are retrieved and presented to the picker in an ergonomic height (Đukić et al., 2021; Al Shehhi et al., 2019; Lee et al., 2020; Hanson et al., 2018). In their research on a horizontal carousel, Đukić et al. (2021) found that the average energy expended per pick can be reduced by ⅓ and leads to significantly lower risks of fatigue and musculoskeletal disorders. However, some authors highlight that introducing a GTP system does not automatically guarantee low musculoskeletal risks (Lee et al., 2018; Al Shehhi et al., 2019). Instead, attention must be brought to what actions are still performed by humans. Zhang et al. (2023) mean that ergonomic gains can mainly be achieved when humans and robots get distinct, ergonomically sensible roles such as allowing humans to pick high frequency items closest to depots, while robots handle slow moving items.

3.4 Automated Storage and Retrieval Systems

This section describes the different automation technologies that in consultation with Volvo Penta have been deemed relevant for this thesis. The technologies are VLM, horizontal carousels, vertical carousels and mini-loads. AS/RS such as these are typically supported by an integrated software system which can track where in the module the item is located, and can provide organisational benefits such as decreasing costs and increasing efficiency, both by efficient storage but also through an increase in the possibility to apply smart picking for orders (Calzavara et al., 2019).

3.4.1 Vertical Lift Modules

Đukić et al. (2015) explain that lift modules are structures of columns that consist of trays that move vertically to achieve GTP, meaning that the goods to be picked are brought to the picker through a dedicated access bay. The lift modules main characteristics are the improvement of efficiency in the picking process, height utilisation and improvement of both ergonomics and safety for the workers (Đukić et al., 2015).

Vertical lift modules are a solution used for order picking of mainly smaller components stored in a vertical manner, using a middle lift with storage on each side. The middle mechanised lift moves vertically inside of the lift module, retrieving trays from the different levels, delivering them to the access point of the module (Battini et al., 2016). VLM:s are built on a modular design, meaning that the system can be adapted to fit different ceiling heights, however a minimum height of 5-6 metres is recommended (Döllinger & Larsson, 2016). Döllinger and Larsson (2016) explain that VLM:s can dynamically adjust the distance between the internal trays, depending on the storage needs and demand patterns. VLM:s can have access points on both sides, allowing for simultaneous picking and replenishment (Döllinger & Larsson, 2016). They can further be customised to fit different storage assignment policies. Döllinger and Larsson (2016) present market research regarding different AS/RS:s, in which they compare solutions given by different commercial providers. Regarding the VLM:s researched, the height can range between 2.5 to 16 metres. In order to achieve higher throughput, the same picker can operate multiple VLM:s simultaneously in a so-called pod.

Battini et al. (2016) explain that a downside of current VLM:s is the idle waiting time when the picker has to wait for the lift module to store and extract the next item to be picked. A solution to this is dual-bay VLM:s. Dual-bay VLM:s are particularly suitable for picking activities due to its dynamic characteristics where the picker picks a component from a tray and the system simultaneously retrieves the following component to an adjacent picking spot, resulting in higher system output with less idle time (Battini et al., 2016). One such solution can be seen in figure 3.2 below showing a dual-bay VLM.

Figure 3.2. Example of a VLM (Outsource Equipment, n.d.).

Calzavara et al. (2019) propose that using VLM:s reduces the risk of mistakes in the picking process, since the picker only is presented with a single tray with a limited assortment of items. There may be a light indicating where the correct item is located. There is also an ergonomic aspect of using VLM:s, the picker will always receive the tray of components in the predefined height of the tray presented. This will in turn not require the picker to reach into positions where the posture is sub-optimal, decreasing the risk of injuries and long-term musculoskeletal issues (Calzavara et al., 2019).

3.4.2 Vertical Carousel Modules

Carousels are an AS/RS based on a closed loop structure. The carousel consists of a set of rotating shelves, presenting the corresponding shelf, containing the desired SKU to the picker, an example can be seen in figure 3.3 below.

Figure 3.3. Example of a vertical carousel module (VitalValt, n.d.).

A vertical carousel is a simple AS/RS system that moves on a vertical axis, utilising height as storage and optimising the usage of floor space. Since minimal internal volume is required for aisles or lift devices, carousels can achieve a very high space utilisation (Döllinger & Larsson, 2016). Bertke et al. (2024) propose that vertical carousels can save up to 90% of floor space in warehouses. The system presents the desired shelf containing the needed SKU to the user at a central access point, which therefore does not have to move when storing or picking items. Vertical carousels are usually used for smaller or medium-sized items which are presented at a fixed, ergonomic height (Buley & Knott, 1986). In their market research, Döllinger and Larsson (2016) found that vertical carousels usually have heights of 3 to 15 metres, but are normally restricted to 9 metres due to weight restrictions. The implementation of vertical carousels can increase the tracking rate of items, minimising the risk for human errors in both the storing and picking process (Gabriel-Santos et al., 2016). Arnold et al., (2008) propose that if the system is filled according to demand patterns a very high throughput can be achieved. This is done by putting items that are often ordered together on the same or close shelves. Allowing one picker to operate several systems at once in a so-called pod arrangement can also increase productivity, as idle waiting time is reduced (Bartholdi III & Hackman, 2017). However, the vertical carousel also comes with some disadvantages. Due to the fact that the entire shelving mechanism must rotate for each retrieval, a higher wear out can be expected (Döllinger & Larsson, 2016). The system is also prone to weight imbalances, and can risk tipping if balanced improperly (Döllinger & Larsson, 2016). The system does not generally perform well during surges in demand (Bartholdi III & Hackman, 2017) and should mainly be implemented when demand is continuous with low variation (Arnold et al., 2008). Scalability is another issue for the vertical carousel, as it is usually not possible to increase the number of racks after installation, or add a second access point and would instead require entirely new systems (Arnold et al., 2008).

3.4.3 Horizontal Carousel Modules

Đukić et al. (2015) explain that a horizontal carousel module is a storage system that is linked to either a floor-mounted or roof-mounted driving mechanism for moving the carousel in a complete loop. Several modules can be placed in proximity and operated by a few pickers, as seen in figure 3.4 below. This grouping provides the pickers with the possibility of simultaneously picking from one space while the other spaces move to present the upcoming components needed, decreasing the idle waiting time, contributing to a high throughput. Often, a single picker operates a number of these carousels to reach a large picking productivity and are therefore especially effective for batch picking (Đukić et al., 2015). Each column in the carousel has a number of trays or storage loads containing a specific component. However, in contrast to both the VLM and vertical carousel, the horizontal carousel is often limited in height as the picker must be able to reach all the different picking locations (Döllinger & Larsson, 2016). The authors also mention that the carousel body can either consist of a single drive mechanism or multiple sub-carousels stacked on each other, where the latter allows for picking from sub-carousel while another is rotating allowing for an even lower idle time.

Figure 3.4. Example of several horizontal carousels (Modula, n.d.).

3.4.4 Mini-load

Mini-load systems are composed of multiple narrow parallel aisles of storage racks where an operating machine stores and retrieves plastic bins containing SKU:s which are called mini-loads (Bartholdi III & Hackman, 2017). If space allows, it is therefore viable to increase the amount of racks horizontally and deliver the bins to a specific pick station. The machine can move both horizontally and vertically as seen in Figure 3.5. The machine retrieves the mini-loads to a dedicated picking station and when the items have been picked from that mini-load, moves back to store the mini-load at the dedicated rack.

Figure 3.5. Example of a mini-load (MecaLux, n.d.).

Bartholdi III and Hackman (2017) differentiate between single command cycles and dual command cycles in mini-load systems. In a single command cycle, the device either puts away or retrieves a load and then returns to the access point, while in a dual command cycle, it can put away one unit load and retrieve another before returning. Operating a dual command cycle is generally more productive. According to He et al. (2023), a single stacker crane with two racks can satisfy more than 100 items per hour. Döllinger and Larsson (2016) also provide insight from market research, noticing that mini-load systems can handle both standard and in certain cases customised bins, typically for loads up to 120 kg. Some systems are also capable of carrying two bins at once but are highly limited in terms of maximum throughput, as there is only one access point per aisle. Their research indicates a typical performance of around 130-150 cycles per hour. Lastly, Lerher et al. (2011) describe mini-load systems as fairly inflexible and difficult to adapt to future demand changes, as well as changing assortment due to fixed bin sizes, which may present challenges.

3.5 Risks and challenges with automation

Any project comes with risks and challenges, and an automation project is no different. This section will aid in answering RQ3 by providing an overview of risks and challenges previous authors have identified can arise when implementing automation in an OPS.

To begin with, a major hurdle is the upfront investment cost. This can be substantial and must be weighed towards potential benefits, especially if the project has a long pay-back time (Baker & Halim, 2007). Granlund and Wiktorsson (2014) discuss a generic overview of the different phases of a warehouse automation project, divided in the pre-project phase, the implementation phase and the post-project phase. They go on and describe several key barriers to exploiting automation technologies within internal logistics. As a start, they mention that lack of knowledge can be hindering. This is especially visible in the pre-project phase. For example, companies are often unable to answer questions such as “How do we find potential technologies?”, “How do we identify the benefits?” and “How do we use the technology properly?”. Related to the unpreparedness, unrealistic or undefined objectives is another risk that can lead to investing in unnecessarily expensive or complicated automation equipment in the end (Granlund & Wiktorsson, 2014). Another risk is not designating a clear owner, both in terms of the specific automation investment and also of the strategic responsibility (Granlund & Wiktorsson, 2014). Not doing so can result in no one having an overall view of the system and its performance, and can inhibit the management and future development of the system leading to sub-optimisation (Granlund & Wiktorsson, 2014). On the other hand, Baudin (2004) means that an automation system can take a lot of focus from other important areas, due to it being so expensive. Baker and Halim (2007) mention the potential lack of future flexibility in adapting the system, either as an effect of changing capacity requirements or a change in the SKU characteristics. Further, Baker and Halim (2007) mention the risk of the implementation of automation technologies having disruptive effects on the ongoing operations of the warehouse. This in turn can result in a decreased service level, especially in the short term such as longer delivery times (Baker & Halim, 2007; Marchet et al., 2014). Such effects are usually resolved as time is spent on fine-tuning the equipment and new activities (Baker & Halim, 2007).

However, the literature also proposes some steps to take to increase the likelihood of a successful implementation. Winroth et al. (2007) claim that before taking any decisions and investing ad hoc, companies should evaluate their direction, strength and weakness and from that develop an implementation strategy. For example, Granlund and Friedler (2012) recommend thoroughly formulating specifications and requirements on automation equipment. The company should have a clear functional strategy for how the automation technology supports the overall goals, and also to guide future improvements. Baker and Halim (2007) also highlight the importance of having a realistic timescale, that also includes how the ongoing operations will be affected. Other success factors include involving and communicating with employees, benchmarking over time and with different solutions and acquiring relevant knowledge, if not already present, involving experts or consultants (Granlund & Wiktorsson, 2014).

4. Empirical Findings

This section describes the different empirical findings of the thesis, starting with describing both the order picking and kitting activities at the Vara Site. Then, a brief description of the VPDC item characteristics follows. The time study conducted is described and the results are presented. Finally, a brief discussion of Volvo Penta's expectations on the new warehouse operations performance is given. The empirical findings were mainly gathered during the four site visits and through the continuous interviews and dialogues that were held.

The site is located just outside Vara, Sweden and houses two distinct operations. The first one being a Volvo Penta factory producing among other things D4 and D6 marine engines as well as operating a production line for specialised heavy-duty engines, and the second VPDC, the central distribution warehouse. These are located in separate structures, however these are next to each other with openings to move between the two. As this thesis is not considering the production operations besides the kit building process, it will be excluded in the following description.

4.1 Kitting at VPDC

Kitting is done at a dedicated area within the factory. Kits are produced for the production line but also for the VPDC warehouse and contain different amounts of items from 2 items per kit, all the way up to 25 items with an average of 5 items per kit. Examples of kits are shown in figure 4.1. The building of kits are steered according to a weekly demand, according to specific customer orders. However, the demand for the entire week is batch built and not immediately for the order shipment. Therefore, there is a stock of kits in VPDC until all orders are picked and shipped during the week.

Figure 4.1. Finished kit in a plastic bag (Left). Retrieved items to be included in kits (centre). Finished kit in a quarter pallet (Right).

There are four kitting stations where different kits are built, separated according to the total weight of the kits. Each station has a scale to weigh the kits as a means of quality control. The smallest kits contain screws, bolts and similar items, in a plastic bag. For this station the ingoing items are presented immediately around the operator in easy-accessible racks. For larger kits, either differently sized cardboard boxes or small wooden pallets are used, as seen in figure 4.2 below. For these kits, one operator is responsible for material handling as the items are located throughout smaller storage areas in the factory (not VPDC). The material handler moves around and retrieves the relevant items, similar to order picking, brings them to the kitting station and puts away the leftover pallets. One operator is constantly building kits. Some smaller and high frequency items are stored in two VLM:s at the kitting area, and can be accessed directly by the operators. Certain larger kits also contain smaller kits built at the other kit stations, and must therefore wait for these kits to be built. Finished kits are transported to the VPDC storage to be further picked by order pickers at some point during the week.

Figure 4.2. Example of a finished kit on a quarter pallet.

