

# From Hurdles to Highways: Overcoming Barriers to Robotics Adoption in Supply Chains

by

Bartholemew Hegarty

B.S. Petroleum Engineering, New Mexico Tech, 2009

Submitted to the System Design & Management Program  
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Authored by: Bartholemew Hegarty  
MIT System Design and Management  
August 09, 2024

Certified by: Dr. Chris Caplice  
Senior Research Scientist, Thesis Supervisor

Accepted by: Joan S Rubin  
Executive Director  
System Design Management Program



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## ABSTRACT

Macroeconomic events are putting unprecedented pressure on the warehouse industry. Among these are labor shortages, increased operating costs, and the desire for greater customization and higher throughput from these facilities. Focused on these challenges and strategic issues for warehouse applications, this thesis investigates the obstacles to implementing robotic automation in supply chains. The thesis explores this environment and the lens of using three common integration methods. These are the traditional purchase, lease, and emerging robotic-as-a-service (RaaS) model. With these methods in scope, the study incorporates a multicriteria decision-making framework (MCDM) that is built based on an analytical hierarchy process (AHP) and combined with the technique for order of preference by similarity to the ideal solution (TOPSIS). From this framework, the research identifies key decision criteria and their impact on selecting the most suitable integration strategy for automation.

Through a literature review, the study identified the essential criteria for the project design decision. These include infrastructure requirements, system capabilities, usability, provider reputation, project duration, and the total cost of ownership. We then gained insight from industry professionals familiar with automation integration using a focused field study. Furthermore, we underlined practical issues and general opinions on the criteria and how well they correspond to their integration plans. The results highlight notable trade-offs in the decision criteria, emphasizing the need for a more tailored strategy to make automation adoption more efficient.

This thesis provides an effective decision support system to guide the choice of appropriate automation solutions. It helps clarify how decision makers give the most importance to different criteria when implementing robotic automation. The research findings offer helpful details for practitioners who are navigating the challenging warehouse automation environment. This, therefore, encourages better informed and more efficient decision-making procedures.

Thesis supervisor: Dr. Chris Caplice

Title: Senior Research Scientist



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# Chapter 1

## Introduction

### 1.1 Research Motivation

In today's warehouse environment, several macroeconomic factors are putting unusual pressure on the industry. An example is the reporting on the Consumer Price Index (CPI) in the United States. Since December 2020, the report has presented some of the highest yearly inflation rates in previous decades. We can see a consistent rise in Core Services inflation in Bloomberg Financial's Figure 1.1, which reflects CPI data through April 2024. [1] This area directly impacts warehouses and operations because it is associated with labor costs, facility overhead, and maintenance services. The report acknowledges that these economic impacts may likely remain elevated in the foreseeable future. In addition, pressures are evident in the demand for higher throughput efficiency for today's warehousing facilities to stay competitive. This requires rapid scalability in warehouse operations, which can adapt to seasonal and trending demands.[2] Furthermore, we see the pressure on warehouse capabilities to be highly adaptable to accommodate more customization and shorten delivery-time guarantees to the customer in each processed order. This flies in the face of a growing risk of disruption in these operations, which results from observed labor shortages compounded by trends toward unprecedented volumes of sales processed by a given facility. [3] This presents a unique challenge for the warehousing sector, and strategic planning and cost management are of certain importance. Thus, such a focus incentivizes the warehousing industry to find novel ways to account for this in their budgeting and pricing strategies. This barrage of challenges is handled by implementing state-of-the-art robotic automation. However, technology alone is no silver bullet, and implementing this automation solution has become one of the most challenging design decisions these facilities must first overcome. [4]

The rise of the "Robot as a Service" business model comes from companies seeking alternatives to adopt the rapid advancements in robotic innovation. This uniquely fitted platform has been marked in the literature as a potential paradigm shift by offering a new approach to adopting robotic technologies. [5] This focus has explicitly addressed the traditional barriers and concerns, such as the high overhead of a leased or purchased system, that have hindered their implementation in the past. Ultimately, this idea shifts the focus to an "as-a-service" model for integrating robotics into operations. This model helps overcome these initial problems by encouraging the utilization of scalable resources, giving companies interested in automation access to the latest technologies, and eliminating the uncertainties of the common total cost of ownership. [6]

The recognized benefits of automation are now combined with more versatile methods

## U.S. CPI by components

YoY percentage change



Source: Bloomberg Financial L.P. Data as of April 10, 2024.

Figure 1.1: Year-over-year percentage change in various U.S. Consumer Price Index (CPI) components from February 2020 to February 2024. The components include core services, core goods, food, and energy. Figure adjusted from J. Veit.[1]

to implement them. This gives system operators an array of available solutions to help them address the challenges they face in their environment. The observed results in the successful applications have ultimately shown how warehouses can keep up with the growing production levels and remove the potential risk of overreliance on human labor. [7] This transition has even been shown to have the added benefit of freeing human labor for more challenging and worthwhile tasks, while reducing the likelihood of injury and the resulting costs and improving worker safety by performing dangerous tasks. [2] Today, an expansive landscape of supporting logistics automation technologies is available, allowing operators to address their increasingly complex operational scene. Technology integration typically involves an intricate interoperable layering of software, middleware, and hardware systems. [8]

As shown in Figure 1.2, these solutions also complement more advanced Warehouse Management Systems (WMS) and Warehouse Control Systems (WCS) that can incorporate the associated Internet of Things (IoT) device networks, further strengthening this backbone of the facility. Upon successful integration of these technologies, the literature expresses how these modern automation systems often help deliver improved overall efficiency across all core management systems. This is done by enabling the adaptability and response rate in the decision-making of operations to become more real-time. [9] This steady conversion is only expected to increase as external pressures further increase standards for the industry. This ultimately highlights how traditional operations will continue to feel additional stress due to the limitations of the manual processes they have in place.

Although we have these primed conditions for a move to automate and the means to do so, industries have faced challenges in successfully navigating this highly fragmented

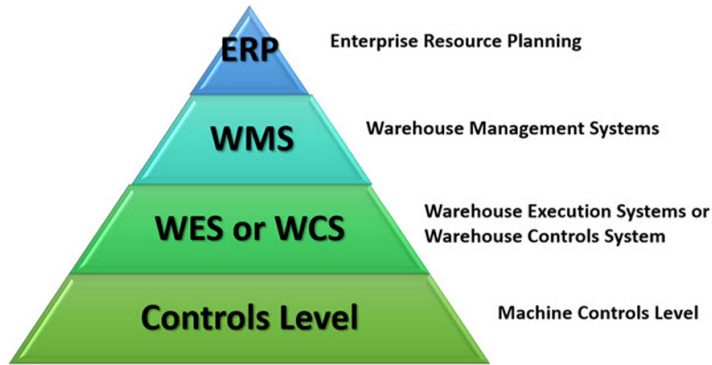


Figure 1.2: Some of the most common areas improved through automation to support a warehouse operation. Common software systems directly tied into automation systems are found in warehouse operation's WCS and Control levels. Figure adjusted from C. Marketing.[10].

field of service providers and the rapidly advancing rate of available technology. We also see from the reviewed case studies that these decisions' financial weight or project cost are relatively high when considering the best means to implement any given system. With the rapid pace of technology, many available solutions are considered novel and limited in their track record of delivering on expectations. [7] These systems also present common gaps in a company's internal organizational competency to operate more complex facility infrastructures. Variable risk is also associated with the safety implications of these automation systems, as robotics often share a common workspace with workers. These factors complicate the design decisions that companies must make when incorporating automation. Following a review of the available literature, we have found that the means to evaluate alternatives on how a warehouse operator should make this decision have been somewhat limited.[6]

From this review, we can identify the problem as being two-fold. The first problem relates to effectively understanding what level and form of automation is appropriate to meet the challenges in the macro-operating environment, and the other relates to the business capacity to evaluate the most suitable methods available to implement a desired automation system. So, even though it may be universally identified that an automated system would be unmatched in its flexibility compared to those reliant on human procedures, an organization still faces many other vital considerations when considering the implementation of robotic automation. This design environment is one of the primary motivations for this study. In this context, we explore these obstacles in the decision-making process and how they commonly dissuade operators from implementing robotic automation solutions in their operations. Establishing support for the core decision criteria will allow us to systematically identify the most viable implementation method. Finally, we will test these decision criteria through a field study and provide industry professionals' prevailing sentiment, considering their unique system requirements, functionality, and adaptation to risk sensitivity as decision makers. The study will produce findings that identify the importance placed on our established design decision criteria by respondents.

## 1.2 Research Objectives

This study hopes to provide a deeper understanding of the importance that decision makers assign to various criteria when evaluating the implementation of robotic automation in warehouse applications.

### Research Question:

*What are the prevailing decision criteria considered when adopting warehouse automation, and how do decision makers consider these criteria in their ranking as a preferred method of implementing a desired automation system?*

To address this question, this thesis will outline and review the decision-making attributes that significantly impact the desirability of any warehouse automation system and its ultimate value to the operator. The thesis will outline an objective framework from this foundation to complete this evaluation. This framework will help us understand the preferences of decision makers when asked to systematically evaluate their preferred warehouse automation project.

