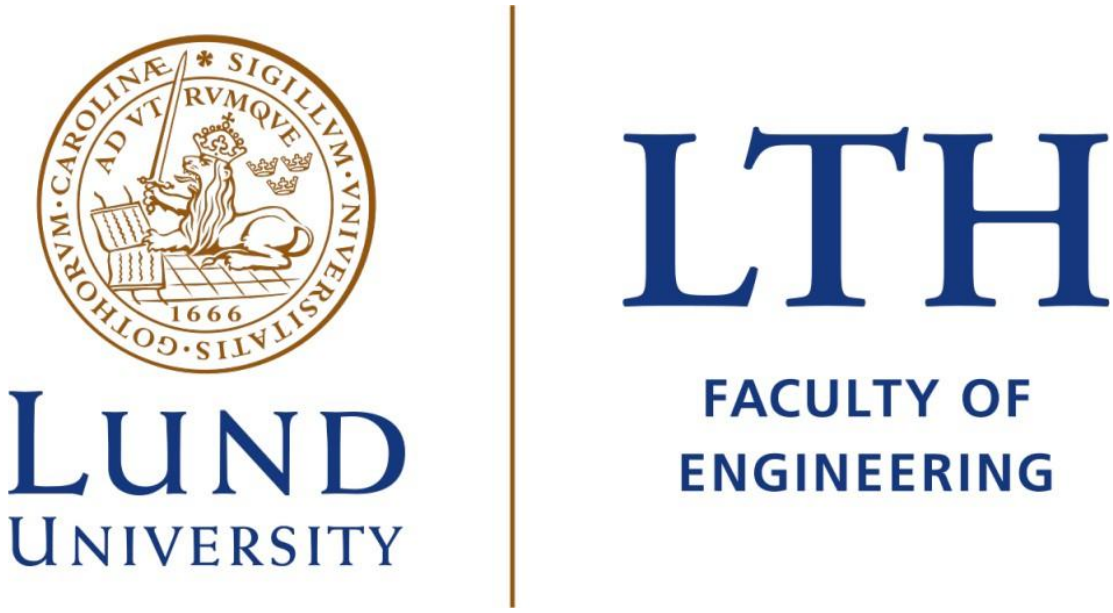
Master's Thesis

Goods-to-Person or Goods-to-Robots? The Emergence of Robotic Pick-and-Place Technology in Automated Retail Warehouses



The Faculty of Engineering at Lund University

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Sweden, Lund, May 2026

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Abstract

Title	Goods-to-Person or Goods-to-Robots? The Emergence of Robotic Pick-and-Place Technology in Automated Retail Warehouses
Authors	Akhil N Babu & Guyon De Abreu
Supervisor	Joakim Kembro, Faculty of Engineering – Lund University
Background	Retail warehouses are becoming more automated, yet item-level picking often remains manual. Pick-and-place technology has emerged as a possible next step, but its role and future potential are still not fully understood.
Purpose	The purpose of this thesis is to examine the emergence of pick-and-place technology in retail goods-to-person warehouses by investigating its current adoption, human-robot interaction, context of use, persistent limitations, and anticipated future development.
Research Objectives	**RO1:** *To investigate the current state of the adoption and HRI of PaP technology in retail G2P warehouses.* **RO2:** *To analyze the current limitations of the picking aspect of warehouse automation, with particular emphasis on the reliance on manual picking in retail G2P warehouse systems.* **RO3:** *To investigate the anticipated future of the PaP technology in retail G2P warehouses.*
Methodology	This thesis adopts a qualitative and exploratory design, combining an integrative literature review with thirteen semi-structured interviews to examine adoption, challenges, human-robot interaction, and future development.
Conclusion & Findings	The findings show that pick-and-place technology is in an early adoption phase, and that adoption depends on the fit between the technology, the warehouse operation, and the strategic pressure to automate.
Keywords	Pick-and-place technology, robotic picking, goods-to-person, warehouse automation, retail warehousing, human-robot interaction, technology adoption, integrative literature review

Acknowledgements

Writing this thesis has been a meaningful and rewarding journey for both of us. It has given us the opportunity to explore a topic that we found both challenging and genuinely interesting, while also allowing us to grow academically and personally throughout the process. Looking back, we are grateful not only for what we have learned, but also for the many people who supported us along the way.

First, we would like to sincerely thank all of our interviewees for taking the time to contribute to this thesis. Your willingness to share your experiences, insights, and expertise added great value to our work and helped us develop a much deeper understanding of the topic.

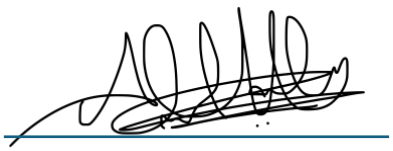
We would especially like to express our sincere gratitude to our supervisor, **Joakim Kembro**, for his guidance, encouragement, and thoughtful feedback throughout the thesis process. Your ability to challenge our thinking while also supporting us along the way was greatly appreciated. Your comments and suggestions played an important role in helping us strengthen the quality of this thesis.

A warm thank you also goes to our peers and friends who supported us throughout this process. We are grateful for the feedback, encouragement, and conversations that helped us during challenging moments.

Finally, we would like to thank our families for their constant support, patience, and belief in us. Your encouragement has meant a lot throughout this journey, and we are thankful for it.

This thesis may carry our names, but it would not have been possible without the support of many people around us. For that, we are sincerely grateful.

Lund, May 2026



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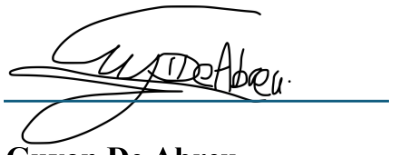

Guyon De Abreu

List of Abbreviations

AI = Artificial Intelligence

API = Application Programming Interface

DOI = Diffusion of Innovations

G2P = Goods-to-Person

G2R = Goods-to-Robot

HRI = Human-Robot Interaction

INT = Institutional Theory

KPI = Key Performance Indicator

PaP = Pick-and-Place

RO = Research Objective

ROI = Return on Investment

SKU = Stock Keeping Unit

TOE = Technology-Organization-Environment

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1. Introduction

This introductory chapter opens with background on retail warehouse automation, followed by the problem formulation that identifies the gap this research addresses. Subsequently, the purpose and research objectives are presented, after which the scope and unit of analysis are defined. Last but not least, the thesis outline is presented.

1.1. Background

The emergence of e-commerce and omnichannel in retail has significantly changed supply chains in the retail industry. These raised the bar for operational flexibility, high delivery reliability, and quick order fulfillment. In this regard, warehouses have evolved from passive storage facilities to vital fulfillment hubs, where competitiveness and service quality are directly affected by operational performance (Rodríguez-García and Agmoni, 2024). As order volumes and product variety increase, retail warehouses face growing pressure to improve efficiency while maintaining flexibility and cost control (Scholl and Deuse, 2010).

Within retail warehousing, order picking plays an important role. It is consistently identified as one of the most labor-intensive and cost-driving activities, accounting for a large share of total operating costs, while also strongly influencing throughput, lead times, and service performances (Rodríguez-García and Agmoni, 2024; Boysen and De Koster, 2025). As a result, order picking has become a focal point for operational improvement and automation investments (Ong and Joseph, 2014).

To overcome these issues, retailers have increasingly turned to automation technology in their warehouses. The most popular automation paradigm implemented in many warehouses is the Goods-to-Person (G2P) system, in which storage systems move products to pick stations. G2P is a warehouse order picking method where goods are brought to the person using automated systems, rather than the picker moving to the goods (Feng *et al.*, 2024). The effectiveness of the G2P system in reducing travel times, space utilization, and increasing storage, retrieval, and internal transport automation has been demonstrated in many studies (Boysen and De Koster, 2025; Perotti *et al.*, 2025). However, despite these advances, the picking task at the workstation typically remains manual (Grosse, 2024).

Meanwhile, the trend of pick-and-place (PaP) robotics is increasing rapidly, with a market size reaching 2,87 billion US dollars in 2026, see **Figure 1.1** (Kardex, 2026a). PaP is defined in the scope section of this chapter. Start-ups such as Sereact and Smart Robotics have attained €110 and

€10 million in funding, respectively, to develop this technology (Chesnokova, 2026; Venture News, 2026).

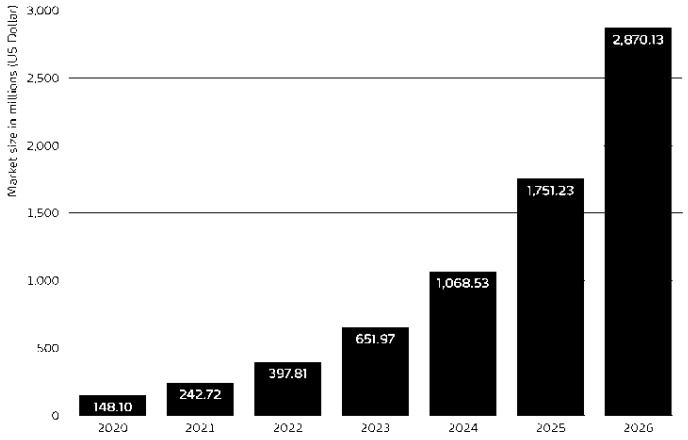

Figure 1.1. *Growth of market size PaP robotics in million US dollars from 2020 to 2026. Adopted from Kardex (2026).*

1.2. Problem Formulation

The continued reliance on manual labor at pick stations represents a key bottleneck in current warehouse automation solutions. Although retail warehouses are becoming increasingly automated and digitally controlled, item-level picking remains difficult to automate reliably. This is largely due to the inherent characteristics of retail environments, such as high product variety, heterogeneous packaging, frequent assortment changes, and highly variable order profiles (Rodríguez-García and Agmoni, 2024; Boysen and De Koster, 2025). As a result, pick stations frequently remain labor-intensive, cost-driving, and capacity-constraining points within otherwise highly automated warehouse systems (De Koster, Le-Duc and Roodbergen, 2007).

This is a form of the automation paradox, in that while warehouse activities such as storage, retrieval, and transportation are often highly automated in nature, the final step in order fulfillment remains a heavily labor-dependent process. An examination of highly automated warehouse systems reveals that while automation is increased, this is not to diminish human involvement in warehouse activities, but to shift this involvement to where it is most relevant, namely, where humans and machines interact to ensure operational success (Rodríguez-García *et al.*, 2025). Thus, the concept of fully automated retail warehouses is, in fact, more aspirational in nature, with current industry realities failing to indicate any likelihood of widespread replacement of human labor with machines (Kembro and Norrman, 2022).

In response to this challenge, advancements in robotics, machine vision, and grasping technologies have been leveraged for the development of piece picking PaP solutions for the execution of item-level picking tasks. Experimental and simulation-based studies have demonstrated the potential effectiveness of these PaP systems under constrained conditions, especially for environments with limited variability (Custodio and Machado, 2020). However, empirical research has also brought

attention to the shortcomings in terms of system integration, exception handling, and variability for actual retail warehouses (Boysen and De Koster, 2025).

At the same time, the existing knowledge on warehouse automation and robotic piece picking remains scattered. The literature may focus on technical feasibility or algorithmic performance, while other sources may highlight the importance of pilots or vendors. This creates a fragmented picture of the potential for advanced PaP robots to be effectively integrated into existing automated warehouse systems or for manual picking to be replaced or augmented by the robots (Perotti *et al.*, 2025).

1.3. Purpose and Objectives

The following research objectives (ROs) are structured to collectively examine PaP technology within retail G2P warehouse environments. Beginning with the current state of PaP adoption and the Human-Robot Interaction (HRI), followed by analyzing the persistent reliance on manual picking and the limitations this imposes, and ending in an exploration of the expected future of the

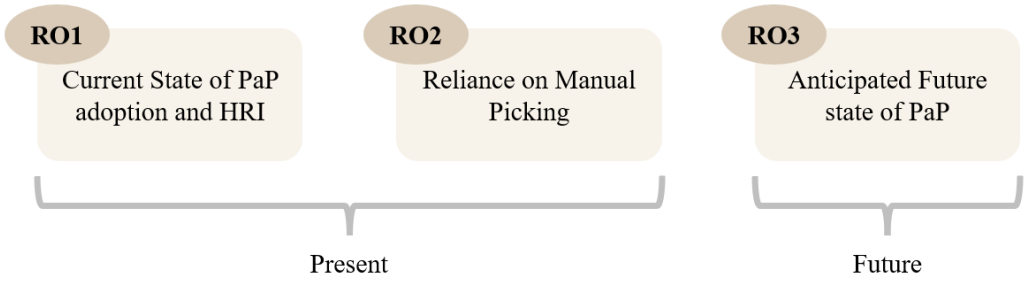

Figure 1.2. *Research objectives and their order.*

technology (see **Figure 1.2**). HRI is defined as the study of humans, robots, and their mutual influence (Wei, Seet and Sim, 2005). The objectives are structured in a manner because understanding the future of PaP technology first requires examining the current state of adoption. Subsequently, it can be established why manual picking persists despite advancements in automation.

The Research Objectives are formulated as follows:

RO1: *To investigate the current state of the adoption and HRI of PaP technology in retail G2P warehouses.*

The first research objective investigates the current state of PaP technology adoption and HRI within retail G2P warehouses. As organizations increasingly explore automation solutions, understanding the degree to which PaP systems have been integrated into existing operations becomes critical. This objective further examines the PaP technology's characteristics, benefits, challenges, and context of usage. The findings will contribute to identifying the conditions under which such technologies are implemented.

RO2: *To analyze the current limitations of the picking aspect of warehouse automation, with particular emphasis on the reliance on manual picking in retail G2P warehouse systems.*

The second research objective seeks to analyze the existing body of knowledge surrounding warehouse automation, with particular emphasis on the limitations that persist in current systems to adopt this technology. Despite significant advancements in automation, manual picking remains a predominant activity in retail G2P warehouse environments. This objective aims to establish a comprehensive understanding of why full automation of the picking process has not been widely achieved. It serves as the inherent basis for understanding the gap between G2P and goods-to-robot (G2R).

RO3: *To investigate the anticipated future of the PaP technology in retail G2P warehouses.*

The third research objective explores the anticipated future of PaP technology in retail G2P warehouses. Given the rapid pace of technological development, understanding how practitioners and academics envision the evolution of these systems is of considerable relevance. This objective seeks to capture forward-looking perspectives on capability improvements, scalability, and broader adoption potential. In doing so, it provides a prospective dimension that complements the current-state analyses of the objectives.

1.4. Scope and Unit of Analysis

This section presents the scope and unit of analysis of the thesis. It clarifies the boundaries within which the study is conducted and explains what is specifically being examined. By defining these elements, the section helps establish the focus of the research and provides a clearer basis for understanding how the purpose and research objectives are addressed.

1.4.1. Scope

Given the broad and interdisciplinary nature of research on warehouse automation and robotic order picking, it is important to define the boundaries of this thesis. The field spans multiple industries, warehouse system architectures, technological solutions, and analytical perspectives, and without explicit delimitations, the analysis risks becoming fragmented and lacking focus. The deliberate decision to narrow the scope of the study to a specific operational and technological context that directly supports the research purpose.

Overview

The scope of the thesis is defined across several key dimensions, including industry context, warehouse system configuration, process focus, technology type, level of automation, disciplinary perspective, and methodological approach. Together, these dimensions shape the conceptual and empirical boundaries of the research and guide key choices related to literature selection, interview sampling, and analytical framing. The study focuses on pick stations in retail G2P warehouse systems, as this is where robotic picking technologies are currently most actively developed, tested, and discussed in both academic and practitioner domains.

At the same time, certain areas are intentionally excluded to maintain analytical depth and practical feasibility. These exclusions include alternative warehouse paradigms, logistics processes not directly related to order picking, fully autonomous warehouse concepts, and highly technical engineering-oriented analyses that fall outside the logistics and operations management perspective adopted in this thesis. A structured summary of the aspects considered within scope and those deliberately excluded across these dimensions is presented in **Table 1.1.** Scope of the Thesis across different aspects **Figure 1.3** shows the scope (indicated in light brown) of the project with respect to the industry context, warehouse system, and the focus on the pick stations.

Table 1.1. *Scope of the Thesis across different aspects*

Aspect	In Scope	Out of Scope
Industry Context	• Retail	• Manufacturing warehouses • Production logistics • Non-retail facilities
Warehouse System	• G2P systems	• Picker-to-parts systems • Fully autonomous warehouse concepts
Process Focus	• Order picking at pick stations • Human-robot interaction at pick stations	• Storage system design (e.g. Automatic Storage and Retreaval Systems or conveyors) • Internal transport
Technology Focus	• Piece Picking Robots (software and hardware)	• Mobile robots performing aisle-based picking (e.g. Automated Guided Vehicles or Autonomous Mobile Robots) • Non-robotic picking aids (e.g. pick-to-light or voice picking) • Other pick-and-place technologies that are non robotic arms for picking (e.g. Delta Robots, Cartesian Robots etc.)
Automation Level	• Partial and hybrid automation • Robots replacing or complementing human pickers	• Fully automated or lights-out warehouses
Discipline Perspective	• Logistics perspective • Operations management perspective	• Robotics engineering • Control algorithms • Mechanical design optimization
Methodological Approach	• Integrative literature review • Empirical interview study	• Mathematical modeling and simulation • Field experiments • Case study • Action research • Survey

Figure 1.4 shows the different types of PaP technologies that are known, where this thesis focuses on ‘Piece Picking Robots’. To establish a clear understanding of differences, we shortly define each type of this technology.

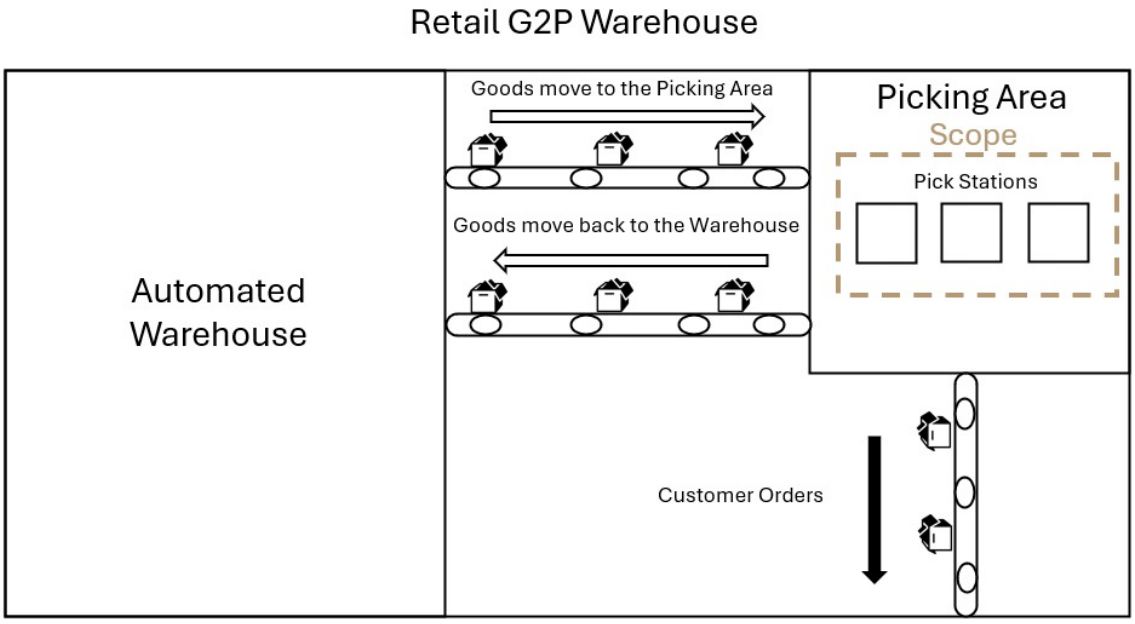

Figure 1.3. *Scope with respect to Industry (Retail), Order Picking System (G2P) and Process (Picking)*

Piece-picking robots are built to retrieve individual items from bins or grouped collections and relocate them elsewhere. Leveraging Artificial Intelligence (AI) and vision technology, these systems handle diverse objects across sectors such as e-commerce order fulfillment, pharmaceutical packaging, and grocery handling (AutoStore, 2026).

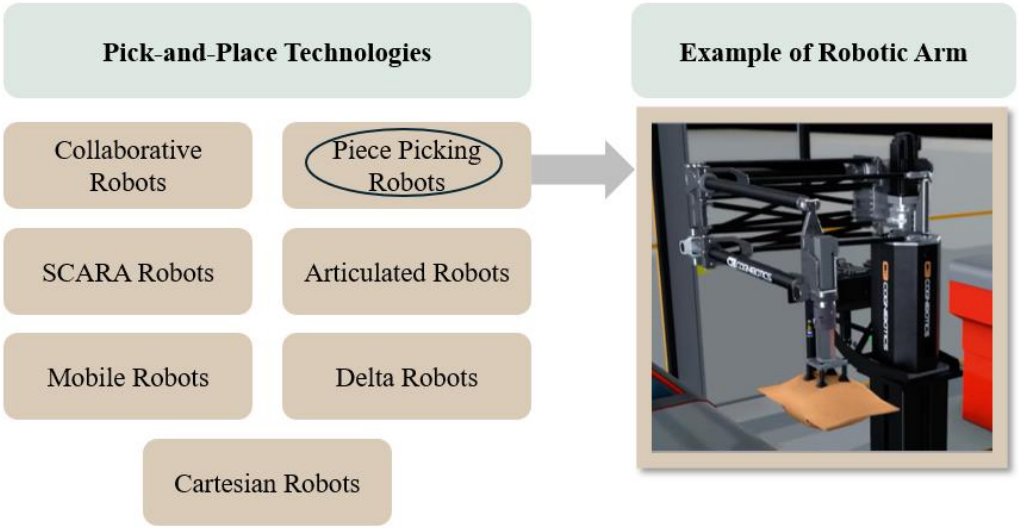

Figure 1.4. *Different PaP technologies and a robotic arm are exemplified. (AutoStore, 2026; Cognibotics, 2026)*

AI could be defined as the emulation of human intelligence in computers that have been trained to think and behave like humans, demonstrated by machines as opposed to natural intelligence

involving consciousness and emotionality (C and Salis, 2021). Where Piece Picking Robots could be categorized as 'physical AI': an evolution from AI that interacts directly with the physical world and mimics human functions to a greater extent (Dewi *et al.*, 2025). **Figure 1.4** indicates an example of this technology from (Cognibotics, 2026). For simplicity, PaP technology is defined as piece-picking robots in this thesis.

Cobots are engineered to operate safely within shared human-robot environments, relying on integrated sensors and safety mechanisms. They find application in manufacturing assembly, healthcare assistance, and logistics sorting (AutoStore, 2026).

Selective Compliance Assembly Robot Arms (SCARA) are characterized by their ability to execute fast, precise movements within a horizontal plane. They are widely deployed in electronics assembly, product packaging, and quality inspection processes (AutoStore, 2026).

Articulated robots offer a broad range of motion through multiple rotary joints, closely resembling the flexibility of a human arm. Their versatility supports applications in welding, heavy material handling, and component assembly (AutoStore, 2026).

Equipped with autonomous navigation and obstacle-detection capabilities, mobile robots move freely through their surroundings. They are commonly used in warehouse logistics, hospital supply delivery, and security patrol operations (AutoStore, 2026).

Cartesian robots operate along a fixed overhead structure, making them well-suited for precision tasks that span large surface areas. Common use cases include item transportation, pallet stacking, and machine loading and unloading (AutoStore, 2026).

Decision-Making Levels Focus

In addition to defining the technological and process-related boundaries of the study, it is also important to clarify the organizational decision-making levels at which the analysis is situated. Decisions related to warehouse automation and robotic picking do not occur at a single organizational layer, but span strategic, tactical, and operational levels, each associated with different objectives, time horizons, and degrees of uncertainty. Without explicitly delimiting these levels, the analysis risks extending into areas such as long-term corporate automation roadmaps or detailed operational optimization, which fall outside the intended focus of this thesis.

This thesis primarily concentrates on the strategic motivations and constraints shaping retailers' interest in automating order picking, as well as the tactical decisions involved in evaluating, introducing, and configuring robotic picking solutions at pick stations within existing warehouse systems. We consider these levels to be particularly relevant for understanding how robotic picking technologies are assessed, justified, and integrated into practice**.** In contrast, the study deliberately excludes broader warehouse network design decisions, long-term capital budgeting models, and detailed operational control or scheduling problems, as these would require different data sources and methodological approaches.

By explicitly distinguishing between in-scope and out-of-scope decision levels, the thesis maintains conceptual focus and analytical coherence while still capturing the organizational contexts in which robotic picking technologies are adopted and used. A structured overview of the organizational decision levels considered within and outside the scope of this research is provided in **Table 1.2.**

Table 1.2. *Scope of Organizational Decision Levels*

Organizational Decision Levels	In Scope	Out of Scope
Strategic	• Retailer's strategic interest in warehouse automation • Long-term labor cost pressure • Motivation to automate order picking	• Warehouse network design • Make-or-buy automation strategies • Long-term capital budgeting models • Corporate automation roadmaps
Tactical	• Current and future state of the robotic picking technology • Evaluation of robotic picking technology • Configuration of human-robot work at pick stations • Context: When to complement humans with robots • Scaling decisions with existing warehouses	• Long-term structural decision making • Cross-warehouse coordination decisions • One-off implementation phases • Organization-wide change programs
Operational	• How pick stations are executed by robots vs humans • Day-to-day interaction between humans and robots	• Detailed work measurement • Robots time scheduling algorithms • Performance optimization

1.4.2. Unit of Analysis

Within the research design, the unit of analysis plays a central role. It refers to the entity being examined in a scientific study, and in research, identifying it requires careful consideration of variables, data analysis techniques, and other interconnected elements that shape it (Dolma, 2010).

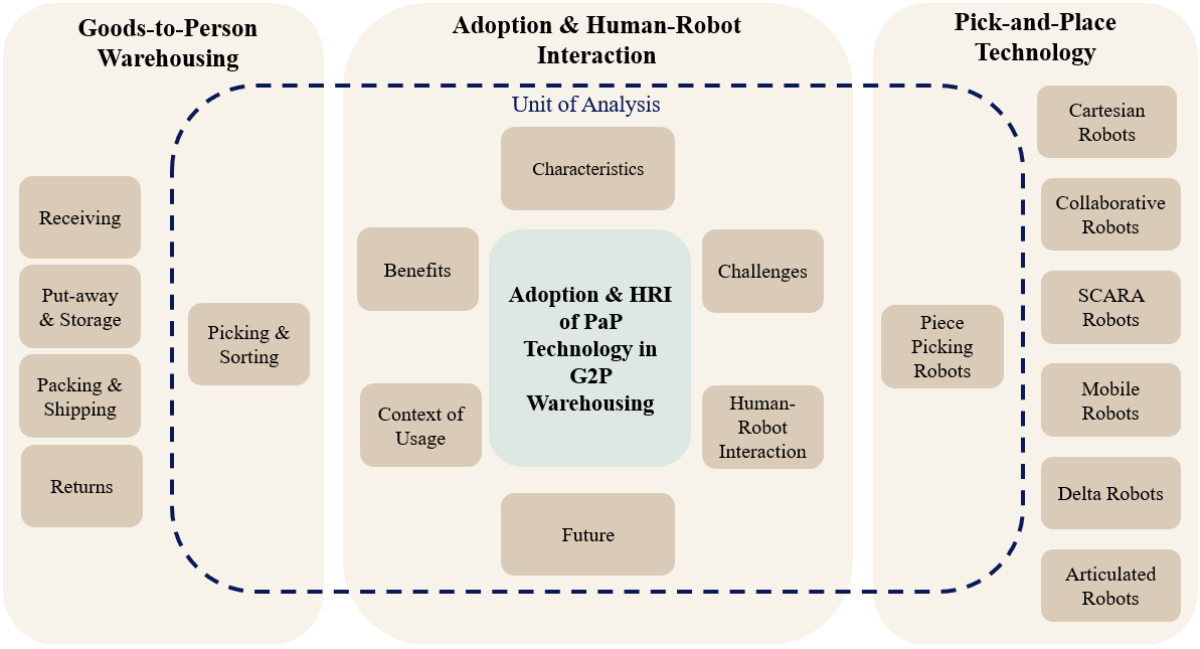

Figure 1.5. *Unit of Analysis*

This thesis investigates the adoption and HRI of PaP technology in retail G2P warehouses. It discovers the characteristics, benefits, challenges, HRI, context of usage, and potential of technology (see **Figure 1.5**). The combination of the empirics of the interview study, in combination with an integrative review, is used for the conceptual framework.

The frameworks that are utilized are Institutional Theory, Diffusions of Innovation, Levels of HRI, the Technical-Organizational-Environmental framework, and the hype cycle. These existing frameworks are combined to form the thesis conceptual framework.

1.5. Thesis Outline

We aim to structure the thesis into six main chapters, together presenting the research background, methodological approach, theoretical foundations, empirical findings from Interviews, and conclusion with our final comments.

Chapter 1: Introduction

Introduces the research context and background, outlining the problem foundation, and presenting the purpose, research objectives, and scope of study.

Chapter 2: Methodology

Describes the overall research design and methodological approach adopted in the thesis. It explains the integrative literature review methodology and the empirical interview study, including data collection procedures.

Chapter 3: Theoretical Foundation

Establishes the conceptual lens for the thesis by reviewing retail warehousing automation and the technical characteristics, components, and trade-offs of robotic PaP systems. Also, the frameworks are introduced followed by the conceptual framework of this thesis.

Chapter 4: Empirics and Analysis

The Empirics and Analysis chapter synthesizes data from qualitative interviews and a literature review to evaluate the adoption of robotic PaP technology. It organizes findings into six key themes: benefits, challenges, and HRI, interpreted through theoretical lenses like DOI, Institutional Theory, and the Gartner Hype Cycle.

Chapter 5: Discussions

By combining insights from both research stages, this chapter develops a more comprehensive understanding of the role, limitations, and future potential of robotic picking technologies in retail warehouse environments. Building on this combined analysis, we formulate six propositions and synthesize them into the Pick-and-Place Adoption Fit Framework, which brings together the central conditions shaping adoption in practice.

Chapter 6: Conclusions and Final Remarks

Summarizes the main findings of the thesis, answers the research objectives, discusses the theoretical and practical implications, and reflects on the study's limitations.

2. Methodology

This chapter presents the methodological approach used to investigate the adoption of PaP technology in retail G2P warehouses.

The study was conducted as a qualitative and exploratory thesis, combining semi-structured interviews with an integrative review of academic and grey literature. The chapter covers the research approach and design, data collection, data analysis, and research quality. An overview is presented **Figure 2.1**.

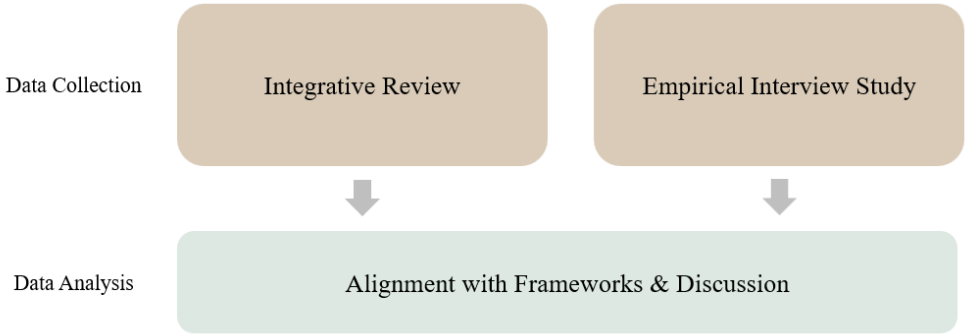

Figure 2.1. *Methodology Overview.*

2.1.Research Approach and Design

This thesis adopted a qualitative research approach to explore the adoption of PaP technology in retail G2P warehouses. We chose a qualitative approach because we wanted to understand how the technology is perceived, evaluated, implemented, and expected to develop. Our aim was not to measure adoption statistically, but to build a deeper understanding of the current state of the technology and the conditions that shape its adoption in practice.

The study was also exploratory. This was suitable because PaP technology in retail G2P warehouses is still developing, and there is limited structured empirical evidence available. Exploratory research is useful when the phenomenon is complex, evolving, and not yet fully understood, especially when technological, organizational, and environmental factors interact dynamically (Saunders, Lewis and Thornhill, 2023). This fits our thesis because the topic sits between several areas, including warehouse automation, robotics, logistics, technology adoption, HRI, and industry practice.

The overall research design is shown in **Figure 2.2** It illustrates how the thesis developed from the initial definition of the topic, purpose, research objectives, scope, and unit of analysis, through data collection and analysis, and finally into discussion and conclusions. It provides an overview of the methodological logic of the study before the individual components are described in more detail.

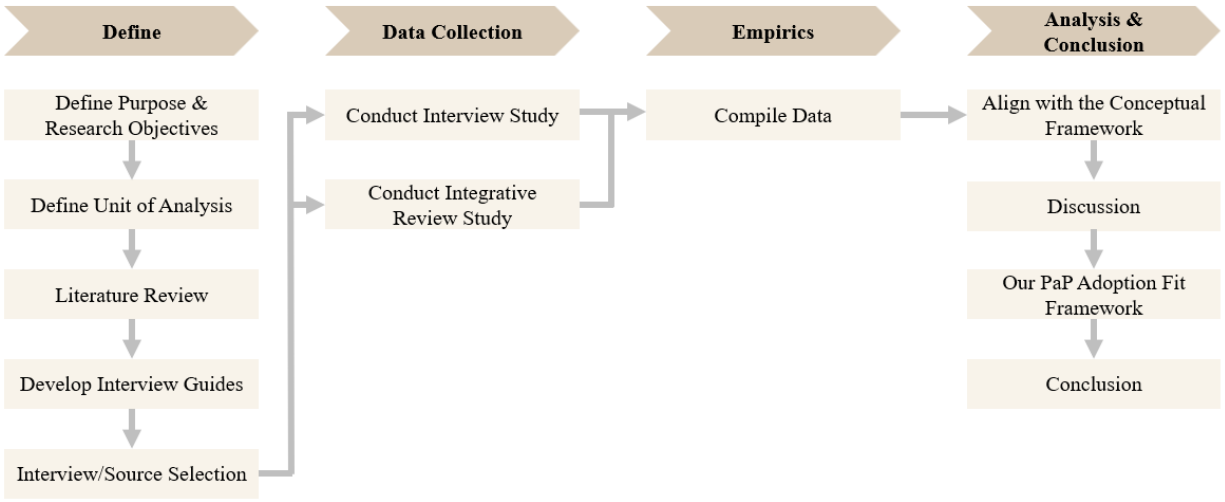

Figure 2.2. *Research Design.*

First, we defined the thesis topic, purpose, research objectives, scope, and unit of analysis. In this stage, we also started reviewing literature, developed the interview guides, and identified relevant interviewees and sources. Second, we collected data through the empirical interview study and the integrative literature review. Third, we compiled the material into the empirics and analysis chapter, where interview findings and literature-based insights were organized into themes and aligned with the selected theoretical frameworks. Finally, we used the discussion chapter to reflect on what the findings meant, develop six propositions, and build the PaP Adoption Fit Framework. The conclusions were then drawn in relation to the research objectives.

We selected an integrative literature review because the knowledge around PaP technology is fragmented. Relevant insights are spread across supply chain management, operations research, industrial engineering, robotics, HRI, technology adoption, and practitioner-oriented sources. Some important information is found in peer-reviewed academic articles, while other current developments are found in industry reports, company websites, white papers, brochures, and news articles. Integrative reviews are useful when different types of knowledge need to be brought together into one coherent understanding (Torraco, 2005; Elsbach and Van Knippenberg, 2020; Cronin and George, 2023).

At the beginning of the thesis, we planned the study around two main sources of knowledge: an integrative literature review and an empirical interview study. As the research developed, however, these two parts were not treated as separate or strictly sequential. Instead, they were used together in an iterative way. The integrative literature review played an especially important role early in the process, as it helped us define the scope, formulate the research objectives, identify key concepts, develop the interview guides, and choose the theoretical frameworks.

As the study progressed, the interviews became the main empirical foundation of the thesis. They gave us more direct insight into how technology developers, adopters, and academic experts

understand the current state, challenges, benefits, HRI, and future development of PaP technology. At the same time, the literature remained important throughout the process. Rather than being completed once and then left aside, it was revisited continuously as new themes emerged from the interviews. For example, when interviewees discussed SKU variability, order-level automation, software maturity, intervention frequency, and changing human roles, we returned to the literature in a more focused way to understand these themes better and position them in relation to existing research.

This iterative process became important for the thesis. At first, we had a broader understanding of robotic picking and warehouse automation. As the interviews progressed, we became more aware of which issues mattered most in practice. The literature then helped us connect these practical insights to existing research. In this way, the study was developed through repeated movement between empirical material, literature, and theory.

The research can also be positioned using the framework from Malhotra and Grover (1998), see **Figure 2.3** which classifies research based on its orientation toward theory or practice and whether it is mainly conceptual or empirical. Our thesis can be positioned as exploratory and applied, with both conceptual and empirical elements. It is conceptual because we synthesize fragmented knowledge and use theoretical frameworks to structure the analysis. It is empirical because we conducted semi-structured interviews with technology developers, adopters, and academic experts. It is applied because the findings are meant to support practical decision-making in retail warehouse automation.

