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Determining the Optimal Level of Automation for Order-Picking Systems: A FUCOM-Based Case Study

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Abstract

Manual order-picking systems (OPS) often suffer from inefficiencies that manifest as the seven forms of lean waste, including motion, defects, over-processing, and waiting. Consequently, order-picking accounts for approximately 55% of warehouse operational costs and 30–40% of total operational time. Automation emerges as a promising solution, yet its broad scope and diverse trade-offs leave businesses uncertain about where to begin or how to determine the right level of investment. This study addresses these challenges by classifying the levels of automation (LOA) in OPS into three categories: 1) digitalized picking, 2) robot-assisted picking, and 3) fully automated picking. Each category is explored in depth, highlighting the technologies and their applications. Furthermore, a decision-making framework is proposed based on the Full-Consistency Method (FUCOM) to guide businesses in selecting the optimal LOA tailored to their specific requirements. This framework is demonstrated through a case study on a direct-to-consumer foodtech startup, where criteria such as cost and infrastructure flexibility were prioritized, resulting in the selection of digitalized picking. The main contribution of this study is the clear classification of automation levels in OPS and a practical decision-making framework to guide businesses in optimizing their operations. This research concludes by recommending lean automation as an area for future research, emphasizing its importance in ensuring the selected LOA will not introduce waste during any phase of implementation.

Keywords
Order-Picking Systems, Warehouse Automation, Full-Consistency Method

1. Introduction

Order-picking is a critical warehouse activity that involves locating, retrieving, and moving requested items to a designated area for verification and delivery (Pinto et al., 2023a). This process is labor-intensive and costly, accounting for approximately 55% of warehouse operational expenses and 30–40% of total operational time (de Koster et al., 2007). In manual warehouses, these challenges are even more pronounced due to the inherent variability in human performance; human workers cannot be expected to consistently follow specific routes, maintain constant walking speeds, or restrain from social interactions with coworkers. Additionally, humans are prone to errors, which further delays the process (Lesch et al., 2021). These inefficiencies present themselves as the seven forms of lean waste – unnecessary motion, waiting, overproduction, overprocessing, defects, excess inventory, and underutilized employee talent (Lin, 2010).

Despite significant advancements in Industry 4.0 technologies, manual order-picking systems remain prevalent, with many warehouses still fully relying on human operators for this task (Silva et al., 2024). Among the key barriers to automation adoption is the phenomenon of “analysis paralysis”, wherein businesses face an overwhelming array of technological solutions and struggle to determine the most suitable approach. This uncertainty hinders decision-making, often constraining companies to the inefficiencies of their manual operations despite their willingness to invest in automation.

This research addresses this gap by reviewing state-of-the-art technologies for warehouse automation and categorizing them into distinct levels of automation (LOA). The study also introduces a decision-making framework based on the Full Consistency Method (FUCOM) to help businesses determine the most appropriate level of automation for their specific requirements (Pamučar et al., 2018). To demonstrate the practical application of this framework, the research examines a case study on a direct-to-consumer healthy meal plan provider, with the aim of guiding similar businesses in navigating the complexities of warehouse automation and helping them make informed decisions that enhance efficiency and support their long-term goals.

1.1 Objectives

This research aims to provide a comprehensive review of the levels of automation (LOA) for order-picking systems, examining the technologies associated with each category. It also seeks to develop a decision-making framework using the FUCOM approach to assist businesses in selecting the optimal LOA based on their unique requirements and objectives. Additionally, the research will demonstrate the practical application of the proposed framework through a case study, offering guidance to other businesses facing similar operational challenges in optimizing their order-picking systems.

2. Literature Review

This section reviews the existing literature on order-picking systems (OPS), focusing on their fundamental role in warehouse operations and the challenges they present. It emphasizes the methods and technologies, particularly automation solutions, that have been proposed in the literature to optimize OPS and improve efficiency.