4.2 Order picking at VPDC

The warehouse itself is divided into zones such that one zone mainly contains smaller items, up to 25 kg and can be handled by hand or simple lifting devices, and one zone contains larger, heavier items, often on pallets that must be handled with forklifts. The small item zone is around 2000 m^2. There are currently around 1400 unique SKU:s in the small item zone and around 360 SKU:s in the larger items zone. Orders are usually picked the day before they are supposed to be shipped out, given no disruptions such as missing items. Synchronised zoning is used between the two zones, such that the order is split into two lists according to the respective items. For the small items picking, a picker forklift with a three level rack is used (Figure 4.3-left below), and for large items picking, a counterbalance forklift is used (Figure 4.3-right below). Thus, for each order, two separate picking rounds are performed. The items are brought to a joint area to be merged back into one order again (P4 in Figure 4.5). However, small items must first also be packed in pallets with pallet collars and lids similar to Figure 4.2, built by the picker at the end of the picking round.

As this thesis focuses on the small items, only this picking process will be further described and analysed. Within the small item zone, low level picking is used where pickers only pick from the shelves accessible from the ground floor. Certain items are however picked from the third level, where the picker is able to raise the truck to reach these. A typical partial order for the small item zone contains around 15-20 order lines, with around 30-50 orders picked per day, which amounts to on average 15 000 order lines per month. A big reason for the variation in order volume per day is material shortages, as orders can not be partially picked and must therefore wait to be picked until all items are available. This thus creates a backlog of orders that all get released to be picked simultaneously as the missing items are received by the warehouse. While the planners can view backlog orders, they have no insight into when the missing items will arrive and can thus not plan for a more balanced workload. They are also unable to change the picking date of backlog orders, so all backlog orders will need to be picked as soon as they can which creates large fluctuations in orders per day. Within the small item zone, a class based storage system is partially used. This means that each item class is stored in its respective area, however within each area a random storage allocation is used. Certain items follow a static, dedicated storage policy. This includes high frequency items, as well as certain items that are pre-programmed according to specifications from the customer. Item reallocation is done in an ad hoc manner, rather than a continuously applied defined logic, risking sub-optimal allocation.

A summary of the above figures of the order and SKU process is shown below in table 4.1.

Table 4.1. Summary of figures of the VPDC small order picking.

Warehouse area	2000 m^2
Item weight	Up to 25 kg
Unique SKU:s	1400
Typical order size	15-20 order lines
Typical orders volume	30-50 orders per day

Figure 4.3. Picker forklift (Left). Counter-weight truck (Right).

While picking, item confirmation is done by scanning respective items' barcodes together with a barcode representing the correct quantity (Figure 4.4-Right) with a barcode scanner worn directly on the finger of the picker (Figure 4.4-Left). A floor plan of the Vara site can be seen in figure 4.5 below, with the VPDC picking area with racks shaded in blue and the order merging area in yellow. The small item picking round starts at location P1 with the picker preparing the picking list and truck. They then move to P2 where certain items have to be programmed according to specific customer specifications, which must be done before the picking can start. They then move in an S-shape throughout the warehouse. At P3, a VLM is used as storage for certain low-frequency items. The picker enters the specified information into the terminal and the VLM retrieves their items, with a light signaling where on the tray the item is. The picking route finishes at P1 again, and the picker prepares the items by building the pallets and placing them at P4, where the order waits to be merged with the partial order with large items and then finally loaded and shipped out. During this process, the picker again confirms that all items have been correctly picked before signing the order as complete.

Figure 4.4. Finger-mounted barcode scanner (Left). Barcodes for quantity (Right).

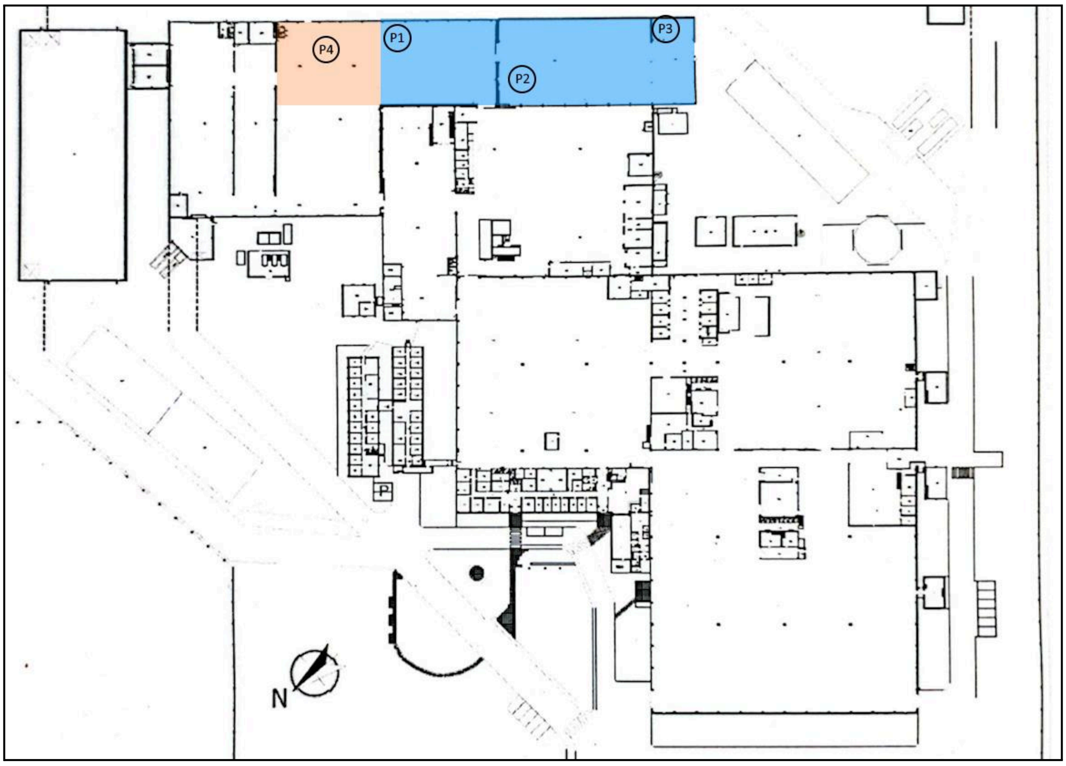

Figure 4.5. Floor plan of VPDC and the Vara factory.

VPDC receives between zero and three claims per month about the customer receiving incorrect items. This does not necessarily mean that the wrong item has been picked during the picking round, but could depend on other factors such as the order has been loaded on the wrong truck. If all claims would be caused by picking errors, VPDC would have an error rate of 0.0002% (on average 15 000 order lines per month). VPDC has an internal goal of continuously reducing their claim rate.

4.3 Item characteristics at VPDC

Today VPDC stores around 1800 unique SKU:s, with around 1400 being allocated to the small item zone. In the items in VPDC, kits are also included. New articles are added continuously as parts get updated and replaced. As a way to future-proof a new warehouse, it should be able to accommodate an increase of around 100% workload in the near future. The items are different kinds of accessories and spare parts used in shipbuilding and adjacent industries, and usually sold and shipped together with an associated marine or industrial engine. Some examples of items seen below in Figure 4.6 are hoses, instrument readers and electrical components such as joysticks and extension cables. The items picked in the small item zone weigh between a couple of grams up to 25 kg.

Figure 4.6. Examples of items stored and picked at VPDC.

4.4 Time study

A time study was conducted to get a baseline of the current performance related to the throughput of the manual small item order picking process at VPDC. 12 orders were documented following three different pickers, 3 orders contained fewer than 10 order lines, 2 contained between 10 and 20 order lines and 7 contained more than 20 order lines. The time distribution was noted from starting the order at P1, throughout the entire picking round and finishing back at P1. The time spent on building and packing the pallets was not documented, as this activity would remain if automation technologies were to be implemented. The results can be viewed in Figure 4.7 below. The different activities documented were “setup”, “travel”, “search”, “pick” and “other”. The setup activity included picking up and looking over the order list and setting up the computer, and made up 6.9% of the total picking time. The travel activity consisted of travelling between the different storage locations, as well as vertical travel if the picking location were on the second or third level, and made up 30.6%. The search activity consisted of trying to identify the correct item after having traveled to the location, but before picking it. This mainly occurred at the zone with order-specific pre-programmed items, as the picker had to identify the exact one matching the corresponding order. Search made up 6.7%. The pick activity consisted of picking the item or items, scanning them as well as the quantity barcode and placing them on the truck. It made up 49.6%. Finally, the activity labelled other mainly consisted of administrative activities such as reading and managing the order list, reorganising the items on the truck, idle time while waiting for the VLM to be free or system errors. It made up 6.2%.

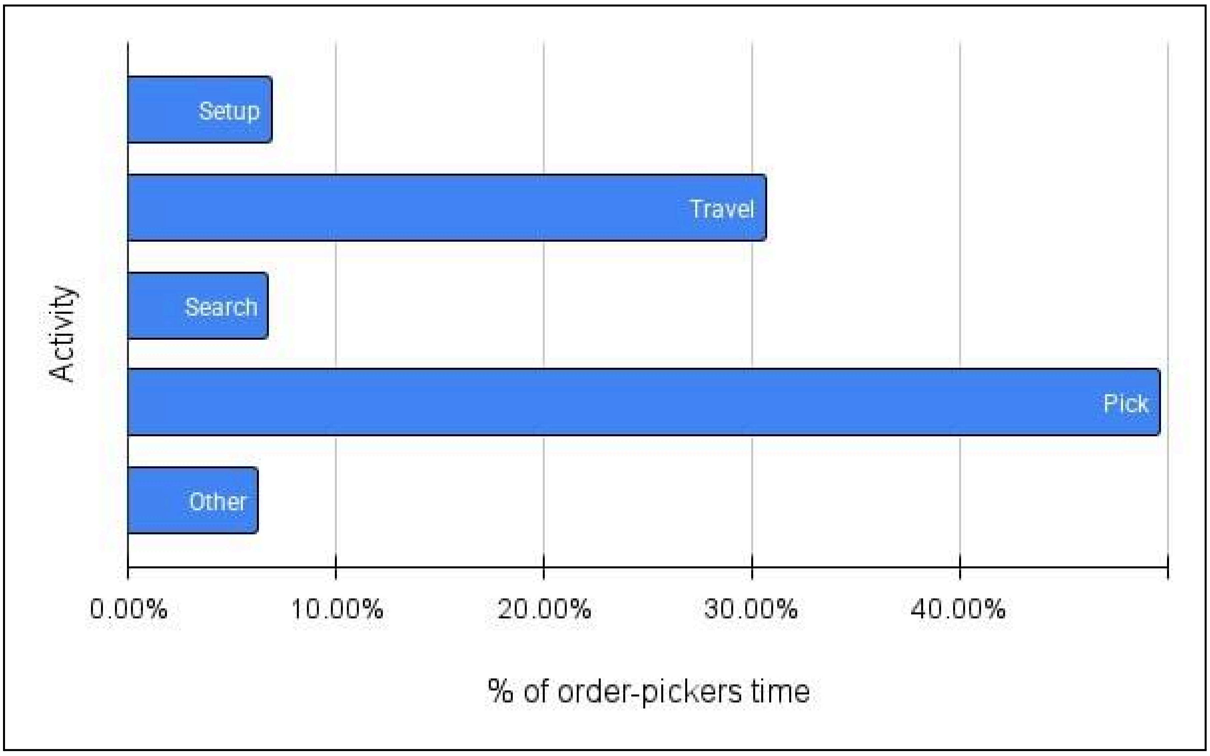

Figure 4.7. Time distribution per activity in picking rounds.

4.5 Volvo Penta's expectations

As stated in section 1.1, Volvo Penta is currently investigating the possibility of building VPDC 2.0, a new warehouse building with the intent to consolidate their currently scattered footprint in Vara. The new building would be located just beside the current operations of VPDC and the Vara factory. As a result of this project, the current operations are being studied to identify potential improvements, including the order picking and kitting operations.

Volvo Penta is expecting that the workload and number of SKU:s of ingoing items being used at the kitting activity will double in the near future. The current setup does not have the capacity for this increase, mainly due to workspace constraints. Thus, Volvo Penta is exploring the possibility of transferring the kitting operations from its current organisation within the factory building to the warehouse organisation, and also potentially reorganise the process itself by making kit building a sub-activity within the order picking. This would mean that the kits are built directly in connection to when the order is picked, up to one day beforehand, and immediately picked during the order picking round to be packed and shipped instead of being placed in inventory. This would result in a loss of efficiency for the kitting process, as they would no longer be batch building kits. However, this suggested change is motivated due to the fact that a major cost driver and constraint for VPDC is space, and currently the batch kit building process results in additional inventory. Furthermore, the current process results in each kit being an individual transport handling unit (THU), being either small plastic bags, cardboard boxes or small wooden pallets with collars. Each THU requires some handling, and 3PL-actors invoices per handled THU. Finally, the THU:s are not always sized appropriately for the items and are often oversized. This both results in unnecessary inventory volume, as well as being questioned by customers. Thus Volvo Penta wants to question this process, and explore the possibility of consolidating several kits going to the same order on one THU. For example, the largest kits are built on quarter pallets and several may be consolidated into one EUR-pallet.