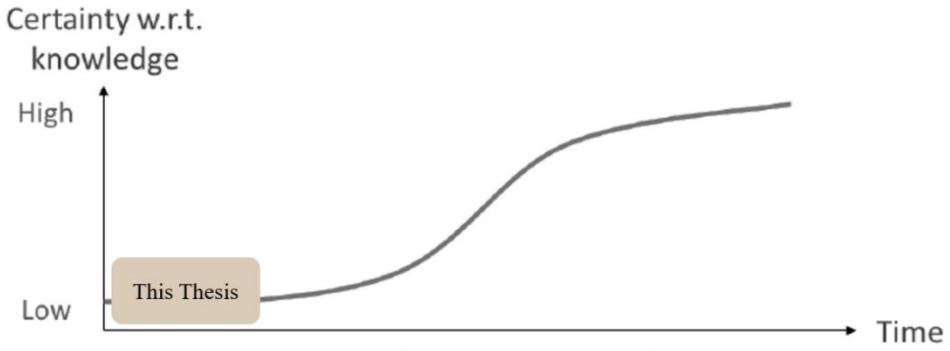

Figure 2.3. *Positioning of the thesis in the maturity framework. Adopted from Malhotra and Grover (1998).*

2.2. Data Collection

The interviews were the main empirical data source of the thesis. They helped us understand how PaP technology is currently developed, evaluated, implemented, and discussed by different actors. This was especially important because the technology is still emerging, and many practical implementation issues are not yet fully captured in academic literature. The literature complemented the interviews. Academic literature helped us build the theoretical foundation and

connect the findings to existing research. Grey literature helped us capture recent developments, company activity, vendor claims, market changes, funding, and implementation examples. This was necessary because emerging technology fields are often partly documented outside traditional academic publications, especially when practice is moving faster than peer-reviewed research (Adams, Smart and Huff, 2017).

Figure 2.4 shows the five categories of companies and institutions we consulted during the data collection process. These categories were hardware developers, software developers, hardware and software developers, adopters, and academia. Hardware developers specialize in the physical parts of PaP systems, such as robotic arms, end-effectors, and supporting mechanical infrastructure. Software developers focus on AI, vision systems, and control software. Hardware and software developers combine both the physical and computational parts of the solution. Adopters are retail warehouse operators that have implemented or are evaluating the technology in G2P operations. Academia includes researchers and domain experts who study warehouse automation, robotics, and logistics systems.

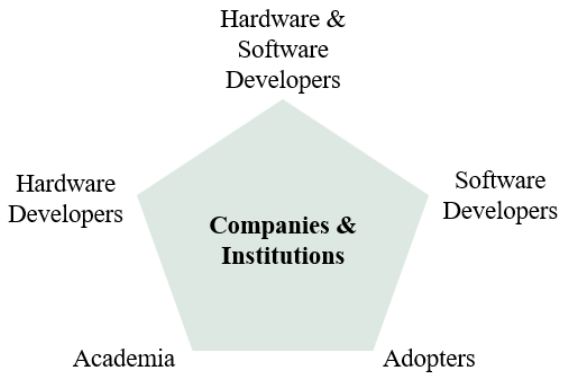

Figure 2.4. *Different Companies & Institutions Consulted in this thesis.*

We included these categories because we wanted to understand the technology from different angles. Developers helped us understand technical capabilities, software, hardware, integration, and market positioning. The adopter perspective helped us understand the business case, operational use, implementation, and limitations in practice. Academic experts helped us connect the practical findings to broader research. By comparing these perspectives, we could see both common patterns and differences between actors.

Figure 2.5 shows the source types used in the thesis and **Table 2.1** indicates the number of sources utilized with their main purpose for this thesis. These included academic journals, industry journals, interviews, company reports, company websites, brochures, eBooks, and news articles. Academic journals provided peer-reviewed knowledge. Industry journals and eBooks gave practitioner-oriented perspectives. Interviews provided the main primary empirical data. Company reports,

websites, and brochures gave information about technology characteristics, vendor positioning, and implementation examples. News articles helped us capture recent developments, partnerships, funding, and market movement.

By combining these sources, we were able to compare insights from interviews, academic literature, and industry material. This helped us avoid relying too much on one type of source. Interviews gave us rich and current insights, but they reflected the views of specific actors. Academic literature gave us theoretical depth, but not always the most recent industry developments. Grey literature gave us up-to-date market information, but sometimes included commercial claims. Using them together made the analysis more balanced.

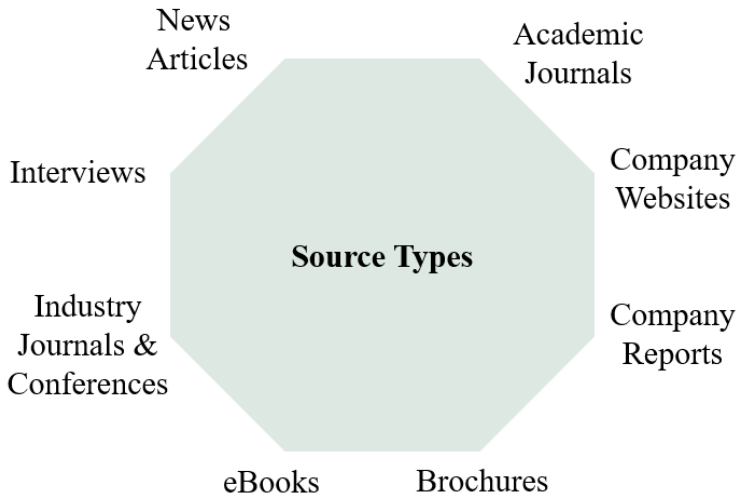

Figure 2.5. *Source Types Utilized.*

2.2.1. Empirical Interview Study

The empirical interview study was the main primary data source of the thesis. An interview can be understood as a purposeful conversation between at least two people, where the aim is to collect data and insights that help answer the research (Voss, Tsikriktsis and Frohlich, 2002; Saunders, Lewis and Thornhill, 2023). Interviews were especially useful for this thesis because they allowed us to speak directly with people who develop, evaluate, use, or study PaP technology. Kumar (2019) explains that an interview normally involves the interviewer asking questions verbally while recording or taking notes. However, the quality of an interview also depends on the interviewer's skills. In our case, most interviews were conducted by both authors. One of us usually led the conversation, while the other focused on taking notes and identifying follow-up questions.

***Table 2.1**. Number of each source type used and the purpose of this thesis.*

Source Type	Number Used	Main Purpose
Academic Journal Articles	69	To build the theoretical foundation and support the analysis with peer-reviewed research on warehouse automation, robotics, technology adoption, and human-robot interaction.
Conference Papers / Proceedings	9	To capture newer and more specialized research on robotic picking and warehouse technologies that may not yet be widely covered in journal articles.
Books / eBooks	9	To support methodological choices and explain research methods used in the thesis.
Industry Reports	1	To describe current industry trends, market developments, and practical challenges related to pick-and-place technology.
Company Websites	5	To identify relevant technology developers and adopters, and to gather up-to-date information on systems, solutions, and company positioning.
Company Brochures/reports	10	To understand how vendors describe their robot capabilities, technical features, and implementation use cases.
News Articles	3	To capture recent developments such as funding rounds, partnerships, product launches, and other current market movements.
Interviews	14	To provide the main primary empirical foundation of the thesis through direct insight from developers, an adopter, and academic experts.
Total	**120**	

This helped us capture the answers more accurately and gave us a better chance to follow up on important points. This is also in line with Voss, Tsikriktsis and Frohlich (2002), who note that having more than one interviewer can improve the quality and completeness of data collection.

There are different types of interviews depending on how structured they are. Kumar (2019) and Saunders, Lewis and Thornhill (2023) distinguish between structured, unstructured, and semi-structured interviews. Structured interviews follow a fixed set of questions in a fixed order. Unstructured interviews are more informal and allow the conversation to develop freely. Semi-structured interviews are placed between these two. They use a prepared interview guide, but still allow flexibility to change the order of questions, ask follow-up questions, and explore new topics.

We used semi-structured interviews because this format gave us both structure and flexibility. The structure helped us make sure that the interviews covered the main themes connected to the

***Table 2.2.** Elements of the interview study summarized.*

Element	Description
Interview Format	Semi-Structured, with a pre-defined guide and room for questions on emerging themes
Duration	Between 30 and 45 minutes per intervew
Modality	Video conference (primary) or in-person
Recording	Audio - recorded with consent, transcribed by software utilized
Target Interviewees	CTOs, CEOs, Researchers, Professors, VP Sales ect.
Documentation	Notes taken during the interview, transcripts reviewed for accuracy before analysis

research objectives. The flexibility was important because PaP technology is still emerging, and we could not know in advance which topics would become most important. For example, themes such as order-level automation, intervention frequency, system stewardship, and the difference between robotic hardware and software maturity became clearer as the interviews progressed. A summary of the interview elements is shown in **Table 2.2**.

To identify suitable interviewees, we first created a longlist of approximately 40 technology developers and known adopters. This longlist was developed through the integrative review and became our primary sampling frame. We then contacted potential interviewees through several channels. For practitioners, we used LinkedIn and searched for role-specific terms such as “PaP,” “robotic piece picking,” “automation engineer,” “CTO,” and “CEO.” We also filtered the search based on companies identified in the longlist. For academics, we used the literature review to identify researchers with relevant expertise in warehouse automation and picking technologies.

The response rate differed between channels. Outreach to consultants and adopting companies produced limited responses. Contacting technology developers directly through official website contact forms gave the highest response rate, especially when we framed the request as a short 30-minute interview. In addition, our thesis supervisor helped us establish contact with the Chief Technology Officer of Boozt, which gave us an important adopter perspective.

The interviews were conducted online through Microsoft Teams or Zoom, except for the interview with Cognibotics, which was conducted on-site. The interviewees are summarized in **Table 2.3** The interview guides were adapted depending on the type of interviewee. Developers were asked more about technological capabilities, integration, deployment challenges, hardware, software, and customer expectations. Adopters were asked more about the business case, operational use, implementation experience, human interaction, and decision-making. Academic experts were asked more about broader trends, theoretical interpretation, future development, and the role of automation in warehouse systems. The semi-structured interview guide can be found in Appendix A.

Table 2.3. *Interviewees for interview study.*

	Company / Institution	Type	Role	Based in	Duration and Date
1	Smart Robotics	Hardware & Software Developer	Head of R&D	Eindhoven, Netherlands	45 min (07-04-2026)
2	Osaro	Software Developer	Sales Director	Providence, United States	30 min (07-04-2026)
3	Sereact	Hardware & Software Developer	Vice President of Sales	Stuttgart, Germany	30 min (08-04-2026)
4	Mujin	Hardware & Software Developer	Operations Lead	Eindhoven, Netherlands	30 min (09-04-2026)
5	Yaskawa	Hardware & Software Developer	Automation Engineer	Frankfurt, Germany	30 min (09-04-2026)
6	RSM	Academia	Department Chair, Technology and Operations Management	Rotterdam, Netherlands	45 min (14-04-2026)
7	Fizyr	Software Developer	CTO	Delft, Netherlands	30min (16-04-2026)
8	Boozt	Adopter	CTO	Malmö, Sweden	45min (17-04-2026)
9	Cognibotics	Hardware Developer	Robot System Architect & Team Lead	Lund, Sweden	45min (17-04-2026) (on site)
10	MIT	Academia	Researcher	Cambridge, United States	30 min (21-04-2026)
11	TGW Logistics	Hardware & Software Developer	Business Development Manager	Mölndalz, Sweden	45 min (23-04-2026)
12	Mech-Mind Robotics	Software Developer	Country Manager	Munich, Germany	30 min (29-04-2026)
13	Mech-Mind Robotics	Software Developer	Engineer	Munich, Germany	30 min (29-04-2026)
14	DeltiLog	Adopter	CEO	Hannover, Germany	30 min (12-05-2026)

The interview guides were improved during the data collection process iteratively. Kallio *et al.* (2016) describes the following steps for an iterative improvement of interview guides: "*(1) identifying the prerequisites for using semi-structured interviews; (2) retrieving and using previous knowledge; (3) formulating the preliminary semi-structured interview guide; (4) pilot testing the guide; and (5) presenting the complete semi-structured interview guide"*. This improves the objectivity and trustworthiness of the interview guides (Kallio et al., 2016). Based on these

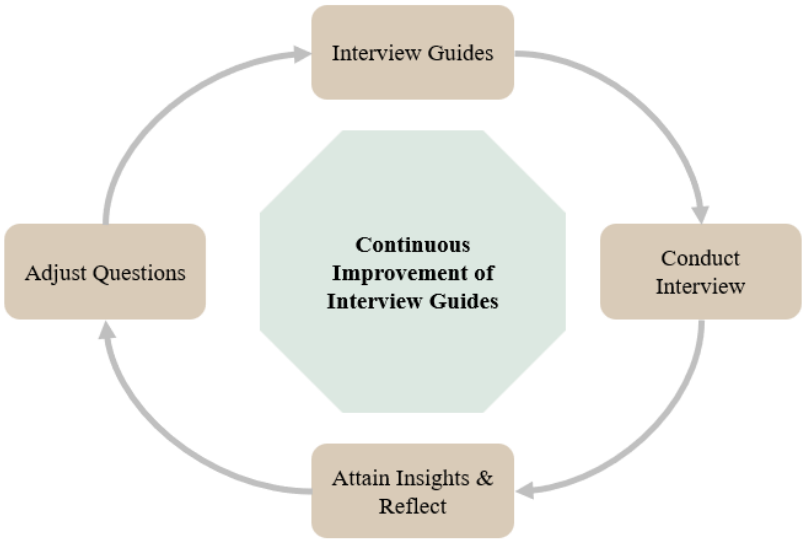

Figure 2.6. *Cycle of Continuous Improvement of Interview Guides.*

steps, we developed our own iterative process steps shown in **Figure 2.6**. To exemplify, in the first interviews, we reflected on what we learned, what themes were recurring, and what areas needed more detail. Based on this, we adjusted the later interview questions. For example, after the first interviews, we became more aware of the importance of SKU variability, software maturity, item presentation, order-level automation, intervention frequency, and the changing role of human workers. These topics were then explored more clearly in later interviews. This helped us make the later interviews more focused and relevant.

For us, this iterative process was necessary because the field is still developing. If we had used a fully fixed interview guide, we might have missed important insights that only became visible during the interviews. By adjusting the guides, we could follow the direction of the empirical material while still keeping the interviews connected to the research objectives.

2.2.2. Integrative Literature Review

In addition to the interviews, we conducted an integrative literature review. The purpose of this review was to bring together existing knowledge from academic and practitioner-oriented sources and use it to support the empirical analysis. The review helped us build the theoretical foundation, define key concepts, understand the technical and operational background of PaP technology, and connect interview findings to existing research.

We chose an integrative review because the research field is fragmented. Knowledge about PaP technology in warehouses is not located in one single research stream. Some literature focuses on warehouse automation and order picking. Other literature focuses on robotics, grippers, computer vision, HRI, technology adoption, or smart warehousing. In addition, many current developments are discussed in grey literature rather than peer-reviewed academic sources. Integrative reviews are useful in this type of situation because they allow different kinds of literature to be combined

and interpreted together (Torraco, 2005; Adams, Smart and Huff, 2017; Elsbach and Van Knippenberg, 2020; Cronin and George, 2023).

In our thesis, the integrative review had four main roles. First, it helped us establish the theoretical foundation. Second, it helped us define concepts such as G2P systems, PaP technology, robotic picking, technology adoption, and HRI. Third, it helped us support and contrast what interviewees said. Fourth, it helped us cover descriptive and technical aspects where interviews alone were not enough, such as robot characteristics, market developments, and recent company activities.

Figure 2.7 shows the methodology used for data collection in the integrative literature review. We started from the research objectives and scope, developed search terms, searched for white and grey literature, screened the sources, and selected the most relevant material. As the thesis developed, we adjusted the search terms based on what we learned from both the literature and interviews.

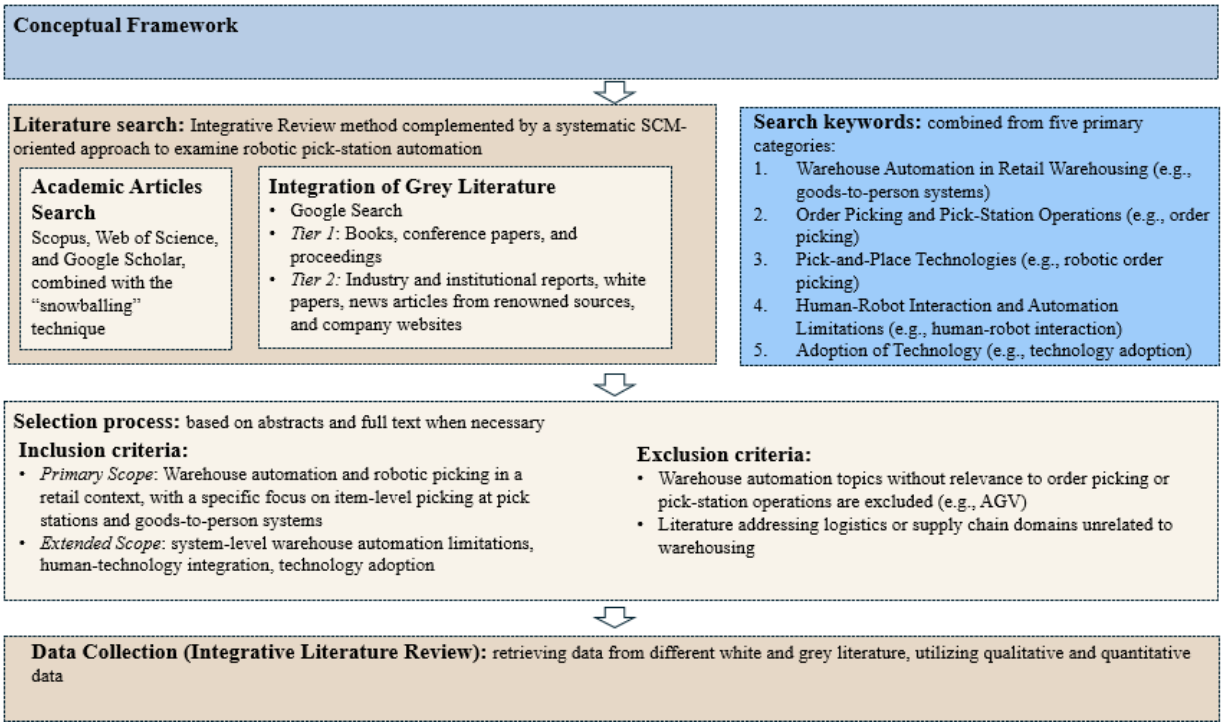

Figure 2.7. *Methodology for data collection in the Integrated Literature Review. Figure inspired by Rodríguez-García et al. (2025).*

For the integrative review, the search terms were not fixed from the beginning. We adjusted them continuously to better capture the relevant literature, see **Figure 2.8**. Articles we analyzed inspired new search terms, and interview insights also led us to search for additional literature. An iterative process for refining search strategies in literature reviews enhances the rigor by addressing keyword errors and leveraging previous systematic reviews (Abi Khalil *et al.*, 2023).

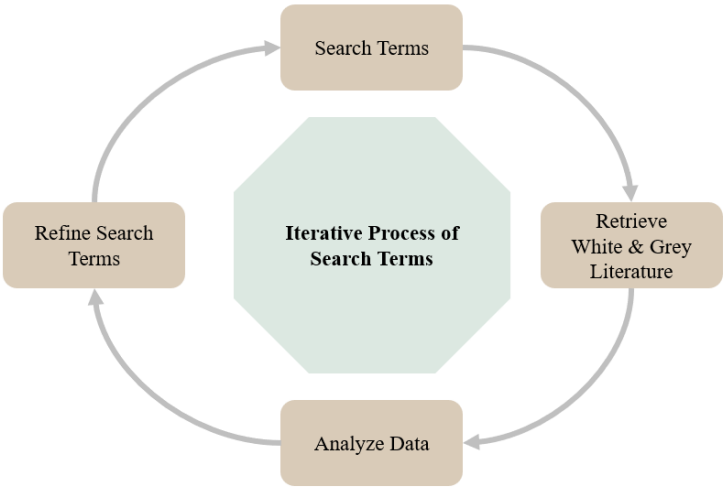

Figure 2.8. *Iterative process of adjusting search terms.*

White Literature

The white literature search focused on academic and scholarly sources. We searched for literature related to warehouse automation, order picking, G2P systems, robotic picking, PaP technology, HRI, technology adoption, and technology maturity. The keywords utilized for the search are shown in **Table 2.4**.

The search was conducted through Web of Science, Scopus, Google Scholar, and Google Search. At the beginning, we used broader terms such as warehouse automation, order picking, G2P systems, and robotic picking. As our understanding developed, the search became more specific and included terms such as robotic piece picking, PaP technology, pick stations, SKU variability, HRI, warehouse automation adoption, and technology maturity.

Table 2.4. Keywords for search (White Literature).

Category	Example keywords	Purpose in the review
Warehouse Automation (Retail Context)	Goods-to-person systems; G2P; Parts-to-Picker	To identify literature on automated warehouse systems and fulfilment environments relevant to retail and e-commerce
Order Picking Pick-Station Operations	Order Picking; Item-level picking; pick station; picking operations; manual picking; AI picking; Artificial Intelligence picking	To capture studies focusing on the process and performance of order picking and pick stations
Robotic Picking & Pick-and-Place Technologies	Robotic Picking; Robotic order picking; pick-and-place robots; robotic manipulation; Bin picking; Grippers; Artificial Intelligence picking	To identify literature on robotic solutions used for picking and handling items in warehouses
Human–Robot Interaction & Automation Limitations	Human-robot interation; Human-robot collaboration; Automation limitations; Exception handling; Variability	To capture research discussing human involvement, variability, and limits of automation in warehouse contexts
Implementation, Integration & Adoption	Technology adoption; System Integration; Automation implementation; Scaling Automation; Separational Deployment	To identify studies addressing real-world deployment, integration, and scaling of automation technologies

The search process was iterative. Articles that we analyzed inspired new search terms and helped us identify related concepts. We also used snowballing, where the reference lists of relevant articles were examined to identify additional sources (Hilend *et al.*, 2023). This was useful because relevant research was spread across different disciplines and did not always use the same terminology. When repeated searches produced irrelevant results, the search was stopped, following the logic suggested by Hastig and Sodhi (2020), where repeated irrelevant results can indicate that further searching is unlikely to add relevant material.

The selection process followed two stages. In the first stage, we screened titles and abstracts based on relevance to the research objectives and the scope of the thesis. The focus was on warehouse automation and robotic piece-picking in retail G2P warehouses. In the second stage, we reviewed the full texts to check whether the sources provided relevant insights into item-level picking, pick station use, automation limitations, HRI, or the adoption of robotic PaP technologies.

We excluded sources that were outside the thesis scope, such as studies focusing on non-warehouse applications, purely technical robotics studies without operational implications, or logistics topics unrelated to warehousing and order picking. Methodological literature was included only when it supported the research design, integrative review approach, interview method, or research quality criteria.

Grey Literature

Grey literature was included because PaP technology is developing rapidly. Peer-reviewed academic literature alone does not fully capture recent technological advances, market activity, funding developments, and implementation experiences. Therefore, industry reports, company websites, brochures, eBooks, and, news articles provided important supplementary insight. We included grey literature following Adams, Smart and Huff (2017), who discuss the value of grey literature in management and organizational studies when relevant knowledge exists outside traditional academic publications. In our thesis, grey literature was especially useful for understanding current developments in the PaP robotics market, vendor claims, active deployments, company-specific technology characteristics, and industry expectations. **Table 2.5** shows the keywords we used for our search.

We used the two-tier approach from Adams, Smart and Huff (2017) to assess grey literature. Tier 1 includes sources with a higher level of academic rigor and legitimacy, such as academic books, peer-reviewed conference papers, and conference proceedings. Tier 2 includes industry and institutional reports, white papers, and news articles from established organizations or media outlets. These sources can provide important practical insights, but they need to be interpreted carefully because they may include commercial or promotional claims.

Google Search was used to identify companies that develop the technology, have adopted the technology, or may potentially adopt it in the future. Based on these results, we collected company reports, newsletters, articles, and website material. These sources helped us understand vendor positioning, funding activity, implementation examples, and current market developments.

The grey literature selection process followed two stages, similar to the white literature process. In the first stage, we screened sources based on source type, title, summary, and alignment with the research objectives and scope. Priority was given to sources produced by recognized industry actors, established technology providers, reputable media outlets, and institutions with expertise in logistics, robotics, or warehouse automation.

Table 2.5. *Keywords for Search (Grey Literature).*

Category	Example keywords	Purpose in the review
Companies that develop/provide the technology	Pick-and-Place Technologies Robotic picking solutions warehouse; Robotic picking solutions warehouse; Robotic arm warehouse order picking; Automated piece picking system for retail distribution; Names of providers	Assess what the technology is and how far it is in terms of capabilities
Companies that have adopted pick-and-place technology for picking	Names of Companies that develop/provide the technology; Name of the technology; Pick-and-Place technology; Robotic Arm; Names of Adopters	How it gets adopted, also see the impact at case companies
Consultancy Firms that researched pick-and-place technology	Robotic Arm; Pick-and-Place Technology; McKinsey, BCG, Bain & Company, Accenture	Impact, Challenges, strategic lens, expected future

In the second stage, we reviewed the full content to assess relevance, credibility, and informational value. We focused on insights related to real-world implementation, operational challenges, system capabilities, integration with existing warehouse systems, and performance considerations. We also evaluated the sources based on transparency, consistency with other evidence, and overall reliability.

In the final thesis, grey literature played a larger role in some parts than others. It was especially important for describing recent market developments, company activities, vendor characteristics, funding rounds, and technical claims. In more interpretive parts of the analysis, grey literature was combined with interview insights and academic literature rather than used as the only basis for conclusions.

2.2.3. Integration of Interviews and Literature

Although the interview study and integrative literature review are presented separately for clarity, they were integrated throughout the research process. The final thesis was therefore not developed as two separate studies placed next to each other. Instead, we moved back and forth between interview insights, academic literature, grey literature, and theoretical frameworks.

The interviews provided the main empirical foundation of the thesis. They helped us understand how actors in the field currently view PaP technology, what benefits and challenges they identify, how they evaluate adoption, how humans interact with the systems, and how they expect the technology to develop. The literature was then used to support, contrast, and deepen these insights, which is consistent with the purpose of an integrative review: bringing different types of knowledge together to understand a complex phenomenon (Torraco, 2005; Cronin and George, 2023).

In practice, the role of the literature changed during the study. Before the interviews, it helped us understand the research field, define the scope, and develop the interview guides. During and after the interviews, it was used more selectively to investigate themes that became important in the empirical material, such as order-level automation, software maturity, integration, and changing human roles. For us, this combined approach was necessary because PaP technology is both an emerging technology and an operational phenomenon. It could not be understood only through literature, because many practical issues are still developing and are best captured through expert interviews. It could also not be understood only through interviews, because expert statements needed to be connected to broader academic and industry knowledge.

2.3.Data Analysis

The data analysis brought together the empirical findings from the interviews and the findings from the integrative review. The goal was to develop a coherent understanding of the characteristics, benefits, challenges, HRI, context of usage, and future potential of PaP technology in retail G2P warehouses. The data analysis frameworks and discussion after that are visually shown in **Figure 2.9**.We opted to present the empirics and the understandings we get from them, which helped us to create the themes and also, the alignment with the frameworks.

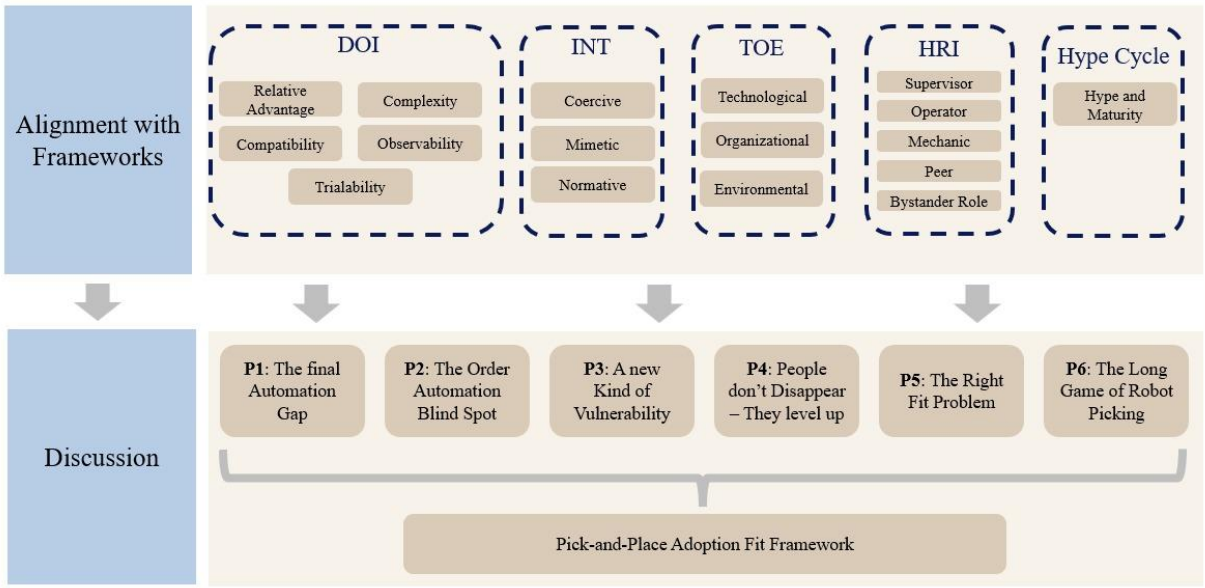

Figure 2.9. *Frameworks and their aspects are utilized for analysis, followed by discussion.*

We analyzed the data through an iterative thematic process. First, we reviewed the interview material to identify recurring themes connected to the research objectives. These themes were then compared with insights from academic and grey literature. The main themes became characteristics, benefits, challenges, context of usage, HRI, and future development of the

technology. We did not analyze interviews and literature as two separate result streams. Instead, we developed the findings by moving between empirical statements, secondary sources, and theoretical frameworks. For example, interview statements about SKU variability, software maturity, integration challenges, and order-level automation were compared with literature on robotic picking and warehouse automation. Interview insights about labor shortages, Return on Investment (ROI), market pressure, and adoption uncertainty were interpreted through technology adoption theories and institutional perspectives.

The findings were then aligned with the theoretical frameworks selected for the thesis: Institutional Theory (INT), Diffusion of Innovations (DOI), the Technology-Organization-Environment (TOE) framework, HRI roles, and the Hype Cycle. Characteristics, benefits, and challenges were interpreted through Diffusion of Innovations and Institutional Theory. Context of usage was interpreted through the Technology-Organization-Environment framework. HRI was interpreted through the role-based HRI framework. The future of the technology was interpreted through the Hype Cycle.

After this, we developed the discussion chapter. The discussion was divided into six propositions: the final automation gap, the order automation blind spot, a new kind of vulnerability, people do not disappear - they level up, the right fit problem, and the long game of robot picking. These propositions were not intended as universal rules or statistically tested claims. Instead, they were developed as our condensed reflections based on the combined interpretation of interviews, literature, and theory.

Finally, these propositions were synthesized into the PaP Adoption Fit Framework. The framework positions adoption potential according to two dimensions: Operational Automation Fit and Strategic Business Pressure. For us, this framework brings together the central learning of the thesis: adoption depends not only on whether the robot is technically mature, but on whether the technology fits the warehouse operation and whether the business pressure is strong enough to justify implementation.

2.4.Research Quality

Research quality can be assessed in different ways. In quantitative research, the conventional approach often includes internal validity, external validity, reliability, and objectivity (Guba and Lincoln, 1989). However, since this thesis is qualitative and exploratory, we used the quality criteria discussed by Halldórsson and Aastrup (2003): credibility, transferability, dependability, and confirmability. These criteria were more suitable for our thesis because the study is based on semi-structured interviews combined with an integrative review. The methodological choices and how they contributed to research quality are summarized in **Table 2.6**.

Table 2.6. Quality Criteria with their definition and methodological choices that align with the criteria. Adopted from Halldórsson and Aastrup (2003).

Quality Criteria	Definition	Methodological choices
Credibility	The findings accurately reflect the realities as understood by the research participants.	Were possible, multiple expert perspectives are triangulated across both the interview data and the integrative review to ensure that findings are not based on a single, potentially unrepresentative source.
Transferability	The findings are sufficiently contextualized to allow readers to judge their applicability to other settings.	By providing detailed descriptions of the interview participants and companies utilized for the integrative review, readers can judge whether the findings are applicable to their own context.
Dependability	Any changes in research design throughout the study are documented and justifiable.	Specifically describing the research methodology as done in chapter 2.
Confirmability	The findings can be traced back to the data rather than reflecting the researcher's personal bias.	By directly linking each conclusion to specific quotes from interviews or sources from the integrative review, the reader can verify that the findings reflect the data rather than the researcher's personal opinion.

Credibility

Credibility is comparable to internal validity in the conventional approach. It concerns whether the study represents the phenomenon in a trustworthy way. In qualitative research, this is important because actors may have different perceptions of the same reality depending on their role, context, and experience (Halldórsson and Aastrup, 2003).

In our thesis, credibility was strengthened through triangulation. Triangulation is a research strategy where multiple methods or data sources are combined to increase confidence in the findings (Lawlor, Tilling and Davey Smith, 2017). It can also strengthen research credibility by allowing researchers to compare evidence across different sources (Benavides and Gómez-Restrepo, 2005).

We used triangulation by combining interviews, academic literature, grey literature, company material, and industry sources. This allowed us to compare insights from several perspectives instead of relying on one type of evidence. The interview sample also supported credibility because it included different actor categories. Developers often focused on technical capability, integration, and system performance. The adopter perspective gave more insight into business case, implementation, operational use, and limitations. Academic experts helped us connect the technology to broader research on warehouse automation and logistics systems. By comparing these perspectives, we could identify both recurring patterns and differences between actors.

Transferability

Transferability is similar to external validity in the conventional approach. It concerns whether the findings may be relevant beyond the specific interviewees and sources included in the study (Halldórsson and Aastrup, 2003). Since this thesis is qualitative and exploratory, our aim was not statistical generalization. Instead, we wanted to provide enough contextual detail so that readers can judge whether the findings may be relevant in other settings.

To support transferability, we clearly defined the scope and unit of analysis. The thesis focuses on PaP technology in retail G2P warehouse environments, especially where robotic picking robots are considered as a next automation layer at pick stations. Therefore, the findings are most transferable to similar contexts, such as high-volume e-commerce or omnichannel warehouses with existing G2P infrastructure.

The findings may be less transferable to very different warehouse contexts, such as low-volume manual warehouses, manufacturing environments, or warehouses with highly standardized products. However, some insights may still be relevant for other automation contexts, especially the importance of operational fit, organizational readiness, human role design, and technology maturity.

Dependability

Dependability is related to reliability in the conventional approach. In quantitative research, reliability often concerns whether the same results could be replicated under the same conditions. In qualitative research, however, dependability is less about exact replication and more about making the research process transparent and followable (Halldórsson and Aastrup, 2003).

In this thesis, we supported dependability by explaining the logic of the research process and the methodological decisions we made. This chapter describes the research approach, the interview study, the integrative review, the integration between interviews and literature, and the data analysis process. We also explain how the analysis moved from empirical themes to theoretical interpretation, then to discussion propositions, and finally to the PaP Adoption Fit Framework.

It is important to mention that the research process was not fully linear. Our understanding of the topic changed as the study developed. We do not see this as a weakness. Since the technology is emerging and the literature is fragmented, an iterative process was necessary. For us, dependability was strengthened by making this process clear instead of pretending that the study followed a perfectly linear path from the beginning.

Confirmability

Confirmability is related to objectivity in the conventional approach. It concerns whether the findings are grounded in the data rather than only in the researchers' assumptions or biases (Guba and Lincoln, 1989; Halldórsson and Aastrup, 2003).

In this thesis, confirmability was supported by linking our interpretations to interview statements, literature, and theoretical frameworks. In Chapter 4, interview statements were used to show where empirical claims came from. These statements were then supported, contrasted, or contextualized through academic and grey literature. In the discussion chapter, we made a clearer distinction between empirical findings, literature-based insights, and our own interpretation. This was important because the discussion required us to take a more active role in synthesizing the findings and developing propositions. Also, the continuous improvement of the interview guides contributes to this aspect of the research quality (Kallio *et al.*, 2016).

Using “we” in the methodology and discussion was therefore intentional. In the methodology chapter, “we” helps us clarify what we did, how we conducted the study, and how the research process developed. In the discussion chapter, “we” helps us clarify our own interpretation and synthesis of the combined findings. At the same time, we aimed to make clear when an insight came from interview data, when it came from literature, and when it represented our own interpretation.

Altogether, the use of credibility, transferability, dependability, and confirmability helped us reflect on the trustworthiness of the thesis and on the methodological choices made throughout the research process.

3. Theoretical Foundation

This chapter presents the theoretical foundation of the thesis. It introduces the main concepts and frameworks used to understand pick-and-place technology in retail G2P warehouses.

As shown in **Figure 3.1**, the theoretical foundation is structured around four main pillars: warehousing automation in retail, piece-picking robots as a pick-and-place technology, their application in warehousing, and the theoretical models used to examine technology adoption and HRI. Together, these pillars provide the conceptual basis for interpreting the empirical findings.