2.1 Order-Picking Systems

Order-picking is one of the primary activities in warehouses, involving the search for requested stock keeping units (SKUs), retrieving them, moving them to the Pick-Up/Drop-Off (P/D) area for checking, and finally preparing them for delivery (Wang et al., 2020). While order-picking is a fundamental warehouse activity, it is also one of the most challenging. Significant issues include incorrect picking, high operational costs, and extended lead times. Due to its reliance on manual labor, the process is prone to errors and order mismatches, leading to customer dissatisfaction (Zelada-Muñoz et al., 2022). Additional challenges involve optimizing space utilization and layout, as inefficient layouts can increase travel distances and lead times (Van Gils et al., 2018). These challenges highlight the need to optimize OPS design to improve performance and efficiency.

2.2 Automation in Order-picking Systems

Streamlining order-picking processes through intelligent automation is critical for companies aiming to meet the growing demands of today’s dynamic marketplace (Arangarajan et al., 2024). Automating OPS has been shown to offer numerous benefits, including cost reduction, shorter delivery response times, and better space utilization (Jaghbeer et al., 2020). Furthermore, automation improves picking accuracy and speed while reducing the distance traveled (Pinto et al., 2023). The advent of smart technologies has given rise to "smart warehouses”, fueling a wave of industry transformation with the potential to drive significant improvements in efficiency (Tiwari, 2023). However, each organization’s goals and objectives differ, meaning that the choice of technology must be suitable for their specific needs. Automation in order-picking can be classified into three levels: digitalized picking, robot-assisted picking, and fully automated picking.

2.3 Digitalized Picking

A digitalized picking system is a low level of automation that includes one or more picking technologies such as pick-to-light, voice-directed picking, and RFID handheld scanners, which are used to increase accuracy in warehouse operations as well as efficiency (Pinto et al., 2023). These systems replace traditional paper-based picking lists with digital interfaces that guide workers through the picking process. Additionally, digitalized picking systems are gaining popularity for their flexibility, as they easily adapt to existing warehouses and integrate with Warehouse Management

Systems (WMS), enabling quick deployment without significant changes to infrastructure or processes (Fontin & Lin, 2020). Pick-to-light technology, according to most studies, improves accuracy by up to 30% and increases picking speed by visually directing, via illuminated signals, pickers to the correct locations (Chondromatidis et al., 2022). Voice-directed picking technology, on the other hand, relies on oral instruction, allowing workers to pick hands-free, thereby reducing picking times by up to 50% (Dujmešić et al., 2018). Radio Frequency Identification handheld scanners enable workers to scan items more quickly than traditional barcode systems, increasing both accuracy and speed when identifying items. Studies have shown that RFID scanning significantly reduces error, making it the popular option for environments that have high SKU variability (Vijayakumar & Sgarbossa, 2021).

2.4 Robot-Assisted Picking

Automated Guided Vehicles (AGVs) and Autonomous Mobile Robots (AMRs) represent a level of order-picking automation where human pickers are assisted by these robots in picking, movement, or both (Vijayakumar & Sgarbossa, 2021). AGVs operate by following fixed, pre-defined routes using mechanisms such as magnetic strips to transport items between picking areas (X.-L. Wang et al., 2017). In contrast, AMRs are more flexible and dynamic, utilizing sensors and artificial intelligence to navigate warehouses without relying on fixed infrastructure (Pugliese et al., 2022). AGVs and AMRs are becoming increasingly common in modern warehouses due to their ability to enhance and streamline picking efficiency. Research indicates that AGVs can reduce workers' travel time by up to 50%, significantly boosting productivity in large-scale operations (Christopher & Aktas, 2007). Similarly, AMRs improve productivity by optimizing the movement of goods in real time, adapting to changes in the warehouse environment, and accommodating varying SKU locations (Christopher & Aktas, 2007) .