The above change would impact the order picking process, transferring the workload as kits would be built in parallel with order picking. This puts a real constraint in the area, as the kitting activity is currently located within the factory with racks that are picked from being spread throughout the factory. Consolidating this activity and transferring it would further increase the already limited required area, especially when considering the 100% increase. This results in higher requirements for the performance aspect of inventory space utilisation. Regarding the throughput aspect, this is an important but not deciding factor. VPDC can currently manage their workload with at most 3 simultaneous order pickers. Backlogs are mainly due to missing items from suppliers. However, considering the potential change in operations as kits would be built in parallel as the order is picked, more workload would be moved closer to the scheduled loading time putting more emphasis on the throughput performance aspect. The cost aspect is another important but not crucial measurement. The current operating costs are quite low, and the main cost drivers are instead found in the space constraints. Any potential automation technology should be able to address these limitations rather than aiming primarily at reducing labor costs. Therefore, investment decisions should prioritise solutions that optimise space efficiency and operational flexibility. As regards to quality, Volvo Penta aims to continuously reduce the number of customer claims resulting from picking errors. This performance is already very good, so it can not be considered a driver for an investment even with the high accuracy of automation technologies.

5. Analysis

This section will analyse the literature and empirical findings in order to answer the research questions. Section 5.1 evaluates the current manual OPS at VPDC on each performance aspect, while section 5.2 evaluates the four candidate automation technologies against the same aspects. These two act as input to section 5.3, which will synthesise it into the AHP model and provide a final scoring for each OPS. In section 5.4, firstly an association analysis is conducted to prove initial correlation between items. Further, the association analysis acts as input for the cluster analysis, which provides an optimal bundle of items for storage in VPDC, based on the most relevant items from the association analysis.

5.1 Current order picking at VPDC

This section will analyse the small order picking at VPDC based on the site visits, dialogues and interviews making up the empirical findings according to the performance aspects stated in section 3.3. The analysis will serve as guidance in determining the relative performance of the current manual OPS for the AHP analysis in section 5.3 and aid in answering RQ2 regarding what OPS is the most suitable for VPDC.

Today, the order picking is manually performed by 2-3 pickers on a low-level picker-to-parts system. The picker follows a set route and can pick from the first and second level in racks. At certain places, also the third level is pickable. Items are for the most part allocated to different zones, and have within their respective zones dynamic storage allocation. Certain high-runners have a set location, which can be changed if the situation changes. Items can be said to follow a rudimentary ABC-classification, with high-runner items being closer to the starting area and usually on the first or second level as to make them more easily accessible. The order picker confirms the correct item by scanning the item barcode with a scanner attached to their finger, and the correct quantity by scanning pre-taped barcodes on the truck to represent different quantities (1-4).

5.1.1 Current Situation - Throughput

Throughput here means the number of order lines picked per staffed hour, so it captures both customer facing speed and internal labour efficiency. Our time study shows that an average pick tour spends about 30% of total time simply travelling between slots, and another 7% searching before any item is handled. As a result, the small parts team handles around 84 order lines per hour, divided by a typical three pickers on duty, that is around 28 order lines per labour-hour. The figure is acceptable for today’s volumes, yet as Volvo Penta expects SKU count to increase this can become a constraint. Without automation that increase would increase the average travel distance, raise travel times and decrease throughput unless the workforce and floor space increase proportionally. In short, the current manual setup meets daily targets but offers limited headroom once SKU count increases and kit-building is moved to VPDC.

5.1.2 Current Situation - Cost

Cost is an important aspect for Volvo Penta and can be analysed in several ways. First of all, there are the operational costs, mainly consisting of the 2-3 operators performing order picking on any given day. Implementing automation technologies would likely do little to reduce these costs, as an automated system still requires a minimum of pickers to operate the modules. Other costs would also be introduced such as maintenance, technicians and electricity. Costs related to material handling could potentially increase as well, as more handling is required to replenish the automated systems. Secondly, there are the costs related to the investment, both in terms of the machines themselves but also any investments in software and WMS. Finally, there are storage costs related to holding inventory, both direct and indirect, with the one most relevant in this project relating to the storage utilisation and item density, discussed in section 5.1.4.

5.1.3 Current Situation - Quality

The quality aspect relates to picking accuracy, that is what percentage of order lines are incorrectly picked, either as detectable or propagating errors as defined by Battini et al. (2015a). VPDC uses a finger-held scanner to directly scan the article barcode as well as a barcode representing the picked quantity. This system makes it very easy to intercept and immediately correct what Battini et al (2015a) calls detectable errors. The picker also performs a control after the entire picking round as they pack the items in boxes, being able to also catch any propagating picking errors. Thus, it can be said that the quality control at VPDC is high, evident in their claim rate at 0.0002%. While a direct measurement of accuracy is difficult to track due to its very nature, customer claims can be used as a substitute. As a result, while potential for quality improvements can be a driver for implementing automation technologies, this does not seem applicable in Volvo Pentas case due to their already low claim-rate.

5.1.4 Current Situation - Space Utilisation

Another measurement of productivity is inventory space utilisation in item density per m^2. This is important for Volvo Penta, given that the current area is seen as a crucial constraint for their operations. They currently have around 1400 pickable SKU locations, mainly consisting of the first and second levels in storage racks, with some items in simple shelves. The upper levels are otherwise mainly used as a reserve zone to replenish empty items. The current pickable small item zone is around 2000 m^2. This results in a pickable item density of around 0.7 items per m^2. With the current density, the increase of SKU:s would require about an additional 2000 m^2 of standard storage racks, assuming that it would scale linearly. This can be another driver for introducing automation technologies as they often make better use of height compared to traditional warehouse racks, resulting in fewer m^2 required in order to house the same number of items.

5.1.5 Current Situation - Scalability

The small-item zone already holds about 1400 SKU:s on 2000 m^2, leaving only about a few empty pallet locations at any given time. Volvo Penta expects SKU count and picking workload to increase, yet the current area and synchronised two-zone process were designed for today's volumes, not including the kit building. Because orders cannot be released until all lines are available, a single inbound delivery can trigger a sudden spike from 30 up to 50 orders per day, most likely resulting in even larger spikes in the future with the same system. With only 2-3 pickers and a low-level picker-to-parts system, the throughput can be increased short-term by adding labour, even though the aisles would quickly get crowded. Especially the current use of the VLM not being properly utilised could become a major idle point, as several pickers want to retrieve items from the same module. However, medium to long term, the floor space limits capacity. The current setup would not be able to absorb the forecasted increase.

5.1.6 Current Situation - Flexibility

The current system performs moderately well when it comes to flexibility. Human pickers can quite easily adapt and solve simple issues that arise, such as simple software issues or improvising the route throughout the warehouse. Human pickers can also handle a very broad range of items, both in weight and size, and the available capacity can easily be adapted short-term to match the current workload. However, there still exists some inflexibility in the way order backlogs are managed. For example, when one order line is missing, the entire order waits and when that part arrives, every frozen order releases at once. Planners cannot easily stagger these drops or change promised ship dates, so workload still comes in spikes even though labour is flexible.

5.1.7 Current Situation - Ergonomics

Although foot travel is minimal during the order picking, the current system still exhibits ergonomically straining factors. While the items are under 25 kg, because items are distributed from knee height to the third rack level, pickers repeatedly switch between bending and overhead reaches, including stretching to reach items. All items are also handled twice, once during the picking and once during the pallet building which adds unnecessary ergonomic load. While minor, the finger-mounted scanner, while eliminating a handheld scanner, still involves a very repetitive motion in barcode scanning. Consequently, while VPDC seems to perform ergonomically acceptable as a manual OPS, there are still some inherent factors that add a lot of strain.

5.2 Analysis of Automation Technologies

This section will analyse the potential automation technologies from the perspective of the discussed performance aspects and Volvo Pentas preconditions and expectations. For each performance aspect, an AHP matrix is created with scores reflecting the analysis. This section will serve as guidance in determining the relative performance of each automation technology in the AHP analysis in section 5.3, and aid in answering RQ2 regarding what OPS is the most appropriate for VPDC.

5.2.1 Throughput

All four GTP alternatives offer higher throughput than today's manual picker-to-parts system, but they differ in how much of the picker's idle time they can eliminate. A mini-load can retrieve the next box while the operator scans and picks from the current one, so bin-change delay can be reduced to almost zero. A dual-bay VLM also pre-stages the next tray, yet each lift still handles trays sequentially. Both vertical and horizontal carousels remove walking but must rotate the entire carrier set for every retrieval, letting only shelves sit at the access point at a time. The manual baseline, constrained by travel and search averages 20-30 items per hour per picker. These characteristics justify the AHP ordering of mini-load, followed by VLM, ver. car., hor. car. and lastly manual seen in table 5.1 below.

Table 5.1. AHP matrix considering the performance aspect throughput.

THROUGHPUT	Manual	VLM	Ver. Car	Hor. Car.	Miniload
Manual	1	1/5	1/4	1/4	1/7
VLM	5	1	2	2	1/3
Ver. Car	4	1/2	1	1	1/4
Hor. Car	4	1/2	1	1	1/4
Miniload	7	3	4	4	1

5.2.2 Cost

Regarding the cost aspect, a purely manual process most likely incurs the lowest total cost in the VPDC context as investments are negligible and existing labour covers current volumes appropriately, so pay-back on automation will not be immediate. Among the automation options, a VLM represents the least costly upgrade. Its modules can be purchased incrementally, installation is limited to anchoring and power and maintenance is largely confined to a single lift drive. Labour savings can appear as soon as the first unit is installed. A vertical carousel requires a comparable footprint but due to the mechanism rotating all the shelves and weight balancing, a higher wear resulting in a greater lifecycle expense can be anticipated. A horizontal carousel is costly due to multiple separate motors per unit, floor-mounted rails and the opportunity cost of the larger footprint. Mini-Load ranks the highest in cost, as every capacity increment demands aisles, cranes, rails and integration with the existing units, and while unit labour falls, the large investment and ongoing service are significant in the total cost. The AHP ranking for cost is thus Manual receiving the highest score followed by VLM, followed by the two carousel options placing similarly and lastly the mini-load system, seen in table 5.2 below.

Table 5.2. AHP matrix considering the performance aspect cost.

COST	Manual	VLM	Ver. Car	Hor. Car.	Mini-load
Manual	1	2	3	3	4
VLM	1/2	1	2	2	3
Ver. Car.	1/3	1/2	1	2	2
Hor. Car.	1/3	1/2	1/2	1	2
Mini-load	1/4	1/3	1/2	1/2	1

5.2.3 Quality

VPDC's existing small parts order picking already records a very low claim rate, so any automation will at most deliver marginal gains. All four GTP systems reduce human errors, yet the degree of which still differentiates them. Mini-load ranks highest: a single sealed bin is fed to a dedicated station, exposing only the intended SKU, leaving little scope for incorrect picks. VLM:s and vertical carousels follow closely, each presents one tray or shelf at ergonomic height with optional pick-to-light, but a limited assortment remains visible on the carrier. Horizontal carousels perform slightly lower, as multiple access points and variable pick heights raise the cognitive load and the risk of picking the wrong item. Given the already high baseline, these nuances justify the modest AHP scoring with mini-load just slightly on top followed by VLM, ver. car. and hor. car. at a similar scoring and lastly manual, seen in table 5.3 below.

Table 5.3. AHP matrix considering the performance aspect quality.

QUALITY	Manual	VLM	Ver. Car.	Hor. Car.	Mini-load
Manual	1	1/2	1/2	1/2	1/3
VLM	2	1	2	2	1/2
Ver. Car.	2	1/2	1	2	1/2
Hor. Car.	2	1/2	1/2	1	1/3
Mini-load	3	2	2	3	1

5.2.4 Space utilisation

Because VPDC's footprint is constrained, the degree to which a technology converts building volume into SKU capacity is important. Mini-loads deliver the highest utilisation with narrow aisles and densely stacked boxes. VLM:s rank next, the modules exploit the full height of the building and can slot items dynamically, although each access point reduces the utilisation somewhat. A vertical carousel also stores vertically, yet the rotating drum reduces the internal capacity relative to a VLM. A horizontal carousel improves on manual shelving by eliminating walk-aisles, but it uses the floor space rather than height, so density gains are modest. Traditional shelving remains the least efficient, with aisle cross-sections and uneven slotting limiting both capacity and utilisation. Thus, the AHP ranking is mini-load scoring the highest followed by VLM, then ver. Car., then hor. car. and lastly manual, as seen in table 5.4 below.

Table 5.4. AHP matrix considering the performance aspect space utilisation.

SPACE UTILISATION	Manual	VLM	Ver. Car.	Hor. Car.	Mini-load
Manual	1	1/6	1/5	1/3	1/7
VLM	6	1	3	4	1/2
Ver. Car.	5	1/3	1	2	1/3
Hor. Car.	3	1/4	1/2	1	1/3
Mini-load	7	2	3	3	1

5.2.5 Scalability

As shown in table 5.5 below, the two most scalable options are the VLM and the vertical carousel. Since both are self-contained systems, it's easy to add more units with minimal disruption to operations. This means capacity can increase almost linearly as more units are added, at least until labour and space availability becomes a limiting factor.