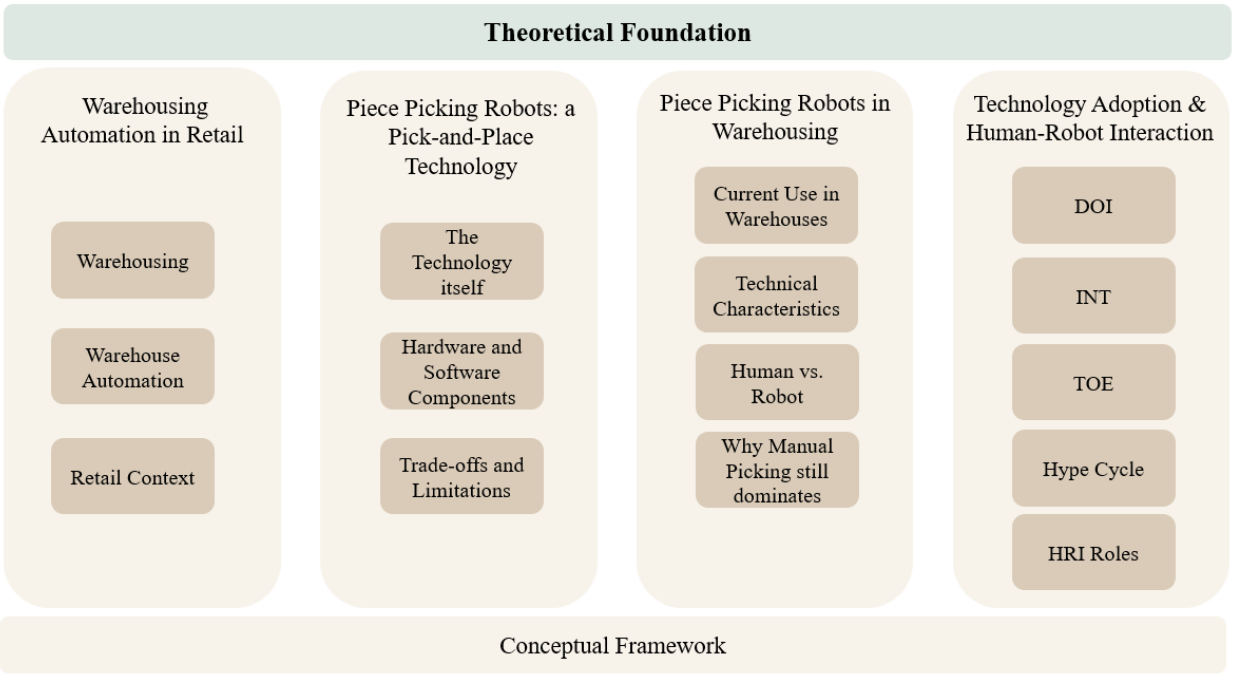

Figure 3.1. *Overview of Theoretical Foundation.*

3.1. Warehousing Automation in Retail

This section establishes the warehousing operations and retail context within which this study is situated. It covers the core warehouse processes, the broader landscape of warehouse automation, and the retail-specific conditions, including omni-channel retailing, e-commerce growth, labor scarcity, and high SKU variability, that together form the operational foundation of this thesis.

3.1.1. Warehousing

Warehousing is the activity with the aim of storing goods for further distribution, sales, or manufacturing. The goal is to satisfy the customer's needs effectively (Sivakumar and Ruthramathi, 2019).

Warehouses are filled with Stock Keeping Units (SKUs), which are defined as a unique identifier for each distinct product that enters the warehouse. This is utilized in data management to track inventory and product availability, attached to a product, shade and pack size (Pandey, 2013).

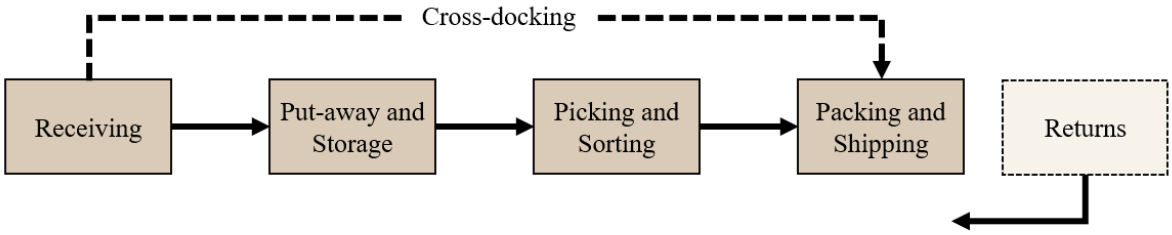

Figure 3.2. *Overview of warehousing operations. Adopted from Kembro, Norrman and Eriksson (2018).*

These SKUs go through the process shown in **Figure 3.2**. This process is described in Kembro, Norrman and Eriksson (2018) starts with receiving goods at inbound, where checks are performed based on quality, quantity, and damage. Then the SKUs are stored at a storage location, which is the put-away process. Subsequently, when an order is released, the items go through the picking and sorting process. Picking is the majority of the operation costs, which is 55% (Bartholdi and Hackman, 2010). Our thesis focuses on the activity 'picking and sorting'. Order picking can be defined as the assembly of customer orders from SKUs in storage. It is a critical component in the supply chain and a major cost component of warehousing (Charles and Peterson, 1997). Order picking aims to manage the process of clustering, scheduling, and fulfilling orders to minimize labor and capital costs, which significantly impact total operating costs (Chackelson *et al.*, 2011). From there, the packing and shipping of SKUs is the last step before they exit the warehouse (Bartholdi and Hackman, 2010). Multiple forms of order picking systems exist; see the framework of Dallari, Marchet and Melacini (2009) in **Figure 3.3**.

G2P systems improve picking speed and reduce the physical demands placed on staff (Zhao and Zhang, 2025). The main G2P technologies currently in use include Vertical Lift Modules, Automated Storage and Retrieval Systems, and Robotic Mobile Fulfillment Systems, the last of which has attracted particular interest due to its flexibility and ability to scale alongside fluctuating e-commerce demand (Zhao and Zhang, 2025). Zotou *et al.* (2024) provide a concrete illustration of what these systems look like in practice, describing an Autonomous Mobile Robot-based implementation where autonomous robots navigate warehouse aisles and deliver product bins to human pickers at fixed workstations. In a G2P system, automation handles transportation and storage while people remain responsible for the picking.

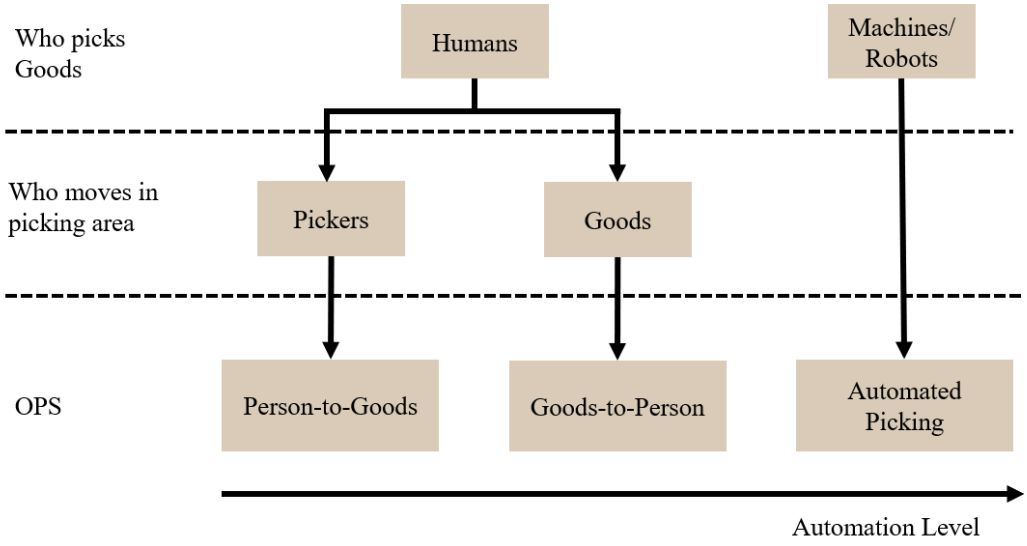

Figure 3.3. *Order picking systems. Retrieved from Dallari, Marchet and Melacini (2009).*

European Warehouses are inflexible in workforce deployments and have high labor costs (Bartholdi and Hackman, 2010). This makes PaP technologies especially interesting in countries in Europe. The research from Bartholdi and Hackman (2010) support this by indicating that the adoption of automation solutions is greater in European warehouses than the ones in North American.

3.1.2. Warehouse Automation

In the area of Industry 4.0, a significant amount of research contains the subject of transitioning from manual processes to Highly Automated Warehouse Systems. These papers typically entail the deployment of industry 4.0 technologies (Rodríguez-García *et al.*, 2025). The different types of technologies in highly automated warehouse systems are shown in **Figure 3.4**. The research from Rodríguez-García *et al.* (2025) categorizes the technologies in four distinct categories: core automation, supporting automation, management software, and digital technologies. Core Automation includes technologies such as Automatic Storage and Retrieval Systems, multi-shuttle configurations, and Autonomous Mobile Robots (Kembro and Norrman, 2025; Fragapane *et al.*, 2021). Additionally, cube storage systems are technologies utilized in this categorization (Azadeh, De Koster and Roy, 2019). Secondly, supporting automation, like Piece Picking Robots. These robots are utilized for precision piece picking (Rodríguez-García and Agmoni, 2024). This thesis focuses on this technology. The other categories contain management software and Digital Technologies (Rodríguez-García *et al.*, 2025). These technologies are less relevant in this thesis, but are necessary for the technology to integrate into the operations.

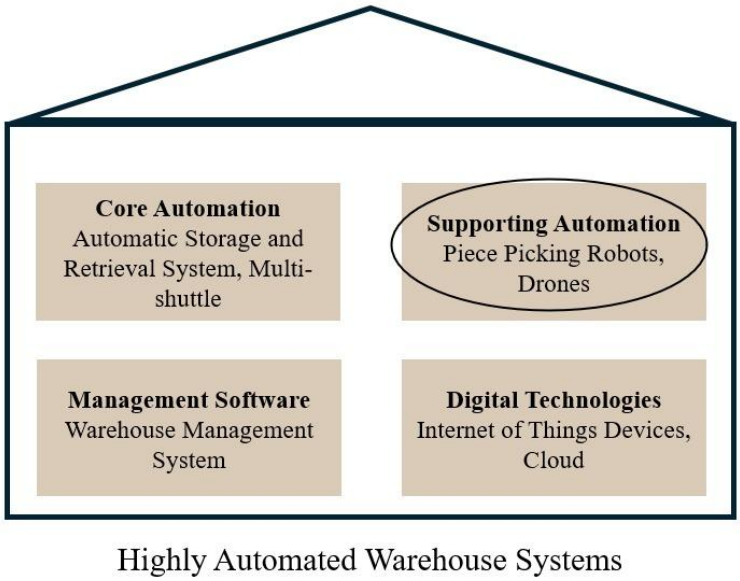

Figure 3.4. *Highly automated warehouse system attributes. Adopted from (Rodríguez-García* et al.*, 2025)*

3.1.3. Retail Context

Retailers presently integrate physical stores and online channels into a seamless shopping environment, this phenomenon is known as omni-channel retailing (Kembro, Norrman and Eriksson, 2018). An omnichannel environment is both competitive and changing (Ishfaq *et al.*, 2016). Different types of warehouses exist within omni-channel, encompassing Distribution Centers, direct fulfillment centers (handling e-commerce orders and delivery to customer) , and forward fulfillment centers (utilize storage of retailers as logistic hubs in the customer's proximity) (Kembro, Norrman and Eriksson, 2018).

The broader evolution of warehousing itself has corresponded with an increase in interest in G2P. The evolution of facilities from basic G2P arrangements to highly automated environments was assessed by Boysen and De Koster (2025). This is a result of global supply chain disruptions, delivery expectations, and the demands of e-commerce. Cube storage systems are among the developments in this trend. These systems have autonomous robots that retrieve items from bins within a grid-based structure (Boysen and De Koster, 2025). However, the advantages of this technology, these systems introduce new coordination challenges (Boysen and De Koster, 2025).

Given the emergence of e-commerce, labor scarcity, and the increasing complexity that omni-channel retailing brings, PaP technologies could be of major importance (Azadeh, De Koster and Roy, 2019). Important to note that retail warehouses have a high SKU variability. This creates increased complexity due to sorting high SKU assortments in low quantities (De Koster, Johnson and Roy, 2017). This marks that for PaP technologies, a retail environment is especially interesting.

PaP technologies (like Piece picking robots) are a part of warehouse automation. These robots are designed to identify, grasp, move, and deposit individual items, replicating tasks that human

workers currently perform manually (Jotawar, Soni and Kumar, 2017; Huang and Mok, 2018). The field has emerged in recent years, due to AI, computer vision, robot kinematics, and sensor integration, though several important challenges remain unresolved (Jotawar, Soni and Kumar, 2017; Huang and Mok, 2018).

3.2. Piece Picking Robots: a Pick-and-Place Technology

This section reviews the literature pertaining to PaP technology as applied in warehouse environments. It begins by defining the technology itself and its hardware and software components, before examining its current use in practice and why manual picking continues to dominate. It then addresses the technical characteristics that determine system performance, the trade-offs and limitations that constrain adoption, and concludes with an examination of the relationship between humans and robots in warehouse picking.

3.2.1. The Technology Itself

PaP technology refers to robotic systems that identify an item, grasp it, remove it from a storage location, and place it into another destination, such as a tote, order bin, pallet, or transport unit. In warehouse environments, this usually appears as robotic piece-picking or bin-picking and is increasingly discussed as part of wider warehouse automation and robotization trends. The relevance of this technology has grown because warehousing remains labor-intensive, order picking is still one of the most time-consuming and expensive warehouse activities, and e-commerce has intensified the need to handle large SKU assortments, small order lines and fluctuating order volumes with high speed and accuracy (De Koster, Le-Duc and Roodbergen, 2007; Burinskiene, 2010; Casella *et al.*, 2023)

Recent literature positions PaP technology within the broader development of robotized and automated warehouse systems. These include shuttle systems, robotic mobile fulfilment systems, autonomous mobile robots, and hybrid human–robot systems, all of which aim to improve warehouse efficiency, flexibility, and responsiveness (Azadeh, De Koster and Roy, 2019; Da Costa Barros and Nascimento, 2021). However, robotic picking is not a single standardized solution. Instead, it includes a range of applications, from fixed piece picking robots working in bin-picking cells to mobile autonomous picking robots operating in existing warehouse aisles (Da Costa Barros and Nascimento, 2021; Zhang, Grosse and Glock, 2023).

3.2.2. Hardware and Software Components

A useful distinction in the literature is between the hardware and software components of PaP systems. On the hardware side, a typical system consists of a robotic manipulator, an end-effector or gripper, sensors and cameras, and in some applications a mobile platform that allows the robot to travel through the warehouse (Niu *et al.*, 2021; Wong *et al.*, 2022). The end-effector is particularly important because it directly determines which items can be handled and how reliably the system can perform across different product categories.

The gripper literature shows that successful PaP operations require high speed, reliable gripping and release, low maintenance, low weight and the ability to adapt to a range of product shapes and textures (Blanes *et al.*, 2011). Although that review focuses on fresh fruit and vegetables, the underlying argument is directly relevant to warehouse order picking, where products also differ substantially in shape, surface, fragility and packaging.

On the software side, PaP systems depend on perception, decision-making, and control architecture. This includes object detection, object sorting, pose estimation, grasp planning, coordinate transformation, motion planning, and collision avoidance (Niu *et al.*, 2021; Wong *et al.*, 2022). Wong *et al.* (2022), for example, describe a ROS (Robot Operating System)-based bin PaP system that integrates object detection, object sorting, pose estimation, coordinate transformation and bin collision avoidance into one modular architecture. Likewise, Niu *et al.* (2021) show that even a vision-guided PaP task requires camera calibration, hand-eye calibration, object registration, pose alignment, and execution planning before the grasp can be performed. This makes clear that warehouse robotic picking is not merely a mechanical task, but a tightly integrated hardware–software system.

3.2.3. Trade-Offs and Limitations

The literature shows that PaP technology involves several trade-offs rather than representing a simple productivity improvement. One major trade-off is between automation and investment. Autonomous picking robots may reduce labor intensity and improve operational consistency, but they also require relatively high initial investment, system setup and maintenance resources (Azadeh, De Koster and Roy, 2019; Zhang, Grosse and Glock, 2023).

A second trade-off is between productivity and ergonomics. Hybrid systems can reduce human travel and lower some aspects of physical workload, but they may also intensify other movements if tasks are not allocated carefully. Zhang, Grosse and Glock (2023) show that collaborative hybrid order picking systems can reduce both operational costs and human workload, but they also caution that reduced travel may increase the frequency of picking actions and thereby raise ergonomic risks if item allocation is poorly designed.

A third trade-off concerns technical sophistication and deployability. Advanced approaches, including reinforcement learning, promise more adaptive robotic picking behavior, but current research still identifies major problems in validation, generalization, and grasp pose selection (Lobbezoo, Qian and Kwon, 2021). This means that while advanced control methods are promising, they do not yet remove the practical challenges of reliable industrial implementation.

A fourth trade-off is between analytical optimization and operational realism. Azadeh, De Koster and Roy (2019) note that analytical models are useful in the conceptual design phase because they reduce the search space, but more detailed models and simulations are often needed to represent real system behavior. The more recent simulation-oriented literature also confirms that queueing,

battery use, congestion, and dynamic routing remain important practical issues in robotic warehouse operation (Samolej, Baturyna and Davidrajuh, 2025).

3.3. Piece Picking Robots in Warehousing

Piece picking robots are increasingly being explored as a solution to the physical demands and throughput pressures of warehouse order picking. This section examines how PaP technology is currently applied, what technical factors shape its performance, and how it compares to and increasingly collaborates with human pickers. It also considers why manual picking continues to dominate despite growing automation capabilities.

3.3.1. Current use of Pick-and-Place Technology in Warehouses

The current use of robotic picking technology is especially visible in warehouses facing high throughput pressure, high SKU variety, and labor constraints. This is particularly relevant in e-commerce and retail distribution, where systems must manage large assortments, variable order structures, and short lead times (Azadeh, De Koster and Roy, 2019; Casella *et al.*, 2023). Azadeh, De Koster and Roy (2019) argue that robotic handling systems are particularly suitable for e-commerce because they can work continuously, require less space, and offer greater flexibility in handling varying demand requirements.

In practice, however, robotic picking is used in different ways. Some systems automate transport and storage access rather than the physical item grasp itself, as in robotic mobile fulfilment systems (Da Costa Barros and Nascimento, 2021). Other systems use autonomous mobile picking robots that can move through warehouse aisles, identify items, retrieve them, and transport them to a depot or packing location (Zhang, Grosse and Glock, 2023). This means current applications range from supportive automation to partially automated and highly automated picking systems rather than reflecting one uniform technology path.

Recent literature also suggests that the practical direction is increasingly toward hybrid systems, where robots and humans work together rather than one fully replacing the other. In these settings, robots may perform repetitive, physically demanding or transport-intensive tasks, while humans continue to handle more variable or difficult picking activities (Jacob *et al.*, 2023; Zheng, Glock and Neumann, 2025).

3.3.2. Technical Characteristics of Pick-and-Place Robots

Several technical characteristics determine the performance of warehouse PaP systems. One of the most important is the pick rate or throughput. In warehousing, the economic relevance of a robot depends heavily on whether it can achieve short cycle times while maintaining reliable grasping and placement. Blanes *et al.* (2011) stress that profitable PaP requires both high speed and high reliability, while Mnyusiwalla *et al.* (2020) show that performance evaluation should extend across the full PaP sequence, including pre-grasping, grasping, transport and placement. Another critical factor is the robot's degrees of freedom and motion capability. Wong *et al.* (2022) implement a

six-degree-of-freedom manipulator in their bin PaP system, while Niu *et al.* (2021) use a Kuka LBR iiwa arm, a lightweight collaborative robotic arm used for precise and flexible manipulation tasks, in a 3D vision-guided setup. Higher movement flexibility improves the robot's ability to reach cluttered or awkward target positions, but it also increases computational and control complexity.

The end-effector is equally important because it directly affects grasp reliability. Depending on the product type, the robot may require suction-based, contact-based or adaptive grippers. As the gripper literature shows, product heterogeneity makes this one of the main technical bottlenecks in PaP design (Blanes *et al.*, 2011). This challenge becomes even more significant in warehouse settings with mixed inventories and frequent product variation.

The perception system also plays a decisive role. Warehouse items are often stacked, partially occluded or randomly oriented, so robots need reliable vision systems for object detection and pose estimation. Wong *et al.* (2022) use YOLOv4 (You only look once), CAD-based pose estimation and point cloud alignment, while Niu *et al (*2021) rely on 3D vision, object registration and pose alignment algorithms. These studies highlight that robotic picking is not simply about arm motion, but also about robust visual understanding of the environment.

Finally, collision avoidance is crucial in warehouse picking because robots must operate near bins, shelves, objects and sometimes human workers. Wong *et al.* (2022) therefore develop a dedicated bin collision avoidance method, reinforcing the idea that reliable warehouse picking requires safe and context-sensitive motion planning.

3.3.3. Humans versus Robots in Picking

The literature increasingly frames the issue not as a direct competition between humans and robots, but as a question of how to combine them effectively. Human–robot collaboration has become a major research stream because it offers a way to use robots for repetitive and physically burdensome tasks while retaining human flexibility for complex and variable picking work (Jacob *et al.*, 2023; Zheng, Glock and Neumann, 2025).

Zhang, Grosse and Glock (2023) show that collaborative hybrid order picking systems can reduce operating costs and human workload when task assignment is configured appropriately. Pasparakis, De Vries and De Koster (2023) add that collaboration with robots can positively influence worker job satisfaction, although the effects differ depending on whether the human leads the robot or follows it. Jacob *et al.* (2023) further show that acceptance of human-robot collaboration depends on factors such as safety, perceived effort, organizational support and psychosocial concerns.

This suggests that humans and robots should not be treated as direct substitutes in every context. Human workers still outperform robots in flexibility, exception handling and adaptation, while robots offer consistency, repeatability and relief from repetitive or strenuous work. In many current warehouse environments, the most effective approach is therefore a hybrid or collaborative design,

rather than a purely manual or fully robotic one (Vijayakumar and Sobhani, 2023; Zheng, Glock and Neumann, 2025).

In terms of performance, there is no clean number in human picks per hour, since the SKU characteristics and station design play an important role. A one G2P ergonomic study reports that low-load picking at under 700 picks/hour did not produce high physical stress, while higher frequencies above that raised the workload (Steinebach, Wakula and Mehmedovic, 2021). A separate simulation study reported a maximum hourly productivity of 394 picks per worker under its modeled conditions (Huerta *et al.*, 2013). This data is necessary to compare the performance of the robots compared to human.

3.3.4. Why Manual Picking still Dominates in Order Picking

Despite advances in warehouse automation, manual order picking still remains highly relevant. Research has long recognized order picking as one of the most labor-intensive warehouse functions, and recent studies continue to show that many picker-to-parts systems are still manually operated or only partially automated (De Koster, Johnson and Roy, 2017; Zhang, Grosse and Glock, 2023). Zheng, Glock and Neumann (2025) note that end-to-end automation remains rare, and that modern warehouses often rely on partial automation, leaving humans responsible for tasks such as item picking and replenishment.

There are several reasons for this. First, manual picking offers a level of flexibility that robotic systems still struggle to match. Human pickers can handle irregular objects, damaged packaging, unexpected stock placement and rapidly changing order mixes without the need for retraining algorithms or redesigning the system. Second, robotic systems still face substantial technical challenges in perception, grasping and handling in cluttered or uncertain environments (Mnyusiwalla *et al.*, 2020; Wong *et al.*, 2022). Third, automation often requires high investment, setup effort and maintenance capability, which is not always feasible or economically attractive, especially when demand or product variety is uncertain (Azadeh, De Koster and Roy, 2019; Zhang, Grosse and Glock, 2023).

The persistence of manual systems is also reflected in research on supportive and substitutive technologies. Grosse (2024) shows that technologies in manual warehouse picking are often introduced not to eliminate human work entirely, but to support and augment it. This suggests that manual picking remains dominant not simply because automation is absent, but because it continues to offer operational advantages in many warehouse contexts.

3.4. Technology Adoption & Human-Robot Interaction

The section presents five theoretical frameworks sequentially (DOI, INT, TOE, HRI levels, and the Hype Cycle), each in its own subsection. It then concludes with the synthesis section that combines all five into a single conceptual framework. Each framework subsection follows a consistent pattern of introducing the theory, explaining its components, and linking it to the thesis topic.

3.4.1. The Diffusion of Innovations Framework

Rogers (2003) created the DOI model, which describes the pattern and speed of how a new product, innovation, or a solution is adopted and therefore is suitable to have when looking at emerging technologies. The theory explains adoption as a process that unfolds over time through communication channels among members of a given system, influenced by both the characters of the innovation and the context in which it is introduced.

The DOI framework is built around four main elements, (1) the innovation itself, (2) communication channels, (3) time and (4) the social system. Among these, the innovation element is especially important, as it includes five characteristics that help explain the rate at which a technology is adopted. According to Rogers (2003), these five attributes account for a large share of variation in innovation adoption, often between 50% to 80% of the adoption rate. These attributes are relative advantage, compatibility, complexity, observability, and trialability, which can be seen in **Figure 3.5**. Because of the explanatory value, these attributes are sometimes used independently without the rest of the framework and sometimes in combination with other frameworks, which will be done in this thesis.

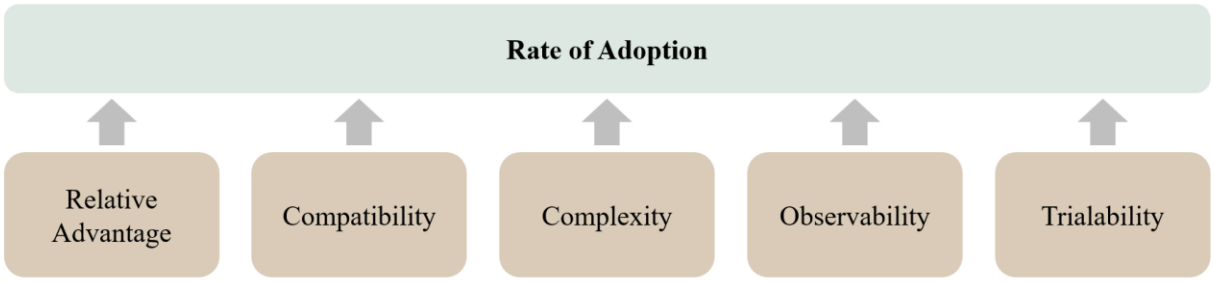

Figure 3.5. *DOI Framework. Adopted from Rogers (2003).*

First, relative advantage refers to the extent to which a new technology is seen as better than the current solution. This can include different types of benefits depending on the technology being studied. Rogers (2003) points out that economic benefits are often the most important and most commonly used aspect of relative advantage. In many cases, the size of the initial investment strongly affects how quickly a technology is adopted. At the same time, other benefits may also matter, such as improved efficiency, higher productivity, faster task execution, or better operational quality. Previous studies have also used cost efficiency, lower maintenance costs, and improved inventory processes as examples of relative advantage in industrial technology adoption (Tsai, Lee and Wu, 2010; Oliveira, Thomas and Espadanal, 2014). In the context of this thesis, relative advantage is relevant for understanding whether robotic PaP technologies are perceived as offering meaningful improvements over manual picking at retail warehouse pick stations.

Compatibility is the extent to which a new technology is seen as fitting with existing values, working methods, and business processes. If a technology is perceived as being consistent with the current way of working, it is generally more likely to be adopted and adopted faster Rogers

(2003). Compatibility can, for example, mean that the technology matches the work style of employees or fits with the organization's current operations, culture, values, and existing software or hardware systems (Oliveira, Thomas and Espadanal, 2014). Although Rogers (2003) suggests that compatibility may have less influence on adoption than relative advantage, it still remains important in understanding whether an organization sees a technology as realistic and workable in its own setting.

Complexity refers to how difficult an innovation is perceived to be to understand and use. Technologies that require new knowledge, advanced skills, or major changes in routines are often adopted more slowly (Rogers, 2003). Rogers (2003) further notes that while complexity may sometimes be less important than relative advantage and compatibility, it can become especially significant in the case of more technical innovations. This is supported by Tsai, Lee and Wu (2010), who argue that relative advantage and complexity are among the strongest predictors when evaluating the benefits and challenges of technology innovation. In practice, complexity may increase when a technology demands high mental effort, specialized employee skills, or difficult implementation processes (Oliveira, Thomas and Espadanal, 2014). In this thesis, complexity is particularly relevant because robotic PaP technologies must often be integrated into already automated warehouse systems, which can make them difficult to evaluate, implement, and operate.

Observability explains the extent to which the results and benefits of an innovation are visible to others. When the outcomes of a technology can be clearly seen, understood, and communicated, it becomes easier for potential adopters to recognize its value. According to Rogers (2003), visible benefits can positively influence adoption because individuals and organizations are more likely to accept a technology when they can observe its practical effects. In warehouse settings, observability may involve being able to see improvements in picking speed, accuracy, labor utilization, or overall operational efficiency after a technology has been introduced.

Lastly, trialability refers to the extent to which an innovation can be tested or experimented with before full adoption. According to Rogers (2003), technologies that can be tried on a limited basis tend to create less uncertainty and are therefore more likely to be adopted more quickly. Trialability is important because it allows decision-makers to evaluate whether a technology fits their operational needs before committing significant time and financial resources.

DOI also distinguishes between different categories of adopters: innovator, early adopters, early majority, late majority, and laggards, which together describe how a technology spreads over a social system over time (Rogers, 2003), this can be seen in **Figure 3.6**. These categories are not only useful for classifying adopters, but also for understanding that the factors influencing adoption are not equally important across all groups. Rogers (2003) argues that the perceived attributes of an innovation may matter differently depending on where adopters are positioned in the diffusion process. Rogers (2003) specifically mentions that trialability is especially important for innovators and early adopters, since these groups make adoption decisions at a stage when few prior examples are available. Unlike later adopters, they cannot rely as much on proven cases or

lessons from others and therefore place greater value on being able to test and evaluate the technology directly before making a full commitment. Rogers (2003) also notes that, within relative advantage, early adopters may be influenced not only by practical benefits but also by the potential to gain social status or be perceived as leaders through early adoption.

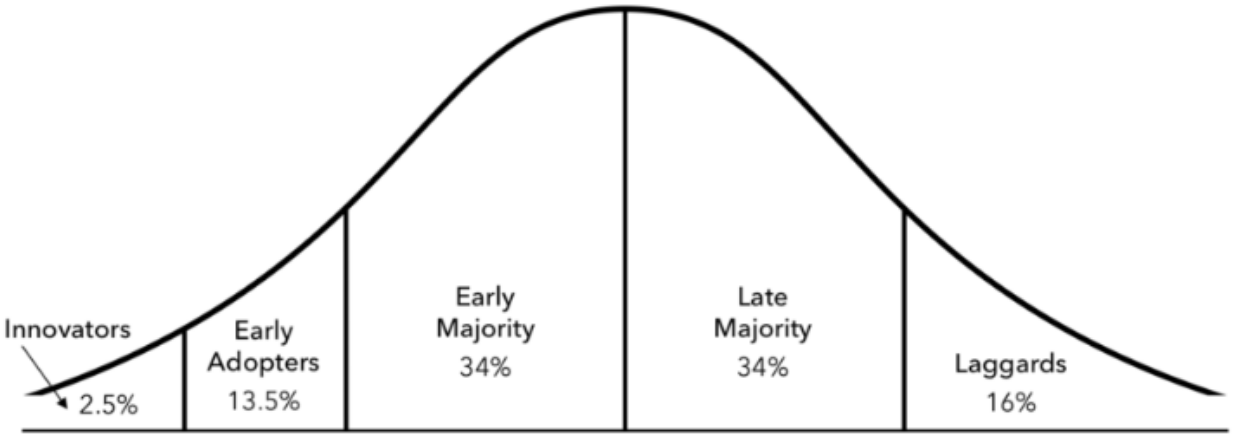

Figure 3.6. *Different adopters of a new innovation (Rogers, 2003)*

The diffusion curve resembles a normal distribution, where most adopters are concentrated in the middle categories, while only a smaller share adopt either very early or very late. This pattern reflects the fact that organizations differ in their willingness to take risks, their access to information, and their readiness to engage with new technologies. Although the importance of each innovation attribute may vary across adopter groups, the general logic remains the same: technologies that are perceived as offering a clear relative advantage, fitting well with existing systems and practices, being less complex, producing visible results, and allowing some degree of experimentation are more likely to be adopted faster. In other words, the more positively a technology is perceived across these dimensions, the stronger its chances of diffusing more rapidly through the market.

3.4.2. Institutional Theory

INT is developed by DiMaggio and Powell (1983) as an institutional theory to explain why organizations within the same field tend to become increasingly similar over time, even in the absence of evidence that such conformity improves efficiency (see **Figure 3.7**). The theory argues that organizations are shaped not only by competitive market pressures but also by broader institutional forces that push them toward homogeneity in pursuit of legitimacy and social acceptance. The central concept of the theory is institutional isomorphism, which refers to the process through which organizations adopt similar structures, practices, and behaviors. DiMaggio and Powell (1983) identify three mechanisms through which this occurs.

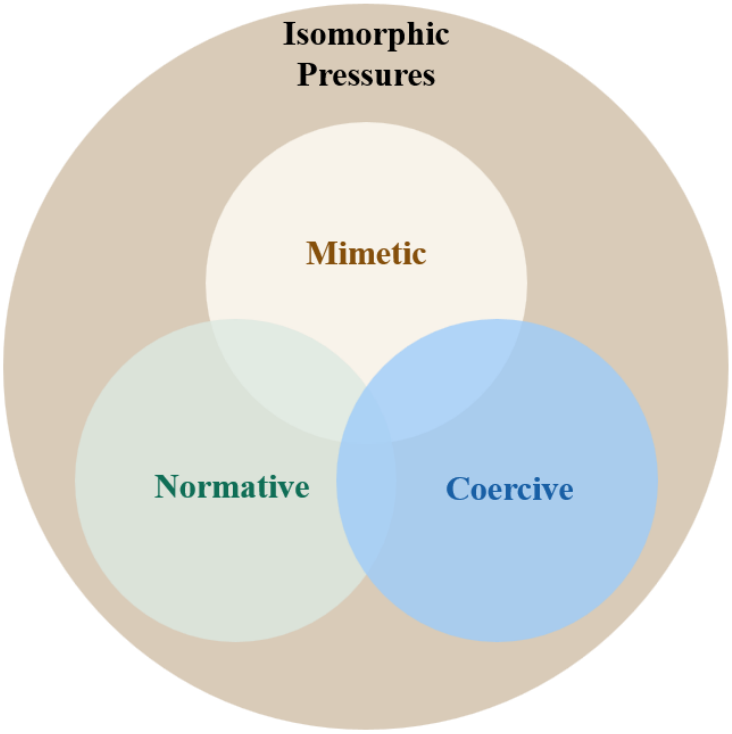

Figure 3.7. *INT framework. DiMaggio and Powell (1983)*

The first mechanism, coercive isomorphism, arises from formal and informal pressures exerted by governments, regulatory bodies, or other organizations upon which a firm is dependent. These pressures may take the form of legal mandates, financial requirements, or societal expectations, compelling organizations to adopt certain structures or practices in order to maintain their legitimacy. The second mechanism, mimetic isomorphism, occurs when organizations face uncertainty regarding their goals, technologies, or environment. Under such conditions, organizations tend to imitate others that are perceived as more successful or legitimate, often through the transfer of personnel, the use of consulting firms, or the adoption of widely recognized industry practices. This imitation does not necessarily stem from a conscious strategic decision, but rather from a pragmatic response to ambiguity. The third mechanism, normative isomorphism,

stems from professionalization. As managers and specialists are trained through similar educational institutions and professional networks, they develop shared norms, values, and cognitive frameworks. These commonalities lead professionals across different organizations to approach problems in comparable ways, further driving convergence within organizational fields (DiMaggio and Powell, 1983).

In a supply chain context, Simões, Soares and Barros (2020) applied institutional theory to capture the external pressures that influence managers' decisions to adopt cobots beyond purely rational or economic motivations. Since adoption decisions are also shaped by competitive pressure, regulatory requirements, and industry norms, institutional theory provides a lens to account for these socio-political and inter-organizational influences on technology adoption.

Together, these three mechanisms help explain how and why organizations operating in the same environment converge toward comparable structures and practices, regardless of whether doing so genuinely enhances their operational performance (DiMaggio and Powell, 1983).

3.4.3. The Technology-Organization-Environment Framework

The TOE model from (Tornatzky and Fleischer, 1990) describes the company context could influence the adoption and implementation of innovations (Baker, 2012). It was developed to expand the scope of the domain of the technology adoption literature, revealing that the process of technology adoption is affected not only by the nature of the adopted technology but also by the conditions within the organization and the external environment in which the firm is operating. According to the TOE model, the concept of technology adoption can be explained through the following three contexts: technological, related to the perceived attributes of the innovation and the organization's technological infrastructure; organizational, related to the organization's resources, structure, and support; and environmental, related to the external conditions, including the organization's competitors, market conditions, and external stakeholders (Chen, Preston and Swink, 2015; Ediriweera and Wiewiora, 2021), see **Figure 3.8**.