2.5 Fully Automated Picking

Fully automated picking represents the highest level of automation in warehouse OPS, capable of performing both picking and transportation tasks autonomously. In some systems, storage is also automated. This level of automation can be subdivided into two categories: automated picking and robotized picking systems. In robotized systems, robots autonomously pick and transport items directly to designated areas. Equipped with advanced vision systems, artificial intelligence, and robotic arms, these robots can locate, retrieve, and transport items with minimal human intervention. Large-scale operations, such as Amazon's fulfillment centers, have successfully deployed these robots, achieving a productivity increase of 30–40% (Vijayakumar & Sobhani, 2023). In automated picking systems, various functions are integrated, including storage, picking, transportation, and shipping of SKUs. These systems offer benefits such as high storage capacity, efficient space utilization, rapid responsiveness, and minimal waste (Pinto et al., 2023). Examples include A-Frame and Dispensers that use conveyor belts to handle SKUs, as well as Automated Storage and Retrieval Systems (AS/RS), vertical or horizontal carousels, and vertical lift modules (VLM). This system is more structured, focusing on automating the storage and retrieval process, which streamlines the movement of items within fixed infrastructure (Pinto et al., 2023). Both systems require significant infrastructure changes, including reconfiguring facility layouts to accommodate automation technologies. These systems are particularly suited for high-density, high-volume environments where space optimization and rapid order fulfillment are critical. However, implementing such systems can take several months, and integrating them with existing systems can present challenges (Vijayakumar & Sobhani, 2023). Despite these hurdles, the long-term benefits include improved operational efficiency and reduced labor costs, making it an ideal solution for large-scale warehouses seeking full automation of their order-picking operations.

In conclusion, this literature review highlights the critical role of OPS in warehouse operations and the challenges they present, such as high costs, extended lead times, and errors. It underscores the potential of automation technologies, ranging from digitalized picking systems to fully automated solutions, in addressing these challenges. While low-level automation offers flexibility and immediate improvements in accuracy and efficiency, advanced systems like AGVs, AMRs, and fully automated picking solutions provide transformative benefits for large-scale operations, although they come with significant infrastructure demands.

3. Methods

The Full Consistency Method (FUCOM) is a multi-criteria decision-making tool used to minimize subjectivity and ensure consistency in criteria prioritization among different decision-makers (Fazlollahtabar et al., 2019). It is used to establish the optimal weights for the requirements, guaranteeing that the deviation from consistency is minimized (Pamučar et al., 2018b). FUCOM will be used to prioritize the company's requirements, ensuring that the most critical factors are emphasized, with the help of three key decision makers involved in automation processes.

4. Data Collection

Data for this study was collected through interviews with three key decision-makers at a direct-to-consumer healthy meal plan provider. The company's order-picking system is entirely manual, resulting in considerable waste and a production capacity limit of 4,000 orders per day. With a projected annual demand growth rate of 10%, the company risks significant unmet demand, losing up to $2,137,107 annually, potentially doubling to $4,487,922 the following year as unmet demand compounds. These challenges underscore the urgent need for a scalable, efficient order-picking system that can adapt to future growth.

During the interviews, the decision-makers identified and prioritized several requirements for automating their order-picking system. According to the decision-makers, the proposed solution must be flexible to infrastructure (C_1), given that the company operates several branches across the Gulf, all experiencing the same inefficiencies in their order-picking process. Additionally, the solution must be adaptable in material handling (C_2), as the company's meals come in various shapes and sizes, necessitating a system capable of handling a diverse range of products. Cost-effectiveness (C_3) was also highlighted as a critical factor, with the decision-makers emphasizing the need for a solution that delivers the desired outcomes at the lowest possible cost. Scalability (C_4) was identified as another key requirement, as the solution must be capable of accommodating fluctuating demands. Furthermore, the solution must be quick-to-implement (C_5), as the company seeks to deploy the system as soon as possible to stay ahead of increasing demand. Finally, the solution should be innovative (C_6), providing the company, a food-tech company invested in advanced technologies, with a competitive edge. These requirements were ranked by the decision-makers using a scale from 1 to 9, with 1 indicating the most crucial factor. Table 1 presents each decision-maker's subjective prioritization.