A horizontal carousel also expands unit by unit, yet every additional unit consumes more valuable floor space, so footprint rather than installation effort constrains growth. Mini-load ranks the lowest among the automated options: increasing throughput requires constructing new aisles and integrating additional stacker cranes, an investment step that is large, capital-intensive and often accompanied by operational downtime. Manual racking remains least scalable overall because extra volume demands proportional floor space and labour. The AHP ranking thus becomes VLM and ver. car. scoring the highest, followed by hor. car. and then mini-load and lastly the manual system, seen in table 5.5 below.

Table 5.5. AHP matrix considering the performance aspect scalability.

SCALABILITY	Manual	VLM	Ver. Car.	Hor. Car.	Mini-load
Manual	1	1/5	1/5	1/4	1/3
VLM	5	1	1	2	3
Ver. Car.	5	1	1	2	2
Hor. Car.	4	1/2	1/2	1	2
Mini-load	3	1/3	1/2	1/2	1

5.2.6 Flexibility

As shown in Table 5.6 below, a manual system performs the best in flexibility. Human pickers can absorb volume spikes, new SKU:s and altered routing with negligible re-configuration effort. Among the automated options, VLM and the horizontal carousel offer comparable flexibility. The horizontal carousel's different levels also allows for changing order profiles. A vertical carousel is less flexible, its single closed loop and weight-balance limitations restrict re-racking and does not allow for extra access points. Mini-load is the least flexible due to fixed aisle dimensions and bin sizes. Thus, the AHP ranking for flexibility as seen in table 5.6 below shows that manual performs best, with VLM and hor. car. performing second best. In third place is the ver. car. and scoring the least well in flexibility is mini-load.

Table 5.6. AHP matrix considering the performance aspect flexibility.

FLEXIBILITY	Manual	VLM	Ver. Car.	Hor. Car.	Mini-load
Manual	1	4	5	4	6
VLM	1/4	1	2	2	4
Ver. Car.	1/5	1/2	1	2	3
Hor. Car.	1/4	1/2	1/2	1	3
Mini-load	1/6	1/4	1/3	1/3	1

5.2.7 Ergonomics

All four GTP systems mitigate the primary risks identified in literature for manual picking, long travel, high or low reaches and heavy lifts, yet they do so to different extents. VLM and Mini-load provide the greatest relief: each delivers a single tray or bin precisely at waist height, eliminating awkward postures and most manual handling. Vertical carousels achieve nearly the same effect, the picker still works at ergonomic height, though occasional shelf depth and reach can lengthen grasp distance. Horizontal carousels reduce walking but require bending or higher reaching on the different levels of the rack, so residual musculoskeletal load is higher. Manual shelving remains the least favourable, combining travel with repetitive lifting at variable heights. These qualitative differences result in the AHP ordering of VLM and mini-load scoring similar followed by ver. car. and then hor. car. with manual receiving the lowest score seen in Table 5.7 below.

Table 5.7. AHP matrix considering the performance aspect of ergonomics.

ERGONOMICS	Manual	VLM	Ver. Car.	Hor. Car.	Mini-load
Manual	1	1/6	1/5	1/3	1/6
VLM	6	1	2	3	1
Ver. Car.	5	1/2	1	2	1/2
Hor. Car.	3	1/3	1/2	1	1/3
Mini-load	6	1	2	3	1

5.3 AHP Analysis

This section will apply the AHP-technique in order to compare the different automation technologies and the manual system. RQ1 relating to what performance aspects are the most important for VPDC will be answered by the initial analysis step on the input data from Volvo Penta. RQ2 relating to what is the most appropriate OPS to use will be answered by the final results of the AHP analysis.

The decision of what criteria that were included was partly based on literature (Staudt et al., 2015) and discussions with Volvo Penta. These criteria used were throughput, cost, quality, space utilisation, scalability, flexibility and ergonomics. The input for the relative importance criteria comparisons were collected through a questionnaire filled by a logistics specialist at Volvo Penta considering their future order picking operations, and the results of this are presented below in table 5.8..

Table 5.8. AHP matrix considering the relative importance of each performance aspect.

	Throughput	**Cost**	**Quality**	**Space Util.**	**Scalability**	**Flexibility**	**Ergonomics**
Throughput	1	1/5	1/6	1/4	1/3	1/4	1
Cost	5	1	1	1	1/3	1/5	3
Quality	6	1	1	2	1	1	4
Space Util.	4	1	1/2	1	1/3	1/7	1
Scalability	3	3	1	3	1	1/5	5
Flexibility	4	5	1	7	5	1	5
Ergonomics	1	1/3	1/4	1	1/5	1/5	1
Column Totals	*24*	*173/15*	*59/12*	*61/4*	41/5	419/140	20

This original matrix is then used to create the normalised adjusted matrix, by dividing each matrix value with its column total seen in table 5.9 below. This allows for the calculations of weights in the rightmost column, by computing the average for each row.

Table 5.9. Adjusted AHP matrix considering the relative importance of each performance aspect.

	Throughput	**Cost**	**Quality**	**Space Util.**	**Scalability**	**Flexibility**	**Ergonomics**	**Row Average**
Throughput	1/24	3/173	2/59	1/61	5/123	35/419	1/20	*0.040*
Cost	5/24	15/173	12/59	4/61	5/123	28/419	3/20	*0.117*
Quality	6/24	15/173	12/59	8/61	15/123	140/419	4/20	*0.190*
Space Util.	4/24	15/173	6/59	4/61	5/123	20/419	1/20	*0.080*
Scalability	3/24	45/173	12/59	12/61	15/123	28/419	5/20	*0.175*
Flexibility	4/24	75/173	12/59	28/61	75/123	140/419	5/20	*0.351*
Ergonomics	1/24	5/173	3/59	4/61	3/123	28/419	1/20	*0.047*
							Total	1.000

The weights representing the relative importance of each performance aspect in order of importance is thus as follows, in table 5.10.

Table 5.10. The intermediate AHP weights, reflecting the relative importance of the performance aspects.

Performance aspect	Weight
Flexibility	**0.351**
Quality	0.190
Scalability	0.175
Cost	0.117
Space Utilisation	0.080
Ergonomics	0.047
Throughput	0.040

The next step in the AHP analysis is to compute the weights for how well each OPS perform in each specific criterion. This is done in a similar fashion as above, only that a matrix must be created for each criterion. The pairwise comparison values are determined based on literature and the discussion in section 5.2. The matrices are presented for each respective performance aspect in section 5.2, as well as in Appendix A. The results of this intermediate step are the weights for how well each OPS performs in each performance aspect, and are presented below in table 5.11.

Table 5.11. The intermediate AHP weights, reflecting how well each OPS performs in each performance aspect. The highest weight for each performance aspect is highlighted.

	Throughput	Cost	Quality	Space Util.	Scalability	Flexibility	Ergonomics
Manual	0.044	**0.398**	0.096	0.042	0.053	**0.505**	0.046
VLM	0.217	0.242	0.236	0.307	**0.326**	0.194	**0.325**
Ver. Car	0.131	0.160	0.180	0.157	0.302	0.138	0.192
Hor. Car	0.131	0.122	0.127	0.102	0.191	0.111	0.112
Mini-Load	**0.477**	0.079	**0.361**	**0.393**	0.128	0.047	**0.325**

This gives us the final weights as to how well each automation technology performs in the respective performance aspects highlighted in red in the tables above. Finally, for each OPS a final weight can be calculated by summing a weighted average. The calculation for the manual system is demonstrated below. The weight representing the importance of each performance aspect is multiplied with how well the manual system performs in that specific area, and all products are then added together:

(0.040)(0.044) + (0.117)(0.398) + (0.190)(0.096) + (0.080)(0.042) + (0.175)(0.053) + (0.351)(0.505) + (0.047)(0.046) = **0.259**

Similar calculations are performed for each of the OPS and can be seen in Appendix C. The final scores are presented below in Table 5.12.

Table 5.12. The final AHP scores of the OPS.

OPS	Final score
Manual	0.259
VLM	0.247
Mini-load	0.184
Ver. Car.	0.181
Hor. Car.	0.129

Thus, the VLM and the current manual system receive the highest scores, followed by the mini-load, the vertical carousel and finally the horizontal carousel.

5.4 Association and Cluster Analysis

From VPDC, all order data from 2022 - 2024 was acquired to create an association analysis to help answer RQ4 and to help decide on how to allocate items in an automated order picking system. However, because of the large amount of data, only half of the data from 2024 was used, which proved to be sufficient enough for the analysis. The data consisted of:

- 72 000 order rows.
- 7500 unique orders.
- 2189 unique items.

After conducting the ABC analysis to show the top 15% of all picked items in the first half of 2024, it resulted in 328 items with a total number of picks per year consisting of 85% of the total picks, only these will be further considered.

After the initial association analysis, 72 490 unique item pairs were achieved, each with a separate count of how many times the pair was picked. The applied formulas to achieve values of confidence, lift and support were implemented and a score for each item pair was the result.

Instead of arbitrarily picking thresholds, a combined score of the three values confidence, lift and support will be measured. As previously mentioned, an item pair with high confidence but very low lift for example, is not of interest. Therefore, a combined score by multiplying all values and then picking the top 95th percentile of item pairs was done, resulting in 3304 unique item pairs.

To reiterate what was done, table 5.13 below shows which columns are used in excel with example values. Count represents the amount of times Item 1 and Item 2 are picked together in an order. There are two filtering columns to make sure that both of the items are considered in the A-slot in the ABC analysis and that both items are under 25 kg, which is within the scope of the thesis. Furthermore, each item pair got values for confidence, lift and support, relating to the degree of association between the items.

Table 5.13. Example of columns and rows from the association analysis, with made-up item numbers and values.

Item 1	Item 2	ItemPair	Count	Confidence	Lift	Support	Both items A in ABC?	Both under 25KG?	Score
X	Z	X-Z	XXX	0.6	2.4	0.8	YES	YES	1.152
Y	X	Y-X	XXX	0.4	3	0.5	YES	YES	0.6

To further analyse the correlation between items and to further answer RQ4, a cluster analysis was done using programming in python. Using existing repositories in github for similar analysis and using StackOverflow to gain insight into other similar analysis that had been done, a simple code-base was made. Inspiration for the code was also taken from Zhou et al. (2020) who did a similar analysis but more advanced. The first step was to create a simple cluster with a maximum of 9 items in each, made of just the strongest correlations between the different item pairs. Once this clustering was made, an iterative process called simulated annealing was initialised. The basics of the annealing process is to temporarily accept worse conditions than before, to be able to explore further optimal options, if the consequent steps proves to be worse for the ending solution, the iteration reverses. This helps the algorithm not get "stuck" in what seems like an early optimal solution, but rather explores all available solutions. The process moved through 60 000 steps, where for each further step, the less radical changes are made for the algorithm and the item clusters due to the algorithm being more conservative the closer to the end. And for each step, the algorithm decided if it would accept the item cluster change, or dismiss it and reiterate.

To increase the reliability of the algorithm, 100 runs were attempted, with the best scoring final cluster being the decided combination of items. It is important to note that each item was allowed to appear in a maximum of 3 clusters, but only if it would drastically increase the score of the cluster. This is due to the fact that since all the items picked are very frequent due to the early filtering of the analysis, finding one optimal cluster for each item can instead hinder the optimal solution of clusters in the warehouse and limit the algorithm.

The result provided was that some clusters proved to be of great interest with high scores, while some had some lower scores, proving less co-occurrence. The result can be seen in appendix D where 37 separate clusters are shown and an example of a single cluster is shown in table 5.14 below with corresponding item descriptions which were gathered from the Volvo Penta database of items.

Other programs were considered for the analysis, such as Orange, a data mining tool with network optimisation tools, which however did not fit all the constraints needed for the analysis made and therefore the final solution was Python. For the association analysis, data from half of 2024 was used due to performance limitations of the programs used. This limited the analysis by not considering certain aspects such as seasonal variations and could be mitigated by using more historical data.

The resulting appendix D for the entire cluster analysis shows well defined clusters that can be used for implementation in Volvo Penta's warehouse even without implementing automation technologies. This proof of concept in the case of Volvo Penta shows that iterations such as when SKU numbers increase or order combination changes, can be useful to ensure future comprehensive and well designed warehouse design. The full cluster analysis for all clusters is shown in appendix D. The score each cluster receives varies from 0 to 12.95 in this case, and provides only a comparable result relative to each cluster, the score is therefore not absolute.

Furthermore, the cluster analysis did not consider some items that were picked more times as more important than the ones that were picked less, but purely based the analysis on which item pairs from the association analysis had the best scores. To further improve the cluster analysis, weighted scores, based on the number of times the item pair was picked, would be beneficial to provide a more accurate scoring system. To improve the analysis further, weights to consider other variables before doing the cluster analysis would also be beneficial for actual implementation such as Zhou et al. (2020) did in their analysis. Zhou et al. (2020) used different variables and weighed the different clusters, giving a more rigid solution to apply in a real world scenario.

Table 5.14. Example of how a single cluster looks like, with corresponding item number and item description.