Firstly, the context of technology encompasses all the technologies that are important to the firm, including the technologies that are already adopted and technologies that are developed but not utilized by the company. The technologies that are already in place are important, since it outlines in what sense the company is able to innovate (Baker, 2012). Henceforth, the technology context determines the technological readiness of a company (Oliveira, Thomas and Espadanal, 2014). Secondly, the environmental context refers to the physical, market and operational context in which PaP technology is adopted. This aspect includes HRI in the workplace, and for example, when the robot is utilized (only during peak hours or continuously). Thirdly, the organizational context, including the TOE model, is considered an important concept in the supply chain and operations literature, as the concept of technology adoption is considered a contextual and strategic process, rather than being viewed as a purely technological concept.

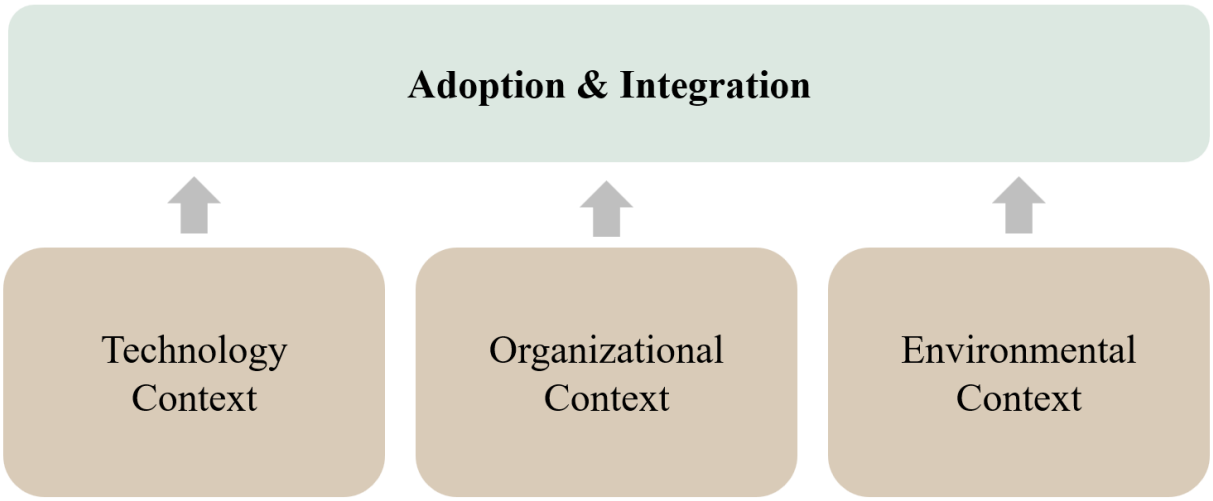

Figure 3.8. *The TOE Framework. (Tornatzky and Fleischer, 1990)*

For example, the TOE model was applied to the concept of big data analytics, revealing that the technological, organizational, and environmental factors influenced the actual adoption and value creation (Chen, Preston and Swink, 2015) .The model was also applied to the concept of RFID (Radio-Frequency Identification) adoption in the retail sector, revealing that the technological, environmental, and value chain-related factors influenced the adoption (Bhattacharya and Wamba, 2015). Moreover, the TOE model was applied to the concept of blockchain adoption in the supply chain, revealing that the relative advantage, trust, compatibility, resources, top management support, business partner pressure, and environmental pressure influenced the adoption (Chittipaka *et al.*, 2023).

The value of the TOE framework is even more evident when firms are faced with newly emerging technologies, such as Industry 4.0 technologies, which often involve an adoption process with inherent uncertainties, limited information, and an evolving business case. Kapoor and Klueter (2021) argue that there is multi-dimensional uncertainty surrounding newly emerging technologies, which is not only linked to the performance of the specific technology but also to its applications, users, ecosystem, and business model, thus making it more of a managerial task than an evaluation of performance. In the same manner, Maghazei, Lewis and Netland (2022) show how, with newly emerging technologies, there is often an exploration process based on use cases, prior to establishing an actual business case, thus necessitating an evaluation of economic, operational, organizational, and behavioral appropriateness, as adoption progresses. This is particularly true for warehouses, logistics, and digital transformation, where adoption is now often influenced by factors such as the maturity of the specific technology, supplier availability, organizational digital capabilities, as well as the appropriateness of technological solutions for operational needs (Kembro and Norrman, 2022; Ansari *et al.*, 2025).

In warehouses with manual and semi-automated processes, for instance, leadership, organizational culture, training, and employee acceptability were found to be critical determinants

of successful adoption, thus indicating how, in such cases, technology adoption is as much dependent on organizational and human readiness as it is on the specific technology (Grosse, 2024). As such, for the purposes of this thesis, it is proposed to utilize the TOE framework as an analytical tool, as it provides an opportunity to evaluate the process of adopting warehouse technologies as an outcome of combining technical suitability, organizational capability, and environmental pressures, while at the same time recognizing the uncertainties and transition challenges inherent in newly emerging technologies for logistics (Ediriweera and Wiewiora, 2021; Kapoor and Klueter, 2021; Maghazei, Lewis and Netland, 2022).

3.4.4. Roles of Human-Robot Interaction

Scholtz (2003) propose distinct interaction models for each of the five HRI roles, structured around four hierarchical levels: goals, intentions, actions, and perception/evaluation (see **Figure 3.9**).

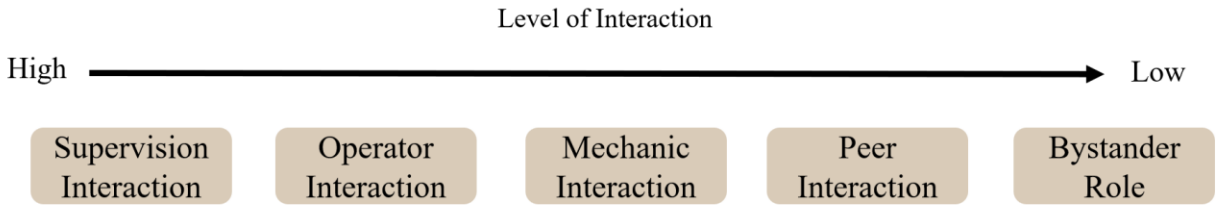

Figure 3.9. *Categorization of HRI roles. Adopted from Scholtz (2003).*

The supervisor operates primarily through continuous monitoring and evaluation, with the robot autonomously generating actions based on its planning system. The supervisor retains the highest level of authority, being the only role permitted to modify longer-term goals and intentions, while also retaining the ability to intervene at the action level when necessary (Scholtz, 2003).

The operator functions at the action level, adjusting robot behavior when it deviates from expectations. Crucially, the operator cannot alter overarching goals or intentions, as that authority is reserved for the supervisor. The operator must verify that corrective actions align with the broader plan (Scholtz, 2003).

The mechanic follows a similar interaction structure to the operator but focuses on physical hardware interventions. Following any physical modification, behavior testing must be conducted in software to confirm that the intended effect on robot performance has been achieved (Scholtz, 2003).

The peer interacts at a higher behavioral level than the operator, issuing natural, high-level directives rather than low-level commands. If the robot fails to comply, the peer may either escalate to the operator role or delegate to a more qualified individual (Scholtz, 2003).

The bystander holds only a restricted subset of interaction capabilities, with no access to the goal or intention levels. Feedback is limited to direct observation, and a key design challenge is

communicating to bystanders which robot behaviors fall within their limited sphere of influence, given the absence of a conventional interface (Scholtz, 2003).

To summarize, the model illustrates that HRI cannot be treated as a uniform phenomenon; the appropriate interaction modality is contingent upon the role the human occupies relative to the robotic system (Scholtz, 2003).

3.4.5. Hype Cycle of New Technologies

When new technologies come out, people are often very hopeful about what they can do in the future. During the initial stages of development, anticipations regarding the potential accomplishments of a technology can significantly influence its direction. These expectations are not just passive predictions of what will happen in the future; they actively shape research agendas, bring in money, get businesses and investors involved, and give legitimacy to ongoing experimentation and development (Van Lente, Spitters and Peine, 2013). In this way, expectations can be helpful in the process of coming up with new ideas. They help gather people, resources, and interest around a technology before it has been fully tested in real life. These dynamics are not neutral, though. When expectations are too high, they can lead to forms of overconfidence that are hard to keep up once the real limits of the technology become clear. If the technology's performance, scalability, or readiness for the market turns out to be worse than expected, people may be disappointed, which could hurt its credibility and slow down further development (Van Lente, Spitters and Peine, 2013; Dedehayir and Steinert, 2016). People often call the pattern of rising excitement followed by falling excitement "hype." The larger pattern of expectations going up and down over time is called the "hype cycle" (Van Lente, Spitters and Peine, 2013).

The Gartner Hype Cycle is one of the most well-known ways to show this process. The model was created to show the general way that new technologies go from being new to being stable and useful (Dedehayir and Steinert, 2016). The hype cycle doesn't just look at technical maturity; it also looks at the relationship between time and expectations or visible value. This shows that technological development is shaped not only by engineering progress but also by collective perceptions, media attention, and strategic decision-making. This viewpoint is especially helpful for logistics and warehousing technologies because many new ideas are first sold with strong claims about automation, flexibility, efficiency, and digital transformation, even though their real operational performance isn't fully understood yet.

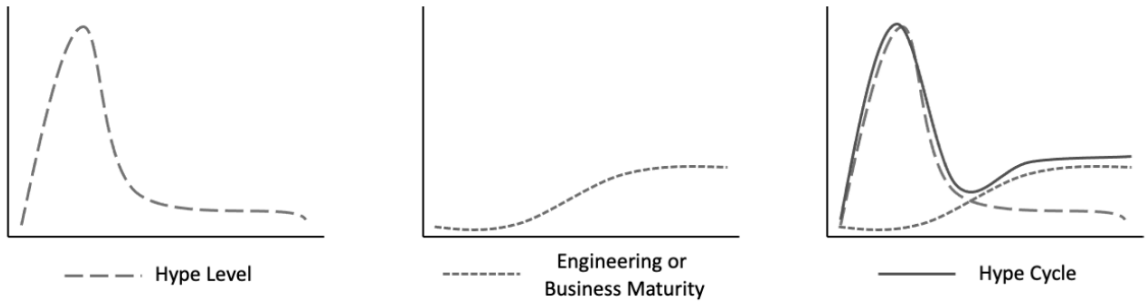

Figure 3.10. *Relationship between hype level, engineering or business maturity, and the resulting hype cycle. Adapted from Dedehayir and Steinert (2016)*

Figure 3.10 shows that the hype cycle is made up of two separate but related dynamics: a human-centered hype curve and a technology maturity curve. The first one is how people react socially and psychologically when a new technology comes out. Dedehayir and Steinert (2016) assert that the initial significant increase in expectations is propelled by an exaggerated and frequently irrationally optimistic response to technological innovation. Fenn and Raskino (2008) contend that this response arises from various facets of human nature, notably the inclination to explore and acquire knowledge autonomously, a fascination with novelty, and social contagion, whereby enthusiasm disseminates swiftly among individuals, organizations, and media platforms.

The second curve shows how the technology itself is growing more slowly and in a more cumulative way. The technology S-curve is a common way to describe this dynamic. It shows how performance gets better over time as more knowledge is gained, more experiments are done, and technical problems are slowly solved. Nieto, Lopéz and Cruz (1998) say that technological development usually goes through four stages: an embryonic stage, a growth stage, a mature stage, and an aging stage, where performance improvements start to slow down. When these two things happen simultaneously, they create the shape of the hype cycle: an early rise in inflated expectations caused by social excitement, followed by a correction phase, and finally a more stable level of value as the technology matures and its uses become clearer (Dedehayir and Steinert, 2016).

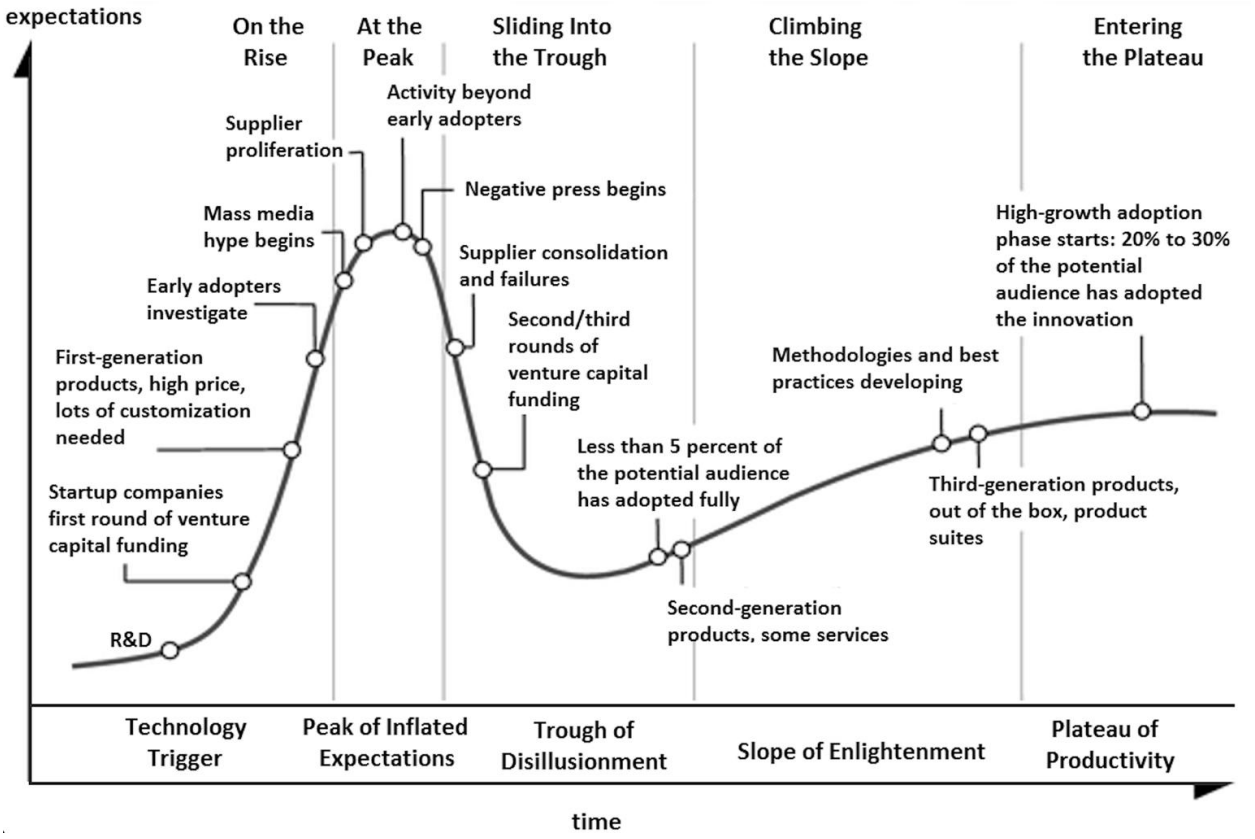

Figure 3.11. *The different stages of the hype cycle (Dedehayir and Steinert, 2016).*

Five traditional stages of hype are depicted in **Figure 3.11**: the Innovation Trigger, Peak of Inflated Expectations, Trough of Disillusionment, Slope of Enlightenment and Plateau of Productive Use. The model can be utilized analytically to assist in understanding how technologies evolve as they are perceived, disclosed, examined and become mainstreamed through time (Dedehayir and Steinert, 2016).

The process begins with the ***Innovation Trigger***, which refers to the point at which a new technological solution, product, or concept first emerges and attracts attention. At this stage, interest from the media and from early technical communities begins to build, often because the technology appears to offer new possibilities or to address existing limitations in current systems. However, commercial viability is still uncertain, and market-ready applications are often not yet established (Kondo, Asatani and Sakata, 2022). Development is typically led by start-up companies, R&D groups, or pioneering actors, and the first products are usually characterized by high cost, limited scalability, and substantial customization requirements (Dedehayir and Steinert, 2016).

This is followed by the ***Peak of Inflated Expectations***, where a small number of promising demonstrations or early success stories generate widespread enthusiasm. At this point, the technology receives substantial media attention, and expectations often rise beyond what the technology can realistically deliver in the short term. Positive narratives dominate, while uncertainty, complexity, and implementation constraints receive less attention (Kondo, Asatani and Sakata, 2022). Under such conditions, firms may begin investing not because of a clear operational strategy or well-developed business case, but because of a bandwagon effect driven by the fear of missing out on a supposedly transformative innovation (Dedehayir and Steinert, 2016) .In organizational contexts, this stage may lead to strategic overcommitment before the technology has been adequately tested against operational needs.

The ***Trough of Disillusionment*** emerges when the practical realities of implementation become more visible. Technical limitations, unexpected costs, integration challenges, and failed commercial efforts lead to a decline in confidence. Suppliers are pressured to improve their offerings, and early adopters begin reassessing whether the expected benefits are truly achievable (Kondo, Asatani and Sakata, 2022). Media attention often decreases during this phase, and skepticism grows as exaggerated claims are replaced by more cautious evaluations. In many cases, this is the stage at which weaker solutions disappear from the market, while only the more robust technologies or committed actors remain engaged (Dedehayir and Steinert, 2016).

If development continues, the technology may then enter the ***Slope of Enlightenment***. At this stage, a more realistic understanding of the technology begins to emerge. Organizations and early adopters that continue to experiment with the innovation start identifying where it can create actual value and under what conditions it performs effectively (Dedehayir and Steinert, 2016). Second- and third-generation versions of the technology appear, products become more refined, and methodologies or best practices begin to develop. The emphasis shifts away from broad and speculative promises toward more specific use cases, clearer implementation knowledge, and better understanding of costs and benefits. Nonetheless, broader adoption remains cautious, as many firms prefer to wait until the technology has demonstrated stable results in practice (Kondo, Asatani and Sakata, 2022).

The final stage is the ***Plateau of Productivity***, where the technology reaches a more stable and realistic valuation. At this point, the capabilities and limitations of the innovation are better understood, practical benefits have been demonstrated in relevant contexts, and adoption spreads beyond pioneers and early adopters to a broader audience (Dedehayir and Steinert, 2016). The technology becomes more standardized, widely recognized, and integrated into routine organizational practice, while expectations align more closely with actual performance (Kondo, Asatani and Sakata, 2022). This does not imply that the technology is perfect or universally suitable, but rather that its productive role has become clearer and more credible.

Taken together, the hype cycle provides a valuable way of interpreting the development of emerging technologies because it highlights that adoption is shaped not only by technical progress

but also by collective expectations, market narratives, and social responses to novelty. For this thesis, the concept is especially relevant because warehouse and logistics technologies are frequently introduced with strong claims regarding higher productivity, greater flexibility, improved responsiveness, and better decision-making through automation and digitalization. Such claims may be justified in the long term, but in the early stages they can also contribute to unrealistic expectations that obscure the operational conditions required for successful implementation.

However, while the hype cycle is useful for understanding the evolution of expectations, it is less effective in explaining why some technologies are adopted successfully by firms while others are delayed, resisted, or abandoned. The model captures the temporal pattern of visibility and enthusiasm, but it does not sufficiently account for the internal capabilities of firms, the readiness of existing systems, the role of management, or the influence of competitive and institutional pressures. In other words, it is more descriptive of expectation dynamics than explanatory of organizational adoption decisions. For that reason, a broader analytical perspective is needed to examine how firms evaluate and respond to emerging technologies in practice.

3.5. Conceptual Framework

To analyze the adoption of the PaP technology in retail G2P warehouses from multiple relevant perspectives, a framework was developed by combining the presented technology adoption and HRI theories. The DOI framework is used to find out what people think about the technology, including its relative advantage, compatibility, complexity, observability, and trialability. The TOE framework builds on this by taking into account the broader context in which the technology is used and evaluated, such as the adopting firm's technological, organizational, and environmental conditions. INT enhances the environmental aspect by emphasizing coercive, mimetic, and normative pressures that may affect adoption decisions. Additionally, the hype cycle adds a time dimension by taking into account how mature the technology is and how excited the market is about it. The HRI roles add the perspective of how different ways that humans and robots and humans interact. Together, these perspectives provide a structured basis for analyzing the adoption and interaction of PaP technologies in retail G2P warehouses. The complete framework is presented in **Figure 3.12**.

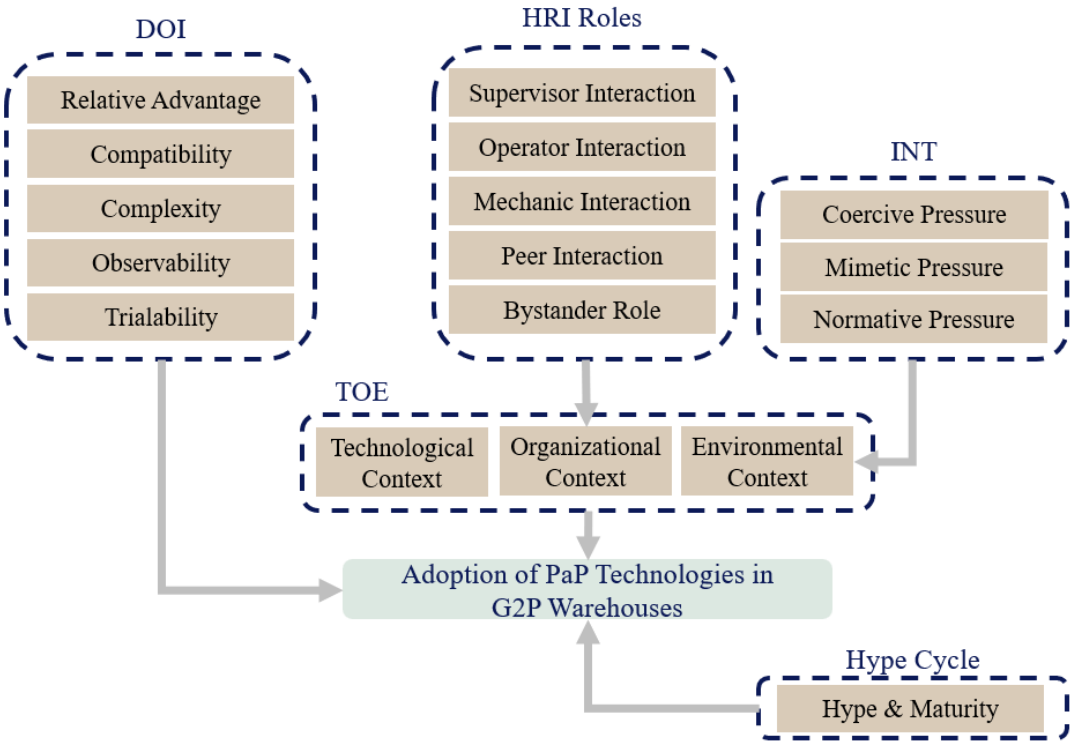

Figure 3.12. *Conceptual Framework. Own Creation.*

4. Empirics & Analysis

This chapter presents the empirical findings and analysis of the thesis. It brings together insights from the interview study and the integrative literature review to examine pick-and-place technology in retail goods-to-person warehouses.

As shown in **Figure 4.1**, the findings are organized around six themes: characteristics, benefits, challenges, context of usage, HRI, and future outlook. These themes are interpreted through the selected theoretical frameworks and together address the three research objectives of the thesis.

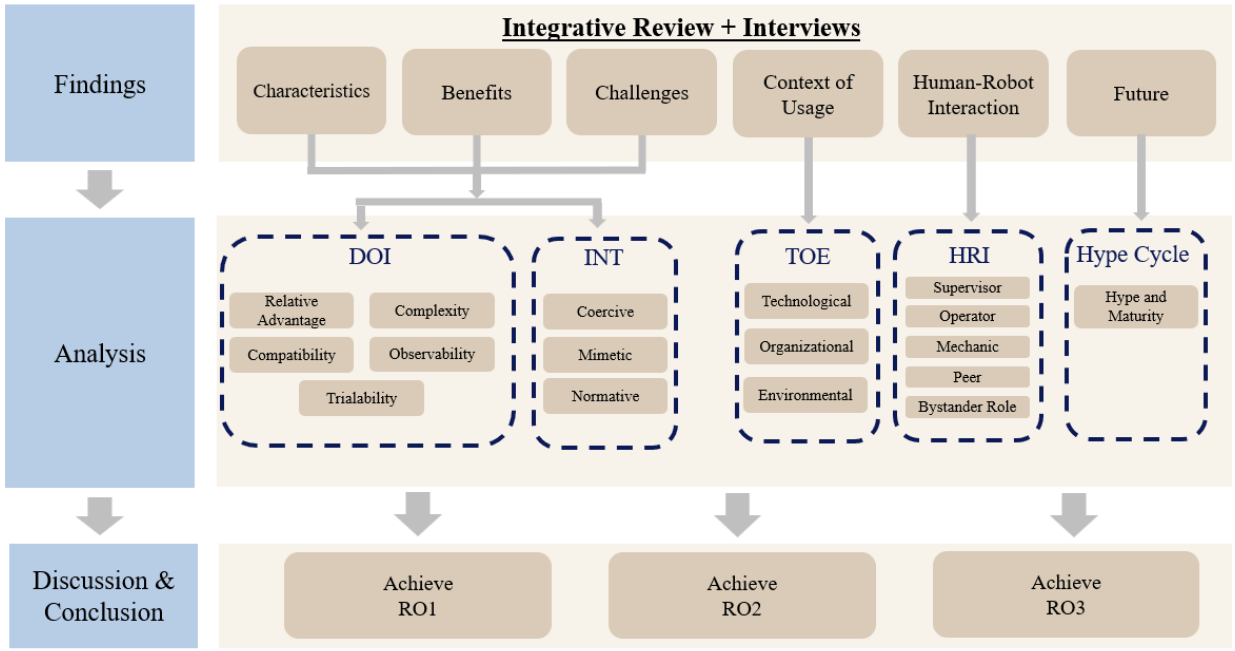

Figure 4.1. *Overview of how empirics and analysis are the foundation for discussion and conclusions.*

4.1. Characteristics, Benefits, and Challenges

This section presents empirical findings on the benefits and challenges of adopting PaP technology in G2P retail warehouses, drawing on semi-structured interviews with technology providers, adopters, and academic experts, and the integrative review. **Figure 4.2** gives an overview of the structure of this section

4.1.1. Characteristics

This section presents the empirical findings related to the characteristics of the PaP technology providers consulted during the data collection process. The findings focus on three main aspects:

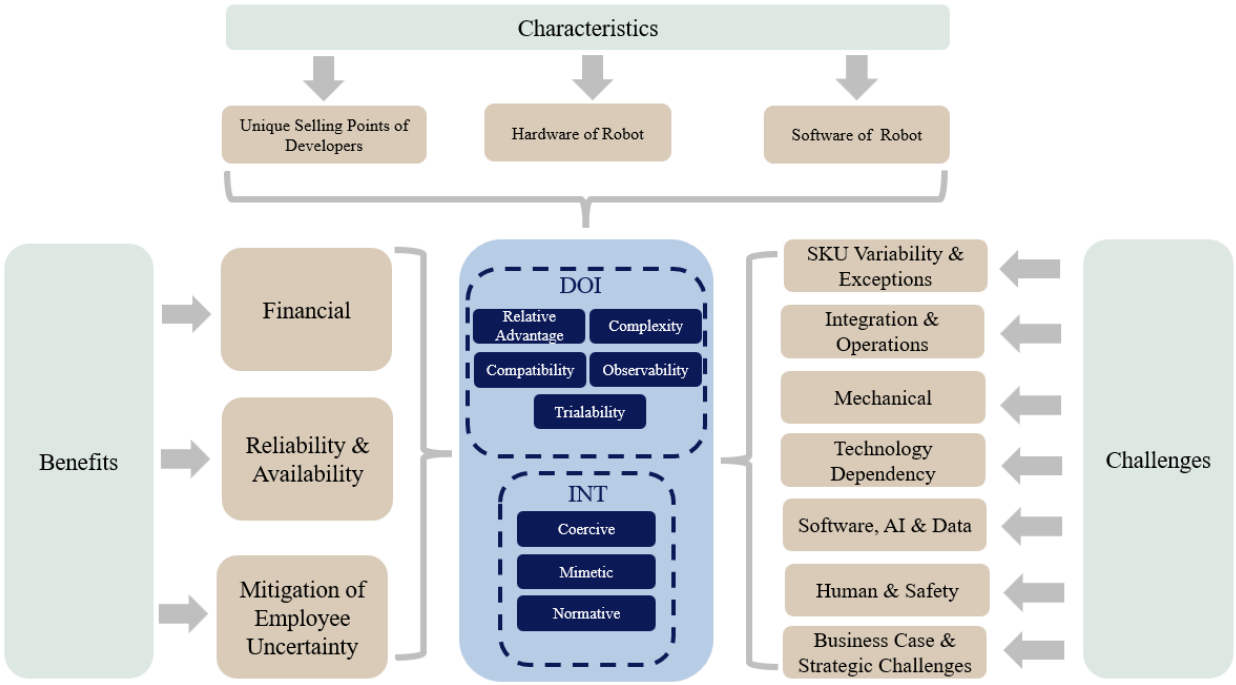

Figure 4.2. *Empirical themes related to Characteristics, Benefits and Challenges into DOI and Institutional Theory Frameworks.*

developers' unique selling points, the hardware characteristics of the robots, and the software characteristics of the systems. Together, these aspects provide a clearer picture of how current PaP solutions are positioned in the market and how they differ in their technical emphasis.

Developers' Unique Selling Points

From the companies that we interviewed, we asked about their unique selling points, meaning the distinctive features or advantages they believe set them apart from competitors. A unique selling point can be understood as a characteristic that makes a business stand out by offering something others do not, or do not offer in the same way (Miller and Henthorne, 2007). **Table 4.1** summarizes these company-level differentiators and shows that providers do not compete on exactly the same basis. Instead, they appear to differentiate themselves through a combination of software capability, integration flexibility, and physical robot performance.

Table 4.1. *Unique Selling Points*

Developer	Unique Selling Points
Smart Robotics	Builds almost everything in-house (except basic hardware), using its own software to 'glue' components like 3D-printed grippers and cameras together (Interview 1).
Osaro	The software suite requires no human in the loop for data annotation; it uses machine learning to teach itself through successful and failed picks in real-time (Interviewee 2).
Sereact	Many companies focus on collecting data in the lab, so synthetic or simulation data. We focus on collecting data from real operations at adopters. This is the foundation from our AI model before we deploy it. We then get more data from the deployment and let the machine continue to learn (leading). Also we have 140 systems live (Interviewee 3).
Mujin	Hardware agnostic and uses a "Digital Twin" concept to automatically plan complex robot trajectories without manual point-to-point teaching (Interviewee 4).
Yaskawa	The software excels at handling complex environments with multiple incoming and outgoing conveyor belts simultaneously (Interviewee 5).
Fizyr	Standing out as a robust, fast-executing processing pipeline and a deep convergence of AI with an algorithmic stack that prevents 'hallucinations' common in pure AI models (Interviewee 7).
Cognibotics	Hardware Reach & Speed: Their robots feature a unique mechanical design that combines a long physical reach (similar to a human arm) with a lightweight, high-speed frame (Interviewee 9).
TGW Logistics	The technology is delivered as a component of a complete fulfillment system. Areschoug notes, "We are selling it as a part of our infrastructure" (Interviewee 11).
Mech-Mind Robotics	Provide a high-performance total solution that integrates hardware and software, while maintaining an open and highly compatible ecosystem (Interviewee 12).

A first pattern is that several providers position themselves primarily through AI and learning capability. Sereact emphasizes training on real operational data for continuous improvement, Osaro highlights self-learning through real-time pick outcomes without human annotation, and Fizyr combines AI with an algorithmic layer to reduce hallucinations in pure AI models. This suggests that one important area of differentiation lies in how providers approach learning, adaptation, and robustness in real picking environments.

A second pattern is differentiation through integration and system flexibility. Mujin presents itself as hardware-agnostic and uses a Digital Twin to automatically plan robot trajectories, while Mech-Mind emphasizes broad hardware compatibility, and Smart Robotics highlights its in-house system integration approach. These differences indicate that some providers compete by making their solutions easier to adapt across warehouse setups, while others compete by controlling more of the full system architecture themselves.

A third pattern concerns physical robot performance. Yaskawa emphasizes the ability to handle more complex conveyor-based environments, while Cognibotics differentiates itself through a long-reach, lightweight mechanical design. This shows that providers are not only competing through software and integration, but also through how their systems are physically designed for different operational settings.

Hardware of Robots

Table 4.2 provides an overview of the hardware characteristics of different PaP providers, including reported picking speed and accuracy. The Table is useful because it shows that there is already a relatively wide range of mechanical performance across the market (Ocado, 2025; Berkshire Grey, 2026; Cognibotics, 2026; Dematic, 2026; Kardex, 2026a; Mecalux, 2026; Mujin, 2026; Sereact, 2026; Swisslog, 2026).

Table 4.2. *Companies and their robot characteristics focused on hardware.*

Company Name	Robot Name	Speed (Picks/hour)	Accuracy/Precision
Cognibotics	HKM1800	3,564	"Active Motion Stabilization" for controlled movement
Sereact	AI-based Autonomous Robotics	1,800	N/A
Berkshire Grey	Robotic Fulfillment Systems	1200	0.9999
Dematic	RapidPick XT (Goods-to-Robot)	1100	20–25% more accurate than human operator"
Swisslog	ItemPiQ	1000	"Failure-free picking"
Mecalux	Picking Robot (Cobot)	1000	"Absolute precision"
Mujin	Piece Picking/ Bin picking	900+	99.9%+ reliability
Ocado Group	Robotic Sort	400	99.7% per-item accuracy
Kardex	Pick and Place Robotics	N/A	Nearly 100% precision

One clear pattern is the variation in picking speed, which ranges from 400 picks per hour at Ocado to 3,564 picks per hour at Cognibotics. At the same time, many systems appear to cluster between roughly 900 and 1,200 picks per hour, suggesting that this may be a common performance range across several providers. This indicates that while some systems stand out at the high end, a large part of the market appears to operate within a narrower throughput range.

A second visible pattern concerns accuracy. Providers consistently report very high precision, with claims ranging from 99.7% to effectively 100%. Several also position their systems as being equal to or more accurate than human operators. These claims are useful for understanding how vendors present their systems, although they should be interpreted with some caution because they are largely vendor-reported and may not be based on identical measurement conditions.

This shows that providers increasingly present their systems in terms of industrial-grade speed and precision, while still differing in how those capabilities are combined and positioned. It therefore provides a useful overview of the current hardware landscape without suggesting that all systems are directly comparable under the same operating conditions.

Software of Robots

The software characteristics of PaP robots vary most clearly across three dimensions: Warehouse Management System/Warehouse Control System integration, vision AI, and zero-shot capability, see **Table 4.3**. Compared with hardware, this is also the area where providers appear to differentiate themselves most strongly.

Table 4.3. *Software characteristics.*

Company	WMS/WCS	Vision AI	Zero-Shot Capability
Smart Robotics	Integrates with the 'Warehouse Control System' (WCS) via translation layers for integrators like Swisslog or Element Logic	Uses an AI model that utilizes cameras to understand which products it is picking and adapts to changing SKUs	No, train a deep learning model to recognize products
Sereact	Connects through APIs that allow an AI environment to communicate with a PLC or robot controller	Vision solution is a core product line used for item counting, grading, and bin filling	Explicitly features "zero shot technology," allowing the robot to pick new SKUs without prior training
Osaro	Generally hardware and system agnostic; has integrated with various ASRS systems	Employs a software suite based on machine learning that uses cameras to identify items in bins	Capable of picking "items that it's never seen before" by learning autonomously without human data annotation
Yaskawa	Integration is typically custom-developed based on specific requirements rather than being "ready to go"	Accuracy is improved through cameras and sensors detecting the pieces for the robotic arm	Views AI-driven picking as being in "baby steps" compared to the maturity of traditional software
Mujin	Uses a hardware-agnostic platform that communicates with WMS/WCS through open APIs	Features a 3D vision detection system that creates a "Digital Twin" to plan robot trajectories automatically	Robot plans its own paths and strategies for unknown items rather than relying on point-to-point manual teaching
Cognibotics	Often integrated with AutoStore; requires custom interfaces to bridge "old" robot software (OT) with modern warehouse IT	Works with partners to implement vision systems that segment images and identify grasp positions	No, uses a continuous learning process to adapt to new articles after an initial test pick
Fizyr	Connects through APIs that allow an AI environment to communicate with a PLC or robot controller	Utilizes a Vision AI stack (often with 3D cameras) complemented by an algorithmic layer to ensure reliability and prevent 'hallucinations'	Models are described as "getting so good out of the box" that they are sufficient for many common cases

The first dimension is system integration. Providers differ in how their systems connect to surrounding warehouse architecture, ranging from API-based communication with PLCs and robot controllers to more hardware-agnostic platforms and, in some cases, more customized integration approaches. This shows that software differentiation is not limited to picking intelligence, but also includes how the system connects to the wider warehouse environment.

The second dimension is vision AI. All providers rely on camera-based machine learning systems to identify and locate items, while some also incorporate more advanced 3D vision and digital twin functionality. This indicates that visual perception remains a central software component across current PaP solutions, even if the exact sophistication differs between providers.

The third and most clearly differentiating dimension is zero-shot capability. Some providers claim genuine zero-shot learning, meaning the robot can handle previously unseen SKUs without prior training or human annotation, while others still require some degree of initial training or describe performance as developing incrementally over time. This suggests that one of the clearest software differences in the current market lies in how broadly providers claim their systems can generalize across changing assortments.