To establish this contribution within our proposed framework, the research will aim to validate it through a targeted field study. This study will rely on the responses collected from verified industry professionals with extensive warehousing experience, who will confirm the importance and application of the selected criteria. The purpose of the survey will be to take advantage of the practical experience of the respondents in integrating various warehouse automation solutions. This will allow us to infer how these decision makers value the selected criteria and how this aligns with their preferred integration mode. We will also conduct a sensitivity analysis of the weighted criteria to better understand which criteria and their importance are most likely to change an overall decision.

As with most survey data, we hypothesize that it will be important to understand how the demographics of the respondents in this study could potentially produce a set of unique decision-maker profiles. To prove this assumption, we focused on ensuring diversity in the profiles of the respondents. We targeted the survey release to improve participation in all focus categories, including distinctions in the industry experience of the respondents, the size of the company, and the role within the organization, among others. We felt that this differentiation in the respondents allowed for a richer data set and the ability to infer how these demographics influence the prioritization of decision criteria, specifically within warehouse automation. These generated profiles were also essential for independently highlighting these different segments' specific needs and preferences, allowing us to identify various tailored approaches in the decision framework to recommend automation solutions.

The verified framework will be one of the primary contributions of this thesis and will be available for practice. Our field study collection will also be a targeted contribution to this work. As with any good project, having a solid foundation is critical. The selected components of our research will enable us to identify the boundaries of our research question and subquestions while establishing the fundamentals around the selected multicriteria decision-making techniques (MCDM) we chose to implement. Upon completing our literature review and supporting field study, we provide supporting information to advance the decision-making process to adopt an automation environment within the warehouse industry.

### 1.3 Scope of the Study

This study will initially build a knowledge base that we will use to support an essential set of considerations associated with the adoption of robotic automation in warehouse operations. We mainly focus on developing an objective decision-support framework that enables decision-makers to systematically evaluate their automation projects. The main methods of implementation we will consider in this study are a traditional purchase option, a lease option, and finally, the more novel approach, a robot-as-a-service strategy. As cited in our paper, the MCDM techniques chosen were those that have a lot of support from related case studies and tactics. Our intention in this study will not be to build justification for their effectiveness further. These methods were found in our literature review, identified as the best aligned with our research objectives, and serve as the primary basis for our decision framework. This strategy will be based on collecting expert opinions and developing the empirical relationships associated with the practitioners involved in these decisions.

### 1.4 Significance of the Research

One significant task of this research was establishing how decision makers see trade-offs in adopting automation. We hope this study will help us establish quantifiable insight into how our field decision makers value these critical decision areas. In addition, this work has the potential to build an understanding of industry trends by summarizing feedback collected from verified practitioners. This work also has the potential to help support possible advancements in the development and validation of more tailored MCDM frameworks as a methodological tool that may extend to other contexts and industries. Finally, we hope this work will identify particular research gaps that could be valuable for future research and provide a foundation for future studies.

### 1.5 Thesis Approach and Organization

The rest of this thesis is structured as follows. Chapter 2 highlights the relevant fundamental information for the research. This segment focuses on improving the ability of the audience with various backgrounds to identify synergies and takeaways compared to their unique industry experiences. The literature review conducted in Chapter 3 provides evidence supporting our chosen design decision criteria that we include in our application of standard MCDM methods. This section helps us confirm the gaps in the reviewed research areas and the appropriateness of our target contributions. Chapter 4 presents and justifies our methodology, demonstrating in more detail how we designed to incorporate the collected data from the industry into the chosen method. We capture any potential limitations in the technique identified in the study, which then allows us to bring into focus the core results of the project, Chapter 5. This chapter details the main empirical findings of the study and helps determine the route to practical application within the industry. Here, we provide a breakdown of the survey information we collected and a summary of the key findings. It should be noted that this research was evaluated and received an exempt determination from the MIT Committee on the Use of Humans as Experimental Subjects (E-5998). Finally, Chapter 6 wraps up the work with a thorough discussion and presentation of the main findings of the research results. We address the

impacts of this research on the incorporated theory and practice. More importantly, we reflect on how the study answers our primary research objectives and motivations. Finally, we underline the main contributions of the work and point to the direction of future work.

# Chapter 2

## Background

### 2.1 Warehousing Fundamentals

Warehouses are a crucial point in any supply chain network. They serve the primary role of housing consumer products and balance the critical metrics of minimizing holding and transportation costs while reducing order fulfillment time. The warehouse does this by combining the many consumer products in one central place and adjusting to the pressures of order demand for its consumer product inventory.[11]

The origins of warehouses date back to ancient civilizations, when they played a critical role in the storage of strategic food or materials. These facilities acted as an initial means for these civilizations to begin trading on a larger scale. From the beginning of the Industrial Revolution in the 18th and 19th centuries, the role of the warehouse steadily advanced with the pace of technology. These adjustments in the warehouse were closely related to improvements in the manufacturing process during that time. The warehouse is strategically located as a key mechanism to improve the efficiency of bringing goods to market as commerce advances. As the surrounding technologies continue to advance, so will the capabilities of the storage strategies in warehouses.[12]

Our review of the fundamentals will introduce some basic principles surrounding warehouse operations. We provide a quick description of the operations we are evaluating. In addition, some concepts and practices critical to efficient and effective warehouse management will be presented to support later sections related to the primary decision attributes for a warehouse operation. The warehouse has several vital functions. This includes coordination of logistics, processing orders, and inventory control. To satisfy a given demand, these procedures must be coordinated with the upstream and downstream logistic elements, such as the manufacturing plant and storefronts. Furthermore, warehouses are highly integrated with the many platforms directly accessible to clients, further feeding the demand side of these procedures.[13] Here, we identify the main functions of a typical warehouse around the six crucial stages of the warehousing operation: receiving, putting away, storage, picking, packing, and shipping (see Figure 2.1). It will be noted that these six areas do have slight variations in scope and terminology depending on the source. However, from this, we can establish a clear boundary for the automation system that we will focus on when considering our decision-framework methods. Together, these stages are the focus of successful warehouse operations management. It is paramount that an operator optimize the handling, storage, and transport of goods to satisfy customer needs and effectively control inventory in the shortest achievable time.[14], [15]



Figure 2.1: Diagram of Warehousing Functions. Figure adjusted from SafetyCulture.[15]

There have been notable transformations within warehouse operations due to the adoption of robotic technologies. Any interruption or inefficiency mixed with a constantly changing global business environment shows why warehouse and factory transformation is important.[16] This momentum is aimed at huge cost-per-pick savings and reinforces the premise that warehouses' competitive edge comes from robotic automation.[17]

## 2.2 Trends in Robotic Automation

Robotic automation can be defined as an interdisciplinary field that merges engineering, computer science, and other disciplines into one. This discipline aims to develop, operate, and leverage machines synchronously so that they can perform tasks in various domains and environments. These tasks are typically found to be undesirable, hazardous to health, or even fundamentally challenging for human operators to complete. A common overarching mission for any robotic application is to improve human abilities, quality, and performance.[18] Robotics has undoubtedly seen some of the fastest technological advancements and incredible spread across various industries in recent years. [19]

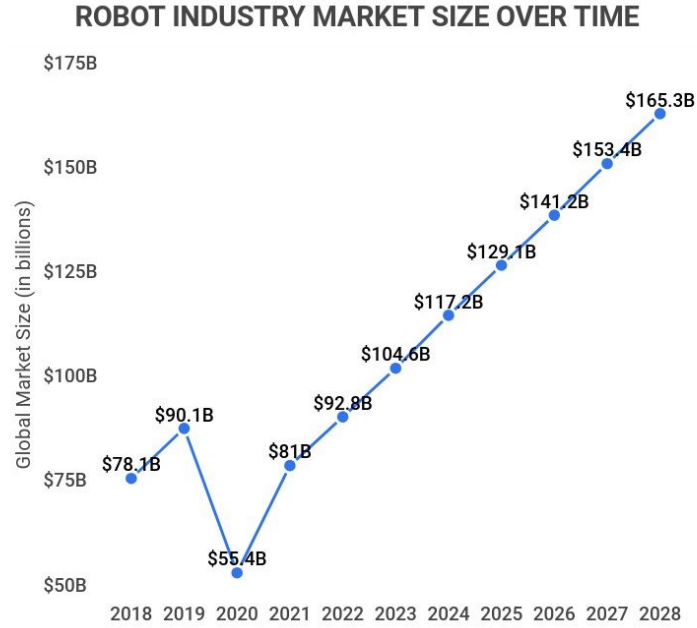


Figure 2.2: Robot Industry Market Size Over Time. Figure adjusted from Zippia.[20].

The reports we reviewed highlight the predominant trend of emerging companies specializing in service robotics.[6] <sup>1</sup>As shown in Figure 2.2, the reporting suggests the expected growth of the service robotics market, highlighting explicitly that this industry is expected to reach USD 165.3 billion by 2028, growing at a compound annual growth rate of 9.7% between 2021 and 2028. Together, these serve as illustrations of the sector’s resilient growth trend.[21]

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<sup>1</sup>A significant takeaway from this report was that a total of 29% of all newly registered companies in the United States were characterized by a primary focus on robotics during 2021.

## Annual industrial robots installed, 2021



Industrial robots are automated, reprogrammable machines that perform a variety of tasks in industrial settings.