Cluster 1	**Item Number**	**Item Description**
Item 1	21628160	Tachometer, 0-4000 rpm, black
Item 2	21785135	Button panel kit
Item 3	3886666	Cable, Multilink 1,5 m
Item 4	22919882	Hose kit, S-drive
Item 5	22919880	Connect kit, S-drive, w/o hose
Item 6	22303438	Hull seal
Item 7	3594745	Aux relay kit, incl cable and
Item 8	22919878	Connect kit, S-drive, w/o hose
Item 9	874708	Mounting kit with bezel ring,
Score	*4.46*	

6. Discussion

This section synthesises the findings from the four research questions, providing a deeper understanding of the practical and strategic implications for Volvo Penta's warehouse operations. Section 6.1 up to 6.4 discusses each research question individually, while section 6.5 synthesises the findings to one cohesive discussion. Section 6.6 looks forward to what topics could be of interest for future research.

6.1 RQ1 - Performance Aspect Importance

Our first research question regarding the importance of different performance aspects of an OPS was answered through the AHP data collection.

RQ1. Which performance aspects are most critical in a decision to implement automation of order picking at Volvo Penta's new warehouse?

The findings demonstrate that flexibility, or the ability to adapt to a changing environment, is the dominant performance aspect for Volvo Penta and VPDC, followed by quality, scalability and cost. This answer is in line with Volvo Penta's current operations in VPDC as it is currently operating in a dynamic environment, demonstrated by a large variation in daily order sizes, future uncertainty regarding SKU range and volume as well as the organisational structure of the kit building activity. It thus follows that flexibility would be considered as very important. The same logic can be applied in regards to the performance aspect scalability, which similarly to flexibility relates to an ability to adjust capacity, but assumes a more long-term perspective. That both quality, cost and space utilisation received moderately high scores of importance can be explained by the fact that all three are more or less connected to the total cost of the OPS, with cost being a major consideration of the warehouse operations, with quality and space utilisation more indirectly.

Finally, throughput scored low even though these are generally considered crucial in warehouse operations and directly determines lead time to customer and service levels. However, this could be explained by the fact that the operations at VPDC are relatively small and the current team of 3 pickers generally meets daily targets, thus making it a relatively minor constraint in relation to the other aspects. It is worth noting that these scores were calculated based on judgements from a single person which can decrease the reliability of the input and a discussion between several involved parties would be preferable. However, this person was deemed representative for the operations at VPDC considering they held the role of logistics specialist and was part of the project team for VPDC 2.0 thus having a comprehensive view of its conditions.

Comparable automation evaluation studies emphasise quite different priorities, which helps to explain why our weighting pattern departs from what is sometimes presented as typical. In Novara's (2020) AHP of eight light-load storage systems, throughput and space utilisation each scored the highest, whereas flexibility scored in the middle, signalling a context where floor cost and line-rate rather than organisational flexibility constrained the design. Similarly, in Döllinger and Larsson's (2016) evaluation of carousel and VLM options for picking operations, space utilisation and productivity scored the highest, even though the authors concede that VLM:s still provide "great flexibility in terms of different products", an aspect regarded as beneficial but not crucial. Johansson and Persson (2023), drawing on interviews across several Swedish warehouses, go a step further and frame throughput capacity and picking accuracy as qualifying factors that must be satisfied before any finer trade-offs are considered. Set against these studies, our findings where flexibility dominates and the two throughput related measures score low underline that the relative importance of performance aspects in potential automation implementation is highly dependent on the site's specific constraints and preconditions.

6.2 RQ2 - Technology Suitability Ranking

The second research question regarding what, or if any, automation technology would be the most suitable to implement is answered through the application of the AHP analysis.

RQ2. Considering those performance aspects, which option among the four candidate automation technologies and the existing manual OPS is the most suitable for order picking in Volvo Penta's future warehouse operations?

The final scores of the AHP placed the current manual OPS on top with a score of 0.259, with VLM following close behind with 0.247. The scores for the remaining solutions were somewhat lower, with the mini-load receiving 0.184, the vertical carousel 0.181 and finally the horizontal carousel receiving 0.129. The main drivers for the high manual score is the flexibility and cost aspects. Both of these were deemed very important (0.351 and 0.117 respectively), and for both the manual OPS scored the highest, making up 85% of the total final score for OPS. For the remaining performance aspects, the automated OPS outperformed the manual but since many of them received lower importance weights they did not impact the final score as much. This is especially true for the performance aspect throughput which heavily favoured automated OPS, but were downplayed due to its relative unimportance. This stands in contrast to Novara (2020), where throughput and space utilisation received the highest weights, resulting in a shuttle-based automation system. The only automated OPS that scored relatively close to the manual system was the VLM system, which scored moderate to high in all performance aspects.

The conclusion is therefore not necessarily that a single solution should be implemented and others disregarded. It is important to consider that the SKU:s that Volvo Penta have in VPDC have lots of different characteristics and need thorough considerations. Therefore this analysis only concludes that in general, both VLM:s and manual OPS seem appropriately suitable in an overall setting for Volvo Penta.

6.3 RQ3 - Implementation Risks and Challenges

The third research question regarding the potential risks and challenges was mainly covered through the literature review, where the most common obstacles were highlighted. These will here be discussed further in the context of Volvo Penta and VPDC.

***RQ3**. What risks and challenges should be addressed to ensure successful implementation?*

The first and most apparent challenge for an automation project is the initial investment costs. Dual-bay pods cost far more than simple racking, and their pay-back time would depend on how quickly SKU volume increases. For Volvo Penta, this argues for a pilot scale start and a payback model that tracks floor space usage and throughput continuously, continuing with the project only if such key metrics are met. Closely related is the risk of a knowledge and skill gap. VPDC has run a purely manual OPS with only limited application of VLM:s and lacks experience of GTP systems. Granlund and Wiktorsson (2014) show that such gaps often derail projects before installation even begins. Strategies that manage and mitigate this gap would be necessary and are discussed by previous authors, for example early supplier workshops, employee trainings and external consultancy (Winroth et al., 2007; Granlund & Friedler, 2012; Baker & Halim, 2007; Granlund & Wiktorsson, 2014). Another risk is that of unclear objectives and ownership. Without a so-called automation owner that is responsible for performance and strategy of a potential automation technology, the focus may become unclear and performance sub-optimised. This is especially applicable if Volvo Penta implements a limited automation and keeping some of their manual processes, and could risk resulting in a usage similar to how they currently do have one VLM but used unconventionally. There would be a need to optimise the warehouse operations as a whole, to avoid sub-optimisation. Setting measurable targets and assigning an automation owner gives the project both direction and accountability.

Further, having two parallel OPS also raises a question regarding future flexibility. Even a modular VLM can become a bottleneck if future SKU dimensions or order profiles become unsuitable for tray specifications (Baker & Halim, 2007; Baudin, 2004). Retaining a certain level of manual shelving will make sure the entire warehouse could manage awkward item dimensions, and slow runners.

Finally, authors warn of a temporary dip in service level during the implementation as operators go through a learning curve and the modules are properly calibrated (Baker & Halim, 2007; Marchet et al., 2014). The risk is especially relevant in a mixed environment, where routing between manual and automated zones can add complexity and decrease throughput times. VPDC has limited seasonality to absorb such a dip, so the project team could create its own buffer by limiting new SKU introductions initially, build a temporarily increased safety stock and incrementally move appropriate items to a VLM pod.

Taken together, these precautions form a coherent initial hybrid implementation strategy, reflecting the phased roadmap outlined by Winroth et al. (2007). Begin with a limited VLM pilot, establish competence among operators and managers early, as well as clear automation ownership and review capacity annually. By building upon this, Volvo Penta should be able to capture the flexibility and efficiency gains that motivate an implementation of automated OPS while mitigating cost increases and operational disruptions.

6.4 RQ4 - Item Allocation Optimisation

The fourth research question was addressed through an association analysis of current items using historical order data, followed by a cluster analysis. This approach both demonstrates the concept and provides Volvo Penta with a practical grouping of items that are frequently picked together, supporting potential implementation.

***RQ4**. Can historical order data be used to generate an association analysis between items, and in turn optimised item clusters for Volvo Penta's warehouse layout design in the implementation of order picking automation?*

One of the largest questions that arise when introducing automation technologies in warehouses that do not currently use such systems is how to correctly implement and increase the operational efficiency through these systems. The performed association analysis proves that an initial filtering of the amount of picks and characteristics of the items is of utmost importance in a warehouse like Volvo Penta's. This is especially true due to the large number of items that would make the analysis much harder to interpret, but also to filter for relevant items that would benefit the optimisation of the warehouse operations. To further filter for the most relevant items before doing the association analysis, an ABC analysis was done, where only the items in category A were used. This was due to the fact that the complexity increases at a rate of $O(n^2)$, and to properly filter for the most relevant items at an early stage is of great importance and reduces the complexity for future analysis.

The association analysis showed that Volvo Penta had 72 490 unique item pairs after the initial filtering process, showing how many times each combination of items were picked. Further using this data, values such as support, confidence and lift were used to combine a score for each item pair, further giving us the possibility to filter through all unique item pairs since 72 490 pairs would be too much. Using the combined score of each of these values, a filtering of the 95th percentile was done, giving us the final results for the association analysis, proving that such analysis was possible using historical data.

Using the association analysis, a cluster analysis was conducted to further optimise warehouse operations. From Volvo Penta's perspective, this type of analysis represents a snapshot based on a specific set of order data collected over a defined period. It does not necessarily account for seasonal fluctuations or other significant variations occurring over multiple years. However, using such time-limited data also avoids incorporating long-term changes that may no longer be relevant. Therefore, carefully selecting which data to include and which to exclude, is crucial for producing meaningful results.

The cluster analysis, using an algorithm to score each cluster, moves through several thousands iterations to find the best solution. The algorithm scored the different clusters in accordance to what score each of the itemsets in the previous association analysis showed, creating an optimal solution. While Volvo Penta could use the cluster analysis to practically improve the location of their items in accordance with the cluster analysis, it also provides a proof of concept that such analysis is possible, and in this case also applicable. If a good framework is set up for future analysis, iterating these steps every now and then, while also implementing weights in accordance to seasonal variations or other variables which are important for Volvo Penta, would provide a sturdy and continuously updated warehouse design and item allocation system. As Appendix D shows, some clusters had a very low score and some even scored a 0. This proves that the cluster analysis needs several iterations, removing the "good" clusters from the analysis and either adding more relevant item pairs that scored high on the association analysis, or to just re-do the cluster analysis with the remaining items.

It is shown that a cluster analysis and correlating allocation of items is applicable for both the manual system that Volvo Penta currently uses, and also is applicable in all other automation technologies that were examined except for the mini-load system. This is because the mini-load system delivers one tray of items per time to the operator, disregarding the potential benefits of presenting several distinct items to the picker at once. Therefore, for a mini-load system, a simple ABC-allocation of items is more applicable, where frequently picked items are closer to the picker, reducing cycle time for the item.

6.5 Synthesis of Findings and Implications

To combine the different analyses done in this thesis, and to conclude the implications of the findings made, this section will tie together the research questions to a bigger narrative. The AHP analysis proved that different solutions in the context of Volvo Penta's operations could be applicable, such as keeping the manual system or introducing VLM:s that received similar scores. The practical implication of this is that Volvo Penta does not face an "all-or-nothing" automation choice. Because the manual OPS scored only 0.012 points above the VLM, the data argues for at most a limited automation implementation, introducing groups of VLM:s to absorb certain more appropriate SKU:s while retaining the current manual OPS for the remaining SKU:s.

Furthermore, an alternative perspective on the performance of an OPS is to consider some performance aspects as trade-offs; it is possible to increase one only if another is decreased for example. This assumes that they are interdependent, which often seems to be the case. Furthermore, quality and space utilisation can also be viewed as static constraints rather than a direct performance aspect, setting a minimum threshold that must be reached, but something that where exceptional performance should not necessarily be aimed for due to costly trade-offs. The same can be said for ergonomics, there exists a minimum threshold that is critical to reach, but performance above that is redundant.

To complement this result, the most applicable SKU:s to implement into an automation solution, which can also be applied to the current manual system is the item clusters provided by the cluster analysis. These items are not only the most picked items but also proves to be the most efficient to bundle to increase overall optimisation in the picking system. Whereas the items not used in either the association analysis due to low pick rate or in the cluster analysis due to low combined score of variables would benefit less from being placed in a VLM or similar automation system. Such a mixed setup could deliver the full flexibility and cost advantage of the manual system, and still capture the throughput and space efficiency gains of the VLM. A similar recommendation appears in Döllinger and Larsson (2016), who conclude that VLM:s should supplement and not replace manual shelving OPS when SKU variety is high and growth uncertain, and Johansson and Persson (2023) likewise caution against complete automation conversion when the cost aspect is important or limited. Thus, the AHP scores point to selective instead of comprehensive automation, as the optimal path for VPDC 2.0.

Further, Racca's (2015) study concludes the importance of distributing the frequent picks of items across several VLM:s rather than keeping all of these in a singular VLM. To ensure less idle waiting time, distributing items across adjacent VLM:s when there are more than one picker is therefore optimal. However, Zhou et al. (2020) also defines the importance of implementing a relevant cluster analysis together with a class based storage system such as an ABC-analysis. Where the clusters with the best score and containing items that are high frequency picks, should be located closest to the start route in the picking. Therefore, it is of great importance to consider both the ABC aspect in correlation to the cluster aspect.