Together, the findings in this subsection show that the current characteristics of PaP technology are shaped by variation across providers in both technical design and market positioning. While many solutions are presented through similar claims of speed, precision, and automation potential, providers still differ clearly in how they compete through software capability, integration approach, and physical system design. This suggests that the current PaP market is characterized less by one standardized solution than by a set of competing approaches with different technical emphases.

4.1.2. Benefits

Financial Benefits

The empirical material indicates that financial considerations are central to how firms evaluate the implementation of PaP technology. Across the interviews, return on investment (ROI), labor savings, and throughput improvements were repeatedly described as the most decisive factors in adoption decisions. This emphasis is consistent with the wider warehouse literature, which characterizes order picking as one of the most labor-intensive and costly warehouse activities, accounting for a substantial share of total operating expenses (De Koster, Le-Duc and Roodbergen, 2007; Grosse, 2024).

Several interviewees directly linked PaP adoption to labor cost reduction. One interviewee stated that the main reason for investment is that "*ROI is the most important factor in decision-making*", particularly because "*the cost savings are substantial*" (Interviewee 2, 2026). This was echoed by another respondent who described the savings from automating workstation-based picking and packing as "*substantial*" (Interviewee 8, 2026). These interview findings align with industry claims that investment in robotic picking systems can generate measurable returns through labor cost reductions and productivity improvements, with reported payback periods typically ranging from one to three years (Berkshire Grey, 2026; Interviewee 1, 2026). User interview evidence nevertheless suggests that the actual payback period is context-dependent. While Interviewee 4 (2026) estimated that the ROI in the European market is typically three to five years, Interviewee 8 (2026) argued that, in some adopter contexts, the technology can achieve an ROI of less than one year. Together, these statements suggest that financial attractiveness varies with operational scale, labor costs, SKU characteristics, and achievable automation rates.

Interview data also indicate that the economic case for PaP technology is strongly connected to labor market conditions. Rodríguez-García (2025) identified the reduction of human labor dependency and mitigation of labor shortages as the primary drivers behind adoption. Similarly, one interviewee emphasized that the challenge is not only labor cost, but also labor availability,

noting that companies increasingly struggle to secure sufficient warehouse workers (Interviewee 1, 2026). This is consistent with the broader literature, which highlights that warehouses continue to rely heavily on manual labor despite increasing automation, while labor availability has become a major managerial concern (Grosse, 2024).

Financial benefits were also associated with performance improvements. Sankar and Vignesh (2024) report labor cost reductions of up to 40% and productivity gains of up to 150% in leading logistics operations. In the interviews, Interviewee 5 (2026) similarly stated that "*the robots have a higher picking speed than humans*". Interviewee 3 (2026) further explained that the financial logic of PaP adoption is evaluated through three key performance indicators: "*units per hour, success rate in percentage and availability in percentage*". This suggests that the financial case is not assessed in isolation, but rather through a combination of speed, system success, and uptime, which together determine whether the investment generates operational value. A further practical benefit identified by the adopter perspective concerns process simplification. Interviewee 14 (2026) explained that one major advantage of the robotic setup was that "*we don't have to scan the products anymore when we pack them,*" and that this process change made the overall workflow faster than before. This suggests that the benefit of robotic picking may not only come from replacing manual picking effort, but also from enabling related process redesign that removes additional manual steps.

An additional financial aspect that emerged from the interviews concerns warehouse space utilization. Interviewee 10 (2026) stated that installing robotic arms above cubic storage grids, such as AutoStore or Ocado-type systems, could increase capacity per square foot by reducing the need for separate peripheral picking stations. This implies that the economic value of PaP technology may extend beyond direct labor substitution to include more efficient use of warehouse space, which can be strategically important in high-cost fulfilment environments.

Some respondents pointed to geographical and institutional differences in the financial feasibility of implementation. Interviewee 7 (2026) argued that the US offers greater potential for rapid technological deployment because of a more risk-seeking "*implement fast, fail fast*" culture. This perception is supported by research suggesting that the US generally provides a stronger environment for start-up experimentation than many European regions (Röhl, 2019). In the empirical material, this suggests that the financial attractiveness of PaP technology is not only determined by internal operational variables, but also by broader innovation environments that influence investment willingness and implementation speed.

The empirical findings show that the financial value of PaP technology is perceived to derive from a combination of labor cost reduction, productivity gains, improved space utilization, and resilience against labor scarcity. At the same time, the data suggest that financial outcomes are highly contingent, meaning that the ROI of PaP technology depends heavily on the operational context in which it is implemented.

Availability and Reliability

A second major theme in the empirical material concerns the importance of availability and reliability. Here, PaP technology was not only discussed as a tool for speeding up operations, but also as a way of creating more stable and dependable warehouse processes. The interviewees repeatedly linked value creation to the ability of robotic systems to maintain performance over time, operate consistently, and reduce process variability.

The adopter interview also suggests that system reliability may improve over time through repeated operation. Interviewee 14 (2026) noted that when the system has "*some fail picks or whatever,*" it is "*somehow improving itself*," so that "*the next round*" it can work better with the same article. This reflects the idea that the value of pick-and-place technology may not only lie in initial performance, but also in how the system learns and stabilizes through operational use.

One interviewee summarized this clearly by stating that "*robots bring reliability and accuracy, they work tirelessly and endlessly*" (Interviewee 4, 2026). This reflects a broader assumption in both interview and secondary material that robotic systems are attractive because they can perform repetitive tasks with a high degree of consistency. In the literature, this is reflected in arguments that automated and digitally supported warehouse systems reduce dependence on manual variability and support more stable operational execution (Kembro and Norrman, 2022).

Availability was also explicitly identified as a critical metric in the interviews. As stated before by Interviewee 3 (2026), the system evaluation revolves around "*units per hour, success rate in percentage and availability in percentage*". This is important because it shows that operational performance is not interpreted only through output volume, but also through whether the system is actually available and functioning when needed. In this sense, PaP technology is valued not merely for maximum speed, but for dependable uptime and repeatable execution.

The literature further supports the importance of reliable performance in warehouse operations. Order picking inefficiencies can create serious performance and quality risks, particularly in environments characterized by high throughput requirements and tight customer service expectations Grosse (2024). In this context, claims from practice that AI-driven computer vision and deep-learning systems can achieve extremely high picking accuracy rates, up to 99.99%, become particularly relevant (Berkshire Grey, 2026). Likewise, Sankar and Vignesh (2024) report that consistent algorithmic picking can improve order accuracy by up to 7%. These Figures support the interview-based view that reliability and accuracy are central parts of the value proposition.

Beyond accuracy, the empirical material also suggests that reliability matters because it creates a minimum operational baseline during disruptions. Interviewee 8 (2026) stated that "*even if only 20% of orders could be picked by the robotic arm, you have a baseline where your operations can run if all your workforce is unavailable*". This is a particularly important finding, as it shows that reliability is understood not only in terms of process repeatability, but also in terms of continuity under adverse labor conditions. In such cases, PaP technology functions as a buffer against operational breakdown. The secondary literature provides further support for this interpretation.

Manual order picking remains dominant in many warehouses partly because of its flexibility, but it also suffers from significant labor dependence and variability (Grosse, 2024). By contrast, smart warehousing literature suggests that automation and digitalization aim to create more connected, stable, and data-driven warehouse processes (Kembro and Norrman, 2022). Within this broader movement, PaP systems appear to be attractive because they improve execution consistency and allow managers to monitor performance using standardized KPIs such as success rate and system availability.

Empirical findings indicate that availability and reliability form a key part of the rationale for PaP adoption. The technology is seen as valuable because it offers consistent execution, high accuracy, and an operational fallback when human labor is unstable or unavailable. Thus, beyond cost reduction, the findings suggest that PaP systems are also adopted to increase process dependability and reduce operational vulnerability.

Mitigation of Employee Uncertainties

The third theme emerging from the empirical material concerns employee uncertainty, particularly in relation to labor shortages, unattractive work tasks, and the future role of warehouse workers. In this section, PaP technology was described both as a response to labor market constraints and as a means of reshaping the nature of warehouse work.

A recurrent finding in the interviews is that warehouses face difficulties attracting and retaining people for repetitive manual tasks. Interviewee 4 (2026) and Interviewee 9 (2026) both emphasized that workers often do not want to perform these "*repetitive task jobs*", and that PaP technology can help address this issue. This is consistent with the broader literature on manual warehousing, which shows that order picking remains labor-intensive and that warehouse managers are increasingly concerned about labor shortages and workforce retention Grosse (2024). In that sense, the technology is seen not only as a cost-saving device, but also as a practical response to the declining attractiveness of repetitive warehouse work. The findings also point to broader human and ergonomic benefits. Interviewee 11 (2026) also emphasized that the main value of the technology lies in removing people from repetitive tasks, particularly in high-cost labor regions such as Northern Europe. He also stressed that automation could reduce the physical wear and tear on workers' bodies and help prevent the cognitive exhaustion that follows from monotonous and repetitive work. This suggests that the benefits of robotic picking are not only financial, but also related to health, ergonomics, and the quality of working conditions.

The findings further indicate that employee uncertainty is closely tied to the volatility of day-to-day workforce management. Interviewee 8 (2026) noted that "*anything around sickness or vacation or all the human aspects ... creates a lot of cost*", as it requires additional planning, resource coordination, and HR involvement. He also emphasized the operational consequences of this uncertainty, explaining that "*you have days sometimes when you come in and you have 20 people are sick and you need to start calling people and you need to find people*". These statements illustrate that labor uncertainty is not only a question of long-term recruitment, but also of short-

term operational disruption. From this perspective, PaP technology can be understood as a means of reducing daily dependence on variable human availability and thereby increasing workforce stability in warehouse operations.

The interviews further suggest that PaP systems can reduce uncertainty by lowering dependence on human labor availability. Interviewee 1 (2026) highlighted that firms experience shortages not only because labor is expensive, but because "*people*" are increasingly difficult to secure in the first place. Interviewee 10 (2026) similarly described labor reduction and labor shortage mitigation as the main drivers of adoption. These statements position PaP technology as a response to structural labor insecurity rather than as a purely efficiency-driven innovation. At the same time, the findings suggest that interviewees do not necessarily view PaP technology as eliminating the need for workers altogether. Instead, it is frequently framed as redistributing human work. Interviewee 10 (2026) argued that the technology is eventually "*freeing human workers from physically demanding or repetitive tasks to focus on more enjoyable work*". This interpretation resonates with the smart warehousing literature, which suggests that future warehouse development increasingly combines automation with a redefinition of human roles, where workers focus on higher-value, less repetitive tasks while machines handle repetitive, time-consuming, or hazardous activities .

The literature also supports the view that many important benefits connected to human work are not easily captured in direct financial metrics. Simões, Soares and Barros (2020) note that benefits such as ergonomic improvement and operational flexibility are often difficult to monetize. This is important for the empirical analysis, because it helps explain why some interviewees described benefits in broader organizational terms rather than only through direct cost savings. In other words, reducing employee uncertainty may create value by stabilizing staffing, improving task attractiveness, and lowering dependence on undesirable manual work, even when these effects are difficult to express as immediate financial returns.

A final aspect concerns scalability during demand fluctuations. Smart Robotics (2026) and the Rodríguez-García and Agmoni (2024) suggest that robotic systems can absorb higher order volumes during peaks without requiring proportional increases in headcount. This is particularly relevant in the context of employee uncertainty, because peak periods often intensify staffing problems. Kardex (2026b) and Smart Robotics (2026) similarly argue that robotic picking enables continuous multi-shift operations without relying on human workforce availability in the same way as manual systems. Taken together with the interview material, this suggests that PaP technology is seen as a way of reducing organizational exposure to uncertain labor conditions while also supporting more scalable fulfilment operations.

Overall, the empirical findings indicate that PaP technology helps mitigate employee uncertainty in two related ways. First, it reduces dependence on scarce labor for repetitive warehouse work. Second, it opens the possibility for reallocating human effort toward tasks perceived as less repetitive and potentially more meaningful. The findings therefore suggest that the role of PaP

technology extends beyond operational performance to include workforce stabilization and the reconfiguration of human work in the warehouse.

4.1.3. Challenges

SKU Variability & Expectations

A central challenge emerging from the empirical material is the high variability of SKUs in warehouse environments. Unlike traditional industrial robotics, which typically operate in stable and repetitive settings, PaP applications in retail and e-commerce must handle highly diverse items that vary in shape, size, color, material, packaging, and orientation. As Interviewee 4 (2026) mentioned, "*traditionally robots handle repeatable jobs, in pick and place the SKUs are not fixed*", and the variability is significant because items appear in tote variation, random orientation, random colors, and random packaging. The challenge of full picking reliability was also emphasized by Interviewee 12 (2026), who stated that "*for the randomly bin picking, we cannot guarantee 100% to pick up from the bin. That is the issue.*" This is important because it reinforces that the challenge is not only whether the robot can perform well in many cases, but whether it can do so with the consistency required for operational dependence. This captures a core problem in the adoption context: the warehouse is not a controlled industrial production environment, but a highly dynamic setting characterized by constant item variation. Several interviewees highlighted that such variability directly affects grasping feasibility and item quality. Interviewee 1 (2026) noted that some items are not fully pickable with vacuum technology without causing damage, explaining that "*books may open when lifted and soft plastic materials can be visibly marked by suction*". In such cases, the technical challenge is not only whether the robot can pick the item, but whether it can do so in a way that preserves product quality. Interviewee 7 (2026) added that some cosmetic products are especially problematic because of "*gold shiny wrapping*" and light-absorbing paint, which are difficult for standard camera systems to interpret. These examples show that SKU variability extends beyond geometry into issues of surface properties, reflectivity, and packaging design.

The interviews further suggest that item diversity makes standardized gripping difficult. Interviewee 5 (2026) explained that "*usually, a specific tool must be chosen based on the objects*", while Interviewee 1 (2026) illustrated this by contrasting the handling requirements of small items with those of a heavy laptop. This implies that no single gripping method performs equally well across the full SKU range, and that end-effector selection becomes a recurring engineering challenge. This aligns with the literature, which shows that gripper design strongly affects grasp success and that no single end-effector performs equally well across all object geometries, clutter levels, and access conditions (Mnyusiwalla *et al.*, 2020).

In addition to grasping, interviewees emphasized that placement itself is a major source of difficulty. Interviewee 6 (2026) noted that "*grabbing is already complicated, but stacking is even harder*", particularly when items need to be placed neatly into totes. This suggests that the technical problem extends beyond object retrieval to include downstream placement quality and

packing logic. In practice, this means that successful implementation depends not only on detecting and grasping a product, but also on solving how it should be arranged in the target container.

The literature supports these observations. Robotic PaP systems continue to struggle in cluttered, random, occluded, or poorly lit environments, where identifying which object is feasible to pick remains difficult (Niu *et al.*, 2021; Wong *et al.*, 2022). Likewise, performance outside controlled environments is still challenging to guarantee because object diversity, clutter, motion disturbances, and lighting variation create instability (Lobbezoo, Qian and Kwon, 2021; Niu *et al.*, 2021). Taken together, the empirical material suggests that SKU variability constitutes one of the most fundamental barriers to robust PaP deployment in warehouse operations.

Integration & Operation

A second major challenge concerns the integration of PaP technology into existing warehouse operations. The findings show that implementation is rarely limited to installing a robotic arm. Instead, it involves aligning the robot with warehouse software, process flows, physical infrastructure, and adjacent equipment. For this reason, several respondents described implementation as highly demanding in operational terms.

Interviewees repeatedly stressed that robotic systems do not easily fit into existing warehouse environments. Interviewee 9 (2026) observed that "*IT systems from warehouses are usually newer than the software where the robots run on, which is from the 80s*". This statement captures the mismatch that can arise between modern warehouse information systems and older underlying robot control environments. Interviewee 1 (2026) similarly stated that compatibility with existing processes can itself become "*an integration challenge*", because the warehouse often has to adapt its process design in order to accommodate the robot. Interviewee 2 (2026) gave a concrete example, explaining that the company had to switch from boxes to totes in order to implement the technology. In addition to this, Interviewee 13 (2026) exemplifies this as *"you also need to configure the whole system related to the robot PLC, gripper, mechanism design, and the safety system"*. These findings suggest that adoption often requires redesigning surrounding processes rather than simply embedding a new tool into the current workflow. A further integration-related challenge concerns data and stock synchronization across connected systems. Interviewee 14 (2026) explained that "*we have to make sure that the stock we are expecting is still the same in our system,*" because the setup involves "*three parties in there. It's our WMS, it's the robot system, and it's AutoStore.*" This shows that robotic picking depends not only on the robot itself, but on consistent communication and alignment across the wider system architecture.

The interviews also indicate that integration challenges carry cost and project implications. Interviewee 3 (2026) noted that "*high fixed costs*" are often needed to create a viable business case, either through the Application Programming Interface (API) development or infrastructure changes. API is a set of rules that allows different software applications to communicate easily with each other (Park *et al.*, 2025). Interviewee 3 (2026) explained that adopters may lack the Information Technology resources needed to connect the robot to the warehouse management

system, and that physical retrofits can require additional workstations, conveyors, or other supporting infrastructure. This shows that the cost of integration is not limited to the robot itself, but includes system interfaces and physical changes to the facility.

Another issue raised in the interviews is that automation in one part of the process may expose bottlenecks elsewhere. Interviewee 8 (2026) stated that "*previously the picking was the problem from the robots, now the problem is the bagging machines*". He added that when technology providers are asked how to solve this, "*they do not know how to solve this*". This suggests that implementation success depends on the wider operational chain, not only on the picking unit. In practice, improving robotic picking performance may simply shift the bottleneck to packing or bagging if surrounding equipment is not equally mature.

These interview findings are strongly supported by the literature. Robotic PaP systems remain implementation-intensive because they require cameras, calibration routines, planning logic, grippers, control systems, and robot hardware to work together reliably (Niu *et al.*, 2021; Wong *et al.*, 2022). Industry sources likewise identify integration with Warehouse Management System, Automated Storage and Retrieval System, and conveyor systems as a significant challenge that prolongs implementation and increases project risk (Berkshire Grey, 2026; Smart Robotics, 2026). Overall, the findings suggest that integration and operational fit are major barriers because the robot must be embedded into a broader socio-technical warehouse system rather than treated as an isolated piece of hardware.

Mechanical

The empirical material also points to specifically mechanical challenges related to grippers, manipulation, and physical execution. These challenges concern not only whether the system can identify an item, but whether it can physically interact with that item in a robust and repeatable way.

A key issue is the limitation of grippers and end-effectors. Interviewee 5 (2026) stated that "*usually, a specific tool must be chosen based on the objects*". The literature supports this point by showing that end-effector design strongly affects grasp success depending on object geometry, clutter, and access conditions, and that no single gripper performs equally well across all situations (Mnyusiwalla *et al.*, 2020). Interviewees also stressed that robotic handling becomes even more difficult when the task includes not only grasping, but also structured placement. Interviewee 6 (2026) noted that "*grabbing is already complicated, but stacking is even harder*", especially "*if you want to get items nicely in a tote*". This highlights that manipulation challenges extend beyond simple retrieval and into how the robot arranges items after grasping them. In operational terms, this is highly relevant because warehouse picking often includes the need for stable and orderly placement into totes, cartons, or outbound containers.

Another practical challenge concerns physical stability in the warehouse environment itself. Interviewee 11 (2026) described a case where mounting a heavy robot on a swaying mezzanine created vibrations that moved the station by 2-3 millimeters. For vacuum grippers, he explained,

this small deviation can be enough to turn a successful pick into a failure. This highlights that robotic picking performance may depend not only on the robot and the item, but also on the physical rigidity of the surrounding installation environment.

The literature further shows that failures can occur across multiple task phases, including pre-grasping, transport, and placement, not only at the moment of grasping itself (Mnyusiwalla *et al.*, 2020). In addition, robust collision avoidance remains necessary, especially in bin-picking and constrained workspaces where the robot may collide with bin walls or surrounding objects (Wong *et al.*, 2022) . This reinforces the view that the mechanical challenge is not a single-point problem, but a chain of closely linked physical actions that all need to work reliably.

The findings indicate that mechanical limitations remain a substantial challenge. Even when perception systems identify an item correctly, the physical execution can still fail because of unsuitable grippers, manipulation constraints, poor placement logic, or collision risks. This means that manipulation remains a core barrier to achieving stable and scalable warehouse deployment.

Software, Artificial Intelligence, and Data

A fourth major challenge concerns the software and data foundations of PaP systems. The empirical material suggests that successful operation depends not only on hardware capability, but on the quality of perception systems, training data, item master data, and the logic used to govern decision-making.

A key issue raised in the interviews is that item data are often less reliable than adopters assume. Interviewee 9 (2026) stated that companies frequently believe they have accurate SKU information, but real-world testing often reveals that dimensions and weights are missing or incorrect. This is significant because robotic systems depend on such data for grasp planning, placement logic, and performance tuning. Poor master data therefore becomes a hidden barrier to deployment. Interviewees also pointed to persistent vision interpretation problems. Interviewee 7 (2026) described how "*exotic*" items, such as cosmetics, or visually difficult materials, confuse camera systems.

A further challenge is that AI systems are non-deterministic. (Interviewee 10, 2026) stated that AI and machine learning operate on probabilities rather than fixed rules. According to the interview material, this creates uncertainty because the system may make unexpected decisions or movements, particularly if reliability safeguards are insufficient. Interviewee 7 (2026) noted that to prevent the AI from making errors or "*hallucinating*" grasp points, developers must layer complex algorithmic logic on top of pure AI models to achieve industrial-grade reliability. This suggests that AI alone is not considered sufficiently robust for operational deployment, and that significant engineering effort is still required to constrain its behavior.

The findings therefore indicate that software maturity remains a central challenge. The issue is not simply whether AI can identify an object, but whether the full perception and control stack can perform consistently enough for industrial use. In this respect, the empirical material supports the

broader conclusion that there is still a gap between technical feasibility and reliable large-scale deployment (BCG, 2025; McKinsey, 2025).

Humans & Safety

The introduction of PaP technology also creates challenges related to people, safety, and organizational adaptation. The interviews suggest that these issues are not secondary, but central to adoption because implementation affects workforce roles, site layout, legal compliance, and safety systems.

Safety concerns were especially clear in the interview material. Interviewee 4 (2026) stated that "*when you move a 1000 kilo robot arm with a very high speed, you do not want humans around*", noting that safety fencing can take up twice the space of a human workstation. This illustrates that robotic systems can create new physical safety requirements and may even reduce space efficiency when protective barriers are needed. The literature also points to collision avoidance as a persistent issue, especially in constrained spaces where manipulators may collide with surrounding objects (Wong *et al.*, 2022).

The findings also suggest that employees may view automation as a threat. Interviewee 6 (2026) argued that resistance is a natural reaction, and that careful change management and early involvement of supervisors are necessary. This is consistent with broader evidence showing that workforce resistance and the burden of organizational change remain significant barriers to automation adoption Sankar and Vignesh (2024). More generally, as tasks shift from manual handling toward supervision, exception management, and technical interaction, employees may experience uncertainty about role changes, required skills, and long-term job content (Lobbezoo, Qian and Kwon, 2021; BCG, 2025).

Legislative and regulatory issues also emerged as relevant. Interviewee 6 (2026) highlighted that the European Union AI Act and General Data Protection Regulation create a complex legal landscape for how worker-related data can be recorded and how AI-supported decisions affect employees. This suggests that implementation is not only a technical and organizational issue, but also a regulatory one.

Findings show that human and safety challenges arise on multiple levels: physical safety around fast-moving machinery, employee uncertainty during role change, and broader organizational resistance linked to automation. These dimensions indicate that successful adoption requires more than technical performance; it also depends on whether the organization can redesign work and manage implementation in a socially sustainable way.

Technology Dependency

Another challenge reflected in the material is growing dependency on digital and automated infrastructure. As warehouses become more reliant on robotic systems, the consequences of technology failure increase.

The secondary material highlights that cybersecurity vulnerabilities associated with multi-robot connectivity and cloud dependence can create material operational risks (Rodríguez-García *et al.*, 2025). It also notes that system downtime is especially damaging in highly automated facilities, where fewer manual fallback options may exist. In addition, vendor lock-in and a lack of communication standards across robotic platforms increase switching costs and dependency on specific suppliers (Rodríguez-García *et al.*, 2025).

This concern is reinforced by one interview-based insight already discussed under financial and operational issues: robotic systems may provide continuity in some circumstances, but they are also rigid in others. Unlike human workers, they depend on stable electricity, cyber infrastructure, and functioning software interfaces. Thus, while automation can reduce labor dependency, it may simultaneously increase technological dependency. The findings therefore suggest that PaP implementation changes the nature of operational risk rather than eliminating it. Dependency shifts away from labor availability and toward infrastructure availability, system interoperability, and cyber resilience.

Business Case & Strategy

Finally, the material points to a broader challenge surrounding the business case for PaP technology. While the benefits may be attractive, the empirical and secondary material suggest that the path from technical feasibility to commercial justification is far from straightforward.

A frequently cited challenge is high upfront investment. Sankar and Vignesh (2024) and Smart Robotics (2026) identify capital cost as one of the most common adoption barriers, particularly for smaller firms. Niu *et al.* (2021) and Wong *et al.*, (2022) similarly note that robotic PaP systems require substantial investments in robot hardware, end-effectors, cameras, calibration procedures, and software before stable operation can be achieved. This means that the business case depends not only on operating savings, but on whether the scale and stability of the environment justify the initial cost.

The empirical material suggests that this uncertainty is amplified by the mismatch between technical demonstrations and real-world deployment. Even when a solution works in controlled pilots, robust operation at commercial scale is more difficult to ensure because performance depends on integration quality, maintenance capability, SKU diversity, and long-term reliability. This aligns with the reviewed literature, which identifies a gap between proof of concept and scalable deployment(Lobbezoo, Qian and Kwon, 2021; BCG, 2025; McKinsey, 2025).

There is also evidence that large-scale deployment can carry major strategic risk when implemented prematurely. One cited example concerns a large write-off in the US after scaling before the technology was fully understood operationally (Rodríguez-García *et al.*, 2025). This underlines that the challenge is not only whether the technology can work, but whether firms can implement it at the right time, with the right pilot scope, and with a realistic understanding of its limitations.

The findings indicate that the business case for PaP technology remains uncertain because it is shaped by a combination of capital intensity, implementation complexity, deployment risk, and the still unresolved challenge of achieving stable performance across the full diversity of retail warehouse conditions.

4.1.4. Alignment with Diffusion of Innovations and Institutional Theory

To move beyond a descriptive presentation of the characteristics, benefits, and challenges, the empirical findings are interpreted through the lenses of the DOI and INT Theory. DOI helps explain how firms evaluate the technology itself through perceived innovation attributes, while INT helps explain how broader external pressures and legitimacy concerns influence adoption decisions. Together, these frameworks provide a structured basis for understanding why PaP technology is simultaneously seen as attractive and difficult to adopt.

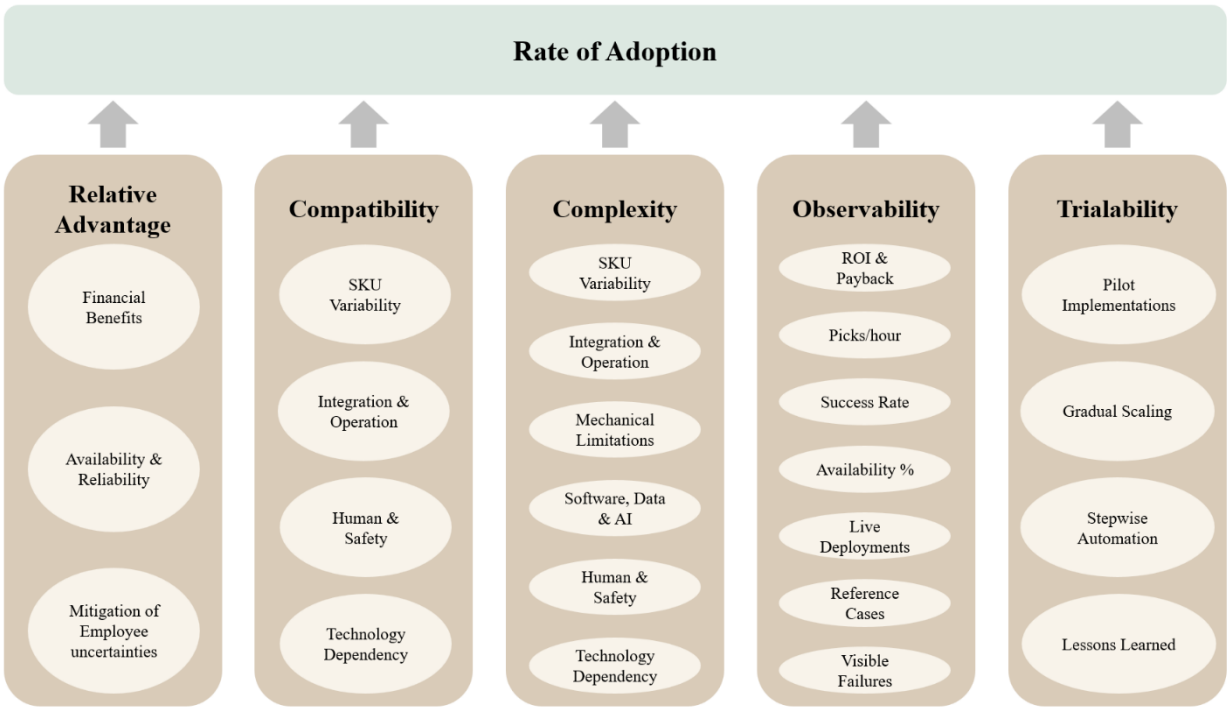

Figure 4.3. *Empirics Aligned with the DOI framework*

Figure 4.3 shows the empirical findings mapped into the DOI framework. The identified benefits mainly strengthen the perceived relative advantage of PaP technology, while the identified challenges are primarily associated with compatibility and complexity. Trialability is reflected in the importance of pilot projects and gradual implementation, whereas observability is visible through measurable KPIs, live deployments, and reference cases.

The strongest DOI dimension emerging from the empirical material is relative advantage. The financial benefits identified in the interviews, including labor cost reduction, higher picking speed, improved throughput, and possible gains in space utilization, suggest that many respondents perceive PaP technology as offering meaningful advantages over manual picking. This is reinforced by the findings on availability and reliability, where respondents associated the technology with uptime, consistency, and continuity under labor disruptions. Similarly, the mitigation of employee uncertainty adds another dimension to relative advantage, as the technology is seen not only as a tool for reducing labor dependence but also as a way of stabilizing operations in contexts characterized by sickness, absenteeism, labor shortages, and the unattractiveness of repetitive tasks. In DOI terms, these findings show that the technology is often perceived as superior to the current solution, at least under certain warehouse conditions.

At the same time, the findings show that adoption is constrained by compatibility. Compatibility concerns whether the technology fits existing systems, work routines, and organizational realities. In the empirical material, this appears most clearly in relation to SKU variability, process redesign, and integration into current warehouse environments. Several respondents explained that successful adoption often requires surrounding operations to be adapted, for example by changing from boxes to totes, redesigning process flows, or building new API connections. These observations suggest that PaP technology is not always compatible with the existing structure of warehouse operations. This is especially important in retail G2P settings, where product variability, order structures, and supporting systems differ substantially from the controlled industrial contexts in which robotics have traditionally performed best. Thus, even where the technology appears beneficial, adoption may be slowed if the innovation is perceived as not fitting the operational logic of the warehouse.

A closely related DOI dimension is complexity, which emerges as one of the strongest barriers in the empirical findings. The data suggest that PaP technology is perceived as highly complex because successful implementation depends on the interaction of multiple technical and operational elements. SKU variability, gripping limitations, dexterity problems, 3D stacking, poor master data, non-deterministic AI behavior, integration into legacy systems, and safety requirements all contribute to this complexity. The findings indicate that the challenge is not only whether the robot can physically pick an item, but whether the full hardware-software-system chain can perform reliably in a cluttered, changing, and commercially demanding environment. This high degree of perceived complexity helps explain why the technology is still not widely deployed at scale despite its acknowledged potential.

The empirical material also highlights the relevance of trialability. Several findings suggest that firms prefer to test the technology through pilots or limited use cases before moving toward broader deployment. This is particularly visible in the discussion of strategic risk and large-scale failures, where respondents and secondary sources emphasized the danger of scaling too early. In DOI terms, this indicates that trialability matters because it helps firms reduce uncertainty. However, the findings also show that successful pilots do not necessarily translate into robust,

scalable long-term operation. This weakens the stabilizing effect of trialability, since firms may still remain uncertain even after limited successful testing.

Finally, observability is strongly reflected in the empirical material. Respondents repeatedly referred to measurable KPIs such as units per hour, success rate, availability, reliability, and ROI when discussing the attractiveness of the technology. This suggests that adoption is influenced by the visibility of results. In addition, the presence of live deployments, visible reference cases, and publicized examples of successful or failed implementation makes the consequences of adoption easier to observe. In this sense, observability works in two directions: visible success stories can strengthen confidence in the technology, while visible failures and costly write-offs can increase caution.

Taken together, the DOI interpretation shows that PaP technology is perceived as offering substantial relative advantage, but that adoption is simultaneously slowed by compatibility and complexity challenges. Trialability and observability help firms evaluate the technology, but they do not fully remove uncertainty. This helps explain why the technology appears attractive in principle while still facing substantial hesitation and uneven implementation in practice.

While DOI explains how firms assess the characteristics of the innovation itself, it does not fully explain why organizations may pursue adoption even under substantial uncertainty. For this reason, the empirical findings are also interpreted through INT.

Figure 4.4 shows how coercive, mimetic, and normative pressures shape the adoption of PaP technology. Firms are influenced not only by technical and financial considerations, but also by labor market pressure, regulation, visible market examples, and broader industry norms around automation and smart warehousing.

Mimetic pressures appear more selectively in the empirical material. In some cases, firms seemed to pay attention to visible adopters, major technology providers, and high-profile implementations in the market, particularly under conditions of uncertainty regarding technical maturity and operational value. Reference cases from large actors may therefore serve as signals that the technology is becoming relevant or viable. However, the interviews also suggest that imitation is far from universal. Some respondents appeared largely indifferent to what competitors or market leaders were doing, and instead emphasized internal operational needs, SKU conditions, integration requirements, and ROI logic as the primary basis for decision-making.

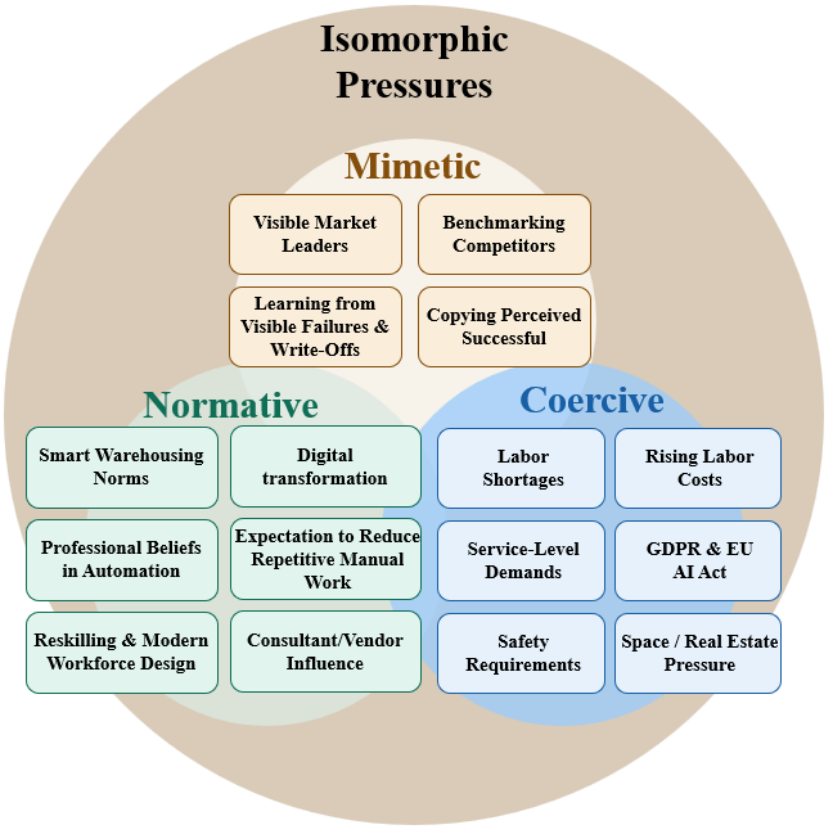

Figure 4.4. *Empirics Aligned with the INT framework*

In the empirical material, **coercive** pressures are the most clearly visible. These appear in the form of labor shortages, rising labor costs, increasing service expectations, and safety and regulatory requirements. Several interviewees described the lack of available warehouse labor as a central reason for considering automation, while others emphasized that safety measures, AI-related uncertainty, and legal frameworks such as the General Data Protection Regulation and the European Union AI Act influence how the technology can be deployed in practice. In this sense, firms are not only attracted by the potential benefits of PaP systems, but are also responding to external constraints that make labor-intensive manual picking more difficult to sustain over time.

Normative pressures are also evident in the findings, particularly in the way respondents framed PaP technology as part of a broader movement toward smart warehousing, digital transformation, and more modern warehouse operations. Across both interviews and secondary sources, automation was frequently described as a natural direction for the future of retail warehousing, especially for repetitive, physically demanding, and unattractive tasks. This suggests that firms are influenced not only by direct business case calculations, but also by shared professional beliefs regarding what a technologically advanced and future-oriented warehouse should look like. In this respect, the technology gains legitimacy through alignment with broader industry narratives about innovation, efficiency, and the redesign of human work.