Table 1. Gathered data

	Decision Maker 1	Decision Maker 2	Decision Maker 3
Requirements Ranking	$C_2 > C_1 > C_3 > C_5 > C_4 > C_6$	$C_3 > C_4 > C_1 > C_5 = C_2 > C_6$	$C_3 > C_5 > C_1 > C_4 > C_6 > C_2$
Requirements Prioritization	$1-2-3-5-6-7$	$1-3-4-6-6-7$	$1-2-3-4-5-7$

Following this, an expert in automation solutions evaluated the three LOA – digitalized picking, robot-assisted picking, and fully automated picking – in terms of these requirements, rating each solution on a scale from 1 to 3, with 3 representing the best performance. The results of this evaluation are summarized in Table 2, which highlights how each alternative aligns with the company's priorities, with digitalized picking generally scoring higher for flexibility and cost, while fully automated picking ranked higher for innovation.

Table 2. Alternatives evaluation

Requirements / LOA	Flexibility to Infrastructure (C_1)	Flexibility in Material Handling (C_2)	Cost (C_3)	Scalability (C_4)	Time to Implement (C_5)	Innovation (C_6)
Digitalized Picking	3	3	3	1	3	1
Robot-Assisted Picking	2	2	2	3	2	2
Fully Automated Picking	1	1	1	2	1	3

5. Results and Discussion

Step 1: Determine the decision criteria

The decision criteria for optimizing the order-picking system are as follows: Flexibility to Infrastructure (C_1), Flexibility in Material Handling (C_2), Cost (C_3), Scalability (C_4), Time-to-Implement (C_5), Innovation (C_6).

$$C = \{C_1, C_2, C_3, C_4, C_5, C_6\}$$

Step 2: Rank decision criteria

The identified criteria were ranked by the decision-makers based on their individual opinions. k represents the rank of the observed requirement.

$$C_{j(1)} > C_{j(2)} > \ldots > C_{j(k)}$$

The ranking of the first decision maker:

$$C_2 > C_1 > C_3 > C_5 > C_4 > C_6$$

Step 3: Estimation of comparative priority

The comparative priority ($\varphi_{\frac{k}{k+1}}$) is assigned by the decision-makers based on subjective preference on a scale of [1-9], where '1' represents the most important criteria. In other words, it signifies the advantage of criterion $C_{j(k)}$ in comparison to the criterion of the $C_{j(k+1)}$ rank.

$$\boldsymbol{\varphi} = \boldsymbol{\varphi}_{(C_2/C_1)}, \boldsymbol{\varphi}_{(C_2/C_3)} \ \ldots, \boldsymbol{\varphi}_{(C_k/C_{k+1})}$$

The comparative prioritization based on the first decision maker is shown in Table 3.

Table 3. Comparative prioritization

Requirements	C_2	C_1	C_3	C_5	C_4	C_6
Weight	1	2	3	5	6	7

Thus, the values of comparative priority are calculated as:

$$\varphi_{(C_2/C_1)} = 2/1 = 2;\ \varphi_{(C_1/C_3)} = 3/2 = 1.5;\ \varphi_{(C_3/C_5)} = 5/3 = 1.\bar{6};$$
$$\varphi_{(C_5/C_4)} = 6/5 = 1.4;\ \varphi_{(C_4/C_6)} = 7/6 = 1.167$$

Step 4: Estimate the weight values $(w_1, w_2, \ldots, w_n)^T$, subject to the two following conditions:

Condition 1: The ratio of weights is equal to the comparative priority

$$\frac{w_k}{w_{k+1}} = \varphi_{\frac{k}{k+1}}$$

Satisfaction of Condition 1 for first decision maker:

$$\frac{w_2}{w_1} = 2;\ \frac{w_1}{w_3} = 1.5;\ \frac{w_3}{w_5} = 1.\bar{6};\ \frac{w_5}{w_4} = 1.4;\ \frac{w_4}{w_6} = 1.167$$

Condition 2: Weights should satisfy mathematical transitivity

$$\frac{w_k}{w_{k+2}} = \varphi_{\frac{k}{k+1}} \times \varphi_{\frac{k+1}{k+2}}$$

Satisfaction of Condition 2 for first decision maker:

$$\frac{w_2}{w_3} = 2 \times 1.5 = 3;\ \frac{w_1}{w_5} = 1.5 \times 1.6 = 2.5;\ \frac{w_3}{w_4} = 1.6 \times 1.4 = 2.\bar{3};$$
$$\frac{w_5}{w_6} = 1.4 \times 1.167 = 1.6$$