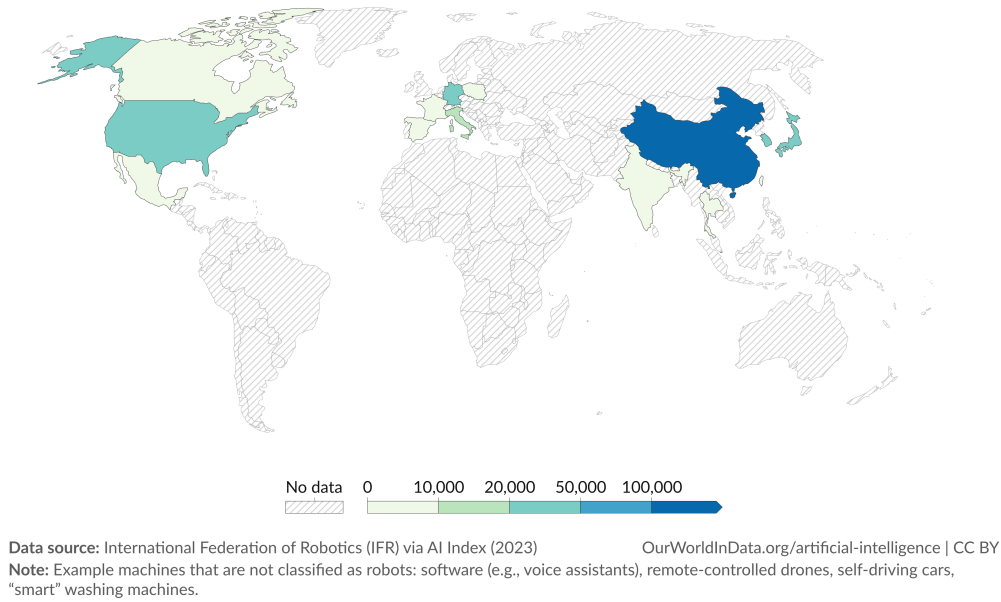


Figure 2.3: Global Hotspots for Industrial Robots Installed in 2021. Figure adjusted from M. Roser, H. Ritchie, and E. Ortiz-Ospina.[22]

## Industrial robots: Annual installations and total in operation, World



Industrial robots are automated, reprogrammable machines that perform a variety of tasks in industrial settings.

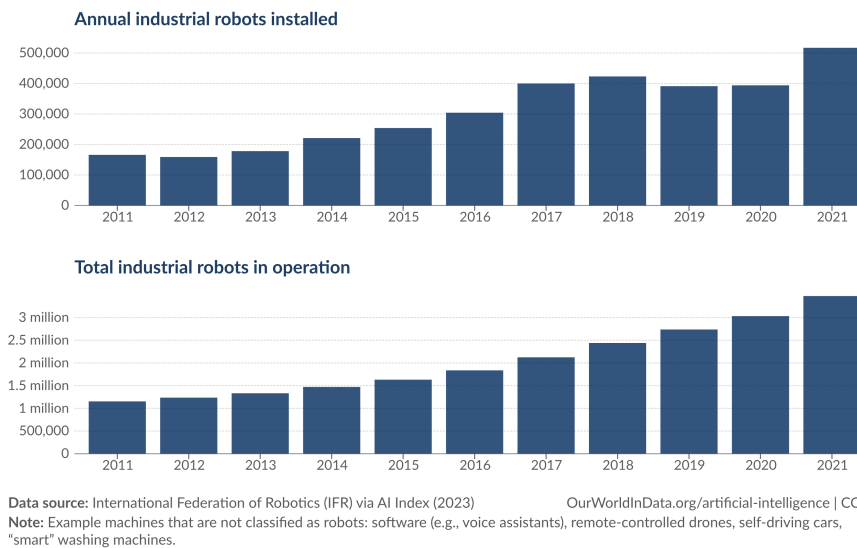


Figure 2.4: Annual Installs and Total Installations. Figure adjusted from M. Roser, H. Ritchie, and E. Ortiz-Ospina.[23]

The industrial service robotics sector is at the forefront of this increase in adoption.<sup>2</sup>

<sup>2</sup>As the Asian-Pacific markets continue to see high demand for their manufacturing industries, this has accelerated the investment in their adoption of robotic installations. These trends are shared in strong growth rates that are observable in many sectors in Europe and the Americas as well. [21]

With an ever-growing number of new use cases and applications emerging due to a surge of innovation, we see this as the primary source of the sector's prominence.<sup>3</sup>

As technology advances, we see a noticeable and repeatable phasing in adopting cutting-edge items from early adopters to the early majority in the market. In his widely read book *Crossing the Chasm: Marketing and Selling High-Tech Products to Mainstream Customers*, Geoffrey A. Moore delves into this idea and offers a valuable structure to observe technology adoption in contemporary industries [25]. Several segments are often recognized when thinking about the consumers of technology as it advances through the adoption lifecycle:

**Innovators:** The first group to embrace new technology is called the innovators. They'll try new things and take chances.

**Early Adopters:** This group is usually prepared to accept new technology early to get a competitive edge, even with its faults. This often comes from their vision in what they see as its advantages.

**Early Majority:** Only once there is proof that a technology is recognized and the advantages are measurable does this group also embrace it.

**Late Majority:** Only once the technology is well-tested and considered the norm does this conservative group embrace it.

**Laggards:** These are the last group to accept new technologies if they even do.

With this breakdown in mind, we identify how the trends in the rate of growth in the market may suggest that we are approaching a transition from the *early adopter* to the *early majority* in the adoption phase for incorporating automation more widely. We can conclude this by understanding how the observed advantages are becoming measurable and applicable. The broadening application in service robotics will likely create a self-contained environment that brings further opportunities for innovation and collaboration between the stakeholders involved. This environment would ultimately lead to a strengthening loop in the demand for advancement in the technological adaptation and capabilities of robotic systems by robot manufacturers, software developers, service providers, and end users.[26]

Apart from the apparent advantages to the business previously discussed, with this shift in the adoption curve, it is now becoming even more essential to establish shared understandings and frameworks, known as ontologies, in robotic automation. In this context, ontology formally represents knowledge as a collection of ideas within a domain and the connections among them. From these guidelines, we can improve our ability to implement robotic systems that can function successfully in their application and blend in with existing systems and procedures. The "as-a-service" implementation techniques, which we will detail in our literature review, directly support this necessary shift in market compatibility.[27] Continued work to cement these frameworks is essential to further improve the ability to increase adoption. Our research further supports this trend and helps establish an overarching ontological framework for robotic implementation. We hope this work will be supportive by demonstrating greater consistency in the adoption assessment process through a structured MCDM decision-criterion approach.

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<sup>3</sup>The report states (as shown in Figure 2.4) that in 2021 the sales volume was about USD 27 billion. An article by Mordo Intelligence estimating the worth of USD 60.16 billion in 2024 complemented this research. [24]

## 2.3 Key Warehouse Automation Technologies

Warehouse technology is typically divided into two core groups: the equipment that helps move goods and the equipment that improves the handling of those goods. From incorporating more automation into the warehouse to retrofitting existing facility hardware with the necessary hardware and software to make ordinary warehouse equipment autonomous, operators continue to look for the advantages of automated systems. Still, they are constantly pressured to incorporate them at a reduced cost.

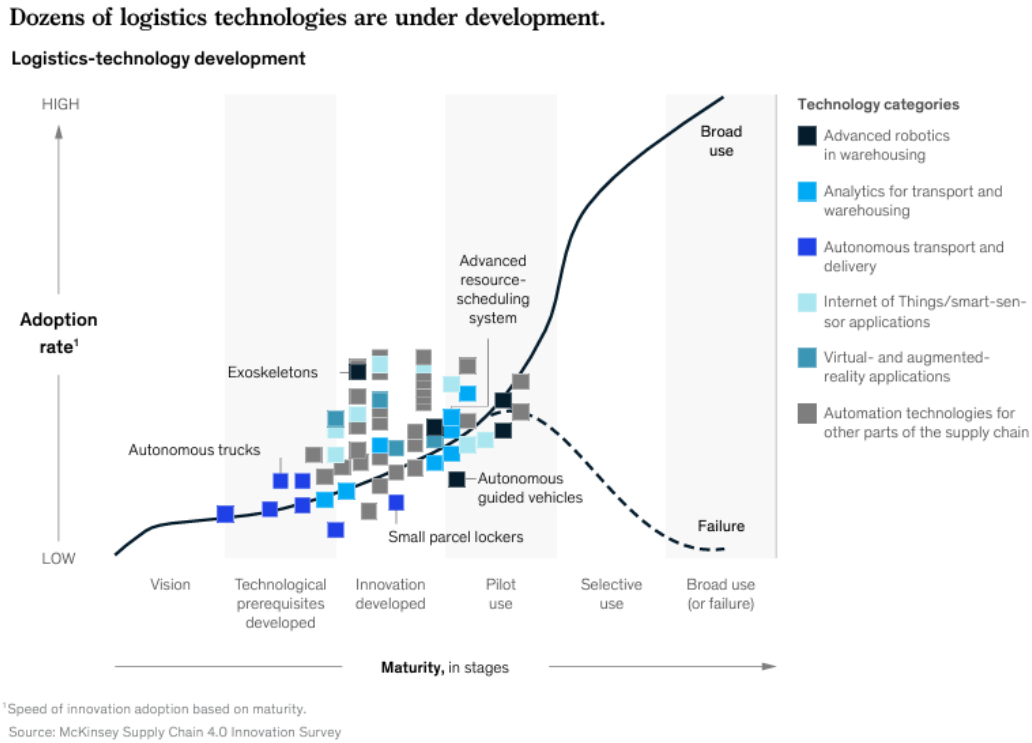


Figure 2.5: Some identified current trends in technology, directly sourced from McKinsey & Company. Figure adjusted from A. Dekhne et al.[28]