Taken together, the findings suggest INT helps explain why firms may pursue PaP technology despite remaining uncertainty. However, the three mechanisms are not equally strong across cases: coercive pressures appear most influential, normative pressures reinforce legitimacy, and mimetic pressures play a more selective role.

4.2. Context of Usage

The findings indicate that the use of PaP technology is highly context dependent. The technology is not equally suitable for all warehouse environments, product categories, or operating models. Instead, its relevance appears strongest where robotic picking can complement an already automated warehouse system, where the product assortment is sufficiently suitable for robotic handling, and where the organization can support the system through clear operational routines and performance expectations. The context of use is therefore shaped by the interaction between warehouse system design, product and order characteristics, technological readiness, and the operational business case. The structure of this section is shown in **Figure 4.5.** Empirical themes related to Context of Usage into TOE framework.Fit with Goods-to-Person and E-Commerce Environments

The empirical material suggests that PaP robots are most relevant in highly automated G2P environments, particularly in e-commerce and omnichannel fulfilment operations. In such settings, storage, retrieval, and internal transport may already be automated, while the final item-picking task at the workstation often remains manual. PaP robots, therefore become relevant as an additional automation layer that can extend the logic of G2P automation into the picking process itself.

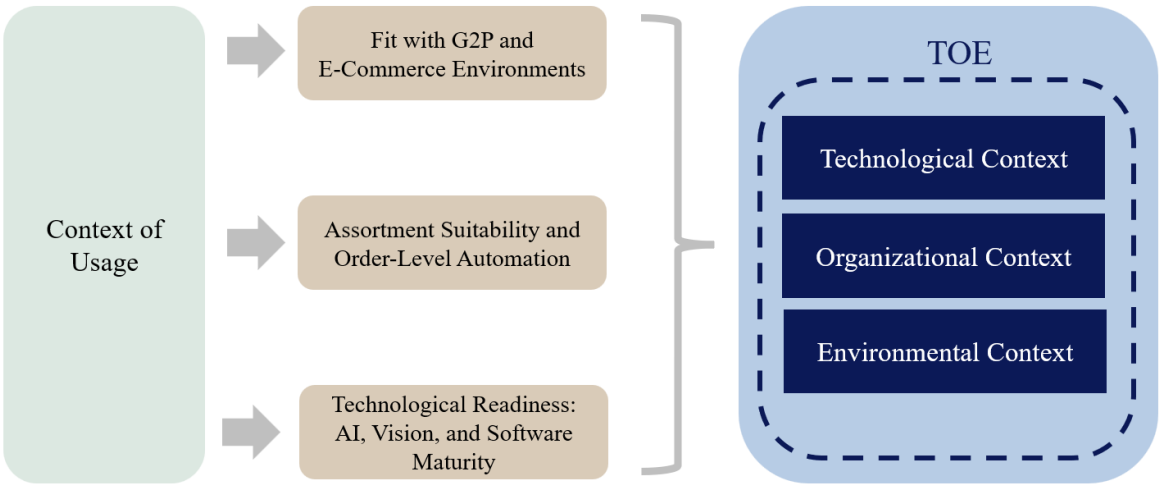

Figure 4.5. *Empirical themes related to Context of Usage into TOE framework.*

Interviewee 6 (2026) described robotic picking arms as the "*next addition*" to existing G2P infrastructures, especially in e-commerce facilities where systems such as AutoStore are already installed. This indicates that the technology becomes more attractive when the warehouse has already invested in automated storage and retrieval, because the robot can be integrated into an existing automated flow rather than introduced as a standalone solution. Interviewee 1 (2026) made a similar point by describing PaP technology as the "*glue*" that can help automate the entire process from the warehouse up until shipping in a G2P environment.

This context is particularly relevant because e-commerce growth has increased SKU proliferation and raised customer expectations for faster delivery, placing additional pressure on warehouse operations (Rodríguez García and Agmoni, 2024). In these environments, the pick station can become a bottleneck if storage and transport are automated, but item-level handling remains manual. PaP robots may therefore be most useful where they close a specific automation gap rather than where they are expected to transform an entirely manual warehouse by themselves. However, the findings also suggest that G2P infrastructure alone is not enough. The warehouse must have a flow profile that allows the robot to be used consistently. This means that high-volume operations, repetitive order flows, and sufficient item presentation at the workstation are important conditions. In smaller or less automated warehouses, the investment and integration effort may be harder to justify, especially if manual picking remains flexible and cost-effective.

Thus, the context of use should not be understood as retail warehousing in general. It is more specific: high-volume e-commerce or omnichannel G2P environments where robotic picking can complement existing automation and reduce the remaining dependence on manual workstation picking.

Assortment Suitability and Order-Level Automation

A second major condition concerns the suitability of the product assortment. The interviews indicate that the technical ability to pick individual SKUs does not automatically translate into the ability to automate complete customer orders. This distinction is important because the operational value of robotic picking depends not only on how many SKUs are technically pickable, but also on how those SKUs appear in real order combinations.

Interviewee 6 (2026) suggested that current technology can handle approximately 70% to 80% of a typical e-commerce assortment. However, he also emphasized that certain products remain difficult or impossible for the robot to handle, including open books, heavy kettlebells, and items with reflective packaging that can confuse vision sensors. This shows that robotic picking is still limited by physical product characteristics such as shape, weight, surface texture, rigidity, packaging quality, and visual detectability.

Interviewee 8 (2026) added a further operational nuance by explaining that a high SKU pick ability rate does not necessarily result in the same level of order automation. In Boozt's case, customer orders typically contain around three items. If one item in the order is difficult to pick, such as a shoebox or another problematic SKU, that item can "*pollute*" the entire order. As a result, even if

70% to 80% of SKUs are technically pickable, the actual share of complete orders that can be automated may fall to around 40% or 50% (Interviewee 8, 2026). This finding is important because it shows that companies should avoid evaluating robotic picking only at SKU level. A robot may be able to pick a large part of the assortment in isolation, but the business case depends on whether it can complete enough real customer orders or order lines without human intervention. Therefore, product mix, order profile, and the frequency of problematic items become central to determining whether the technology is suitable. Another adopter perspective also gives a more concrete picture of how SKU compatibility translates into order-level automation. Interviewee 14 (2026) stated that "*in total I would say right now we picked 99% of the products,*" which in practice meant "*roughly 95% of the orders*." This is a valuable complement to earlier interview material because it shows that, in a favorable operational setting, the gap between product-level and order-level automation can be relatively small, although it still does not disappear completely. At the same time, this level of compatibility requires deliberate process control. Interviewee 14 (2026) explained that products that tend to unfold are excluded from the robotic flow: "*we flag them in our WMS, and then all orders with these kind of products are not going to the robots and they are going to the manual pods*." This suggests that operational fit is not only a property of the robot, but also of how the warehouse actively segments and routes products between robotic and manual workflows.

The challenge is also supported by research on robotic picking. Modern PaP systems increasingly integrate computer vision, deep learning, and trajectory optimization for autonomous object grasping, yet handling irregularly shaped products at low cost remains a fundamental technical challenge Huang and Mok (2018). This aligns with the interview findings, where the main barrier is not simply whether the arm can move quickly, but whether the system can identify, grasp, and place a wide variety of products reliably.

The findings therefore suggest that PaP technology is most suitable for assortments with a high proportion of stable, visible, graspable, and lightweight products. It is less suitable when the assortment contains many heavy, reflective, deformable, fragile, open, or irregularly shaped products. In addition, the technology becomes more valuable when pickable SKUs appear frequently in orders that can be completed without being interrupted by unpickable items.

Technological Readiness: Artificial Intelligence, Vision, and Software Maturity

A third condition concerns technological readiness. Across the interviews, the robotic arm itself was generally described as mature, while the main uncertainty was linked to the software, vision system, AI, and gripping intelligence required to operate in unpredictable warehouse environments. This suggests that the readiness of PaP technology should not be judged mainly by the mechanical arm, but by the system's ability to perceive, decide, and adapt.

Several interviewees emphasized this distinction. Interviewee 7 (2026) stated that "*the magic is in the software, not in the hardware,*" while Interviewee 10 (2026) similarly explained that "*the tough part is the brains of all these robots*" because the mechatronics have not changed much in the last 20 to 30 years. Interviewee 8 (2026) also described robotic arms as mature technology, stating that

"*the arms now are… very mature*", while suggesting that surrounding systems, such as packaging machines, may still be lacking. Together, these findings indicate that the mechanical movement of the arm is not the central challenge. The more difficult part is enabling the robot to understand and respond to the variability of warehouse picking.

This is especially important because warehouse environments differ from manufacturing environments. In manufacturing, robotic systems often operate in controlled and repetitive conditions, where object positions, paths, and processes are more predictable. In retail warehousing, however, items vary in size, shape, packaging, orientation, texture, and presentation. Interviewee 4 (2026) and Interviewee 7 (2026) both emphasized that the primary readiness hurdle is the software and vision AI required to handle this randomness. Interviewee 4 (2026) described AI as a "*bridge*" that allows robots to manage unpredictability, while Interviewee 7 (2026) argued that AI can now make it possible to automate previously unpredictable processes, such as picking high-variability SKUs.

The findings also show that different systems approach learning and adaptation in different ways. Interviewee 2 (2026) described the software suite as essentially based on machine learning, where picking accuracy may start relatively low but improve over time as the system learns. In contrast, Interviewee 3 (2026) explained that Sereact claims to use "*zero-shot technology*," meaning that the system does not require SKU-specific training before picking and should be able to handle new items from the first pick. This indicates that the technological context of use may depend on whether the system needs gradual training or whether it can generalize to new products immediately.

Interviewee 7 (2026) suggested that AI models are becoming very good "*out of the box*" and that the technology has entered a more "*realistic zone*" for many scenarios, moving away from pure experimentation. This suggests that PaP robots are becoming more commercially relevant, especially where product variability is high but still within the capabilities of current AI, vision, and gripping systems.

Recent industry developments also support this movement toward more adaptive robotic picking. For example, Inbolt launched a next-generation bin-picking system using a 3D camera mounted directly on the robot arm rather than fixed overhead cameras, supported by proprietary AI that adapts in real time (Francis, 2025). The system has been reported to achieve under one second per pick and up to a 95% success rate in live production, with use in factories serving customers such as Stellantis, Toyota, and Volkswagen (Businesswire, 2025). Although this example comes from industrial production rather than retail warehousing, it illustrates the broader direction of development: robotic picking is increasingly dependent on adaptive vision and AI rather than only mechanical precision. A final contextual point concerns the time needed to stabilize the system operationally. Interviewee 14 (2026) stated that "*it took us almost all the year of 25 to have a stable process.*" This is important because it shows that implementation readiness should not be

understood as the moment of installation, but as the time required to make the process work reliably under actual warehouse conditions.

In all, the findings suggest that technological readiness is improving, but remains uneven. Robotic arms are mature, but the software, AI, vision, gripper selection, exception handling, and integration with surrounding systems determine whether the technology can work in a specific warehouse context. Therefore, companies evaluating PaP systems should focus less on whether the arm can perform a demonstration pick and more on whether the complete system can perform reliably across the actual SKU mix, order profile, and operating conditions of the warehouse.

Alignment with Technological-Organizational-Environmental Framework

The empirical findings on the context of usage can be positioned through the Technology-Organization-Environment framework. The TOE framework is suitable here because the findings show that the use of PaP technology depends not only on the robot itself, but also on the adopting organization and the wider warehouse environment. The technology becomes relevant only when these three contexts align.

From a technological context, the findings show that adoption depends on the maturity and fit of the robotic system. The robotic arm itself was generally described as mature, while the main uncertainty was linked to AI, vision, software, gripping, and the ability to handle product variability. This means that technological readiness is not determined by the arm alone, but by the full system's ability to perceive, decide, grasp, place, and recover from exceptions. The distinction between SKU packability and order-level automation is also important here. Interviewee 6's estimate that 70% - 80% of an e-commerce assortment may be pickable, and Interviewee 8's point that this may translate into only 40% - 50% complete order automation, show that technical feasibility must be evaluated against real order structures rather than isolated SKU performance.

From an organizational context, the findings show that PaP technology requires operational routines, technical competence, KPI definition, and internal readiness. The technology is not simply installed and left to run independently. It requires staff who can monitor performance, respond to interventions, maintain grippers or suction cups, evaluate system availability, and understand when manual fallback is needed. Interviewee 3's emphasis on defining KPIs and training shift leaders illustrates this organizational dimension. Similarly, Interviewee 6's point about involving shop-floor supervisors early shows that implementation depends on organizational preparation and not only on technical capability.

From an environmental context, the findings show that PaP technology becomes especially relevant in high-volume e-commerce and omnichannel environments. These environments are shaped by SKU proliferation, shorter delivery expectations, labor shortages, and the presence of existing G2P infrastructure. Interviewee 6's description of robotic picking arms as the "*next addition*" to existing systems such as AutoStore, and Interviewee 1's description of the technology as the "*glue*" between warehouse automation and shipping, show that the external and operational environment creates pressure for further automation. The technology is therefore most relevant

where retail fulfilment conditions create a strong need to automate the remaining manual pick-station task.

The TOE interpretation also shows why the technology is not equally suitable for all warehouses. A warehouse may have strong environmental pressure, such as labor shortages or e-commerce growth, but still lack the technological fit if the assortment contains many unpickable items. Similarly, a technically capable robot may fail to create value if the organization lacks the skills, data quality, or integration capacity to operate it. This means that adoption depends on alignment between the technological, organizational, and environmental contexts.

Taken together, the TOE framework positions the context of usage as a question of fit, see **Figure 4.6**. PaP technology is most suitable when the technology can handle the assortment, the organization can support and integrate the system, and the environment creates sufficient operational pressure and volume to justify adoption. This explains why the technology is most relevant in high-volume retail G2P warehouses, but less suitable in smaller, less automated, or highly irregular picking environments.

4.3. Human-Robot Interaction

The findings indicate that the introduction of PaP robots does not remove the human role from the warehouse environment. Instead, it changes the nature of human involvement at the pick station. Across the interviews, HRI was described less as direct collaboration between a human and a robot performing the same picking task simultaneously, and more as a hybrid work arrangement in which robots perform selected picking tasks while humans remain responsible for supervision, intervention, exception handling, and operational support.

This is important because PaP robots are introduced into already automated G2P environments, where humans are still required to manage uncertainty in the final item-handling process. The empirical material therefore suggests that HRI is not only a question of physical proximity, but also of how responsibilities are divided between human judgement and robotic execution.

Figure 4.7 shows the empirical themes and analytical model that is utilized. The empirical themes include: evolving role of human workers, safety risks and technical protection, managing organizational change & worker resistance, and operational interaction & hybrid workstations. These empirics are the foundation of the analysis where the levels of HRI are utilized to indicate the degree of applicability in each taxonomy.

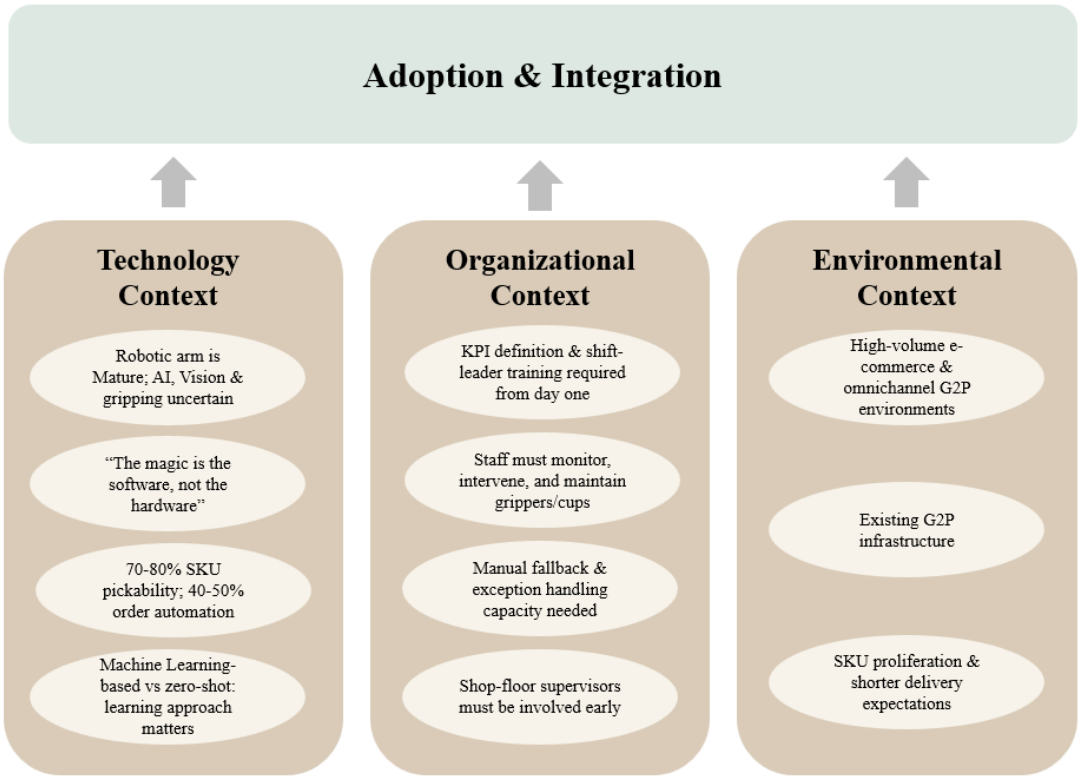

Figure 4.6. *TOE framework aligned with identified themes.*

The Evolving Role of Human Workers

A recurring theme across the interviews was that PaP technology changes the role of warehouse workers rather than eliminating it completely. Several interviewees emphasized that human involvement remains necessary because automation systems still require supervision, intervention, exception handling, and basic technical support (Interviewee 1, 2026; Interviewee 3, 2026; Interviewee 7, 2026; Interviewee 8, 2026).

This suggests that even when robotic systems become more capable, they are still expected to operate within a human-supported work system.

This shift was described most clearly by Interviewee 7 (2026), who compared the future warehouse operator to "*a sheep herder*" who "*herds kind of a bunch of robots and keeps them working.*" This statement captures an important change in the human role. Instead of performing each repetitive

pick manually, the worker becomes responsible for keeping the automated system productive. The interaction therefore shifts from direct manual execution toward monitoring, supporting, and stabilizing the robotic process.

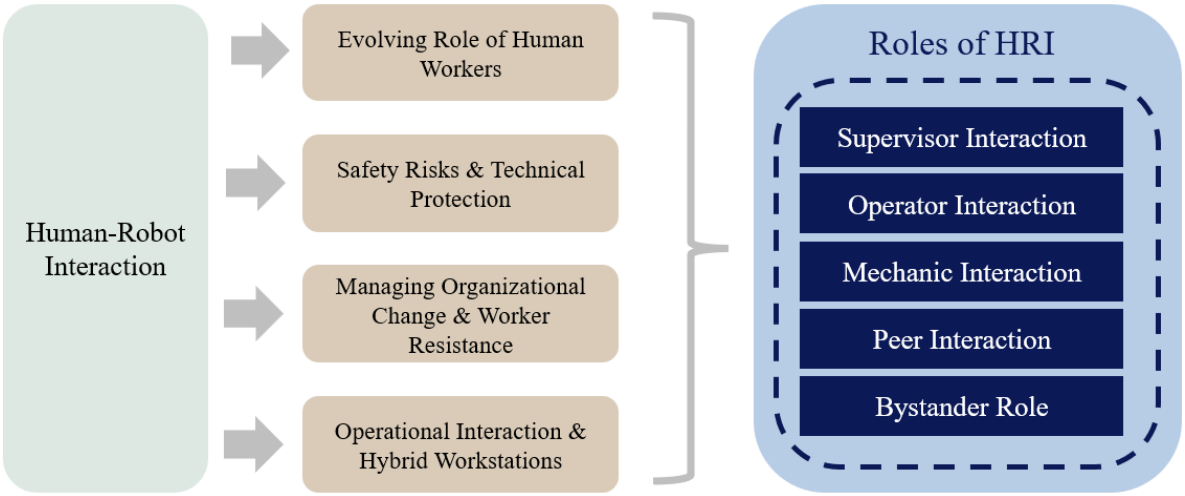

Figure 4.7. *Empirical themes related to HRI into Roles of HRI.*

The continued need for human involvement was also linked to the limitations of current robotic systems. Interviewee 9 (2026) explained that robots still struggle with situations that humans handle almost automatically: "*If the robot tries to pick an article… and it drops the article along the way, that's not a problem if a human does it because the human just picks it up, but the robot can't pick it up.*" This illustrates why humans remain important in environments with product variation, irregular packaging, and unexpected disturbances. Robots may perform well under defined conditions, but humans are still needed when the process deviates from what the system can handle.

At the same time, the interviews show that robots can reduce operational dependence on human labor availability. Interviewee 8 (2026) argued that if "*20% of all the orders*" can be handled by robot arms, the company gains a baseline level of output even during workforce shortages, sickness, or vacations. This does not mean that robots replace the whole workforce, but rather that they can provide a layer of operational resilience. In this way, the value of the robot is not only measured by whether it outperforms humans during peak conditions, but also by whether it can maintain output when labor availability is constrained.

This finding is supported by grey and academic literature, which suggests that PaP systems do not fully eliminate the human element, but instead reconfigure work toward supervisory, maintenance, and exception-handling tasks (BCG, 2025; Rodríguez-García *et al.*, 2025). The empirical material therefore points toward a redistribution of work between robotic consistency and human flexibility.

Robots take over selected repetitive tasks, while humans remain necessary for judgement, adaptation, and system support.

Safety Risks and Technical Protection

Safety emerged as one of the most important aspects of HRI. The interviews show that the physical design of the robotic system strongly influences how closely humans and robots can interact. In some cases, the robot is not designed for direct human proximity and therefore requires physical separation. Interviewee 4 (2026) stated this clearly: "*When you move a 1000 kilo robot arm with a very high speed, you do not want humans around. You want safety fencing*." This indicates that physical risk is shaped by the robot's speed, weight, payload, and movement pattern.

Interviewee 3(2026) made a similar point when explaining why their system uses caged robots: "*We have always a caged robot because otherwise it's not allowed to be used because we do not have a force feedback sensor there. This means if the robot would not be caged and you would go into the operating area of the robot, the robot would hit you and would not stop*." This shows that safety is not only a managerial preference, but also a technical and regulatory requirement depending on the robot type. If the robot lacks force feedback or safe stop functionality, direct human access to the operating area becomes unacceptable.

However, the interviews also show that not all systems approach safety in the same way. Interviewee 1 (2026) explained that their company mainly uses cobots: "*We mainly use cobots. So they are limited up to a certain speed because it should be safe for an operator… they should be able to bump into someone without really hurting someone*." This illustrates a different safety logic. Instead of physically isolating the robot, the system limits speed and force so that closer human proximity becomes possible. However, this also creates a trade-off, because safer proximity may reduce the robot's maximum speed and throughput potential.

The findings therefore suggest a trade-off between speed, safety, and proximity. Industrial robots can offer higher speed and stronger performance, but they often require cages, fences, or controlled access. Cobots allow closer interaction with human operators, but their performance may be constrained by safety limits. Interviewee 8 (2026) also indicated that a caged system may be acceptable in some applications, suggesting that full human-robot collaboration is not always necessary if the robot is primarily used as a separated picking resource.

The safety issue is also connected to the intelligence of the system. Interviewee 10 (2026) emphasized that AI-based robotic systems are not always fully predictable: "*They are non-deterministic. It's not a machine that is working on fixed rules… there is always a risk, even though it's 0.001%, that it makes a move that is unexpected*." This point was also supported by Interviewee 7 (2026), who described how software development is partly aimed at preventing or managing such unexpected robot behavior. This indicates that safety risks in PaP systems are not only mechanical, but also related to AI-based decision-making. As a response, some newer systems are moving beyond fixed cages by using virtual barriers, LiDAR, and computer vision to detect when humans enter the robot's workspace. These systems can stop the robot immediately if a person

crosses the protected zone. However, the empirical material suggests that such technical protection must be trusted by both managers and operators before closer human-robot proximity becomes widely accepted.

The literature supports this concern. In highly automated warehouse environments, PaP robots and human operators may increasingly share physical workspaces, which places HRI at high levels of physical proximity and requires robust safety protocols and collision avoidance mechanisms (Bdiwi, Pfeifer and Sterzing, 2017; Khalid *et al.*, 2022). Incidents involving unintended contact between robotic systems and personnel also show that safety design is not only a technical concern, but a socio-organizational one, with implications for workforce confidence, regulatory compliance, and long-term adoption (Evans, 2020; Cymek, Truckenbrodt and Onnasch, 2023).

Managing Organizational Change and Worker Resistance

The findings also show that HRI is shaped by organizational change and employee perceptions. The robot is not only a technical system placed at a workstation; it is also interpreted by workers as either a supportive tool or a potential threat. This means that acceptance depends partly on how the technology is introduced and communicated.

Interviewee 6 (2026) emphasized that resistance should be expected when automation is introduced: "*Resistance is natural. And that means you have to plan for how to overcome this resistance, because resistance will be there always, whatever it is, with automation.*" This suggests that employee resistance is not necessarily specific to PaP robots, but part of a broader organizational response to technological change.

Interviewee 10 (2026) similarly highlighted the importance of communication and framing. According to him, acceptance depends on whether the company presents automation as something that supports existing workers or as something that competes with them: "*First is, how do you communicate it as a company? If you're bringing automation in to basically enhance what these associates are doing already… they're pretty much going to be on board.*" However, if workers perceive the robot as "*competing with you*", this can lead to resistance and even "*fights with the unions*" (Interviewee 10, 2026). This indicates that the same technology can produce different reactions depending on the organizational narrative around it. Interviewee 4 (2026) framed the long-term role of automation in a more supportive way, stating that "*the goal is not to replace humans, but to elevate humans to do the better job.*" He further explained that there will always be tasks where humans remain best and where there is no clear business case for solving every problem through automation. This suggests that PaP robots may be accepted more easily when they are positioned as removing repetitive or difficult tasks rather than as replacing workers entirely.

This is supported by literature on technology acceptance, which indicates that operator acceptance is shaped not only by technical performance, but also by whether workers perceive the technology as reliable, useful, and non-threatening. Fear of job displacement has been identified as a factor that can negatively influence adoption intentions (Simões, Soares and Barros, 2020; Grover and

Ashraf, 2024). Therefore, successful HRI requires more than functional hardware and software. It also requires attention to communication, training, trust, and the social meaning of automation in the workplace.

In all, the empirical material suggests that organizational acceptance depends on whether workers understand how their role will change. If the robot is introduced as a way to stabilize operations, reduce repetitive work, and support employees, acceptance may be stronger. If it is introduced or perceived as a direct substitute for labor, resistance is more likely. HRI is therefore not only designed through technical interfaces, but also through managerial communication and change management.

Operational Interaction and Hybrid Workstations

The interviews also provided practical examples of how HRI occurs at workstation level. One important finding is that PaP systems are often designed as hybrid workstations, where robots and humans can use the same station under different operating conditions.

Interviewee 3 (2026) described a system where the robotic arm is mounted at the station and can "*swipe to the side*" to allow a human worker to stand at the same platform and pick manually. This type of workstation design shows that HRI does not necessarily mean that humans and robots work side by side at the same time. Instead, it may mean that the workstation can switch between robotic and manual operation depending on workload, robot performance, or labor availability. This hybrid setup is important because humans are still often faster and more flexible during demanding periods. Interviewee 3(2026) explained that during peak hours, humans remain better because they currently pick quicker and more effectively than robots. In this case, the robot is not mainly used to replace humans during the most intense operating periods. Rather, it can be used to extend productive time when labor is less available, such as during lunch breaks, night shifts, or outside normal working hours. Interviewee 3 (2026) described this as a common use case, where humans handle high-throughput picking during standard shifts, while the robot continues operating during breaks or night shifts.

This finding adds nuance to the role of PaP robots. The robot does not need to outperform human pickers in every condition to be useful. Instead, it can provide value by covering labor gaps, maintaining output outside normal working hours, and taking over a portion of repetitive work. This supports the view that PaP robots are currently more complementary than fully substitutive in many warehouse contexts. The level of operational interaction also depends on how often the robot requires support. Interviewee 1 (2026) stated that one system required approximately 1.5 operator interventions per hour, while other technologies in pilot settings required intervention as often as every ten minutes. This shows that the practical workload created by the robot depends strongly on system maturity and reliability. If interventions are limited, the robot may reduce manual workload. If interventions are frequent, the system may instead create additional pressure on operators.

HRI also occurs through signals and alerts. Interviewee 1 (2026) explained that if an item is not reachable, the robot calls for an operator and "*the stack lights will go from green to orange or into red, depends a bit on the error.*" This indicates that much of the interaction is not direct physical collaboration, but exception-based communication through system status indicators. The operator responds when the robot cannot proceed, which reinforces the idea that the human role is shifting toward supervision and exception handling.

This shift also creates a need for new skills. Interviewee 3(2026) explained that shift leaders must undergo on-the-job training to learn how to handle technical upkeep, such as exchanging suction cups. This suggests that workers do not necessarily need to become robotics specialists, but they do need enough technical understanding to solve routine issues and keep the system running. The usability of the interface and the ease of basic maintenance therefore become important parts of the human-robot relationship.

This point is also reflected in the literature. The intuitive programmability and reconfigurability of PaP systems are critical dimensions of the human-technology interface, because the ability of non-specialist operators to adjust system parameters can influence operational flexibility and organizational readiness to adopt the technology (Simões, Soares and Barros, 2020). Therefore, HRI is not only about physical safety or task allocation, but also about how easily warehouse staff can understand, adjust, and maintain the system.

Alignment with Conceptual Framework: the Human-Robot Interaction Roles

The empirical findings on HRI can be positioned through the role-based HRI framework. This framework is suitable because the findings show that human interaction with PaP robots is not uniform. Instead, different warehouse actors interact with the robot in different ways depending on whether they observe, monitor, intervene, maintain, or manage the system. The theoretical framework distinguishes between several human roles in relation to the robot, including bystander, peer, mechanic, operator, and supervisor. These roles differ according to the level at which the human can influence the robotic system, ranging from limited observation to intervention at the level of actions, intentions, or goals.

The strongest empirical alignment is with the operator and supervisor roles. In the empirical material, human workers are not described as continuously performing the same task together with the robot. Instead, they are mainly described as monitoring the system, responding to errors, and intervening when the robot cannot continue. This is visible in Interviewee 1's description of stack lights changing from green to orange or red when the robot requires operator support, and in the finding that certain systems require operator interventions when items are unreachable or when the robot fails. This corresponds closely to the operator role, where the human adjusts or corrects robot behavior when it deviates from expectations.

At the same time, the empirical findings also point toward a supervisory role. Interviewee 7's description of the future warehouse worker as a "*sheep herder*" who keeps multiple robots working suggests that the human role may move beyond single-task intervention toward broader monitoring

of several autonomous systems. In this role, the human does not perform each picking action manually, but oversees system performance, identifies when intervention is needed, and ensures that the robotic process remains aligned with operational goals. This is consistent with the supervisor role in the framework, where the robot performs actions autonomously while the human monitors, evaluates, and retains authority to intervene when necessary.

The mechanic role is also visible in the empirical material, especially where interviewees discussed maintenance and technical upkeep. Interviewee 3's statement that shift leaders need on-the-job training to learn tasks such as exchanging suction cups shows that human interaction with the robot also includes physical and technical intervention. This differs from ordinary operational intervention because it concerns the robot's hardware condition and ability to continue functioning. In the framework, this aligns with the mechanic role, where the human focuses on physical modification or maintenance of the robot and then ensures that the system performs as intended afterward.

The peer role appears to be the least developed in the current empirical material. The interviews did not strongly suggest that warehouse workers interact with PaP robots through high-level natural directives in the way a peer role would imply. Instead, interaction appears to occur mainly through status signals, alerts, manual interventions, technical maintenance, and system monitoring. This indicates that current PaP systems are not yet designed around a peer-like relationship between human and robot. The robot is not treated as a flexible colleague receiving natural instructions, but as an autonomous system that performs a defined task and calls for human support when needed.

The bystander role is less central, but still relevant in relation to safety. In caged robot systems, ordinary workers may share the broader warehouse environment but have little or no direct control over the robot. Their interaction is mainly observational, and the main design requirement is to prevent unsafe contact or misunderstanding of the robot's operating area. This is reflected in the interview findings on fencing, caged robots, and safety zones. In such cases, workers who are not assigned to operate or maintain the robot resemble bystanders, because their influence over robot behavior is limited.

The HRI framework shows that the current human-robot relationship in PaP systems is mainly organized around operator, supervisor, and mechanic roles (see **Figure 4.8**). The worker is not removed from the system, but repositioned from direct manual picking toward monitoring, exception handling, and basic technical support. This supports the broader empirical finding that PaP technology does not eliminate human involvement but changes the level and type of human interaction with the warehouse process. Rather than representing full peer-like collaboration, current systems are better understood as autonomous picking systems supervised, corrected, and maintained by humans.

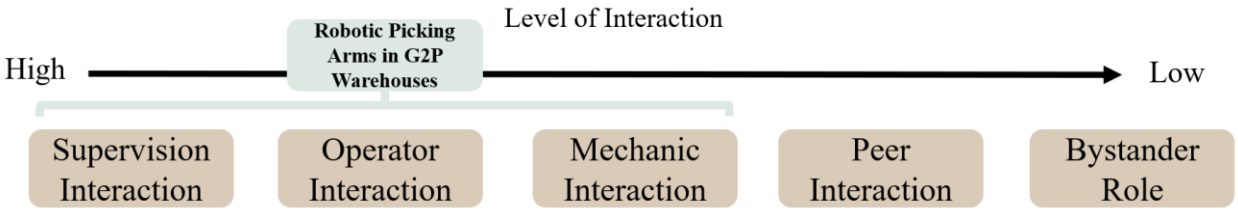

***Figure 4.8**. Place of Robotic Picking Arms in a G2P warehouse.*

4.4. Future of the Technology

The empirics suggest that the future of PaP technology in retail G2P warehouses is promising, but uneven. Interviewees generally viewed the technology as moving beyond pure experimentation, while still recognizing that it is not yet mature enough to automate the full complexity of retail order fulfilment. The future trajectory therefore depends not only on whether robotic arms can pick faster, but on whether the surrounding intelligence, integration, and organizational capabilities can develop enough to make the technology reliable, scalable, and economically meaningful in real warehouse environments.

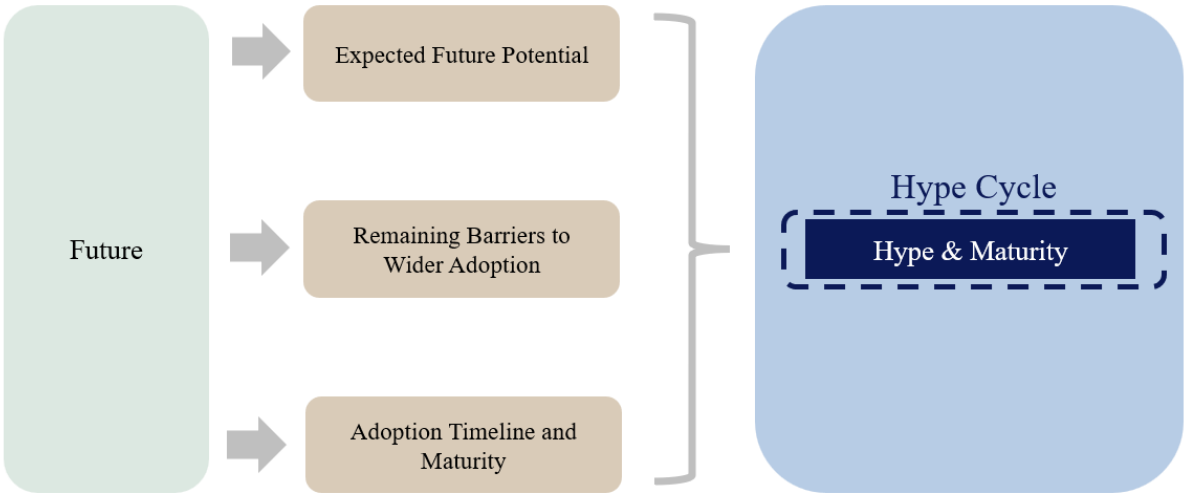

***Figure 4.9.** Empirical themes related to Future of technology into Hype Cycle.*

Expected Future Potential

The positive outlook for PaP technology is mainly driven by the combination of operational pressure in retail warehousing and rapid development in AI-based robotic manipulation. Manual item picking remains difficult to scale in high-volume e-commerce environments, where workers must handle large SKU ranges, short lead-time expectations, and complex order profiles. This creates a clear reason for companies to explore robotic picking, especially in G2P warehouses where storage and transport are already automated, but item-level handling remains manual.

The future potential is also supported by market growth. The global PaP robotics market has been projected to grow from USD 148 million in 2020 to USD 2.87 billion by 2026, while the European intralogistics robotics sector expanded by 21.9% in 2021 (Kardex, 2026a). Such figures should not be interpreted as proof that the technology is fully mature, but they do indicate growing commercial momentum around robotic picking and intralogistics automation. This aligns with the interview finding that the technology is entering an early adoption phase rather than remaining purely experimental. Several interviewees described the technology as being in an early adopter phase rather than a purely experimental phase. Interviewee 3 (2026) stated that their company already has six active systems, suggesting that at least some providers have moved from demonstrations toward operational installations. This is important because active systems create reference cases for potential adopters and make the technology more observable in practice. However, the technology is still not mainstream, as adoption remains concentrated among firms and providers with the scale, resources, and willingness to experiment.