Step 5: Solve the model

For the maximization of consistency, the Deviation from Consistency (DFC) should be minimized, which leads to the following model:

$\mathbf{min}\ \boldsymbol{\chi}$

$\mathbf{s.t.}$

$$\left|\frac{w_2}{w_1} - 2\right| \le \chi;\ \left|\frac{w_1}{w_3} - 1.5\right| \le \chi;\ \left|\frac{w_3}{w_5} - 1.6\right| \le \chi;\ \left|\frac{w_5}{w_4} - 1.4\right| \le \chi;\ \left|\frac{w_4}{w_6} - 1.167\right| \chi;$$
$$\left|\frac{w_2}{w_3} - 3\right| \le \chi;\ \left|\frac{w_1}{w_5} - 2.5\right| \le \chi;\ \left|\frac{w_3}{w_4} - 2.\bar{3}\right| \le \chi;\ \left|\frac{w_5}{w_6} - 1.6\right| \le \chi;$$

$$\sum_{j=1}^{6} w_j = 1 \; \forall \, \mathrm{j}$$
$$w_j \geq 0, \forall \, j$$

By solving the above non-linear model using Python, we obtain the final values of weight coefficients for Flexibility to Infrastructure (0.21), Flexibility in Material Handling (0.47), Cost (0.15), Scalability (0.06), Time to Implement (0.07) and Innovation (0.04). These steps are repeated with other decision-makers who have comparable expertise and knowledge of the company's requirements. Hence, the average of individual weights are used to find the final weights of the requirements. The results are shown in Table 4.

Table 4. FUCOM of decision makers' ranking

		Decision Maker 1	Decision Maker 2	Decision Maker 3
Requirements Ranking		$C_2 > C_1 > C_3 > C_5 > C_4 > C_6$	$C_3 > C_4 > C_1 > C_5 = C_2 > C_6$	$C_3 > C_5 > C_1 > C_4 > C_6 > C_2$
Requirements Prioritization		$1-2-3-5-6-7$	$1-3-4-6-6-7$	$1-2-3-4-5-7$
Weight Coefficients	C_1	0.21	0.12	0.14
	C_2	0.47	0.08	0.06
	C_3	0.15	0.49	0.41
	C_4	0.06	0.16	0.10
	C_5	0.07	0.08	0.21
	C_6	0.04	0.07	0.08
Deviation from Consistency		0.3321	0.0011	0.0022
Average Weight Coefficients		$\bar{C}_1 - \bar{C}_2 - \bar{C}_3 - \bar{C}_4 - \bar{C}_5 - \bar{C}_6$ $0.16 - 0.20 - 0.35 - 0.11 - 0.12 - 0.06$		

The FUCOM analysis shows that cost is the most important requirement for the company, with a weight of 0.35. Then, Flexibility in Material Handling ranks as the second one with a weight of 0.20. While Flexibility to Infrastructure ranks third at 0.16, and Time to Implement follows at 0.12. Then, Scalability comes at a weight of 0.11, lastly is Innovation less critical, with weight of 0.06. The top priorities are ensuring a cost-effective alternative, flexibility in handling meals, and adaptability to infrastructure. Upon completing the evaluation, the weights obtained from the FUCOM method in Table 4 are multiplied by the experts ranking in Table 2, as shown in Table 5.