The latest trends in cutting-edge technologies continue to challenge what is possible for automation. We find examples of sophisticated conveyors that can move goods in any direction. These large racks of advanced automated storage/retrieval systems (AS/RS) hold goods and utilize robotic shuttles on rails attached to the structure to move in three dimensions. This technology has even progressed to the point where it can operate machinery that picks, sorts, and palletizes things automatically, some of the most challenging jobs within the warehouse historically. In even more sophisticated examples, we see the systems going to the goods, picking them up, and moving them all simultaneously. These advances are impressive and, in another trending area, we see applications for parcel operations. Here, the demand for effective sorting has grown in importance due to the retail e-commerce boom. What is most impressive in these applications is how sophisticated conveyor systems, equipped with the latest sensors, can read bar codes on any side of a package and decide what needs to be done. We also find information on autonomous palletizers that use robotic arms and sophisticated analytics that allow equipment to strategically place inventory through the warehouse. These examples capture the diverse and abundant range within the latest development and adoption of technology.[28]

<b>Technology</b>	<b>Description</b>	<b>Source</b>
Automated Storage and Retrieval Systems (AS/RS)	Automates item handling and utilizes vertical space, reducing labor needs.	[29], [30]
Automated Guided Vehicles (AGVs)	Uses advanced sensors for material handling, enhancing warehouse operations.	[29]
Autonomous Mobile Robots (AMRs)	Navigates warehouses with AI, performing tasks like picking and sorting.	[30]
Picking Methods in Automation	Includes various methods like batch and zone picking, integrated with automation tech for efficiency.	[31], [32]
Automated Conveyor & Sorting Systems	Enhances product handling with robotics and sensors, improving sorting and transportation.	[33]
Palletizers and Depalletizers	Automates stacking and unstacking of goods using robotics and vision systems.	[34]

Table 2.1: Key Warehouse Automation Technologies

A McKinsey & Company article, titled "Automation in logistics: Big opportunist, bigger uncertainty," shows that over 50 technologies that could further automate some aspects of the supply chain, including many in logistics (shown in Figure 2.5). Although most systems do not see everyday use, they are much more developed in technological readiness than figments of the imagination and will continue to share the automation space in warehousing in the future. Yet, with all this innovation, they question what technology will take off to provide the highest return on investment. This reaffirms the concerns that most decision makers have when determining a viable application for their operation. Novelty in technology comes with considerable uncertainty in both the reliability of the equipment to meet expectations and the service provider to maintain business continuity in support of that novel technology.

# Chapter 3

## Literature Review

### 3.1 Introduction

This literature review is based on our primary research question and the construction of the field study we conducted. We identify the predominant decision criteria for implementing robotic automation in a physical facility. The review identifies evidence to support the chosen criteria and describes why they are likely the highest value indicators for decision makers evaluating automation solutions. To further establish a boundary for our review and this study, we compare only the three typical implementation methods: a traditional capital purchase program, a self-operated equipment leasing agreement, and a Robot-as-a-Service (RaaS) implementation alternative.

Here, we assume that support shows the usefulness of adopting it in an operation of interest. We note that in real-world practice, there is an almost limitless set of unique considerations within any specific warehousing operation.[35] Therefore, identifying a universal set of criteria and methodology that would produce an approach to considering proposals more efficiently is valuable.

We expect that upon applying these contributions included in this work, future work can be done to further improve the provided framework to enable it to cover a broader range of use cases by evaluating and supporting more dynamic automation proposals. If successful, this work should influence the ability of a firm to assess the most efficient mode of system integration against the objective value of their operational needs when pursuing automation.

### 3.2 Support for Typical Design Decision Criteria

To ensure that we were building on the work of others to make a meaningful contribution, we first reviewed existing resources on the design criteria for automation systems. This provided a foundation for our recommended decision framework and helped identify standard decision criteria that apply broadly across warehouse operations.

Our research shows that decision criteria are commonly used to build the core requirements of a system. Oztaysi et al. [36] neatly fundamental criteria (as shown in Table 3.1) for the typical design decisions needed to evaluate a storage software system. Although this reference does not directly review the decision criteria for a robotic automation system, it still effectively compares complementary areas of consideration to automate a warehouse.

<b>Criteria</b>	<b>Description</b>
Required Infrastructure (REC)	Integration level with existing technology infrastructure.
Capabilities (CAP)	Range of functions provided, including built-in, optional, and custom applications.
Usability (USB)	Ease of use for end-users, with user-friendly interfaces and functionalities.
Customer Service (CS)	Availability and quality of technical support and training post-implementation.
Provider Reputation (PR)	Reputation, experience, and capabilities of the vendor.
Project Duration (DUR)	Time from project start to completion, including installation, training, and testing.
Budget (BUD)	Total cost of ownership, including software, hardware, implementation, and support costs.

Table 3.1: Warehousing Design Decision Criteria [36]

One of the first requirements to consider in a warehouse system is the characteristics of the goods being handled, such as temperature requirements, size, weight, and/or the typology of the unit load. It is also essential to consider the characteristics of the building, including variables such as height, flooring, and form of the warehouse building, which will directly affect the viability and effectiveness of any automation solution. Another essential consideration is how well an automation solution can interact with current hardware and software. This criterion considers the connection between automation technology and current systems. Automating warehouses for brown or greenfield operations is essential, where automation can be added as a new and independent process or implemented to enhance existing methods. These requirements can be associated with the infrastructure required for an automated solution. Poor fielding in these requirements can lead to limited integration or decreased reliability on the site. Oztaysi et al. identify these considerations in a slightly different context but ultimately determine the need to consider the infrastructure required for a system as a critical distinction.

Oztaysi et al. support the inclusion of criteria around the primary objectives of the operation, with which we can determine the necessary balance between the capability and the usability of the selected solution. Considering these two criteria, various combinations of the types of automation equipment and equipment providers can be considered. Within the capability and usability requirements of the system, several sub-components are needed to differentiate the decision to support one solution over the next, such as operational metrics or measurements of the system's utility.

A less considered area of the identified decision criteria was the service provider's reputation and the ability to support the post-implementation customer service aspects of the system. This included the general importance that decision makers place on having the ability to receive assistance with the installed system and the understanding that the provider had a recognized record. This can become a slightly challenging obstacle to overcome within the robotic automation industry due to the highly fragmented and rapidly changing landscape for providers of these solutions. Another question is where the decision makers are on the adoption curve. With the high degree of variability between

companies, this is a very fluid area in the set of criteria for the design decisions of a system.

Last but not least, any decision criteria must include project duration and cost considerations, which are critical to a project's ability to deliver its project management goals. This is bound to the impacts of these areas on the bottom line and overall productivity. For project duration, the benefits of shorter timelines are reasonably intuitive. The duration of the project is directly related to an associated downtime for the impacted facilities, and the sooner the project can be completed, the sooner a facility can realize the benefits of the implementation. However, it is also important to note the pressure to keep up with the competitive edge in adopting new technologies. Successfully managing project costs can reduce the total cost of ownership (TCO) and improve the realized return on investment (ROI). These two criteria are in balance, and decision makers will often make calls to take on a higher value in one category to improve the delivery on the other.

This review emphasizes the trade-offs and common considerations that decision makers make when implementing automation. The reviewed literature primarily provided various prescribed MCDM approaches to support these considerations in the decision criteria. In our methodology section, Chapter 4, we will further establish how we implemented our specific MCDM approach for this study. This approach and, more importantly, the decision criteria identified from our review of the literature here will directly support our efforts to develop a decision framework for robotic automation in the warehouse.