A key reason for optimism is that the limiting factor is increasingly shifting from the robotic arm itself to the intelligence around it. A further nuance in the interviews was the distinction between AI hype and PaP maturity. While AI was often described as a strongly hyped enabling technology, PaP robots themselves were not generally viewed as hype driven. Instead, the robotic arm was described as relatively mature, while uncertainty was concentrated around the software, vision, and learning capabilities that allow the arm to operate in unpredictable warehouse environments. This distinction is important because it suggests that the future of the technology depends less on proving the mechanical arm and more on improving the intelligence around it. Interviewee 10 (2026) explained that "*the mechatronics haven't changed much*" in the last 20 to 30 years, while several interviewees suggested that the real progress is now happening in software, AI, computer vision, and grasp planning. This is important because modern PaP systems increasingly combine perception, pose estimation, coordinate transformation, trajectory planning, and robot execution into one workflow (Niu *et al.*, 2021; Wong *et al.*, 2022) . Advances in AI, machine vision, and reinforcement learning are therefore expected to expand the range of products that robotic arms can handle in warehouse environments (Jotawar, Soni and Kumar, 2017; Rodríguez García and Agmoni, 2024).

The long-term potential is therefore not only that robots become faster, but that they become more generalizable. As systems learn from operational data, their ability to handle variation may improve, allowing them to move beyond narrow, predefined product sets. This is particularly relevant for retail G2P warehouses, where the value of the technology depends on whether it can gradually handle broader assortments without extensive SKU-specific training. In this sense, the future potential of PaP technology lies in the combination of mature robotic hardware with increasingly capable AI-driven perception and manipulation.

Remaining Barriers to Wider Adoption

Despite this positive outlook, the findings indicate that several barriers continue to limit wider adoption. The most important technical barrier is the variability of retail products. PaP systems still struggle with items that are irregularly shaped, reflective, deformable, heavy, fragile, or difficult to grasp consistently. This means that although the technology may work well for selected product categories, it is not yet universally applicable across the full retail assortment.

This limitation is supported by previous research, which argues that substantial progress is still needed in computer vision, pose estimation, and adaptive end-effector design before reliable autonomous grasping of broad retail SKU assortments can be achieved at commercially viable cost (Jotawar, Soni and Kumar, 2017; Huang and Mok, 2018). This aligns with the empirical findings, where interviewees generally did not describe the robotic arm as the main problem, but rather the system's ability to perceive, decide, and adapt in a high-variability warehouse environment.

A second barrier is that picking is only one part of the fulfilment process. Interviewee 8's (2026) indicated that picking is easier to adopt than bagging in retail warehouses, while Interviewee 6 (2026) and Interviewee 1 (2026) highlighted the "*Tetris*" problem: placing items neatly and efficiently into boxes or bags is more complicated than simply picking them. Interviewee 6 (2026) explained that while grabbing an item is becoming more mature, 3D stacking remains significantly less ready for full automation. The adopter perspective also suggests that once robotic picking becomes more stable, the next bottleneck shifts downstream. Interviewee 14 (2026) explained that the current focus after robotic picking is to find an automation machine for packing, but that the challenge is to identify a solution that "*works for all our customers*." He further noted that once packing is automated, "*you have to do something with the bags or boxes afterwards*," which creates a further need for robotic sorting or downstream handling. This suggests that the future of PaP technology depends not only on successful grasping, but also on whether downstream activities such as placing, bagging, packing, and space optimization can be automated effectively. This challenge is becoming more relevant because of packaging and sustainability requirements. Interviewee 6 (2026) noted that in the EU, "*the air in the boxes should be minimized now,*" while Interviewee 11 (2026) stated that companies "*can't send more than 50% air.*" These requirements may increase the need for more intelligent packing solutions, which are currently more complex than basic item picking. Therefore, future adoption may be constrained if robotic systems can pick products but cannot place them in a way that satisfies packaging efficiency, product protection, and regulatory expectations.

A third barrier is integration complexity. As G2P warehouses adopt more automation technologies, PaP robots must interact with existing storage systems, conveyors, Warehouse Management Systems, Warehouse Control Systems, packing equipment, and exception-handling routines. The proliferation of heterogeneous automation technologies increases system complexity and creates a need for staff capable of managing multi-solution environments (Rodríguez-García and Agmoni, 2024) . This suggests that future adoption depends less on the robot as a standalone machine and

more on whether it can be integrated into the wider warehouse system without creating new bottlenecks.

This is why narrowly scoped pilots can be misleading. Berkshire Grey (2026) notes that robotic picking pilots that focus only on one subprocess often produce disappointing operational results. In relation to this thesis, this means that future adoption should not be evaluated only by whether the robot can perform a successful pick in isolation. It should be evaluated by whether it improves the full G2P fulfilment flow, including throughput, reliability, exception handling, packing, labor planning, and system uptime.

Finally, organizational capability remains a barrier. Rodríguez-García and Agmoni (2024) & Smart Robotics (2026) highlight a shortage of professionals who combine supply chain operations knowledge with data analytics, AI, and robotics expertise. This is important because PaP systems require more than installation; they require continuous monitoring, tuning, maintenance, data interpretation, and operational integration. Therefore, the future of the technology depends not only on technical development, but also on whether retailers can build the internal capabilities needed to operate increasingly intelligent automation systems.

Adoption Timeline and Maturity

The interviews show that there is no single agreed timeline for when PaP technology will become mainstream. Some interviewees expected rapid adoption within a few years, while others were more cautious and emphasized that robotic manipulation remains difficult to predict. This variation suggests that the technology's maturity should be understood in stages rather than through one fixed adoption date. Interviewee 1 (2026) gave one of the more optimistic estimates, suggesting that "*within now and three years*" item-picking robots could become a commodity. This aligns with more optimistic industry expectations that robotic picking may become commonly utilized within the next few years, especially in suitable high-volume environments. Interviewee 8 (2026) also presented a near-term roadmap for his organization, where 2026 is used for pilots and discovery and 2027 becomes the point for larger-scale implementation. Interviewee 8 (2026) also linked this roadmap to the hype curve, arguing that the technology has moved beyond the initial hype and is entering a more practical implementation phase. This does not mean that PaP robots are already mainstream, but it indicates that some adopters perceive the technology as mature enough for structured operational evaluation. In this sense, the future is not framed only as a distant possibility, but as something that can be tested through concrete pilots and investment decisions. These views suggest that in favorable contexts, particularly existing G2P warehouses with suitable assortments, the technology may scale relatively soon.

Interviewee 6 (2026) provided a broader long-term perspective, anticipating that within ten years the industry may see a "*completely different type of warehouse*" with widespread use of robotic systems. This view does not imply that all picking will be fully automated, but it suggests that robotic arms may become a more normal component of automated fulfilment environments. In

this sense, the next decade may be characterized by gradual expansion rather than sudden replacement of human pickers.

Interviewee 10 (2026), however, was more cautious about predicting the timeline. He stated: "*I do not have a crystal ball for that… we're still far from it… I can tell you, I do not know, 10, 20 years, but I have no clue… maybe 30, maybe it's five.*" This uncertainty is important because robotics development can progress unevenly. A major breakthrough in AI-based robotic manipulation could accelerate adoption, while the absence of such a breakthrough could leave the technology limited to narrower use cases for longer.

Interviewee 10 (2026) also compared this uncertainty to developments in large language models, suggesting that if robotics could accumulate large amounts of data from thousands of environments and generalize across them, progress might accelerate dramatically. However, he also noted that this approach "*hasn't worked yet*" and that "*we are not at that point*." He emphasized that "*replicating the human hand is so, so hard*," which highlights a fundamental difference between digital AI and physical robotics. Robotic systems must interact with real objects, surfaces, weights, shapes, and unpredictable physical conditions, making progress slower and harder to generalize.

Overall, the expected adoption timeline is best understood as differentiated. In the short term, PaP robots are likely to expand through pilots and targeted deployments in favorable environments. In the medium term, they may become more common in high-volume G2P warehouses where product characteristics and operating hours support the business case. In the longer term, broader transformation may occur if AI, vision, gripping, and packing capabilities improve enough to handle more complex retail assortments. Therefore, the most realistic future is not immediate full automation, but gradual and uneven adoption, where PaP robots become increasingly important in the parts of retail warehousing where the technology, assortment, and operational context fit.

Alignment with Conceptual Framework (Hype-Cycle)

The empirical findings on the future development of PaP technology can be interpreted through the Hype Cycle. This perspective is relevant because the findings reveal a combination of strong expectations and continued uncertainty surrounding the technology. While interviewees generally considered PaP systems to have significant potential and to be progressing toward wider use, they also stressed that the technology has not yet reached the level of maturity required to manage the full complexity of retail warehouse fulfilment.

The findings suggest that PaP technology is no longer only at the Innovation Trigger stage. Sereact's USD 110 million Series B round also supports the interpretation that the technology is moving from early experimentation toward scale-up. The round, led by Headline with participation from Bullhound Capital, Daphni, and Felix Capital, is intended to scale Cortex 2.0 and support expansion into the United States (Sereact, 2026). In Hype Cycle terms, this type of late-stage venture funding suggests that the technology is no longer only at the innovation-trigger stage but is entering a phase where investors expect clearer commercialization, operational deployment, and market expansion. However, because the funding is mainly directed toward improving the AI-

based “robotic brain,” it also confirms that broader maturity still depends on advances in software intelligence and adaptive manipulation.

The presence of active systems, pilots, provider deployments, and planned investments indicates that the technology has moved beyond early conceptual experimentation. Interviewee 3’s statement that their company already has six active systems and Interviewee 8’s roadmap of pilots in 2026 followed by larger investments and implementation in 2027 both suggest that the technology is entering practical evaluation. This means that it is not merely a future idea, but a technology being tested and implemented in operational environments.

At the same time, the findings do not suggest that the technology has reached the Plateau of Productivity. The technology is still limited by SKU variability, software maturity, vision performance, gripper adaptability, integration challenges, and downstream activities such as packing and bagging. The “*Tetris*” problem described by Interviewee 6 and Interviewee 1 shows that even if robotic picking improves, full fulfilment automation remains more complex. Interviewee 10’s caution that timelines could be five, ten, twenty, or even thirty years further reinforces that the technology has not yet stabilized into a mature and predictable solution.

The empirical material instead suggests that PaP technology is somewhere between the Peak of Inflated Expectations, the Trough of Disillusionment, and the Slope of Enlightenment, depending on the stakeholder perspective. From a general market perspective, AI remains highly hyped, and some claims around robotic manipulation may still create inflated expectations. However, several interviewees distinguished AI hype from PaP robots themselves, describing the robotic arm as mature while identifying software and perception as the real uncertainty. This suggests that the physical technology may be further along the maturity curve than the intelligence required to generalize it across retail environments.

Interviewee 8’s view is particularly important because he described the technology as having moved beyond the initial hype and toward a more practical implementation phase. This indicates a possible movement toward the Slope of Enlightenment, where expectations become more realistic, and firms begin identifying specific use cases where the technology creates value. In this stage, the question is no longer whether robotic picking is exciting, but where it works, under what conditions, and how it should be integrated into real warehouse operations.

The Hype Cycle also helps explain why the expected future is uneven. For favorable contexts, such as high-volume G2P warehouses with suitable assortments, the technology may be close to wider adoption. For more complex retail environments with irregular products, difficult packaging, and downstream packing requirements, the technology remains less mature. This means that PaP technology may move toward productive use in selected applications before becoming broadly mainstream.

From this perspective, the Hype Cycle interpretation suggests that PaP technology is entering a more realistic phase of development, the position is shown in **Figure 4.10.** Position of PaP technology in hype cycle.It is not purely hype, but it is also not fully mature. The technology

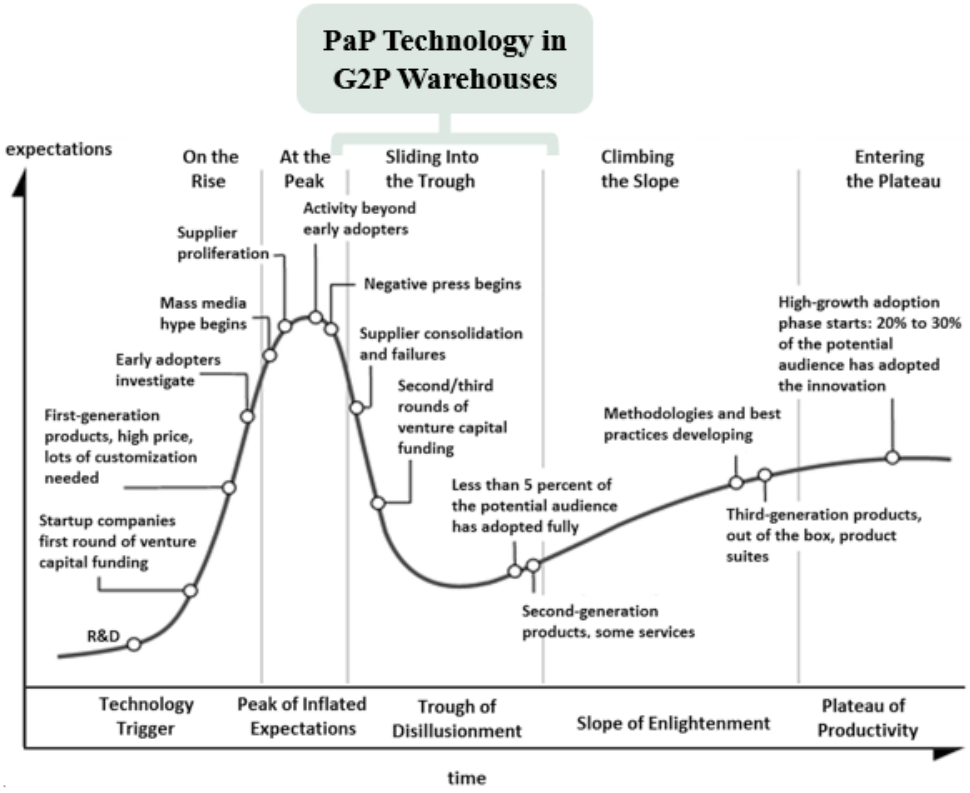

Figure 4.10. *Position of PaP technology in hype cycle.*

appears to be moving toward the Slope of Enlightenment, where early adopters and providers are learning from pilots, refining use cases, and developing a clearer understanding of the conditions under which robotic picking creates value. Full mainstream adoption remains dependent on further improvements in AI, vision, gripping, integration, and organizational readiness.

5. Discussion

This chapter discusses the findings of the thesis by bringing together insights from the empirics, literature, and theoretical frameworks. It develops the main interpretations of the study and uses them as the basis for the six propositions and the Pick-and-Place Adoption Fit Framework.

In this thesis, we set out to understand whether PaP technology could address one of the remaining limitations in highly automated retail warehouses: the continued reliance on manual picking at G2P workstations. At the beginning of the study, it was tempting to view this technology as the next logical step in warehouse automation. If goods can already be brought automatically to a person, then it seems natural to ask whether they can instead be brought to a robot.

As the study progressed, however, our understanding became more nuanced. PaP robotic arms are not simply an additional machine that can be inserted into an existing G2P system. They expose the complexity of the final item-handling task itself. While storage, retrieval, and internal transport can be structured and standardized to a large extent, item-level picking remains highly variable, physical, and context-dependent. The main challenge is therefore not only whether a robot arm can move quickly or accurately, but whether the whole robotic system can perceive, grasp, place, recover, and integrate reliably within a real retail fulfilment environment.

In this chapter, we take a step back from the individual findings and reflect on what they mean for our understanding of PaP technology. We use the discussion to connect what we learned from the interviews with insights from the integrative review and the theoretical frameworks. Each subsection develops one central reflection from the thesis and ends with a proposition, as shown in **Figure 5.1**. These propositions are not intended as universal rules, but as condensed statements of what our findings suggest about the conditions under which PaP technology can create value, create risk, or develop further in retail G2P warehouses.

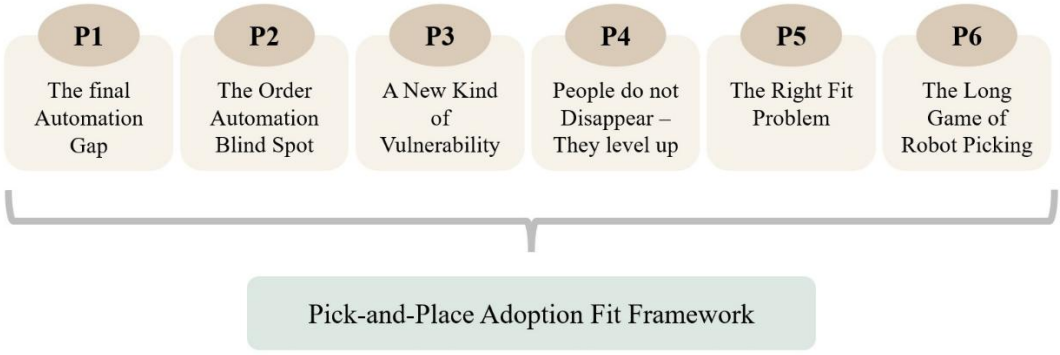

Figure 5.1. *Propositions and the Adoption Fit Framework.*

5.1. The Final Automation Gap

One of the clearest insights we developed during this thesis is that the remaining manual picking task in G2P warehouses should not be understood as a simple “last gap” in automation. At first, it seemed logical to view robotic arms as the next step after automated storage and retrieval. If the system can already bring goods to a person, then bringing goods to a robot appears to be a natural continuation. Although, the more we compared the interviews, the integrative review, and the theoretical perspectives, the more we came to understand that the final picking step is not simply the next step. It may be the most difficult step.

The reason is that item-level picking brings together several forms of complexity at once. A human picker does not only move an item from one place to another. The picker recognizes the product, judges how to grip it, adapts to damaged or unusual packaging, handles dropped items, and decides how to place the item in a tote or order container. Much of this happens almost automatically for a human, but for a robot each of these small actions becomes a technical and operational problem. This was visible in the interviews, where several respondents described the robotic arm itself as relatively mature, while the real difficulty was connected to vision, software, gripping, placement, and exception handling.

This distinction became clearer when comparing the interviews with the scientific literature. The literature shows that a successful robotic pick requires multiple components to work together: object detection, pose estimation, grasp planning, motion planning, collision avoidance, and placement. From a warehouse perspective, this means that robotic picking is not only a hardware challenge. It is a system challenge. The robot must not only move correctly, but understand enough of the surrounding environment to act reliably in a setting that was previously handled by human flexibility.

The grey literature and vendor material often emphasize speed, accuracy, uptime, and the potential to reduce labor. These claims are relevant, because the technology clearly has potential to address real operational pain points. However, the interviews and scientific literature helped us see that these benefits depend on whether the robot can handle the variability that exists at the pick station. This is where the discussion becomes more nuanced. PaP robots are not being introduced into the easiest part of the warehouse. They are being introduced into the part where human adaptability has been doing a lot of hidden work.

This also helps explain why manual picking continues to dominate despite the growth of warehouse automation. G2P systems have solved important parts of the fulfilment problem by reducing travel and automating storage and transport. Yet they often leave the most variable task untouched: the final physical interaction with the item. In our view, this creates a paradox in highly automated warehouses. The more automated the surrounding system becomes, the more visible the remaining manual picking task becomes as the unresolved point of dependency. The adopter perspective also suggests that once robotic picking becomes more stable, the next bottleneck may

shift downstream into packing and post-packing sorting. In this sense, the automation gap does not necessarily disappear; it may instead move to the next unresolved step in the fulfilment flow.

For us, this means that PaP technology should not be understood as a simple substitution of human hands with robotic hands. It represents an attempt to automate the part of the warehouse where human adaptability has been most important. This explains why the technology is attractive, but also why adoption remains difficult. The final manual step is not difficult because it has been ignored by automation. It is difficult because it concentrates the most variable and least standardized part of the fulfilment process.

Proposition 1: *In retail G2P warehouses where storage, retrieval, and internal transport are already automated, PaP robotic arms are most likely to create value when manual item picking is treated as the remaining automation gap within the wider fulfilment system, rather than as an isolated task replacement.*

5.2. The Order Automation Blind Spot

A second major insight from the thesis is that PaP technology cannot be evaluated only through SKU pickability. This became one of the most important distinctions in our study. At first, it may seem useful to ask what percentage of the assortment a robot can pick. However, the interviews made it clear that this number can be misleading if it is not connected to real order structures.

Retail orders are not isolated SKUs. They are combinations of items. This means that a robot may be able to pick a large share of individual products, but still fail to complete a much smaller share of actual customer orders. If one difficult item appears in a multi-item order, the entire order may require human intervention. For us, this became the order automation blind spot: the risk that firms overestimate the value of robotic picking because they focus on what the robot can pick at item level, rather than what it can complete at order level.

The interviews made this blind spot especially visible. One expert view suggested that current technology may handle around 70–80% of a typical e-commerce assortment. However, an adopter-side perspective showed that this does not necessarily translate into 70–80% automated orders. If a customer order contains several items and one of them is unpickable, the robot may fail to complete the full order. In such a case, the actual share of automatable orders can drop much lower than the share of pickable SKUs. This contrast helped us understand that SKU-level metrics can create an overly optimistic picture of adoption readiness.

This was one of the clearest examples where the interviews added something beyond the literature and grey sources. Technical literature often focuses on grasp success, pick rates, pose estimation, and object detection. Vendor material often highlights high success rates, accuracy, speed, and payback potential. These measures are important, but they do not fully answer the question a retailer needs to answer. A retailer does not only need to know whether the robot can pick a selected item in a controlled or semi-controlled setting. It needs to know whether the robot can automate enough of its actual fulfilment flow to justify the investment.

This distinction also changes the way pilots should be interpreted. A pilot can look successful if it is based on a favorable SKU group or if the tested products are selected because they fit the robot well. Yet this may not reveal how the robot performs when exposed to real order profiles, difficult combinations, unexpected packaging, and downstream process requirements. This is where trialability, as discussed in the Diffusion of Innovations framework, becomes more complicated. Trialability is valuable because it reduces uncertainty, but only if the trial reflects the operational reality that the adopter will later face. A narrow trial may reduce perceived uncertainty while leaving the most important uncertainty untouched.

The order automation blind spot also helps explain why the business case can be difficult to generalize. A robot may have a high technical pick rate, but the economic value depends on how often those successful picks translate into completed orders, reduced labor needs, fewer interventions, and smoother downstream handling. This means that firms should not only evaluate the robot's performance at the station. They should evaluate how robotic picking affects the whole order flow.

For us, this became one of the most important contributions of the thesis because it connects technical capability with operational value. It shifts the adoption question from "*Can the robot pick this item?*" to "*Can the robot automate a meaningful share of our real fulfilment flow?*" This is a small change in wording, but a major change in how the technology should be evaluated.

Proposition 2: *When retail warehouses evaluate PaP technology primarily through SKU-level pickability, they risk overestimating adoption potential because operational value depends on the share of complete orders and order flows that can be automated without human intervention.*

5.3. A New Kind of Vulnerability

Another important reflection is that PaP technology does not simply reduce dependency. It changes the type of dependency. A common argument for warehouse automation is that it reduces dependence on manual labor. Our findings support this to some extent. Robotic arms can reduce exposure to labor shortages, sickness, absenteeism, unattractive repetitive work, and the difficulty of staffing certain shifts. In that sense, the technology may create a more stable operational baseline. This was visible in several parts of the empirical material. Interviewees repeatedly linked adoption to labor cost reduction, labor shortage mitigation, and the need to stabilize operations when human availability is uncertain. One particularly important point from the interviews was that robots may still create value even if they automate only part of the order flow, because they provide a baseline level of output when workforce availability is disrupted. This means that the value of the robot is not only measured by whether it is faster than a human during peak hours. It may also be measured by whether it keeps part of the operation running during labor shortages, sickness, vacations, breaks, or night shifts.

The grey literature often supports this positive view by emphasizing continuous operation, labor savings, higher availability, and reduced dependence on scarce warehouse workers. This is

important because it reflects a real managerial motivation. However, the scientific literature on highly automated warehouses provides a more cautious counterweight. It shows that automation may introduce new vulnerabilities connected to system downtime, cyber-security, vendor lock-in, data dependency, and the loss of manual fallback capacity. When we compared these perspectives, we came to see resilience as more complicated than simply replacing labor with robots.

A warehouse that adopts PaP robots becomes more dependent on software, master data, cameras, sensors, grippers, APIs, electricity, cyber-security, vendor support, spare parts, and maintenance capability. If any of these elements fail, the robot may stop creating value. In that sense, automation creates a new kind of vulnerability. It reduces exposure to some human-related uncertainties, but increases exposure to technical and infrastructural uncertainties.

This changed how we viewed the resilience argument. It is too simple to say that robots make warehouses more resilient. They may make warehouses more resilient against one type of disruption, especially labor instability. However, they may also make warehouses more vulnerable to other types of disruption, such as system downtime, poor integration, cyber incidents, lack of spare parts, vendor dependency, or insufficient technical competence. The real question is therefore not whether automation reduces risk, but which risks it reduces and which risks it creates.

This insight also nuances the idea of relative advantage from the Diffusion of Innovations framework. PaP robots clearly offer potential relative advantages: labor reduction, consistency, availability, accuracy, and operational continuity. Yet these advantages are only realized if the organization can manage the complexity that comes with them. Otherwise, what appears to be a labor-saving investment may become a technology-dependency problem.

From a Technology-Organization-Environment perspective, this means that adoption readiness should not only be assessed through the robot's technical capability. It should also include the organization's ability to operate, maintain, troubleshoot, secure, and recover the system. This is especially important because warehouse automation does not fail only at the moment of picking. It can fail through weak data, poor interfaces, missing maintenance routines, unstable vendor support, unclear escalation procedures, or lack of fallback capacity.

For us, the key learning is that automation should be discussed as a transformation of dependency, not as the removal of dependency. This does not weaken the case for PaP technology. Rather, it makes the case more realistic. The technology can be worth pursuing, especially in contexts with high labor pressure and strong ROI potential, but firms must understand what kind of operational vulnerability they are accepting in return.

Proposition 3: *In retail G2P warehouses facing labor uncertainty, PaP adoption can improve operational resilience when firms also develop the technical and organizational capabilities needed to manage new dependencies on software, data, integration, maintenance, cyber-security, and vendor support.*

5.4.People Do Not Disappear - They Level Up

A fourth reflection concerns the role of human workers. Before conducting the thesis, it would have been easy to frame the discussion as a question of whether robots replace humans. Though the empirical findings made this framing feel too limited. The more accurate interpretation is that humans are repositioned. In current and near-future PaP systems, humans remain necessary as operators, supervisors, mechanics, exception handlers, and decision-makers when the system cannot continue independently.

This was one of the strongest human-related insights in the thesis. The interviews did not describe a future where the human disappears from the pick station completely. Instead, they described a shift in the type of human involvement. Workers may respond to stack lights, handle unreachable items, replace suction cups, restart processes, monitor several robots, or take over when manual flexibility is required. One interviewee compared the future operator to a “sheep herder” who keeps multiple robots working. We found this metaphor useful because it captures the move from direct manual execution toward system supervision.

The HRI framework helped us interpret this role shift more precisely. The strongest alignment was not with a fully peer-like relationship between human and robot, but with the operator, supervisor, and mechanic roles. The operator appears when a worker responds to robot errors or corrects the system at the action level. The supervisor appears when a worker monitors one or several systems and decides when intervention is needed. The mechanic appears when workers or shift leaders perform basic technical upkeep, such as replacing suction cups. This suggests that current PaP systems are not yet designed around humans and robots as equal colleagues. They are better understood as autonomous systems that still depend on human support, correction, and maintenance.

The interviews and literature also created a useful contrast. On the positive side, several interviewees framed robotic picking as a way to reduce repetitive, physically demanding, and unattractive work. This aligns with literature on supportive and collaborative warehouse technologies, where robots can reduce physical burden and allow humans to focus on more complex or supervisory tasks. On the challenging side, the literature on human-robot collaboration warns that robots can also create new mental, social, and organizational demands. This was also visible in the interviews, where respondents emphasized resistance, trust, training, and communication. The role may become more skilled, but it may also become more stressful if workers are expected to keep unstable systems running without sufficient support.

This is where we think the discussion needs balance. It would be too negative to describe robotic picking as only a threat to workers. It would also be too optimistic to describe it as automatically improving jobs. The reality appears to be more conditional. The human role can become more skilled, supervisory, and less physically repetitive, but only if the organization designs that role properly. If workers are simply made responsible for unstable systems without training, authority, or clear procedures, the technology may create stress rather than support.

This was one of the points where our understanding changed most. We began by studying a robotics technology, but the findings pushed us toward work design. The robot is only one part of the implementation. Firms also need to decide what kind of human role they are creating around the robot. Who monitors it? Who intervenes? Who maintains it? Who decides when manual picking should take over? Who is responsible when the system stops? These questions are not secondary to adoption. They are part of adoption.

This also connects to Institutional Theory. Automation can gain legitimacy because it fits broader narratives around smart warehousing, digital transformation, and future-oriented operations. Yet legitimacy inside the warehouse depends on whether employees understand and accept their changed role. If the technology is communicated as a direct substitute for labor, resistance may increase. If it is communicated and designed as a way to support workers and stabilize operations, acceptance may be stronger.

For this reason, we use the term system steward to describe the future human role. By system steward, we mean a worker whose role shifts from performing every pick manually to supervising, supporting, and stabilizing the automated picking system. This term captures both sides of the transformation: the worker is no longer only a manual picker, but the worker is also not removed from the system. The human becomes responsible for keeping the automated process functioning.

In this sense, PaP technology is not only a robotics project, but also a human-robot work design project.

Proposition 4: *In retail G2P warehouses adopting PaP robots, implementation is more likely to be sustainable when firms redesign human roles around supervision, exception handling, and basic technical support, thereby repositioning workers as system stewards rather than treating them as labor to be replaced.*

5.5. The Right Fit Problem

A fifth insight is that PaP robotic arms should not be presented as a general warehouse solution. Their value is highly dependent on context. This became one of the clearest patterns across the thesis. The technology is most attractive when it solves a specific problem in a warehouse that is suitable for robotic picking. It is less attractive when firms try to apply it broadly without considering the fit between the robot, the products, the order profile, the organization, and the wider operating environment.

The empirical material suggests that PaP robots are most relevant in high-volume G2P environments, particularly in e-commerce and omnichannel fulfilment. In these settings, storage and transport may already be automated, while the final item-level picking task remains manual. Several interviewees described robotic arms as a logical next addition to existing G2P systems rather than as a standalone solution for every warehouse. This is important because the robot's value depends partly on whether the surrounding system is already structured enough to feed it with suitable work.

The Technology-Organization-Environment framework helped us make sense of this. From the technological side, the robot must fit the SKU assortment, order profile, item presentation, vision conditions, gripping requirements, and downstream packing needs. From the organizational side, the firm must have the competence, routines, KPIs, maintenance capability, change management, and integration capacity to support the system. From the environmental side, there must be enough pressure to justify adoption, such as high labor cost, labor shortage, delivery-speed expectations, competitive pressure, or existing investment in automation.

The business case shows why these conditions matter. The grey literature often highlights attractive ROI and productivity potential. The interviews confirmed that ROI is central, but they also showed that ROI varies strongly between contexts. In the interviews, one perspective suggested that ROI in Europe may typically require three to five years, while another adopter-side view suggested that payback can be less than one year in favorable conditions. This contrast helped us understand that ROI is not a fixed property of the robot. It is an outcome of labor cost, operating hours, order profile, integration cost, and achievable automation rate.

Labor cost is a clear example. A robotic picking system may have a stronger financial case in Sweden than in a lower-labor-cost country such as Vietnam, not because the robot performs differently, but because the value of replacing or reducing labor dependency is different. Operating hours also matter. A robot that can run during night shifts, lunch breaks, or multiple shifts has more opportunity to generate value than a robot used only during limited hours. Existing infrastructure matters as well. If a warehouse already has a G2P system, the robot may function as an additional automation layer. If the warehouse lacks such infrastructure, the same robot may require too much surrounding investment.

This is why we think the adoption decision should not begin with the question of whether PaP robots are generally mature. A more useful question is whether the warehouse has the right fit. A firm may face high labor pressure, but if its assortment contains many unpickable items, the fit may be weak. Another firm may have a robot-friendly assortment, but if labor is inexpensive and volume is low, the business pressure may not be strong enough. The most favorable adoption context appears when both operational automation fit and strategic business pressure are high.

This also helps nuance institutional pressures. Labor shortages, rising service expectations, and industry narratives around smart warehousing may push firms toward automation. In some cases, firms may also observe visible adopters and feel pressure to follow. However, these pressures do not make adoption automatically appropriate. Mimicking another firm's automation strategy can be risky if the underlying warehouse context is different. Therefore, institutional pressure may explain why firms become interested in PaP technology, but contextual fit determines whether adoption is likely to create value.

For us, this means that PaP technology should be understood as selective rather than universal. It will likely diffuse first in warehouses where the operational and business conditions align: high volume, suitable assortments, sufficient order-level automation potential, long operating hours,

high labor pressure, existing automation infrastructure, and organizational readiness. In less favorable contexts, manual picking, supportive technologies, or hybrid systems may remain more effective for a longer time.

This is not a criticism of the technology. It is a more realistic understanding of its role. PaP robots are not "the solution" to warehouse picking in general. They are a potentially powerful solution under the right conditions.

Proposition 5: *In retail G2P warehouses, PaP robotic arms are most likely to progress from pilot to scale when operational automation fit and strategic business pressure are both high, because technical feasibility alone is insufficient to justify adoption without contextual business value.*

5.6. The Long Game of Robot Picking

Our final reflection is that PaP technology may become transformative, but its adoption is likely to unfold gradually through suitable use cases rather than as an immediate warehouse-wide shift. The findings do not support the idea that retail warehouses are about to become fully automated in the immediate future. At the same time, they also do not support the view that robotic picking is only hype. The technology appears to be moving into a more practical phase where early adopters and technology providers are learning which use cases work, what limitations remain, and how the technology should be integrated.

The interviews showed different expectations about the timeline. Some respondents were optimistic and suggested that item-picking robots could become common within a few years, especially in favorable G2P environments. Others were more cautious and emphasized that robotic manipulation remains difficult to predict because physical robotics develops differently from digital AI. This variation was important for us because it showed that the future of PaP technology should not be understood through one fixed date. It should be understood as a staged maturity process.

The Hype Cycle helped us interpret this uneven maturity. PaP robotic arms are no longer only at the innovation-trigger stage. Active systems, pilots, funding rounds, market growth, and provider deployments show that the technology is moving beyond conceptual experimentation. At the same time, the technology has not reached a plateau of productivity in the full retail warehouse context. SKU variability, order-level automation, gripping, placement, integration, safety, and downstream packing still limit broader adoption.

The evidence was not fully aligned, and that is what made the Hype Cycle useful. Grey literature and market data create a more optimistic impression through growth projections, funding announcements, and provider claims about success rates or deployment potential. The interviews were more mixed: some interviewees described the technology as moving into a practical implementation phase, while others emphasized that broader generalization remains uncertain. Scientific literature was more cautious still, because it continues to highlight grasping, pose estimation, validation, and real-world variability as unresolved issues. Interpreted together, these

sources suggest that PaP technology is neither simply hyped nor fully mature. It is entering a more use-case-specific phase of development.

This is where we found the distinction between AI hype and PaP maturity especially important. AI is clearly surrounded by strong expectations, and advances in AI are one of the reasons robotic picking is becoming more realistic. Yet physical robotics is not the same as digital AI. A robot must interact with real objects that vary in weight, shape, texture, packaging, and position. It must operate safely in a physical environment and recover from physical disturbances. This makes progress harder to generalize than in many purely digital applications.

The interviews helped us understand this distinction. Several respondents described the robotic arm itself as mature, while emphasizing that the "brain" of the robot is still the central development area. This suggests that the future of PaP technology depends less on proving that robotic arms can move and more on improving the intelligence, perception, learning, and exception handling around the arm. Grey literature and funding activity support the idea that investment is increasingly moving toward these software and AI capabilities. Scientific literature, however, remains more cautious by showing that generalization, validation, and robust grasping in variable environments remain unresolved.

This combination of optimism and caution is why we see the technology as moving toward a more realistic phase of development. The question is no longer whether robotic picking is exciting. The question is where it works, under what conditions, and how it can be scaled without creating new bottlenecks. In Hype Cycle terms, this suggests movement toward the slope of enlightenment in favorable contexts, where early adopters and providers begin to learn the practical limits and value of the technology.

This staged view also helps avoid two extremes. One extreme is to assume that PaP robots will quickly replace human pickers across retail warehousing. The findings do not support that. The other extreme is to dismiss robotic picking as hype because it cannot yet handle every product or every order. The findings do not support that either. A more realistic view is that the technology will expand through focused use cases, especially where the assortment, order profile, operating model, and business case fit.

From this perspective, the future of retail G2P warehouses is likely to be hybrid. Robots may take over selected repetitive picking tasks, humans may move toward supervisory and exception-handling roles, and warehouse systems may become increasingly dependent on the integration between automation layers. This is perhaps the main learning of the thesis. PaP robotic arms should not be seen as the final step toward human-free warehouses. They should be seen as one step in the gradual redesign of warehouse work, where the challenge is not only to automate more tasks, but to decide carefully which tasks should be automated, under what conditions, and with what consequences for the wider fulfilment system.