Table 5. Alternatives' ranking

Alternative	Sum Product of Weight and Evaluation	Score
Digitalized Picking	$(0.16 \times 3) + (0.20 \times 3) + (0.35 \times 3) + (0.11 \times 1) + (0.12 \times 3) + (0.06 \times 1)$	2.66
Robot-Assisted Picking	$(0.16 \times 2) + (0.20 \times 2) + (0.35 \times 2) + (0.11 \times 3) + (0.12 \times 2) + (0.06 \times 2)$	2.11
Fully Automated Picking	$(0.16 \times 1) + (0.20 \times 1) + (0.35 \times 1) + (0.11 \times 2) + (0.12 \times 1) + (0.06 \times 3)$	1.24

Digitalized picking achieved the highest score of 2.66, outperforming robot-assisted picking (2.11) and fully automated picking (1.24). This result demonstrates that digitalized picking is the most suitable level of automation for the company's current requirements. Digitalized picking has proven to significantly reduce both the time required and error rates in order-picking processes, directly enhancing efficiency and increasing production capacity. For the company, this means the ability to meet their growing demand while maintaining operational excellence. Moreover, it integrates seamlessly with their existing infrastructure without requiring major modifications, which will help them apply this solution to all their branches. Additionally, it supports diverse material-handling needs to accommodate their wide range of products and offers a cost-effective solution compared to robotics and automation. The system is also scalable, allowing the company to expand operations by adding hardware as needed. Hence, digitalized picking is considered the best choice to address the company's current needs and support their future expansion.

5.1 Proposed Improvements

To enhance the practical applicability of the framework, an alternative weighting approach can be employed to prioritize decision-makers based on their organizational roles and influence. In this case study, Decision Maker 1 – the chief executive officer (CEO) – may be assigned greater weight due to his overarching authority and strategic vision. While the perspectives of Decision Maker 2 – the cofounder – and Decision Maker 3 – the automation manager – are also significant, the CEO's input can be prioritized to reflect his decisive role within the organization. This adjustment ensures the framework better mirrors decision-making hierarchies, thereby improving its relevance and utility in practice.

5.2 Validation

The validation of digitalized picking as the optimal LOA for the company was approached through benchmarking against companies of similar scale and industry, such as HelloFresh and Blue Apron, which successfully utilize technologies like pick-to-light, voice-directed picking, and RFID handheld scanners. These systems have been shown to improve accuracy by up to 30% and reduce picking times by up to 50%, aligning with the company's goals of reducing cycle time and improving efficiency. For precise validation of whether digitalized picking will meet the company's projected 10% demand growth, simulation-based analysis is recommended.

5.3 Limitations

This study is limited by the fact that it considers only three decision-makers, which may not fully capture the range of perspectives typically present in more complex decision-making scenarios. Moreover, as the number of criteria and alternatives increases, the consistency checking process becomes more complex and computationally intensive.

6. Conclusion

Automation is critical to addressing inefficiencies that drive costs and waste in manual order-picking systems. This study proposed a comprehensive framework for determining the optimal level of automation, supported by a FUCOM-based decision-making model and demonstrated through a case study. By classifying automation into digitalized, robot-assisted, and fully automated categories, the framework provides a clear path for businesses to align their operational needs with appropriate automation solutions.

While this research lays the groundwork for automating OPS, future efforts should focus on optimizing key design areas – routing, layout, batching, zoning, and storage strategies – through advanced simulation tools, such as Visual Components, Simio, or Flexsim. Furthermore, the authors recommend investigating the concept of "lean automation" to ensure that efficiency gains from automation are not offset by waste introduced during implementation.

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Biographies

Waleed Mirdad is an Associate Professor of Industrial Engineering at King Abdulaziz University. He earned his Bachelor of Science and Master of Science degrees in Industrial Engineering and subsequently completed his doctoral studies in the Industrial Engineering department at Oregon State University in 2018. His areas of expertise lie in Machine Learning, Stochastic Processes, and Production Planning and Control. Dr. Mirdad's research primarily centers around the application of machine learning techniques in the field of production.

Areeb Abubaker is a senior industrial engineering student at King Abdulaziz University. Her interests include process optimization and lean methodologies, with a focus on integrating automation technologies to enhance operational efficiency. Areeb has a keen interest in research as a leisure activity and has contributed to various projects aimed at improving industrial systems and operations.

Khadijah Bashatah is a motivated and dedicated senior industrial engineering student at King Abdulaziz University with a strong academic foundation in industrial engineering principles, techniques, and methodologies. Khadijah demonstrates excellent analytical and problem-solving abilities with a commitment to continuous learning and professional growth.

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