## Reference Architecture for a Warehouse Automation System

A reference architecture is commonly used to build standardization across projects and ensure system design consistency. Here, we use it to support our understanding of the required infrastructure of a warehouse automation system and the expectations of a system relative to a standard warehouse automation framework. Our intention in reviewing an appropriate reference architecture is to use it to confirm the decision criteria discussed above that we look to include in the MCDM analysis. The system architecture chosen for our review here was the product of a Smart Factory (SF) application. Here, we cite Diaz et al., presenting an architecture designed after an extensive examination of the successful implementations of automation architecture within existing warehouse frameworks. From the details of this system, Diaz et al. confirmed the functional assessments of this architecture and its practical application for steering automation design. Their work supported this architecture and ensured their review was complete by examining how it satisfied the requirements for a typical SF design. The ideal composition for each component was only possible through extensive functional testing and a review of case studies. As seen in Figure 3.1, the final product is the complete supported view of these critical elements, their necessary interdependence, and any prerequisites for application.[37]

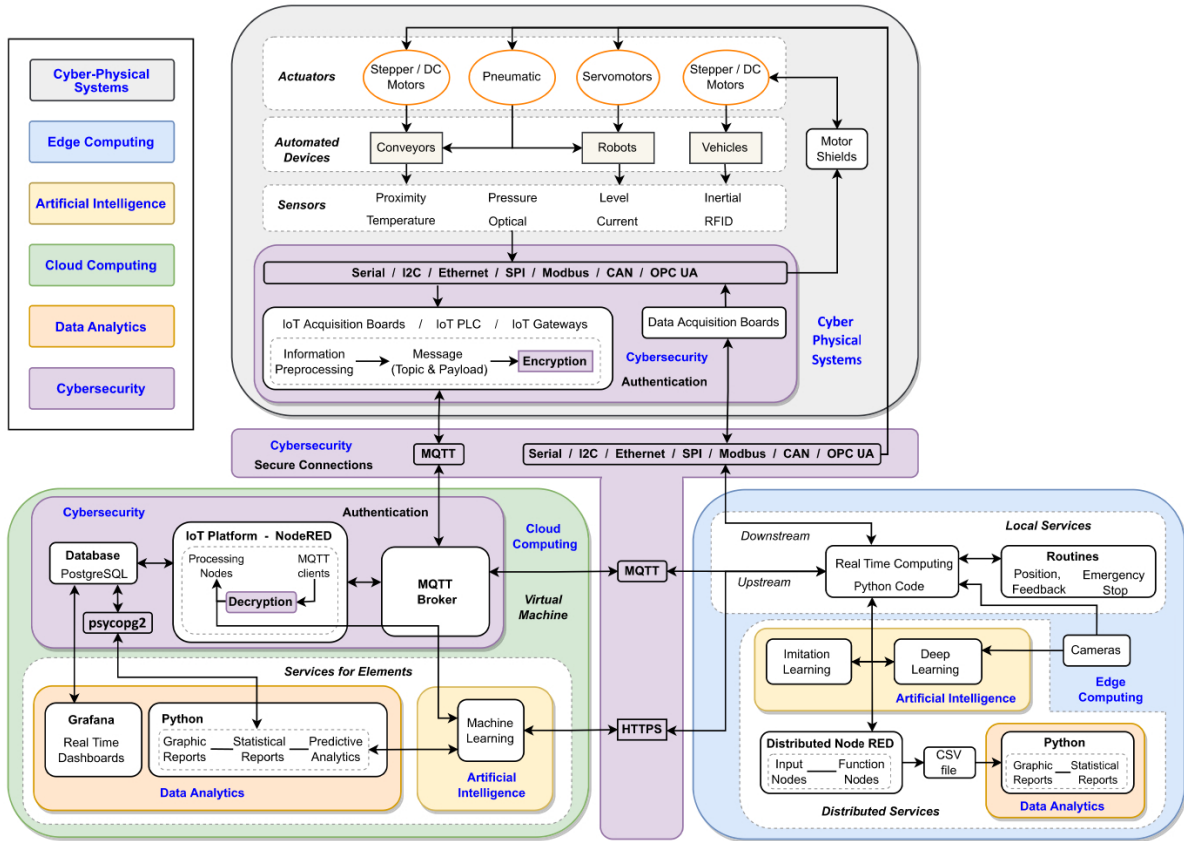


Figure 3.1: The Smart Factory architecture, referenced directly from its source, is found to be a viable base for our review of what is included in the required infrastructure of a system. Figure adjusted from J. A. Fortoul-Diaz et al.[37]

Looking more closely, we observe several core areas of the architecture. Our review of these systems shows what the authors considered most important in the capabilities and considerations around these system components.[37] Table 3.2 highlights these core areas as detailed in the literature.

Key Area	Description
Cyber-Physical Systems	Consists of hardware automation with communication through acquisition boards, PLCs, sensors and actuators using IoT protocols (OPC UA, MQTT, HTTP, CoAP, AMQP, DDS).
Edge Computing	Runs local real-time routines and distributed services through Edge Nodes for load distribution.
Artificial Intelligence	Uses deep learning, imitation, or machine learning to make decisions and recognize patterns.
Cloud Computing	Supports services like MQTT Broker Server, the IoT Platform, and databases with minimal configuration.
Data Analytics	Preprocesses data for insight, visualization using dashboards, and forecasting warehouse performance.
Cybersecurity	Facilitates encryption, decryption, and identity verification to protect data and connections.

Table 3.2: Key Areas of Automation Architecture

This detailed architectural design within its defined Smart Factory framework offers a vetted reference case architecture to base our decision criteria on.<sup>1</sup> We can confirm that this design is bound to a knowledge base that Diaz et al. have extensively reviewed. More specifically, this affirms the importance of system capability in design decisions and when considering system implementation.[37]

## Desired Utility in Warehousing Automation

Considering the design of an effective automation system in the context of a warehouse application requires careful consideration of the "ilities" of the system. These "ilities" are real non-functional requirements that are used to assess a system's performance. They help us understand how these systems demonstrate quantifiable enhancements to an operation, such as operational efficiency, improved fulfillment accuracy, or increased overall facility throughput. These areas directly support the evaluation of the overall capability of a system.

In our literature review, these utility areas are also sometimes called quality attributes. These attributes provide a more efficient framework for evaluating how well one system design meets its operational objectives compared to another. We find documented in the literature the following common system quality attributes: interoperability, flexibility, reliability, scalability, and safety/security. When these elements are individually assessed and then combined, there is greater confidence that the specific design of the automation system will perform its intended functions. This understanding of system utility is important for any warehouse automation decision-making process because it enables a more uniform comparison of an automation system's ability to meet its desired requirements.[38], [39]

Aspect	Description
Interoperability	Cooperation between systems, devices and applications within a single system to ensure effective information flow and minimal disruptions. [40]
Flexibility	Ability of a system to perform tasks and processes, including real-time tracking and order fulfillment. [41]
Reliability	Level of system continuity and dependability of the system during operation, with minimal downtime and reactive maintenance.[42]
Scalability	Capacity to meet growing workloads and handle expansion without major system changes, ensuring future-proofing. [43]
Safety/Security	Ensuring cyber-resilience against security threats and protecting human workers and systems from accidents and malfunctions. [44]

Table 3.3: Key Aspects of Warehouse Automation

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<sup>1</sup>Diaz et al.'s analysis also comprehensively compares more than 14 different SF architectures of similar projects and identifies the pros and cons of each. From this review, we agree that their architecture is the most applicable when considering physical components, cloud connectivity, and process digitization.

## Establishing Common Attributes for Warehouse Performance

Performance evaluations are one strategy for understanding the measurable changes relating to the core processes of a warehouse operation and the relative usability of the operation in focus. As the primary goal in the warehouse is to improve the speed and efficiency of shipping orders to clients, effective monitoring of associated process elements in the warehouse's performance is necessary. This focus on the operation makes it easier to determine the extent of any possible improvement relative to any changes in the operation. Thus, we include this in our review to support the development of strong indicators to understand what affects the operational health of a warehouse. In practice, these Key Performance Indicators (KPIs) allow firms to establish a benchmark for regular improvements and help identify the specific areas that can directly impact overall business economics and general competitiveness. Here, we summarize the work of Faveto et al. and their objectives to focus on the precise definition and thorough examination of some of the most influential KPIs for warehouse operations.[45]

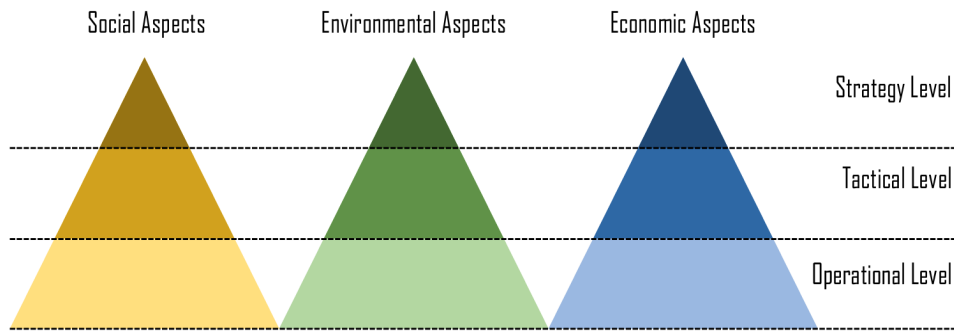


Figure 3.2: Presented method by Alberto Faveto et al. on Warehouse KPI Evaluation. Figure adjusted from A. Faveto et al.[45]

A detailed description of these influential performance metrics can be found in Appendix A. Here, we assess the feasibility of evaluating an automated warehouse system using a predefined set of performance criteria. The approach identified here (shown in Figure 3.2) is based on their framework of prioritizing three perspectives (social, environmental, and economic) and three levels of importance (strategic, tactical, and operational). From there, Faveto et al. conducted a systematic review of the literature to identify the indicators most often used in the performance of a warehousing operation. This section will share the results of the most documented KPIs identified in this work.[45]

This review emphasized the importance of being aware of the state of these typical performance indicators when determining the overall usability of a warehouse automation system. A significant highlight is how a simple indicator, such as cycle-time, offers a minimal understanding of the entire automation system and its overall usability for an operation. With the Faveto et al.'s system of indicators and investigation, we have various ways to provide a more systematic measure of the usability of warehouse automation systems. This, in turn, helps establish a top-to-bottom review of the benefits of a system for organizations considering investing in warehouse automation.