Proposition 6: *In retail G2P warehouses, PaP technology is likely to diffuse first through focused use cases in favorable operational contexts, before expanding into broader applications as AI, vision, gripping, packing, and integration capabilities mature.*

5.7. The Pick-and-Place Adoption Fit Framework

The propositions developed above show that PaP adoption cannot be explained by one factor alone. Across the discussion, one recurring pattern became increasingly clear to us: adoption depends on the relationship between what the technology can realistically handle and why the organization wants to adopt it. A robot may perform well technically, but still fail to create value if the order profile, workstation design, integration conditions, or organizational readiness are unsuitable. At the same time, a warehouse may face strong labor shortages, rising throughput pressure, or demanding service requirements, but still not be ready for robotic picking if the products and processes do not fit the technology.

This became one of the main lessons of the thesis. At the beginning, it was tempting to think about robotic picking mainly as a question of technological maturity: is the robot good enough yet, or not? But as we moved between interviews, literature, and theory, that question felt increasingly incomplete. In practice, the more relevant question seemed to be whether the technology is good enough for this specific warehouse, under these specific operational and strategic conditions.

For this reason, we propose the PaP Adoption Fit Framework. The framework is intended to bring together the central learning of the thesis in a way that is both analytically useful and practically understandable. Rather than treating adoption as a simple yes-or-no decision, the framework positions adoption potential along two dimensions: Operational Automation Fit and Strategic Business Pressure. In doing so, it reflects one of the central conclusions of the thesis: PaP technology is not simply adopted when it becomes technically possible, but when the technology, the warehouse, and the business context align sufficiently for it to create value.

The framework should therefore be understood as a maturity-based interpretation of adoption rather than a rigid classification model. It does not imply that every G2P warehouse should eventually become G2P, nor that robotic picking is the inevitable next step in all warehouse automation journeys. Instead, it helps explain why PaP technology may be highly relevant in some retail G2P environments while remaining premature, unsuitable, or strategically unnecessary in others.

5.7.1. Underlying Dimensions of the Framework

The first dimension, Operational Automation Fit, refers to the extent to which the warehouse operation is technically and operationally suitable for robotic picking. This dimension focuses on the actual warehouse context in which the robot is expected to work. It includes whether products are robot-pickable, whether those products appear in orders that can be meaningfully automated, whether the workstation and surrounding processes support robotic execution, and whether the organization has the capability to integrate, operate, and maintain the system after implementation.

The second dimension, Strategic Business Pressure, refers to the extent to which the organization has a strong enough reason to adopt the technology. This includes labor shortages and labor costs, but it also includes throughput growth, service expectations, financial justification, the firm's broader automation strategy, and the wider pressures created by industry developments, competitors, and institutional expectations. In other words, even if robotic picking is operationally feasible, adoption may remain limited if the strategic need is weak. Likewise, strong strategic pressure does not automatically make adoption sensible if the operational fit is poor.

To make the framework more transparent, both dimensions are broken down into underlying factor groups in **Table 5.1** and **Table 5.2**.

Table 5.1. *Operational Automation Fit.*

Factor group	Evaluation focus	Relevance for Adoption
Product and SKU suitability	The extent to which products are physically suitable for robotic handling, including size, weight, shape, packaging, surface, fragility, and reflectivity.	Determines whether the robot can reliably identify, grasp, lift, and place items without damaging them.
Order-flow suitability	The extent to which robot-pickable SKUs appear in orders that can be completed without human intervention.	Prevents overestimating adoption potential based only on SKU-level pickability. Operational value depends on how much of the real order flow can be automated.
Workstation and process fit	The suitability of item presentation, tote/bin standardization, pick-station layout, packing or bagging requirements, existing bottlenecks, and manual fallback options.	Determines whether the robot can function in the actual fulfilment process, not only in isolated demonstrations.
System integration readiness	The ability to connect the robot with Warehouse Management System, Warehouse Control System, G2P systems, conveyors, packing equipment, Application Programming Interfaces, and exception-handling routines.	Determines whether the robot can operate as part of the wider warehouse system rather than as a standalone machine.
Organizational capability	The availability of technical competence, maintenance routines, operator training, KPI monitoring, and change management capacity.	Determines whether the organization can operate, support, and improve the robotic system after implementation.

Table 5.2 shows that Operational Automation Fit is broader than robot capability alone. A warehouse may have access to a robot that performs well in a controlled environment, but still have low operational fit if the assortment is highly problematic, if order combinations frequently include difficult items, if item presentation is inconsistent, or if the organization lacks the technical routines required to support the system. For us, this was one of the clearest lessons from the study: robotic picking should not be evaluated as an isolated machine, but as part of a wider fulfilment system.

Table 5.2. Strategic Business Pressure.

Factor group	Evaluation focus	Relevance for pick-and-place adoption
Labor pressure	The extent of labor cost, labor shortage, absenteeism, difficulty staffing repetitive work, and the need for night-shift or break-time coverage.	Strengthens the business case for reducing dependence on manual picking.
Throughput and service pressure	The extent of order-volume growth, peak demand, shorter lead-time expectations, e-commerce growth, and omnichannel fulfilment pressure.	Creates a need for higher, more stable, and more scalable fulfilment capacity.
Financial justification	Expected payback period, investment capacity, utilization rate, operating hours, and the cost of manual alternatives.	Determines whether adoption can be economically justified beyond technical feasibility.
Strategic automation direction	Existing G2P infrastructure, long-term automation roadmap, and the ambition to extend automation from goods-to-person to goods-to-robot.	Makes pick-and-place technology a logical next automation layer rather than an isolated investment.
External and institutional pressure	Competitor adoption, vendor maturity, industry expectations, smart warehousing narratives, and regulatory or safety expectations.	Explains why firms may feel pressure to explore or legitimize the technology even before it is fully mature.

The second dimension shows that the strategic motivation to adopt PaP technology is also broader than a simple labor-saving calculation. In some cases, the pressure may come directly from labor cost or labor scarcity. In others, it may come from growth in order volumes, more demanding service expectations, or a longer-term ambition to continue automating a warehouse that already has G2P infrastructure in place. In still other cases, the pressure may be more indirect, stemming from industry narratives around smart warehousing, visible investments by competitors, or the organizational desire not to fall behind in a field that is increasingly associated with technological modernization.

Taken together, the two tables show that adoption potential depends on the interaction between warehouse suitability and organizational pressure to act. This means that even a technically promising robot may remain peripheral if business pressure is weak, while strong business pressure may still not justify adoption if the operational use case is poorly aligned.

5.7.2. The Framework and its Four Positions

Based on these two dimensions, the PaP Adoption Fit Framework identifies four possible adoption positions. These positions should not be read as fixed categories, but rather as different levels of adoption readiness. A warehouse may move between them over time as operational fit improves, business pressure increases, or the technology becomes more mature.

	Low Strategic Business Pressure	High Strategic Business Pressure
High Operational Automation Fit	Pilot and Learn	Scale and Integrate
Low Operational Automation Fit	Monitor and Prepare	Redesign and Experiment

Figure 5.2. *PaP Adoption Fit Framework. Own Creation.*

Figure 5.2 visualizes how the two dimensions jointly shape the adoption position of a warehouse. The horizontal axis reflects the degree of Operational Automation Fit, while the vertical axis reflects the degree of Strategic Business Pressure. Together, they create four positions: Monitor and Prepare, Pilot and Learn, Redesign and Experiment, and Scale and Integrate. Each position implies a different strategic response and a different kind of maturity in relation to PaP adoption.

Monitor and Prepare

The Monitor and Prepare position applies when both Operational Automation Fit and Strategic Business Pressure are low. In this situation, immediate adoption is unlikely to be justified. The warehouse may not yet have a robot-friendly assortment, a suitable workstation layout, sufficiently standardized tote or bin presentation, or the technical routines required to support a robotic system. At the same time, labor pressure, throughput pressure, or strategic urgency may still be too limited to motivate serious investment.

In our view, this position is important because it reminds us that “not adopting yet” can still be a mature decision. A warehouse in this position should not necessarily force a pilot simply because robotic picking is attracting industry attention. Instead, the more appropriate response may be to monitor developments, improve data quality, map SKU and order characteristics, strengthen process discipline, and build a clearer internal understanding of where robotic picking might eventually fit. In other words, preparation can itself be a meaningful strategic response.

Pilot and Learn

The Pilot and Learn position applies when Operational Automation Fit is relatively high, but Strategic Business Pressure is still limited. In this case, the technology may fit the operation reasonably well. The assortment may be comparatively suitable, the warehouse may already

operate a G2P system, and the workstation environment may be structured enough for robotic picking to be technically plausible. However, the business case may still not be strong enough to justify broad implementation. Labor pressure may be manageable, throughput may not yet be critical, or the expected payback period may remain too uncertain.

In this situation, pilots make sense primarily as a learning mechanism rather than as immediate proof of large-scale financial return. This was an important distinction for us. Not every pilot needs to prove that the technology should be scaled tomorrow. In some cases, its value lies in helping the organization understand intervention frequency, data quality problems, integration requirements, maintenance needs, and the difference between SKU-level and order-level automation potential. A pilot in this quadrant helps reduce uncertainty and build internal capability, even if broader implementation is still some way off.

Redesign and Experiment

The Redesign and Experiment position applies when Strategic Business Pressure is high, but Operational Automation Fit is low. This is one of the most critical positions in the framework because it describes a situation where the organization has a strong reason to automate, but the current warehouse conditions are not yet suitable for doing so successfully. The company may face severe labor shortages, high labor costs, rapid order growth, or demanding service requirements, but still have products, workstations, processes, or system interfaces that make robotic picking difficult to implement at scale.

For us, this quadrant captures the danger of premature adoption. Strong pressure can push organizations toward technology before the use case is ready. In such cases, the most appropriate response is not immediate scale-up, but redesign. This may involve segmenting robot-friendly SKUs, improving item presentation, redesigning pick stations, standardizing bins or totes, cleaning product master data, and narrowing the pilot scope to contexts where the technology has a realistic chance of succeeding. In other words, experimentation in this quadrant should be directed toward improving fit, not toward forcing the technology to solve the whole warehouse problem at once.

Scale and Integrate

The Scale and Integrate position applies when both Operational Automation Fit and Strategic Business Pressure are high. In this situation, the warehouse has both a suitable operational context and a strong strategic reason to adopt. The assortment, order profile, workstation conditions, and system interfaces are favorable, while labor pressure, throughput growth, or automation ambitions create a clear reason to move beyond limited pilots.

This is the strongest adoption case in the framework. At the same time, even here, we do not think this should be understood as a signal for immediate, full warehouse-wide automation. A phased implementation remains more realistic and responsible. Scaling should therefore be accompanied by KPI monitoring, exception-handling routines, employee training, maintenance planning, and careful integration with Warehouse Management System, Warehouse Control System, G2P

infrastructure, and downstream packing or bagging processes. In this quadrant, the warehouse both can use the technology and needs the technology, but successful adoption still depends on thoughtful execution rather than technological enthusiasm alone.

5.7.3. Maturity Paths within the Framework

The framework can also be understood as a maturity model. Warehouses are not permanently fixed in one position. Their position may change over time as they improve data quality, standardize processes, gain experience with G2P systems, strengthen internal technical competence, or face stronger business pressure. In this sense, the framework is not only useful for describing the current state of adoption readiness but also for identifying possible development paths for adoption fit.

To make this more explicit, **Table 5.3** summarizes the recommended development path associated with each framework position.

Table 5.3. *Development Paths for each framework position.*

Current position	Main limitation	Recommended development path
Monitor and Prepare	Low operational fit and low strategic pressure.	Monitor technology development, improve data quality, map SKU and order profiles, and strengthen basic warehouse processes before considering pilots.
Pilot and Learn	Good operational fit but limited business pressure.	Use small-scale pilots to collect performance data, test integration, and build internal knowledge without committing to full-scale implementation.
Redesign and Experiment	Strong business pressure but weak operational fit.	Redesign the use case by segmenting robot-friendly SKUs, improving item presentation, adapting workstation layout, and testing narrower applications.
Scale and Integrate	Strong fit and strong pressure, but implementation risk remains.	Move toward phased implementation, integrate with Warehouse Management System/Warehouse Control System and packing processes, train staff, define KPIs, and develop exception-handling routines.

Table 5.3 highlights that adoption should not be interpreted as a single decision point. In practice, organizations may need to move gradually from one position to another. A warehouse with high strategic pressure but poor operational fit, for example, may need to spend considerable time redesigning the use case before the robot becomes a realistic candidate for scale-up. Likewise, a warehouse with good operational fit but limited strategic urgency may still benefit from pilot-based learning that prepares it for future adoption.

This maturity perspective also helps avoid two common simplifications. The first is the idea that every warehouse should move as quickly as possible toward robotic picking. The second is the idea that a currently unsuitable warehouse will remain unsuitable forever. The framework instead suggests that readiness evolves. Some organizations may need to focus first on data quality,

process discipline, workstation redesign, or organizational capability before robotic picking becomes realistic. Others may already have strong technical fit but still lack the business pressure required to justify the investment. In both cases, maturity consists of bringing the warehouse context into closer alignment with the actual strengths and limitations of the technology.

5.7.4. Implications of the Framework

Altogether, the PaP Adoption Fit Framework brings together the central learning of the thesis: PaP technology is promising, but its adoption should be selective, evidence-based, and context-specific. The movement from G2P to G2R should not be seen as an automatic next step for every warehouse with existing automation. Instead, adoption becomes most realistic when operational suitability and strategic pressure reinforce one another.

One important implication is that firms should not evaluate PaP robots only through vendor demonstrations, technical pick rates, or SKU-level success rates. They should instead evaluate whether the technology fits the actual order flow, whether the organization can support and maintain the system after implementation, and whether the strategic need is strong enough to justify the investment and complexity involved. This means that the evaluation of robotic picking must move beyond the narrow question of whether the robot can pick a product and toward the broader question of whether the robot can create value within the real warehouse context.

A second implication is that the framework supports a more realistic view of warehouse automation. Some warehouses may be ready to scale, while others may be better served by piloting, redesigning the use case, or simply monitoring the technology while improving internal readiness. In this way, the framework supports a maturity-based understanding of adoption rather than a deterministic or purely technology-driven one.

Finally, the framework reinforces one of the main conclusions of the thesis: PaP technology should be understood as a context-dependent extension of warehouse automation, not as a universal or inevitable replacement for human picking. Their relevance depends on the relationship between the warehouse environment, the strategic challenges faced by the organization, and the evolving maturity of the technology itself.

In this sense, the framework is not only useful for deciding whether to adopt PaP technology today, but also for identifying the development path a warehouse must follow before adoption becomes realistic.

6. Conclusion

The concluding chapter synthesizes the principal findings of the thesis and reflects on their broader significance. The chapter is structured around three central parts: (i) Conclusions are drawn based on the research objectives, (ii) the theoretical and practical contributions, and (iii) the study's delimitations are acknowledged alongside avenues for future research.

6.1. Fulfilling the Purpose

This thesis examined the emergence of Pick-and-Place (PaP) technology, specifically Piece Picking Robots in retail Goods-to-Person (G2P) warehouses. It addresses why manual picking persists despite the growth of warehouse automation, what the current state of adoption and Human-Robot Interaction (HRI) looks like, and what the future trajectory of the technology may be. The study combined an integrative literature review with thirteen semi-structured interviews involving technology developers, an adopter, and academic experts. These two methods were combined together for the data analysis. The following sections address each of the three research objectives in turn, followed by reflections on the thesis's theoretical and practical contributions and its delimitations and avenues for future research. The method that was utilized was a combination of an interview study with 13 participants and an integrative literature review.

RO1: *To investigate the current state of the adoption and HRI of PaP technology in retail G2P warehouses.*

PaP robotic arms are currently in an early adoption phase within retail G2P warehouses. The technology has moved beyond piloting, with several providers reporting active operational installations, but it has not yet reached mainstream deployment. Adoption is concentrated among well-resourced companies with existing G2P infrastructure, and is driven primarily by coercive pressures such as labor shortages and rising operational costs. Perceived relative advantages in labor cost reduction, picking consistency, and operational resilience are strong, but adoption is simultaneously slowed by the compatibility challenges of heterogeneous retail assortments and the complexity of integrating the full hardware-software-system chain. The physical robotic arm is broadly considered mature: the primary source of uncertainty lies in the surrounding intelligence, including vision AI, grasp planning, and exception-handling logic, which determines real-world performance across variable product conditions.

From an HRI perspective, PaP technology repositions rather than eliminates human involvement. Workers interact with current systems primarily as operators responding to errors and alerts, as supervisors monitoring system performance and deciding when to intervene, and as mechanics performing routine technical upkeep. The peer role, in which humans and robots interact as equal collaborative partners, has not yet been observed in practice. Hybrid workstation designs, where the robot can be moved aside to allow manual picking at the same station, are common and reflect a complementary relationship: robots cover off-peak hours, night shifts, and break periods, while

humans remain faster and more flexible during high-throughput windows. The adoption state is therefore best described as early and contextually selective, with human roles shifting toward system stewardship rather than direct manual picking.

RO2: *To analyze the current limitations of the picking aspect of warehouse automation, with particular emphasis on the reliance on manual picking in retail G2P warehouse systems.*

The persistence of manual picking in retail G2P warehouses is not the result of neglect or a simple technology gap. It reflects the inherent complexity of item-level picking, which concentrates physical variability, product uncertainty, and contextual judgment in a way that remains difficult to automate reliably at commercial scale. While G2P systems have successfully automated storage, retrieval, and internal transport, the final step of grasping, orienting, and placing diverse retail items has remained largely manual because the task falls outside the operating envelope for which traditional automation was designed.

The thesis identifies four interlocking limitations. First, Stock Keeping Unit (SKU) variability and grasping complexity are fundamental: no single gripper performs well across soft, reflective, deformable, fragile, or irregularly shaped items, and structured placement into totes adds further difficulty through what interviewees described as the Tetris problem. Second, software and data immaturity constrain real-world performance, as vision AI still struggles with exotic surfaces and cluttered environments, AI pick planning is non-deterministic, and master data quality is frequently poor. Third, integration complexity is substantial, requiring API development, process redesign, and infrastructure changes before robots can function in existing warehouse environments. Fourth, and most critically, the order automation blind spot is frequently underestimated: even if 70 to 80% of SKUs are technically pickable, the share of complete orders that can be fully automated is often far lower, because a single unpickable item in a multi-item order triggers human intervention for the entire order. The thesis concludes that the evaluation of PaP technology must therefore be anchored at the order level rather than the SKU level.

RO3: *To investigate the anticipated future of the PaP technology in retail G2P warehouses.*

The future of PaP technology in retail G2P warehouses is promising but differentiated. Positioned through the Hype Cycle, the technology has moved beyond the innovation trigger stage: active deployments, late-stage venture funding, and planned adopter investments indicate a shift toward practical evaluation. However, the technology has not reached a plateau of productivity. SKU variability, gripping limitations, placement complexity, and integration requirements continue to constrain broader adoption, and the thesis positions PaP technology on the slope of enlightenment in favorable contexts, where early adopters are learning what works and under what conditions.

Future development depends primarily on advances in software and AI rather than in hardware. The robotic arm is already mature: the limiting factors are vision AI, adaptive grasp planning, zero-shot learning, and exception-handling logic. As these improve, the range of handleable products is expected to expand. In the near term, scaled deployment is most realistic in high-volume G2P

environments with suitable assortments, strong labor pressure, and existing automation infrastructure. In the medium to longer term, broader adoption is likely if downstream activities such as packing and bagging can also be automated and if AI-based manipulation becomes more generalizable across diverse retail assortments. Human roles will continue to shift toward system stewardship, requiring deliberate role design and change management rather than simply replacing pickers with robots.

6.2. Theoretical and Practical Contributions

This section presents the theoretical and practical contributions of the thesis, highlighting how the study advances academic understanding of PaP robotic arm adoption in retail G2P warehouses while also offering a framework to support managerial decision-making in practice.

6.2.1. Theoretical Contributions

This thesis contributes to the emerging literature on warehouse automation by developing a structured understanding of robotic PaP in G2P warehouse environments. Existing research has examined warehouse automation, order picking, smart warehousing, robotics, and HRI from different perspectives, but knowledge about robotic PaP adoption at G2P pick stations remains fragmented. This thesis addresses this gap by combining an integrative literature review with thirteen semi-structured interviews involving technology developers, an adopter, and academic experts. In doing so, the study brings together academic, practitioner, and empirical insights to explain how PaP technology is currently understood, evaluated, and applied in retail warehouse contexts. The thesis, therefore, contributes to the literature by positioning robotic picking arms not as a standalone technical solution, but as part of the broader transformation from G2P toward goods-to-robot (G2R) warehouse systems. G2R is a robotic picking method where goods are brought to the robot for processing (Huang, Chen and Pan, 2015).

A central theoretical contribution is the identification of the final automation gap in highly automated retail warehouses. The thesis shows that although G2P systems have automated storage, retrieval, and internal transport, the final item-level picking task often remains manual because it concentrates high levels of product variability, physical uncertainty, and contextual judgement. This contributes to theory by explaining why manual picking persists even in otherwise highly automated warehouse systems. Rather than treating manual picking as a remaining inefficiency that has simply not yet been automated, the thesis shows that it is one of the most complex and least standardized parts of the fulfilment process.

Another theoretical contribution is the development of the order automation blind spot. The thesis shows that robotic picking adoption cannot be evaluated only through SKU level, pickability, since a high percentage of technically pickable SKUs does not necessarily translate into a high percentage of fully automatable customer orders. A single unpickable item in a multi-item order may require human intervention for the whole order. This distinction contributes to the literature by shifting the evaluation of robotic picking from isolated item-level capability toward order-level

automation potential. This provides a more operationally realistic way of understanding the value and limitations of PaP technology in retail fulfilment.

The thesis also contributes theoretically by integrating multiple analytical perspectives into one adoption analysis. By applying the Diffusion of Innovations framework, the Technology-Organization-Environment (TOE) framework, Institutional Theory (INT), HRI roles (HRI roles), and the Hype Cycle, the study explains adoption as a multidimensional phenomenon shaped by perceived benefits, technical complexity, organizational readiness, external pressures, human role changes, and technology maturity. This moves the discussion beyond a purely technical interpretation of robotic picking and shows that adoption is not determined by robot performance alone. Instead, adoption depends on the interaction between the technology, the warehouse context, the organization, and the wider market environment.

Finally, the thesis contributes through the development of the PaP Adoption Fit Framework. The framework positions adoption potential according to two dimensions: Operational Automation Fit and Strategic Business Pressure. This contributes to theory by conceptualizing PaP adoption as a question of fit rather than as a simple question of whether the technology is mature. The framework explains why the same robotic system may be valuable in one warehouse but premature in another. It also provides a basis for future research on robotic picking adoption by linking technical feasibility, order-flow suitability, organizational readiness, and business pressure into one structured model.

6.2.2. Practical Contributions

From a practical perspective, this thesis provides guidance for retailers, warehouse managers, automation providers, and logistics decision-makers who are evaluating PaP technology in G2P warehouse environments. The findings show that adoption decisions should not be based only on vendor demonstrations, picking speed, success rate, or SKU-level pickability. Instead, managers need to evaluate whether the technology fits the actual warehouse context, including the product assortment, order profile, item presentation, integration requirements, operating hours, labor situation, and downstream packing or bagging processes. This helps companies avoid overly optimistic assumptions about robotic picking and supports more realistic automation decisions.

The PaP Adoption Fit Framework is the main practical contribution of the thesis. The framework can support managers in deciding whether to scale, pilot, redesign, or postpone adoption. When both operational automation fit and strategic business pressure are high, companies may move toward scaling and integration. When operational fit is high, but business pressure is low, pilots may be useful mainly for learning. When business pressure is high but operational fit is low, companies should redesign the use case before scaling. When both dimensions are low, companies should monitor the technology and prepare for future opportunities. In this way, the framework provides a practical decision-support tool for evaluating whether PaP robotic arms are suitable for a specific warehouse.

The thesis also offers practical value by highlighting the importance of evaluating automation at the order level rather than only at the SKU level. For practitioners, this means that the business case should consider how many complete orders or order flows can be automated without human intervention, not only how many individual products the robot can theoretically pick. This insight is important for pilot design, Return On Investment (ROI) calculations, and implementation planning. It encourages companies to test robotic systems with realistic order data, mixed product baskets, and actual warehouse conditions rather than with selected robot-friendly SKUs.

Another practical contribution concerns human work design. The thesis shows that PaP robots do not remove the need for human workers; rather, they change the role of workers from direct manual pickers toward operators, supervisors, mechanics, and exception handlers. This means that companies should prepare employees for new roles as system stewards, where they monitor robotic systems, respond to errors, perform basic technical upkeep, and support exception handling. Practically, this requires training, clear responsibility allocation, user-friendly interfaces, change management, and early involvement of supervisors and shop-floor workers. The thesis also provides practical guidance for automation providers. The findings suggest that providers should not focus only on improving robot hardware or maximum pick rate. Instead, they should develop solutions that are easier to integrate with warehouse management systems, warehouse control systems, conveyors, G2P systems, and packing processes. Providers should also communicate more clearly about realistic use cases, intervention frequency, SKU limitations, and order-level automation potential. This can help reduce mismatched expectations between vendors and adopters and support more successful implementation projects.

Altogether, the practical contribution of this thesis is that it helps decision-makers understand that PaP robotic arms are promising but context-specific. The technology is most suitable in high-volume retail G2P warehouses with suitable assortments, strong labor pressure, long operating hours, existing automation infrastructure, and sufficient organizational readiness. In less favorable contexts, companies may benefit more from pilots, process redesign, or continued monitoring rather than immediate large-scale implementation. Thus, the thesis supports a more selective, evidence-based, and context-sensitive approach to robotic picking adoption.

6.3.Delimitations and Future Research

This section reflects on the boundaries of this study and identifies directions for future research that build on its findings.

6.3.1. Delimitations

Several delimitations were established at the outset of this study and are reflected throughout the research process. First, the scope was deliberately confined to piece-picking robots within retail G2P warehouse environments. Other PaP technologies, such as cobots, SCARA robots, articulated robots, and mobile robots, were excluded from the analysis. While these technologies share certain characteristics with piece-picking systems, their operational contexts and adoption dynamics differ

considerably, and including them would have risked broadening the scope beyond what was analytically feasible. The conclusions of this study should therefore not be generalized to the wider landscape of PaP technologies.

Second, the study primarily draws on perspectives from European retail and North American warehousing contexts. Given that labor market conditions, regulatory environments, and levels of technological maturity vary across regions, the findings may have limited transferability to other geographical settings, such as Asia, where adoption and HRI dynamics may differ substantially.

Third, as piece-picking technology is currently subject to rapid development driven by advances in physical AI, machine vision, and grasping technologies, the conclusions of this study reflect a specific point in time. The pace of innovation in this field means that some findings may be subject to change as the technology matures and new capabilities emerge.

Fourth, a delimitation concerns the use of the Gartner Hype Cycle as an analytical lens. The model is a commercially developed framework rather than an empirically validated scientific instrument, and the positioning of PaP technology within its stages relies on a subjective interpretation of interview data rather than a replicable methodology. Future research could therefore treat the hype cycle positioning presented in this thesis as an indicative illustration rather than a definitive empirical finding. Last but not least, the limited number of adopters that were interviewed, due to low response rates. Two adopters of this technology were interviewed, where one is currently piloting and plans to develop it on a large-scale next year, and the other is fully operational. More adopters could have made the findings more rigorous and generalizable. Generating a better generalizability of the PaP Adoption Fit Framework.

6.3.2. Future Research

Several directions for future research emerge from this study, both in terms of content and methodology. From a content perspective, this study identified HRI and adoption as central themes in the current state of PaP technology. Future research could extend this by examining the role of humans in future warehouse environments as automation capabilities expand, including how job roles and skill requirements evolve alongside increasing robot autonomy. Related to this, the prospect of full warehouse automation warrants dedicated investigation, particularly in terms of its operational feasibility and organizational implications. The bagging problem, which remains one of the key technical barriers to broader adoption, also presents a focused and practically relevant avenue for future research. Additionally, the challenges that increased automation poses for the supply chain more broadly, including European Union regulatory requirements around fill rates and product handling, represent an underexplored area with significant practical relevance. In addition, the societal impact could be studied from this technology, with e.g., the focus on what this technology means for national job markets and perception of work in the long run.

From a methodological perspective, since this study identified and conceptualized the phenomenon through an integrative literature review and an interview study, future research

should empirically test and validate these findings across a broader population. A quantitative survey study would be particularly well-suited for this purpose, enabling researchers to validate and quantify the factors influencing adoption decisions among both adopters and non-adopters, measure attitudes toward HRI at scale across warehouse workers and managers, and test relationships between variables such as organizational size, industry segment, or prior automation experience and adoption outcomes. Furthermore, longitudinal case studies would allow researchers to track how adoption barriers and enablers evolve as the technology and physical AI capabilities mature over time.

Finally, the PaP Adoption Fit Framework developed in this thesis could serve as a foundation for a peer-reviewed journal article, contributing to the academic discourse on technology adoption in warehouse automation and transferring the created framework to practitioners in the industry. In terms of practical utilization, the framework could be operationalized as a structured decision-support tool, enabling warehouse managers and supply chain directors to systematically assess their organizational readiness, technological fit, and environmental conditions prior to committing to a PaP investment. Beyond its current scope, the framework could also be extended geographically. The present study was conducted exclusively within a Northern/Western European retail warehousing context, which limits its direct generalizability. A cross-national study applying the framework across northern and non-European markets, e.g., including adopters from North America or Asia, where labor markets differ. Moreover, comparing high-wage European environments with lower-wage contexts in Eastern Europe could also be insightful, as the relative advantage dimension of the framework is heavily shaped by labor cost differentials, meaning the adoption logic and threshold for investment justification may shift considerably across geographies. Such a comparative study would also allow the institutional theory component to be examined more rigorously, given that coercive and mimetic pressures vary meaningfully between different regulatory environments and competitive landscapes. In this future avenue, it is relevant to investigate a significant number of extra adopters, from different company sizes, industries, and geographical locations.

The framework could be extended beyond the picking stage to encompass post-picking processes, most notably bagging, labeling, and order consolidation. These downstream steps represent a logical next frontier for robotic automation in retail fulfillment and remain largely underexplored in the academic literature. Evaluating whether the same adoption drivers and barriers identified for PaP technologies apply to bagging automation, or whether new dimensions emerge, such as product fragility handling, packaging variability, or integration complexity with sorting systems, would constitute a meaningful academic contribution. Given that bagging is frequently the operational bottleneck directly following the picking stage in e-commerce fulfillment environments, and that robotic solutions for this process are still positioned at an earlier stage of the hype cycle than picking technologies, extending the framework in this direction would be both theoretically novel and practically relevant for retailers planning end-to-end warehouse automation roadmaps.

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Appendix A: Semi-Structured Interview Guide

A.1 Introduction and Consent

We are Guyon and Akhil, master's students in Logistics and Supply Chain Management at Lund University. We are writing our thesis on Pick-and-Place technology, referred to in this study as PaP technology, meaning robotic picking arms used in retail goods-to-person warehouses with high SKU variety.

The purpose of this study is to understand the current and future benefits, challenges, downsides, and context of use of PaP technology. The research is based on an integrative literature review and interview study. We are interviewing experts from three main groups: companies that develop PaP technology, companies that adopt or use the technology, and academics with expertise in warehousing, robotics, or automation.

The interview will begin with questions about your background and experience. We will then ask more detailed questions about PaP technology in a retail warehousing context. Your answers will be anonymized in the final thesis report.

Before we begin, do you give consent for us to record the interview? The recording will only be used privately to ensure that no relevant information is missed during the analysis.

A.2 Common Background Questions

These questions were asked to all interviewees, with minor adaptations depending on the respondent's role.

- What is your educational background?
- What is your current position?
- How many years of professional or research experience do you have?
- How long have you worked in your current company, organization, or role?
- What is your experience within warehousing, logistics, or supply chain operations?
- What is your experience with Pick-and-Place technology or robotic picking systems?
- In which country or region do you mainly operate or conduct your work?

A.3 Core Questions on Pick-and-Place Technology

The following questions formed the common basis of the interviews across all respondent groups.

Benefits and Value Potential

- What are the main current benefits of PaP technology?
- What are the potential future benefits of this technology?
- Compared with manual picking or other warehouse automation solutions, where do you see the strongest value potential?
- What capabilities does the technology currently offer?

- What macro trends could support the adoption of this technology, such as artificial intelligence, labor shortages, or developments in warehouse automation?

Challenges, Downsides, and Risks

- What are the main current downsides of PaP technology?
- What are the main risks of adopting or implementing this technology?
- What key lessons have been learned from implementation or testing?
- To what extent is high SKU variety still a major obstacle?
- Is space a major constraint when implementing PaP systems?
- How important are safety standards and regulatory requirements in shaping adoption?
- Are there regulatory or safety standards that constrain or enable deployment in warehouse environments?
- What organizational or managerial barriers seem most important for adoption?

Integration and Operational Compatibility

- How compatible is PaP technology with existing warehouse systems?
- Does the technology require core automation from a specific supplier, such as AutoStore or another goods-to-person system?
- How difficult is it to integrate the technology with current warehouse operations?
- Can operations continue while the technology is being adopted or integrated?
- How compatible is PaP technology with existing operational workflows, order profiles, and SKU characteristics?
- Are there specific product profiles, order profiles, or warehouse characteristics that make adoption more or less feasible?

Context of Adoption

- Why might a company choose PaP technology over other warehouse automation solutions?
- What factors are important in the decision-making process?
- Who usually initiates the adoption of this technology: management, operations teams, consultants, technology providers, or others?
- What is the typical duration of a project from initial evaluation to implementation?
- Is there usually an opportunity to pilot or test the technology before full adoption?
- How do workers interact with the technology?
- Do workers share the same workspace, working time, or operational goals with the technology?
- What are the views of internal stakeholders, such as warehouse workers, management, and technical teams?

Scalability and Future Development

- Is the technology currently scalable? If yes, what enables scaling? If not, what prevents it?
- How mature is the technology today? Is it still in its infancy, or is it moving towards maturity?
- How much hype currently surrounds PaP technology?
- How do you expect the technology to develop in the future?
- Do you believe PaP systems are likely to replace humans, complement humans, or remain limited to specific niche use cases?
- Do you believe PaP technology could become a major solution for future order picking?

A.4 Role-Specific Follow-Up Questions

Questions for Adopters

These questions were directed specifically at companies that had adopted, tested, or considered using PaP technology.

Strategic Motivation

- Why did your company choose this technology over other warehouse automation alternatives?
- Was the decision influenced by labor uncertainty, industry best practices, consultants, competitors, or internal strategic goals?
- Did your company aim to be among the first in the market to use this technology?
- What makes your company stand out from competitors in relation to warehouse automation?

Implementation Experience

- What was the duration of the project from initial decision to integration or adoption?
- Did you have the opportunity to pilot or test the technology before full implementation?
- What were the most important insights or lessons learned during implementation?
- Were there any unexpected challenges during the adoption process?

Internal Organization and Workforce

- How did internal stakeholders view the technology?
- Were there differences between the views of management and the labor force?
- What change management processes were implemented to support workforce acceptance?
- Were these change management processes planned proactively, or developed reactively in response to resistance?

Questions for Developers

These questions were directed specifically at companies that develop, supply, or integrate PaP technology.

Technology Offering and Market Position

- What are the main capabilities of your PaP system?
- What makes your solution stand out from competitors?
- What are the most common use areas for your technology?
- What types of clients are most interested in adopting this technology?

Client Adoption and Implementation

- Why do your clients typically choose PaP technology over other warehouse automation solutions?
- Do clients want to be first movers in the market, or are they more cautious?
- How compatible is the technology with clients' current systems?
- Does your solution require specific core automation, such as AutoStore or another goods-to-person system?
- How difficult is integration from the client's perspective?
- Can clients continue their operations during adoption and integration?

Client Organization and Workforce

- How do workers at client sites usually interact with the technology?
- What are the typical views of client stakeholders, such as labor, management, and operations teams?
- What change management processes do clients usually implement?
- Are these processes normally planned in advance, or developed in response to resistance?

Piloting and Scaling

- Do customers have the opportunity to pilot or test the technology before adoption?
- How do clients usually approach scaling the technology?
- What are the main barriers to scaling from a developer perspective?

Questions for Academics

These questions were directed specifically at academics and researchers with expertise in warehousing, robotics, logistics, or automation.

Research Perspective

- How long have you researched robotics, warehouse automation, or related technologies?
- From a research perspective, what are the main current and potential benefits of PaP technology?
- What does the academic literature suggest about the maturity of PaP technology?
- How significant is the role of high SKU variety in limiting adoption?

Broader Adoption Barriers

- What organizational or managerial barriers are most important for adoption?
- How do regulations and safety requirements influence automation in picking?
- Are there specific warehouse, product, or order characteristics that make PaP adoption more feasible?
- How do you see the relationship between PaP technology and other warehouse automation solutions?

Future Outlook

- How do you expect PaP technology to develop in the coming years?
- Do you believe PaP systems are more likely to replace human workers, complement them, or remain limited to niche applications?
- Do you believe this technology could become a central solution for future order picking?
- How should companies evaluate whether PaP technology is suitable for their operations?

A.5 Closing Question

At the end of each interview, the following open question was asked:

> Is there anything important about Pick-and-Place technology in retail goods-to-person warehouses that we have not asked about, but that you think should be considered in this thesis?