We also recommend iterating the association and cluster analyses a number of times, either when SKU characteristics or volume change, the importance of certain aspects in a warehouse changes, or some other major change that implicitly changes the nature of the warehouse operations. By iterating these analyses, continuous improvements can be achieved.

Finally, while the results are specific to VPDC, this thesis has demonstrated the possibility and potential of applying analytical hierarchy processes as well as association and clustering analysis as tools in warehouse settings and order picking environments. These tools prove useful in identifying critical performance aspects, suitable OPS, as well as ways of optimising item allocation.

The OPS's examined in the thesis have their limitations, and therefore not all of the systems are applicable for all types of companies or items and thorough research needs to be done within the company or project team to ensure that the OPS's are viable to use for the specific context. Furthermore, the correlation analysis conducted needs large amounts of well organised data to be able to provide a correct and scientifically significant relationship between items.

6.6 Future Research

Future research should initially develop the AHP itself, by broadening the input perspectives, for example repeating the performance evaluations with a cross-functional panel and updating the performance scores from a market research study with input from automation suppliers. A natural next step is also to convert the AHP model to an ANP model, which allows interdependent criteria to influence one another. Another point of interest would be to compare the findings of this thesis to that of other similar case studies to identify correlations between the importance of performance aspects and the suitability of different OPS.

Future research on association and cluster analysis should focus on incorporating more complex variables into the clustering process. One promising direction is the development of weighted association rules, where item pairings are not only ranked by metrics like support and confidence but also adjusted for seasonal variability or operational priorities which should preferably be set by responsible individuals. Expanding the dataset of historical order data across multiple years could enable the identification of more stable item relationships, making it easier to distinguish genuine causal relationships from spurious ones and leading to a more accurate dataset than using limited historical data. Moreover, cluster analysis can be refined by integrating weighted scoring mechanisms that factor in item importance just like for the association analysis. Finally, combining class-based storage strategies such as ABC analysis with refined clusters should be further explored to improve picking efficiency while balancing system complexity and scalability. For Volvo Penta, as previously mentioned, a similar analysis should preferably be done in an interval of a set amount of time.

7. Conclusion

This thesis examined whether and to what extent Volvo Penta should automate small-parts order picking in its future warehouse picking operations. Using a multi-criteria decision framework, an AHP model with data from site visits, interviews, time studies, order history data analysis and a literature based risk review, four main insights were found. First, what matters most at VPDC is flexibility, above conventional throughput and space utilisation. Quality, scalability and cost followed, while throughput was deemed secondary. Second, through the AHP analysis it was found that the VLM solution scored marginally higher than the existing manual OPS but the two systems scored high for different reasons. The VLM exploits height, cuts travel and improves picking ergonomics, while the manual system remains cheapest and most flexible. This opens the potential for a hybrid solution, implementing VLM:s for a certain portion of SKU:s in order to gain benefits of both OPS. Third, success of such an automation project will depend on staged implementation and clear ownership rather than on hardware alone. High investments, skill gaps and a disruptive learning curve are the main short term obstacles. A pilot project, super-user training and temporary safety stock are potential risk mitigating actions. Finally, the order history analysis showed that a small, densely packed subset of SKU pairs accounts for about 85% of all picks and forms a number of natural high-runner clusters. Placing those clusters in close proximity to the start of the picking route in the same level on VLM would capture much of the travel and space saving benefit while the remaining assortment in existing racks and in VLMs in close proximity. In other words, the data confirms that a phased, cluster driven VLM project is suitable. It targets the items that matter and preserves manual flexibility for awkward or uncertain future parts.

8. References

AbdelGawad, A. F. (2015). Multidisciplinary engineering for the utilization of traditional automated storage and retrieval system (ASRS) for firefighting in warehouses. *American Journal of Energy Engineering, 3*(4-1), 1-22. https://doi.org/10.11648/j.ajee.s.2015030401.11

Al Shehhi, S., King, N., Amer, S., & Mohammad, J. (2019). Modeling the ergonomics of Goods-to-Man order picking. 2019 *IIE Annual Conference*, 620-625.

Anđelković, A., & Radosavljević, M. (2018). Improving order-picking process through implementation of warehouse management system. *Strategic Management, 23*(1), 3-10.

Arnold, D., Isermann, H., Kuhn, A,. Tempelmeier, H., & Furmans, K. (Eds.) (2008). *Handbuch Logistik*. Heidelberg: Springer-Verlag.

Azadeh, K., De Koster, R. B. M., & Roy, D. (2017). Robotized and automated warehouse systems: Review and recent developments. *SSRN Electronic journal*. https://dx.doi.org/10.2139/ssrn.2977779

Baker, P., & Halim, Z. (2007). An exploration of warehouse automation implementations: cost, service and flexibility issues. *Supply Chain Management, 12*(2), 129-138. https://doi.org/10.1108/13598540710737316

Bartholdi, J. J. III., & Hackman, S. T. (2017). *Warehouse & distribution science* (Release 0.98). The Supply Chain & Logistics Institute, Georgia Institute of Technology. http://www.warehouse-science.com/

Battini, D., Calzavara, M., Persona, A., & Sgarbossa, F. (2015a). A comparative analysis of different paperless picking systems. *Industrial Management & Data Systems, 115*(3), 483-503. https://doi.org/10.1108/IMDS-10-2014-0314

Battini, D., Calzavara, M., Persona, A., & Sgarbossa, F. (2015b). Linking human availability and ergonomics parameters in order-picking systems. *IFAC-PapersOnLine, 48*(3), 345-350. https://doi.org/10.1016/j.ifacol.2015.06.105

Battini, D., Calzavara, M., Persona, A., & Sgarbossa, F. (2016). *Dual-tray vertical lift modules for fast order picking* [Paper presentation]. 14th IMHRC Proceedings. Karlsruhe, Germany.

Baudin, M. (2004). Lean logistics: *The nuts and bolts of delivering materials and goods*. Productivity Press.

Beamon, B. M. (1999). Measuring supply chain performance. *International Journal of Operations & Production Management, 19*(3), 275-292. https://doi.org/10.1108/01443579910249714

Benson, D. (2008). *Storage Space Utilization.* Retrieved May 2, 2025, from http://www.warehousecoach.com/images/Storage_Space_Utilization.pdf

Bertke, A., Cedeno, M., & Pierre, D. (2024). *Vertical carousel storage system.* [Senior Design Report, University of Southern Indiana]. University of Southern Indiana David L. Rice Library. https://doi.org/10.58090/usi.1565557

Bitterling, C., Koreis, J., Loske, D., & Klumpp, M. (2022). Comparing manual and automated production and picking systems. *Hamburg International Conference of Logistics (HICL) 2022*, 327-350. Hamburg, Germany.

Borasi, P., Yogendra, B., & Sumant, O. (2022). *Warehouse automation systems market size, share, competitive landscape and trend analysis report* (Report No. A31490). AlliedMarketResearch. https://www.alliedmarketresearch.com/warehouse-automation-systems-market-A31490

Bottin, M., Faccio, M., Minto, R., & Rosati, G. (2021). Sales kit automated production: An integrated procedure for setup reduction in case of high products variety. *Applied Sciences, 11*(21), Article 10110. https://doi.org/10.3390/app112110110

Buley, D. T., & Knott, K. (1986). Designing vertical carousels to maximize operator utilization. *Computers & Industrial Engineering, 11*(1-4), 271-275. https://doi.org/10.1016/0360-8352(86)90092-6

Cai, X., Heragu, S. S., & Liu, Y. (2014). Modeling and evaluating the AVS/RS with tier-to-tier vehicles using a semi-open queuing network. *IIE Transactions, 46*(9), 905-952. https://doi.org/10.1080/0740817X.2013.849832

Calzavara, M., Glock, C. H., Grosse, E. H., Persona, A., & Sgarbossa, F. (2016). Models for an ergonomic evaluation of order picking from different rack layouts. *IFAC-PapersOnLine, 49*(12), 1715-1720. https://doi.org/10.1016/j.ifacol.2016.07.829

Calzavara, M., Sgarbossa, F., & Persona, A. (2019). Vertical lift modules for small items order picking: an economic evaluation. *International Journal of Production Economics, 210*, 199-210. https://doi.org/10.1016/j.ijpe.2019.01.012

Chan, F. T. S., & Chan, H. K. (2011). Improving the productivity of order picking of a manual-pick and multi-level rack distribution warehouse through the implementation of class-based storage. *Expert Systems with Applications, 38*(3), 2686-2700. https://doi.org/10.1016/j.eswa.2010.08.058

Chuang, Y.-F., Lee, H.-T., & Lai, Y.-C. (2012). Item-associated cluster assignment model on storage allocation problems. *Computers & Industrial Engineering, 63*(4), 1171-1177. https://doi.org/10.1016/j.cie.2012.06.021

Dallari, F., Marchet, G., & Melacini, M. (2009). Design of order picking system. *International Journal of Advanced Manufacturing Technology, 42*, 1-12. https://doi.org/10.1007/s00170-008-1571-9

De Koster, R. B. M., Le-Duc, T., & Roodbergen, K. J. (2007). Design and control of warehouse order picking: A literature review. *European Journal of Operational Research, 182*(2), 481-501. https://doi.org/10.1016/j.ejor.2006.07.009

De Koster, R. B. M. (2018). Automated and robotic warehouses: Developments and research opportunities. *Logistics and Transport, 38*(2), 33-40. https://doi.org/10.26411/83-1734-2015-2-38-4-18

De Lombaert, T., Braekers, K., De Koster, R. B. M., & Ramaekers, K. (2024). What makes order picking so physically demanding? - Ergonomic evidence from a large-scale lab experiment using subjective metrics. *IFAC-PapersOnLine, 58*(19), 181-186. https://doi.org/10.1016/j.ifacol.2024.09.139

Deepika, M., & Vinoline, I. A. (2025). An integrated warehouse system using AS/RS (Automated storage and retrieval) technology. *Indian Journal of Science and Technology, 18*(13), 1038-1045. https://doi.org/10.17485/IJST/v18i13.178

Dibekulu, D. (2020). An overview of data analysis and interpretations in research. *International Journal of Academic Research in Education and Review, 8*(1), 1-27. https://doi.org/10.14662/IJARER2020.015

Döllinger, A., & Larsson, T. (2016). *Selection of automated order picking systems: Automated storage and retrieval within contract logistics.* [Master's thesis, Chalmers University of Technology]. Chalmers Open Digital Repository. https://hdl.handle.net/20.500.12380/236636

Đukić, G., Opetuk, t., & Gajšek, B. (2021). *Space, Time and Ergonomic Assessment of Order Picking Using Horizontal Carousel* [Paper presentation]. Proceedings of the 8th International Ergonomics Conference: ERGONOMICS 2020, Zagreb, Croatia. https://doi.org/10.1007/978-3-030-66937-9_9

Đukić, G., Opetuk, T., & Lerher, T. (2015). A throughput model for a dual-tray vertical lift module with a human order-picker. *International Journal of Production Economics, 170*, 874-881. https://doi.org/10.1016/j.ijpe.2015.04.009

Farioli, M., Bianco, D., Baglio, M., Creazza, A., & Dallari, F. (2024). Order picking technologies as a catalyst for social sustainability in warehouses: Synergies between ergonomics and automation. XXIX Summer School "Francesco Turco" – Industrial Systems Engineering.

Feldmann, F., Seitz, R., Kretschmer, V., Bednorz, N., & Hompel, M. T. (2019). Ergonomic evaluation of body postures in order picking systems using motion capturing [Conference Paper]. 2019 Prognostics and System Health Management Conference-Paris, 204-209. https://doi.org/10.1109/PHM-Paris.2019.00041

Finco, S., Ashta, G., Persona, A., & Zennaro, I. (2023). Investigating different manual picking workstations for robotized and automated warehouse systems: Trade-offs between ergonomics and productivity aspects. *Computers & Industrial Engineering, 185*, Article 109668. https://doi.org/10.1016/j.cie.2023.109668

Gabriel-Santos, A., Rolla, J., Martinho, A., Fradinho, J., Gonçalves-Coelho, A., & Mourão, A. (2016). The rational footsteps for the design of the mechanism of a vertical carousel-type storage device. *Procedia CIRP, 53*, 193-197. https://doi.org/10.1016/j.procir.2016.06.025

Granlund, A., & Friedler, N. (2012). *A model for the formulation of an automation strategy*. [Paper presentation]. 4th World Conference P&OM, Amsterdam, the Netherlands.