## Technical and Organizational Viability of an Integrator

An often overlooked and less glamorous side when considering purchasing an automation system is the reputation of the integrator to deliver on the required infrastructure. This

factor frequently determines the overall success of any automated system deployed. The reputation of the system integrator generally encompasses the economic, technical, and organizational viability of the chosen firm. The financial viability of a given integrator can be challenging to fully capture. In the current market environment with stiff competition from providers, there are no guarantees of the longevity of their support. Thus, we will not discuss this in great depth. Instead, we will cover the other two areas of review associated with a provider's reputation, the technical and organizational areas of consideration.

Technical feasibility is how a provider can accommodate new technology within the possible design of a decision maker facility. This is also a gauge of a provider's adaptability, capability, and general ability to meet a system's service needs more efficiently. Organizational feasibility refers to the ability of providers to incorporate and assimilate new technologies into their current catalog of offerings.

In addition, a firm's organizational infrastructure comprises its knowledge base and policies. Here, knowledge base refers to the employees' overall level of current expertise, know-how, and aptitude. This traditionally includes understanding the technical abilities of engineers, the managerial competencies of executives, and the fundamental skills of the labor force. Evaluating this environment is essential to comprehend compatibility when purchasing automation equipment. If this is insufficient to support the proposed systems, then there needs to be further development or plans to acquire this knowledge base internally or through another provider. Without it, successful purchase, implementation, and supervision of new technologies will not be possible.

Policy has been defined as the comprehensive framework of regulations, protocols, and rules for the organization that governs day-to-day activities and long-term plans. To achieve a successful automation deployment, it is often necessary to modify the internal organizational structure and policy to complement that of the chosen providers for support of the new technology. This could include installing more sophisticated management and control systems, simplifying the company by lowering levels of supervision, or enhancing personnel capabilities to perform wider-ranging tasks.

The collective understanding of these elements leads to the confirmation of an efficient infrastructure. This validation removes any possible inefficiency in communication and coordination between various departments, which is crucial to the smooth functioning of automated systems. As one would expect, insufficient infrastructure can result in inefficiencies and integration problems, undermining the advantages of automation. To successfully implement automation technologies, it is necessary to have both economic and technical preparedness, as well as a strong organizational infrastructure. This enables seamless incorporation and optimizes the advantages of automation.[46]

## **A Case for System Integrator Customer Service**

Once the robotic system is acquired, the organization is bound to the exclusive utility of the designed system and its chosen provider. In this commitment to the system, an operation can face a restriction on its integrator's ability to maintain customer support and adapt to new or developing technological requirements. This is often seen as a considerable risk for the business.[47]

Moreover, operating a robotic automation system involves an obligation (internal and external) to maintain and support that system. This encompasses various additional capabilities organizations often seek support from their chosen integrator, from routine maintenance or general problem-solving in operations to specialized repairs. Inadequate

support often leads to substantial downtime events or even system failure. Furthermore, the complexity of maintaining sophisticated robotic systems can increase operational hazards and inefficiencies if not properly supported. As a result, organizations looking to implement automation incur significant additional expenditures to either build internal capabilities or outsource the necessary maintenance services to accomplish this. Both can be expensive and require a lot of hidden resources and costs.[48]

## Project Cost Composition for Warehousing Operations

The determination of project costs is an essential process in the evaluation of any automation system.[49] The process allows a financial evaluation of the investment and the ability to determine the consequences and potential advantages of executing the project to automate the facilities.[50]

In this context, an accurate understanding of the project cost allows one to confirm the return on investment (ROI). There are many methods to confirm the economic implications of such a deployment, which fell outside our focus for this paper. Still, ROI is widely seen as a standard measurement, a widely used means to evaluate the profitability of the investment to automate a facility. However, to complete this single analysis, a project team must be able to compare the expected net benefits (total benefits minus total costs) with total investment costs. The concept of Total Cost of Ownership (TCO) is reviewed here as what we associate with project cost, which encompasses both capital expenditure (CapEx) and operational expenditure (OpEx) for the entire life of the automation system.[51] We will discuss this concept and how it offers a complete perspective of all expenses related to equipment ownership and operation.

### Total Cost of Ownership (TCO)

Rather than focusing only on the initial purchase price, the Total Cost of Ownership (TCO) is a comprehensive approach that takes into account all expenses related to the buying cycle.[51] The TCO for warehouse automation can be quantified using a formula combining different cost elements, including acquisition, usage, maintenance, indirect, and follow-up costs. The TCO formula can be expressed as follows:

$$TCO = Acquisition\ Costs + Usage\ Costs + Maintenance\ Costs \quad (3.1)$$

$$+ Indirect\ Costs + Follow-up\ Costs \quad (3.2)$$

Breaking down each component further, the formula can be detailed as:

$$\begin{aligned} TCO = & (Purchase\ Cost + Installation\ Cost + Training\ Cost) \\ & + (Energy\ Cost + Labor\ Cost + Productivity\ Cost) \\ & + (Maintenance\ Cost + Software\ Update\ Cost + Downtime\ Cost) \\ & + (Infrastructure\ Cost + Regulatory\ Cost + Insurance\ Cost + Opportunity\ Cost) \\ & + (Expansion\ Cost + Technology\ Refresh\ Cost) \end{aligned} \quad (3.3)$$

Within this broadening, indirect expenses, such as those related to the selection and qualification of suppliers, transportation, and receiving inspection, are included. It is highlighted that TCO is commonly employed when making purchasing decisions that include

significant capital, such as investments in industrial equipment. [51] Other applications include determining make or buy decisions, recurring purchases, selecting components for internal products, and optimizing processes by identifying the actual cost of specific process steps. The initial effort to establish TCO is frequently identified as the most significant obstacle to its use.[52]

The OPM (Object Process Methodology) in Figure 3.3 illustrates a typical cost modeling process to automate a warehouse. This diagram shows the integration of critical objects and methods. We can use this to identify and visualize fundamental interactions and transformations throughout the evaluation and implementation phases of a typical warehouse automation project. The four primary objects shown in this diagram are the existing warehouse, the purposed automation system, an estimated cost model, and the data required for the evaluation.

These objects are found to be the essential areas where cost modeling must capture the different processes involved in the evaluation and the transitions through the states of the project. For example, the warehouse evaluation moves from its existing state to being analyzed and eventually automated. Then the automation system progresses from being planned to implementation and finally operating. The core of the cost model is created from the analyzed data, further analyzed for detailed cost breakdown, and then optimized through processes such as the TCO estimation. At this point, it is also feasible to perform more analysis, such as a risk assessment and a sensitivity study. The information gathered from this optimization study finally finds its way to a summary that establishes the return-on-investment estimation and the capacity to back judgements on moving forward with the implementation.

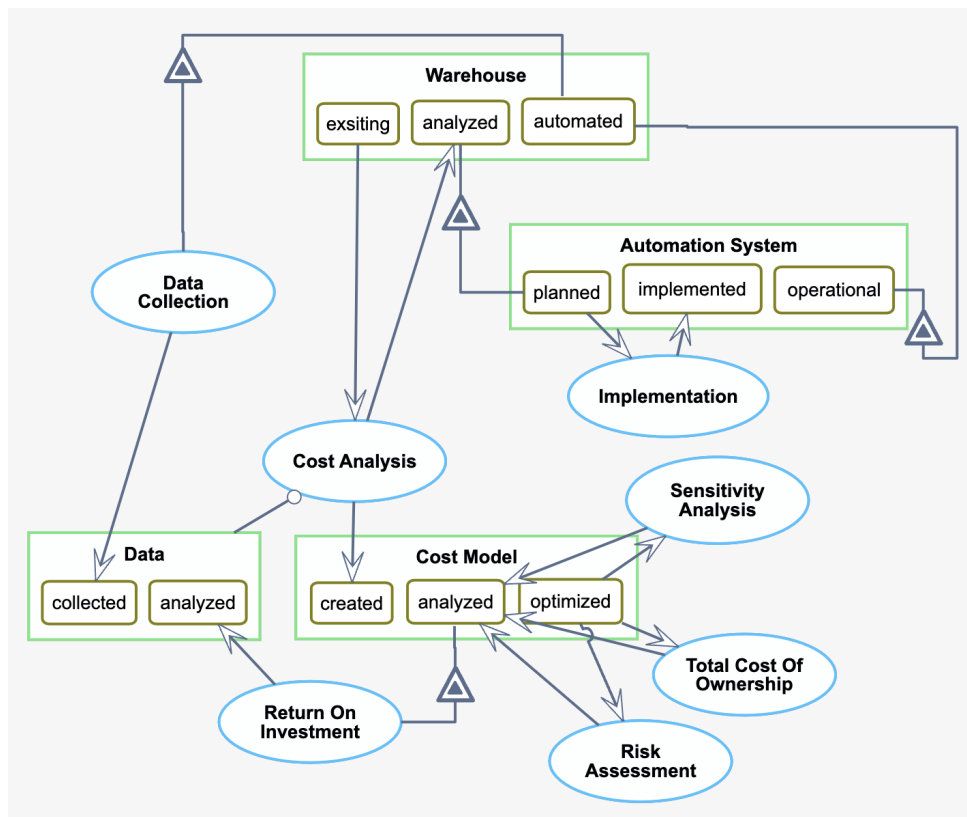


Figure 3.3: Our produced object-process methodology (OPM) diagram for cost modeling in warehouse automation

Cost modeling relies heavily on the acquisition and interpretation of the available operational data of the operation in focus. [53] An added benefit is its ability to support strategic optimization of warehouse layout, such as storage aisles and automation channels, which can result in substantial cost reductions. The form of the warehouse is closely related to its intended function. So, identifying the required processes and considering space and equipment concerns are vital to establishing the core requirements of the system.[54]

Following these guidelines, companies are more likely to create a thorough and accurate project cost structure to install automation equipment in their warehouses. Better informed decisions are made with evaluations like the OPM described, looking to improve operations' ability to see increases in decision efficiency and capture of cost when considering their automation projects.

### 3.3 The Lease vs. Buy Dilemma

When purchasing a robotic automation system outright or leasing it from a system integrator, several factors related to decision criteria must be considered, including the organization's financial, operational, strategic, and risk-related aspects, as well as how best to integrate automation into its processes. These include cash flow, expected equipment use, desired maintenance responsibilities, and business growth strategy. Reviewing these components enables the comparison of these integration modes and establishes the criteria to compare their advantages and constraints effectively. From this comes the ability to distinguish the tipping point when purchasing a robotic automation system outright becomes more advantageous than leasing that system from a system integrator. By considering these areas in the decision-making process, the end user can make a more concrete comparison between options that align with their long-term objectives and operational requirements.[48]

As expected, buying an automation system might be advantageous if a company has extra capital and strong cash flow. However, leasing could be preferable if cash is tight, allowing it to keep some money for unexpected expenses. It is crucial to consider the use of the equipment over its intended life. This is challenging as the pace of technology is hard to gauge, so knowing how and when equipment may become obsolete can be difficult. Purchasing would be preferable for equipment that is felt to be secure from innovation and likely to remain at the innovation front over many years, whereas leasing may be a better option if the reverse is true.

Maintaining the automation system is another consideration. Usually, leasing covers the costs of the service along with maintenance and repairs performed by the leasing company. Lastly, how does a decision maker think about their business structure and growth plans as a differentiator? If the aim is growth, leasing may be more appropriate, as it frees up capital for other assets that support expansion. However, if the goal is to increase profits quickly, purchasing equipment might be better, as owning assets can lower operating costs and increase the company's overall value. Considering all these things can facilitate purchasing or leasing company equipment.[47]

### 3.4 Using the RaaS Alternative for Integrating Automation

The Robot-as-a-Service (RaaS) business model responds to technological uncertainties and the need for better support dynamics. This approach takes a significant leap to enable technological capabilities by rethinking the business model for robotic adoption. This method has enabled even small and medium enterprises (SMEs) to resource robotics providers in a service mode of implementation. This method has many benefits, primarily to offset financial exposure from these decisions.

RaaS is a business model that offers robotics solutions on a subscription or pay-per-use basis rather than requiring customers to purchase, maintain, and upgrade robots. This model benefits both customers and providers. Customers gain flexibility and control by avoiding significant upfront costs and relying on steady service that meets market demand. The key advantage for providers is that they benefit from a recurring revenue stream. This allows service providers to focus on expanding their customer base and improving capabilities and support. They can also maximize fleet utilization by reallocating resources based on market demand, supporting customers during peak periods, and reducing idle times during downturns.[5]

RaaS also offers significant flexibility in using complementary robotic automation systems without buying equipment outright or managing maintenance. The RaaS provider handles all maintenance and support, saving time and resources for the end user and preventing significant technical debt in training programs.[55]

However, there are drawbacks to the RaaS model. The ongoing cost of RaaS can accumulate significantly over time, potentially exceeding the cost of owning and maintaining a robotic system outright. Users typically face limited control over robots, as providers may restrict customization options to maintain efficiency in support and maintenance. There is also the risk of relying on the provider, which can pose significant operational risks if the provider encounters technical issues or goes out of business, potentially disrupting access to the robots and leading to lost revenue.[56]

### Correlations with the Software as a Service (SaaS) Model

Another well-known "as-a-service" platform is Software as a Service (SaaS), which continues to be a revolutionary means of delivering technologies in many industries. The strength of the platform is derived from its ability to maximize data systems through cloud computing. With the advantages of parallel processing and access to the latest analytics, SaaS democratizes access to these services. With all these increased capabilities offered to the customer, there is a quick implementation, leading to increased efficiency, reduced costs, and greater alignment throughout an operation. This business model becomes quickly attractive. Since these services help establish the solid groundwork for future technological progress, this partnership is typically explored in enterprises that want to prep their operations before introducing robotic automation.[57]

RaaS is designed to mimic some disruptive behavior to provide distinct advantages. RaaS performs remarkably well in warehousing environments with a higher level of process standardization and current market pressure, which requires a significant increase in operational capacity. As highlighted previously, the immediate network effect of a RaaS solution quickly enables organizations to expand their warehousing capabilities flexibly and reduces the dependence on manual labor.

So the two platforms exhibit several commonalities: their offering is centered on a cloud-based design, their focus on a subscription-based business model, and the advantage they provide customers to scale in their solution. This ultimately makes them potent instruments for challenging conventional industrial norms. Given that it is the older method, SaaS is currently favored for its extensive track record and enhanced scaling capabilities. Although it is not exactly apples-to-apples when we compare it to RaaS, which may somewhat compete in the software space, it provides unmatched advantages in terms of hardware needed for automation and operational advancement. [\[57\]](#)

We see how unique advantages are made available by both SaaS and RaaS, making them essential in the ongoing development of automation and providing necessary support to the warehouse. Ultimately, thinking about these unique business solutions and how the company's needs could make good use of these business models in any strategic goals is beneficial.

### 3.5 Summary

This review of the literature provided a robust foundation for addressing our core research question: "What are the prevailing decision criteria considered when adopting automation, and how do these criteria relate to the rank of a preferred method of implementing a desired automation system?" From the fundamentals of warehouse management, we highlight critical design decision criteria. This supports our understanding of the characteristics of warehousing goods and the operational objectives typically involved in integrating automation solutions with existing systems. Even in these foundational elements, there is clarity on the specific needs and constraints of a warehouse, which help identify the direct impact of the choice of automation strategy. Understanding these fundamentals allows us to assess better how different automation approaches, including RaaS, meet the unique requirements of various warehouse operations. With the help of this thorough assessment, we can explore a framework to decide how to implement automation in warehouse applications. This will facilitate our last contribution in promoting choices more in line with the practitioners in the industry and increasing the effectiveness of these decisions.

# Chapter 4

## Methodology

### 4.1 Introduction

This study employs a deductive research methodology. Our review here covers the core research areas necessary to frame this properly. Our literature review details our chosen MCDM approach, including the top-down process, to establish its fundamental design. We established how our method helped us to confirm the hypotheses associated with our research question. In our Results section, Chapter 5, we capture how we stimulated various specifics from these initial hypotheses and further discuss these implications in our concluding remarks.

Our primary goals in this section are to describe the efforts to collect a curated data set, from how it was sourced in a targeted field study to how we applied our chosen methodology. We outline the means taken to derive a meaningful context from the study conducted. This review of our methods highlights our use of a cluster and sensitivity analysis within the study for further insight into identifying specific cross-overs in our decision criteria that change the rank of the preferred method for implementing a system. Together, our defined methodology helped us understand the importance of the criteria in focus and supported a quantifiable MCDM framework from which to identify the most optimal alternative.

At its core, our established MCDM decision framework is tied directly to well-researched platforms. [58] Our review here details the intended application of the chosen techniques and explains how the methods chosen fit with our current study, as it was found to be the best way to incorporate the input of the decision makers involved and the decision-scenario-bound data analysis. Furthermore, the chosen methods were found to demonstrate an ability to take advantage of decision maker deduction skills along with our chosen MCDM tools, such as the Analytic Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS). We present a practical application of our MCDM framework model by clearly explaining how these theoretical concepts were applied. From this foundation, we further validated its application and the ability to establish empirical evidence in our field study. The results we obtained from this further confirm this research design.

## 4.2 Research Design

To this point, we have established a basic understanding of the decision trade-offs faced when managing warehouse processes and the level of automation for an operation. We found a set of common considerations that are needed to ensure that these decisions involving automation in the facilities are adequate for the network they support. Our study further confirms this by detailing our design of the decision framework.[58] In this section, we consider several preferred methods based on the reviewed literature to produce a hybrid combination to meet our current goal in the decision framework. This review identifies the specific process of the method we chose and the process we took to complete this review.

From a set of research guidelines, our designed decision-making tool combined two appropriate methods in the evaluation framework for the desired hybrid approach. This is initially tied to an AHP method at the core of our framework. To successfully establish this structure, we draw on the work of Oztaysi et al. [36] Their work helped us confirm in the final decision criteria that we see applied directly in this work. From this similarity in the criteria, this enabled a similar opportunity to use the combined AHP with TOPSIS method, as identified in our reference case. This hybrid approach to assessing and choosing preferred solutions is only partially novel. The research carried out by Wu et al. also detailed a similar approach to leverage the two methods[59] We build on this work by modifying the contributions of both sources in an applied technique that aligns them with our objectives of a decision support framework. Here, we detail how we collected the information associated with the AHP segment of this supported framework.