Granlund, A., & Wiktorsson, M. (2014). Automation in internal logistics: Strategic and operational challenges. *International Journal of Logistics Systems and Management, 18*(4), 538-558. https://doi.org/10.1504/IJLSM.2014.063984

Grosse, E. H., Glock, C. H., & Jaber, M. Y. (2013). The effect of worker learning and forgetting on storage reassignment decisions in order picking systems. *Computer & Industrial Engineering, 66*(4), 653-662. https://doi.org/10.1016/j.cie.2013.09.013

Grosse, E. H., Glock, C. H., & Neumann, W. P. (2017). Human factors in order picking: a content analysis of the literature. *International Journal of Production Research, 55*(5), 1260-1275. http://dx.doi.org/10.1080/00207543.2016.1186296

Hamberg, R., & Verriet, J. (Eds.). (2012). *Automation in Warehouse Development*. Springer London. https://doi.org/10.1007/978-0-85729-968-0

Hanson, R., Medbo, L., & Johansson, M. I. (2018). Performance characteristics of robotic mobile fulfilment systems in order picking applications. *IFAC-PapersOnLine, 51*(11), 1493-1498. https://doi.org/10.1016/j.ifacol.2018.08.290

He, M., Guan, Z., Wang, C., & Hou, G. (2023). Multiple-rack strategies using optimization of location assignment based on MRCGA in miniload automated storage and retrieval system. *Processes, 11*(3), 950. https://doi.org/10.3390/pr11030950

Heragu, S. S., Cai, X., Krishnamurthy, A., & Malmborg, C. J. (2011). Analytical models for analysis of automated warehouse material handling systems. *International Journal of Production Research, 49*(22), 6833-6861. https://doi.org/10.1080/00207543.2010.518994

Hikmawati, E., Maulidevi, N. U., & Surendro, K. (2021). Minimum threshold determination method based on dataset characteristics in association rule mining. *Journal of Big Data, 8,* article 146 (2021). https://doi.org/10.1186/s40537-021-00538-3

Hompel M., & Schmidt T. (2007). *Warehouse Management - Automation and Organisation of Warehouse and Order Picking Systems*. New York: Springer-Verlag Berlin Heidelberg.

Hou, H., Chaudhry, S., Chen, Y., & Hu, M. (2017). Physical distribution, logistics, supply chain management, and the material flow theory: a historical perspective. *Information Technology and Management, 18*, 107-117. https://doi.org/10.1007/s10799-015-0229-1

Huang, G. Q., Chen, M. Z. Q., & Pan, J. (2015). Robotics in ecommerce logistics. *HKIE transactions, 22*(2), 68-77. http://dx.doi.org/10.1080/1023697X.2015.1043960

Jaghbeer, Y. (2019). *On the performance of robotic parts-to-picker order picking systems.* [Licentiate thesis, Chalmers University of Technology]. Chalmers Open Digital Repository. https://research.chalmers.se/en/publication/513777

Jaghbeer, Y., Hanson, R., & Johansson, M. I. (2020). 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

Jane, C. -C., & Laih, Y. -W. A clustering algorithm for item assignment in a synchronized zone order picking system. *European Journal of Operational Research, 166*(2), 489-496. https://doi.org/10.1016/j.ejor.2004.01.042

Johansson, H., & Persson, A. (2023). *Selecting the right warehouse automation solution: A decision-making framework based on qualifying and comparable factors.* [Master's thesis, Chalmers University of Technology]. Chalmers Open Digital Repository. http://hdl.handle.net/20.500.12380/306188

Jukić, N., & Nestorov, S. (2006). Comprehensive data warehouse exploration with qualified association-rule mining. *Decision Support Systems, 42*(2), 859-878. https://doi.org/10.1016/j.dss.2005.07.009

Kardex. (n.d.). *Kardex Shuttle Hissautomater*. Retrieved May 2, 2025, from https://info.kardex.com/sv/ppc/general/shuttle/kr/neeu

Kotu, V., & Deshpande, B. (2019). Association Analysis. In *Data Science: Concepts and Practice* (2nd ed., pp. 199-220). Elsevier Science & Technology. https://doi.org/10.1016/B978-0-12-814761-0.00006-X

Kusrini, E., Novendri, F., & Helia, V. N. (2018, September 13-14). *Determining key performance indicators for warehouse performance measurement – a case study in construction materials warehouse* [Paper presentation]. MATEC Web of Conferences, Volume 154 (2018) 01058. Yogyakarta, Indonesia. https://doi.org/10.1051/matecconf/201815401058

Labus, N., & Gajšek, B. (2018). Use of ergonomic principles in manual order picking systems. *Logistics & Sustainable Transport, 9*(1), 11-22. https://doi.org/10.2478/jlst-2018-0002

Lawrenz, F., Keiser, N., & Lavoie, B. (2003). Evaluative Site Visits: A Methodological Review. *American Journal of Evaluation, 24*(3), 341–352. https://doi.org/10.1016/j.ameval.2003.08.003

Lee, J. A., Chang, Y. S., & Choe, Y. H. (2018). Assessment and comparison of human-robot co-work order picking systems focused on ergonomic factors [Conference Paper]. *Advances* *in Safety Management and Human Factors, 604*, 516-523. https://doi.org/10.1007/978-3-319-60525-8_53

Lee, J. A., Chang, Y. S., & Karwowski, W. (2020). Assessment of working postures and physical loading in advanced order picking tasks: A case study of human interaction with automated warehouse goods-to-picker systems. *WORK, 67*(4), 855-866. https://doi.org/10.3233/WOR-203337

Lee, J. A., Chang, Y. S., Shim, H. J., & Cho, S. J. (2015). A study on the picking process time. *Procedia Manufacturing, 3*, 731-738. https://doi.org/10.1016/j.promfg.2015.07.316

Lehmusto, R. (2024). *Optimizing warehouse operations: ABC analysis and strategic enhancements for case company.* [Bachelor thesis, Metropolia University of Applied Sciences]. THESEUS. https://www.theseus.fi/handle/10024/860268?show=full

Lerher, T., Šraml, M. & Potrč, I. (2011). Simulation analysis of mini-load multi-shuttle automated storage and retrieval systems. *The International Journal of Advanced Manufacturing Technology, 54*, 337-348. https://doi.org/10.1007/s00170-010-2916-8

Li, Y., & Li, Z. (2022). Shuttle-based storage and retrieval system: A literature review. (2022). *Sustainability, 14*(21), article 14347. https://doi.org/10.3390/su142114347

Litvak, N., & Vlasiou, M. (2010). A survey on performance analysis of warehouse carousel systems. *Statistica Neerlandica, 64*(4), 367-511. https://doi.org/10.1111/j.1467-9574.2010.00454.x

Loske, D., Klumpp, M., Keil, M., & Neukirchen, T. (2021). Logistics Work, Ergonomics and Social Sustainability: Empirical Musculoskeletal System Strain Assessment in Retail Intralogistics. *Logistics, 54*(9), 89. https://doi.org/10.3390/logistics5040089

Loske, D. (2022). Empirical evidence on human learning and work characteristics in the transition to automated order picking. *Journal of Business Logistics, 43*(3), 291-412. https://doi.org/10.1111/jbl.12300

Mathers, N., Fox, N. J., & Hunn, A. (2000). Using interviews in a research project. In *Research Approaches in Primary Care* (pp. 113-134). Radcliffe Publishers.

Marchet, G., Melacini, M., & Perotti, S. (2015). Investigating order picking system adoption: a case-study-based approach. *International Journal of Supply Chain Management, 18*(1), 82-98. https://doi.org/10.1080/13675567.2014.945400

Novara, V. (2020). *A new decision making tool for automated industrial storage systems selection.* [Master's thesis, Politecnico di Torino]. Webthesis Libraries. https://webthesis.biblio.polito.it/16394/

Nydick, R. L., & Hill, R. P. (1992). Using the analytic hierarchy process to structure the supplier selection procedure. *International Journal of Purchasing and Materials Management, 28*(2), 31-36. https://doi.org/10.1111/j.1745-493X.1992.tb00561.x

Petersen, C. G. (2002). Considerations in order picking. *International Journal of Operations & Production Management, 22*(7), 793-805. https://doi.org/10.1108/01443570210433553

Racca, S. D. (2015). *Improving operational efficiency of a semiconductor equipment manufacturing warehouse through effective utilization of Vertical Lift Modules* [Master's thesis, Massachusetts Institute of Technology]. MIT DSpace. https://dspace.mit.edu/handle/1721.1/101335

Rana, J., Gutierrez, P. L., Oldroyd, J. C. (2021). Quantitative Methods. In Farazmand, A. (Ed.), *Global Encyclopedia of Public Administration, Public Policy, and Governance*. Springer, Cham. https://doi.org/10.1007/978-3-319-31816-5_460-1

Rosenwein, N. B. (1994). An application of cluster analysis to the problem of locating items within a warehouse, *IIE Transactions, 26*(1), 101-103. https://doi.org/10.1080/07408179408966588

Simões, M. J. (2023). *Operational research models for kitting systems in the warehouse of the future* [Master's thesis, Universidade de Coimbra]. Estudo Geral. https://hdl.handle.net/10316/110833

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research, 104*, 333-339. https://doi.org/10.1016/j.jbusres.2019.07.039

Southern, R. N. (2011). Historical perspective of the logistics and supply chain management discipline. *Transportation Journal, 50*(1), 53-64. https://doi.org/10.5325/transportationj.50.1.0053

SSI Schäfer. (n.d.). *Scalable Material Handling for Every Taste*. Retrieved May 2, 2025, from https://www.ssi-schaefer.com/sv-se/scalable-material-handling-for-every-taste-1256904

Staudt, F. H., Alpan, G., Di Mascola, M., & Rodriguez, C. M. T. (2015). Warehouse performance measurement: a literature review. *International Journal of Production Research, 53*(18), 5524-5544. https://doi.org/10.1080/00207543.2015.1030466

Swedish UN Association. (2023, February). Goal 8: Decent work and economic growth [PDF]. UN Association of Sweden. https://fn.se/wp-content/uploads/2023/02/Ma%CC%8Al-8-Ansta%CC%88ndiga-arbetsvillkor-och-ekonomisk-tillva%CC%88xt.pdf

Swisslog. (n.d.). *Mini-load AS/RS systems for smaller items storage*. Retrieved May 2, 2025, from https://www.swisslog.com/en-us/knowledge/mini-load-asrs-systems

Vaidya, O. S., & Kumar, S. (2006). Analytic hierarchy process: An overview of applications. *European Journal of Operational Research, 169*(1), 1-29. https://doi.org/10.1016/j.ejor.2004.04.028

van den Berg, J. P., & Zijm, W. H. M. (1999). Models for warehouse management: Classification and examples. *International Journal of Production Economics, 59*(1-3), 519-528. https://doi.org/10.1016/S0925-5273(98)00114-5

Van der Gaast, J. P., De Koster, R. B. M., Adan, I. J. B. F., & Resing, J. A. C. (2019). Capacity analysis of sequential zone picking systems. *Operations Research, 68*(1), 161-179. https://doi.org/10.1287/opre.2019.1885

Van Gils, T., Ramaekers, K., Caris, A., & De Koster, R. B. M. (2018). Designing efficient order picking systems: State-of-the-art classification and review. *European Journal of Operational Research, 267*(1), 1-15. https://doi.org/10.1016/j.ejor.2017.09.002

Vargas, L. G. (1990). An overview of the analytical hierarchy process and its applications. *European Journal of Operational Research, 48*, 2-8. https://doi.org/10.1016/0377-2217(90)90056-H

Winroth, M. P., Säfsten, K., & Stahre, J. (2007). Automation strategies: Existing theory or ad hoc decisions? *International Journal of Manufacturing Technology and Management, 11*(1), 98-114. https://doi.org/10.1504/IJMTM.2007.012448

Zhang, M., Grosse, E. H., Glock, C. H. (2023). Ergonomic and economic evaluation of a collaborative hybrid order picking system. *International Journal of Production Economics, 258*, article 108774. https://doi.org/10.1016/j.ijpe.2023.108774

Zhou, L., Sun, L., Li, Z., Li, W., Cao, N., & Higgs, R. (2020). Study on a storage location strategy based on clustering and association algorithms. *Soft Computing, 24*, 5499-5516. https://doi.org/10.1007/s00500-018-03702-

Appendix A - Tables for AHP calculations

Due to rounding, the sum of priorities may not equal exactly 1.000.

THROUGHPUT	Manual	VLM	Ver. Car	Hor. Car	Miniload
Manual	1	1/5	1/4	1/4	1/7
VLM	5	1	2	2	1/3
Ver. Car	4	1/2	1	1	1/4
Hor. Car	4	1/2	1	1	1/4
Miniload	7	3	4	4	1
Column Totals	*21*	*26/5*	*33/4*	*33/4*	*83/42*

THROUGHPUT - adjusted	Manual	VLM	Ver. Car	Hor. Car	Miniload	Row Average
Manual	1/21	1/26	1/33	1/33	6/83	*0.044*
VLM	5/21	5/26	8/33	8/33	14/83	*0.217*
Ver. Car	4/21	5/52	4/33	4/33	21/166	*0.131*
Hor. Car	4/21	5/52	4/33	4/33	21/166	*0.131*
Miniload	7/21	15/26	16/33	16/33	42/83	*0.477*
					Total	***1.000***

COST	Manual	VLM	Ver. Car	Hor. Car	Mini-load
Manual	1	2	3	3	4
VLM	1/2	1	2	2	3
Ver. Car	1/3	1/2	1	2	2
Hor. Car	1/3	1/2	1/2	1	2
Mini-load	1/4	1/3	1/2	1/2	1
Column Totals	*29/12*	*13/3*	*7*	*17/2*	*12*

COST - adjusted	Manual	VLM	Ver. Car	Hor. Car	Mini-load	Row Average
Manual	12/29	6/13	3/7	6/17	1/3	*0.398*
VLM	6/29	3/13	2/7	4/17	1/4	*0.242*
Ver. Car	4/29	3/26	1/7	4/17	1/6	*0.160*
Hor. Car	4/29	3/26	1/14	2/17	1/6	*0.122*
Mini-load	3/29	1/13	1/14	1/17	1/12	*0.079*
					Total	***1.001***

QUALITY	Manual	VLM	Ver. Car	Hor. Car	Mini-load
Manual	1	1/2	1/2	1/2	1/3
VLM	2	1	2	2	1/2
Ver. Car	2	1/2	1	2	1/2
Hor. Car	2	1/2	1/2	1	1/3
Mini-load	3	2	2	3	1
Column Totals	*10*	*9/2*	*6*	*17/2*	*8/3*

QUALITY - adjusted	Manual	VLM	Ver. Car	Hor. Car	Mini-load	Row Average
Manual	1/10	1/9	1/12	1/17	1/8	*0.096*
VLM	1/5	2/9	1/3	4/17	3/16	*0.236*
Ver. Car	1/5	1/9	1/6	4/17	3/16	*0.180*
Hor. Car	1/5	1/9	1/12	2/17	1/8	*0.127*
Mini-load	3/10	4/9	1/3	6/17	3/8	*0.361*
					Total	***1.000***

SPACE UTILISATION	Manual	VLM	Ver. Car	Hor. Car	Mini-load
Manual	1	1/6	1/5	1/3	1/7
VLM	6	1	3	4	1/2
Ver. Car	5	1/3	1	2	1/3
Hor. Car	3	1/4	1/2	1	1/3
Mini-load	7	2	3	3	1
Column Totals	*22*	*15/4*	*77/10*	*31/3*	*97/42*

Space Utilisation. - adjusted	Manual	VLM	Ver. Car	Hor. Car	Mini-load	Row Average
Manual	1/22	2/45	2/77	1/31	6/97	*0.042*
VLM	3/11	4/15	30/77	12/31	21/97	*0.307*
Ver. Car	5/22	4/45	10/77	6/31	14/97	*0.157*
Hor. Car	3/22	1/15	5/77	3/31	14/97	*0.102*
Mini-load	7/22	8/15	30/77	9/31	42/97	*0.393*
					Total	***1.001***

FLEXIBILITY	Manual	VLM	Ver. Car	Hor. Car	Mini-load
Manual	1	4	5	4	6
VLM	1/4	1	2	2	4
Ver. Car	1/5	1/2	1	2	3
Hor. Car	1/4	1/2	1/2	1	3
Mini-load	1/6	1/4	1/3	1/3	1
Column Totals	*28/15*	*25/4*	*53/6*	*28/3*	*17*

Flexibility - adjusted	Manual	VLM	Ver. Car	Hor. Car	Mini-load	Row Average
Manual	15/28	16/25	30/53	3/7	6/17	*0.505*
VLM	15/112	4/25	12/53	3/14	4/17	*0.194*
Ver. Car	3/28	2/25	6/53	3/14	3/17	*0.138*
Hor. Car	15/112	2/25	3/53	3/28	3/17	*0.111*
Mini-load	5/56	1/25	2/53	1/28	1/17	*0.052*
					Total	***1.000***

SCALABILITY	Manual	VLM	Ver. Car	Hor. Car	Mini-load
Manual	1	1/5	1/5	1/4	1/3
VLM	5	1	1	2	3
Ver. Car	5	1	1	2	2
Hor. Car	4	1/2	1/2	1	2
Mini-load	3	1/3	1/2	1/2	1
Column Totals	18	91/30	16/5	23/4	25/3

Scalability - adjusted	Manual	VLM	Ver. Car	Hor. Car	Mini-load	Row Average
Manual	1/18	6/91	1/16	1/23	1/25	*0.053*
VLM	5/18	30/91	5/16	8/23	9/25	*0.326*
Ver. Car	5/18	30/91	5/16	8/23	6/25	*0.302*
Hor. Car	2/9	15/91	5/32	4/23	6/25	*0.191*
Mini-load	1/6	10/91	5/32	2/23	3/25	*0.128*
					Total	***1.000***

ERGONOMICS	Manual	VLM	Ver. Car	Hor. Car	Mini-load
Manual	1	1/6	1/5	1/3	1/6
VLM	6	1	2	3	1
Ver. Car	5	1/2	1	2	1/2
Hor. Car	3	1/3	1/2	1	1/3
Mini-load	6	1	2	3	1
Column Totals	*21*	*3*	*57/10*	*28/3*	*3*

Ergonomics - adjusted	Manual	VLM	Ver. Car	Hor. Car	Mini-load	Row Average
Manual	1/21	1/18	2/57	1/28	1/18	*0.046*
VLM	2/7	1/3	20/57	9/28	1/3	*0.325*
Ver. Car	5/21	1/6	10/57	6/28	1/6	*0.192*
Hor. Car	1/7	1/9	5/57	3/28	1/9	*0.112*
Mini-load	2/7	1/3	20/57	9/28	1/3	*0.325*
					Total	***1.000***

Appendix B - AHP Questionnaire

The questionnaire is translated from Swedish.

AHP or Analytical Hierarchy Process is a decision-making tool where several alternatives are compared against each other in different criteria. AHP formalises such a decision, and can be used to identify the overall 'best' option.

In our report, we want to use AHP to compare the different order picking automation solutions with each other and with the current manual system. An order picking system can be evaluated from many different aspects, or KPIs, and we have identified those we believe are most relevant. The input we need from you is answers to 28 comparisons: "*Which of the following two KPIs is most important, and how much more important?*". Each KPI needs to be compared to every other KPI, and a number needs to be set. The scale used is 1-9, where 1 means that the two KPIs are equally important and 9 means that one is extremely more important than the other. If **A** is compared to **B**, and it is determined that **A** is much more important than **B**, a 6 is written. The table below gives a more concrete definition of the scale. Note that even numbers can be used as intermediate levels.

Verbal preference level	Numerical Rating
Extremely preferred	9
Very strongly preferred	7
Strongly preferred	5
Moderately preferred	3
Equally preferred	1

The various KPIs we have identified as most relevant are the following, with definitions:

- **Throughput**
  - *Number of order lines picked per hour per picker.*
- **Cost**
  - *Total cost related to order picking, including*
    - *Operative costs, salaries*
    - *Investment and installation*
    - *Maintenance*
    - *Storage costs*
  - *Both short term and long term*
- **Quality**
  - *Order picking accuracy, number of wrong picks*
- **Picking productivity**
  - *Number of order lines per hour per worker*

- **Space Utilisation**
  - *How efficiently space is used, item density*
- **Scalability**
  - *How easy it is to change the capacity without major investments or disruptions*
- **Flexibility**
  - *How easily the system can adapt to change in*
    - *SKU assortment*
    - *Order sizes*
    - *Workload*
    - *Layout, processes*
- **Ergonomics**
  - *Heavy picks, twisting, walking distances, weird angles, noise*

For each row, which KPI is most important and how much more important?
Row 1 - Example: **A** is more important than **B**, we write **A**. **A** is much more important than **B**, we write 6.

Performance measurement 1	Performance measurement 2	Most important	Value (1-9)
A	*B*	**A**	**6**
Throughput	*Cost*		
Throughput	*Quality*		
Throughput	*Space utilisation*		
Throughput	*Scalability*		
Throughput	*Flexibility*		
Throughput	*Ergonomics*		
Cost	*Quality*		
Cost	*Space Utilisation*		
Cost	*Scalability*		
Cost	*Flexibility*		
Cost	*Ergonomics*		
Quality	*Space utilisation*		
Quality	*Scalability*		

Quality	*Flexibility*		
Quality	*Ergonomics*		
Space utilisation	*Scalability*		
Space utilisation	*Flexibility*		
Space utilisation	*Ergonomics*		
Scalability	*Flexibility*		
Scalability	*Ergonomics*		
Flexibility	*Ergonomics*		

Appendix C - AHP Calculations

The final score is calculated for each column by multiplying the two values for each performance aspect seen by row. The above number represents the relative importance weight of the performance aspect, and the below number represents how well the OPS performs in that performance aspect. All products in each column are summed together, resulting in a final score.

	Manual	VLM	Ver. Car.	Hor. Car.	Mini-load	
Throughput	0.040	0.040	0.040	0.040	0.040	
	0.044	0.217	0.131	0.131	0.477	
Cost	0.117	0.117	0.117	0.117	0.117	
	0.398	0.242	0.160	0.122	0.079	
Quality	0.190	0.190	0.190	0.190	0.190	
	0.096	0.236	0.180	0.127	0.361	
Space Utilisation	0.080	0.080	0.080	0.080	0.080	
	0.042	0.307	0.157	0.102	0.393	
Scalability	0.175	0.175	0.175	0.175	0.175	
	0.053	0.326	0.302	0.191	0.128	
Flexibility	0.351	0.351	0.351	0.351	0.351	
	0.505	0.194	0.138	0.111	0.052	
Ergonomics	0.047	0.047	0.047	0.047	0.047	
	0.046	0.325	0.192	0.112	0.325	Total
FINAL SCORE	**0.259**	**0.247**	**0.181**	**0.129**	**0.184**	1.000

Appendix D - Cluster Analysis

Below is the table for the cluster analysis. For each cluster there is a specified amount of items ranging from 2 to 9. For each cluster, a score is attached at the bottom.

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8	Cluster 9	Cluster 10
21628160	24003010	3830315	23561737	23677974	23407162	23541766	24125543	3842736	874923
21785135	21653609	21875622	24125545	24016551	24149050	23407159	24057030	3841173	874926
3886666	23248806		21475509	23131607	21227460	23378774	23541765		22499270
22919882	23858830		24037523	24183022	21415883	21856864	23403753		21628159
22919880	23858145		23006233	23254177	21545067	23985529	23407157		874921
22303438	3819448		22793140	23346938	21172469	24252971	22735466		881658
3594745	23677976		23282613	23749674	24050636	23561740	22944322		874733
22919878	23097783		23576708	22828897	23408461	24293044	3587054		874732
874708	23346939		23407160	23249351	23958027	40869732	23282612		3812911
Score: 4.46	Score: 10.20	Score: 0.00	Score: 8.74	Score: 3.13	Score: 3.55	Score: 1.04	Score: 3.70	Score: 0.03	Score: 7.15
Cluster 11	**Cluster 12**	**Cluster 13**	**Cluster 14**	**Cluster 15**	**Cluster 16**	**Cluster 17**	**Cluster 18**	**Cluster 19**	
23778270	24462929	23218537	23562900	21825714	24469186	3812914	874910	23799729	
21380883	24247491	24011652	877763	23407166	23172846	874844	3812881	21825665	
3885841	21939134	23365705	3807229	21509941	23403770	874843	874709		
21628157	23097552	3588206	23719512	21166002	24238743	23612568	874904		
3885840	23749675	24383484	23473023	23897436	23378562	874914	874386		
24282381	22349354	24412641	23510263	22805082	23515697	23904660	874908		
877765	22964039	24510291	23943063	874119	23385770	24410897	874915		
23561736	22693690		21145832	21421945	22396880	21469055	874913		
23839701	23677975		21967719	21330289	22396881	23558208	881649		
Score: 4.08	Score: 5.05	Score: 1.36	Score: 5.77	Score: 8.05	Score: 12.95	Score: 2.24	Score: 3.47	Score: 0.00	
Cluster 20	**Cluster 21**	**Cluster 22**	**Cluster 23**	**Cluster 24**	**Cluster 25**	**Cluster 26**	**Cluster 27**	**Cluster 28**	
3841706	21693206	23561734	23521191	23538042	22479650	23403757	24149051	24462949	
21227463	23403760	24273877	23551752	22919892	22805175	23378772	24210710	23131605	
	22856097	23561741		21576250		23561565	23988166	22693691	
	21469024	23844764		22919874		24125544	23985524	24637761	
	23403751	21875623				24410956	24050633	21664320	
	24037521	22728820				23558209	23219830	3826400	
	23378558	24382289				23407158	24166836	22734116	
	23385773	23475175				23417158	3840677	23398081	
	21475508	23542453				23410287	21227462	23268324	
Score: 0.00	Score: 4.25	Score: 2.04	Score: 0.05	Score: 0.15	Score: 0.00	Score: 6.63	Score: 2.92	Score: 4.17	
Cluster 29	**Cluster 30**	**Cluster 31**	**Cluster 32**	**Cluster 33**	**Cluster 34**	**Cluster 35**	**Cluster 36**	**Cluster 37**	
3825000	22805083	23840725	21575479	3842734	22739429	24596129	3889410	23930878	
23399343	23851420	23979108	23403762	3888589	22797159	24645984	24293060	24293070	
23408454	23513691	23095840	21693202	24180372	22757067	24739523	874759	23363145	
23904669	23513812	843410	22067251	23602509	22815614	24596128		22690795	
21655254	22734117	24037531	24307790	23561738	24122510	3842735			
	21939135	23894229	23561739	23407167		24141904			
	23902940	22499273	23551755	3842737					
	23513709	23411820	1140669	24137105					
		24122509	21734577						
Score: 0.10	Score: 5.66	Score: 1.59	Score: 1.67	Score: 1.26	Score: 1.65	Score: 4.08	Score: 0.00	Score: 1.10	

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