## 4.3 Leveraging the Analytic Hierarchy Process (AHP)

The AHP method has been shown to have three primary functions that support the decision-making process. These help develop prioritizing decision criteria, enable the structuring of complexity, and facilitate the discovery of a preferred alternative. Traditionally, AHP is described as using logic and mathematics to analyze and solve decision-making problems systematically and rationally. It helps translate the intuition and gut feelings of decision makers into figures that others can freely challenge and understand. More fundamentally, AHP supports the desire to make decisions in a hierarchy, which humans naturally tend to do. A hierarchy is a top-to-bottom organized form of a network. The AHP process supports this natural tendency of decision makers by better enabling them to break down complicated issues into smaller ones that can be addressed individually.[60] <sup>1</sup>

Lastly, the AHP lays out a procedure that allows decision making to occur naturally. Complex junctions are naturally involved in group decisions that tend to evolve over multiple iterations. In this process, the AHP enables a more communal decision, a means to consider input, make changes, and better weigh the lessons learned by the decision maker and distribute them to others.[58] From our review, we found that this method is ideal for our efforts to produce a common framework to evaluate automation integration methods. Initially, the problem is decomposed into a hierarchical framework, including

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<sup>1</sup>Psychological research indicates that people can compare only 7 +/- 2 items simultaneously. As such, it is necessary to break down a complicated decision-making issue into its parts. This is a strength of the AHP.

objectives, criteria, sub-criteria, and options. This is the central essential part of decision making. In this case, the hierarchy supports identifying the connection between elements at the various levels within the decision framework. Our primary use of AHP was based on its ability to prioritize our decision criteria into specific weights of significance for the decision.

## Defining the Hierarchy

Figure 4.1 represents our attempt to structure this hierarchical top-level organization for the decision framework. We recognize the potential to add further layering in this design, which could be pursued in future applications of this framework for improved application in practice. These identified links in the figure identify how specific attributes of the overall structure of the AHP are related throughout all levels of the hierarchy. In our case, we are focused on a single level of criteria. However, in practice, AHP allows multiple layering of criteria that can be directly or indirectly associated with all other elements.<sup>2</sup>

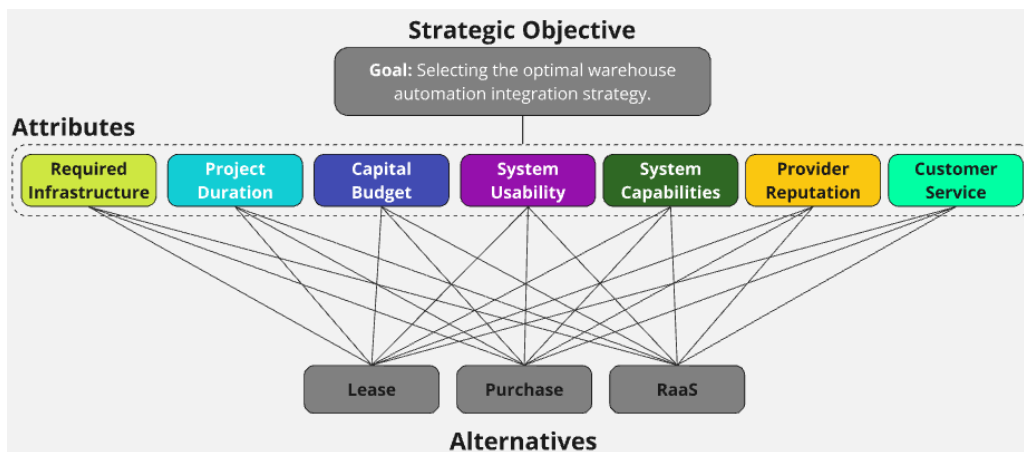


Figure 4.1: Decision hierarchy for evaluating warehouse automation integration options, highlighting key decision attributes and alternatives.

When constructing a hierarchy, it is important to consider the primary goal or objective of the problem under investigation. When comparing elements at each level, a decision maker only needs to consider how elements at the lower level contribute to the upper level, which is a key benefit of AHP.[61]

## Pairwise Comparison

Then, using expert opinion, data are collected from appropriate decision makers, who evaluate the alternatives in the hierarchical framework. This step of the process relies on pairwise comparisons on a qualitative scale, as seen in Table 4.1. Through this process, the attributes are appropriately ranked with the alternatives using a scale that measures the strength of their comparisons. The gradation scale helps to quickly classify elements

<sup>2</sup>We explored various depths of hierarchy and design related to our AHP work. We were inspired by the textbook *Strategic Decision Making - Applying the Analytic Hierarchy Process* by Bhushan et al. The support documentation for this process recommends that an effective way to organize the structure is to start at the top and work as much down as possible. Then, one should move upward from the alternatives until the levels of the two processes are connected to allow comparisons.

from best to worst. In this evaluation process, the evaluator is given the ability to evaluate comparisons as "equal," "marginally strong," "strong," "very strong," or "extremely strong." It is understood that making these judgments is based on the experience of the evaluator with the hypothetical outcomes of each alternative and that it is used as a basis for making comparative judgments.

Option	Numerical value(s)
Equal	1
Marginally strong	3
Strong	5
Very strong	7
Extremely strong	9
Intermediate values to reflect fuzzy inputs	2, 4, 6, 8
Reflecting dominance of second alternative compared with the first	Reciprocals

Table 4.1: Gradation scale for quantitative comparison of alternatives.[61]

### Establish One-to-One Matrix

From there, we create a one-to-one matrix as seen in Table 4.2. This matrix represents each criterion compared to the weight of another criterion as set from the previous part of this process.<sup>3</sup> This process helps identify future evaluations that must be taken into account to accurately capture the pairwise ranking that best reflects the priorities of the decision maker.[61]

	RI	PD	B	CSS	U	C	PR
RI	1	$a_{12}$	$a_{13}$	$a_{14}$	$a_{15}$	$a_{16}$	$a_{17}$
PD	$\frac{1}{a_{12}}$	1	$a_{23}$	$a_{24}$	$a_{25}$	$a_{26}$	$a_{27}$
B	$\frac{1}{a_{13}}$	$\frac{1}{a_{23}}$	1	$a_{34}$	$a_{35}$	$a_{36}$	$a_{37}$
CSS	$\frac{1}{a_{14}}$	$\frac{1}{a_{24}}$	$\frac{1}{a_{34}}$	1	$a_{45}$	$a_{46}$	$a_{47}$
U	$\frac{1}{a_{15}}$	$\frac{1}{a_{25}}$	$\frac{1}{a_{35}}$	$\frac{1}{a_{45}}$	1	$a_{56}$	$a_{57}$
C	$\frac{1}{a_{16}}$	$\frac{1}{a_{26}}$	$\frac{1}{a_{36}}$	$\frac{1}{a_{46}}$	$\frac{1}{a_{56}}$	1	$a_{67}$
PR	$\frac{1}{a_{17}}$	$\frac{1}{a_{27}}$	$\frac{1}{a_{37}}$	$\frac{1}{a_{47}}$	$\frac{1}{a_{57}}$	$\frac{1}{a_{67}}$	1

Table 4.2: Example Pairwise Comparison for the Decision Criteria showing where a decision maker would assign gradation values for cells  $a_{ij}$  (i not equal to j).

**Acronyms:** RI - Required Infrastructure, PD - Project Duration, B - Budget, U - Usability, C - Capabilities, CSS - Customer Service Support, PR - Provider Reputation.

### Principal Eigenvalue and Eigenvector

From this, the AHP evaluation defines the comparison matrix's principal eigenvalue and the matching normalized right eigenvector. The principal eigenvalue and eigenvector in

<sup>3</sup>If the element is the diagonal element, it is assigned a value of 1, indicating that the criterion is being compared to itself and is equal. If the component is greater than 1, the criterion in the i-th row is better than that in the j-th column. When the element is less than or equal to 1, it implies that the criterion in the j-th column is considered better. The value of the element at position (j, i) is taken as the reciprocal value of the element at position (i, j) if both are different from 1.

AHP are crucial in demonstrating the rigor of the method.<sup>4</sup> These normalized eigenvector components are called weights when discussing criteria or sub-criteria and ratings when considering alternatives. In making decisions, these weights or ratings indicate the importance of each criterion or alternative.

The consistency of the pairwise comparison matrix is evaluated using the principal eigenvalue in the Analytic Hierarchy Process (AHP).<sup>5</sup>[62] A full demonstration of this process can be found in Appendix A.[58]

## Integrating Grey-TOPSIS into our AHP results

TOPSIS assumes that the best option is closest to the ideal solution and farthest from the worst.<sup>6</sup> Each part of the decision matrix has a utility that increases or decreases consistently. This means that the preference for the 'benefit' criterion increases as its utility increases. This effectively allows for comparing any non-numerical result to an appropriately scaled one. Decision-makers assign weights to criteria because not all requirements are equally important. A full demonstration of this process can be found in Appendix B.[63], [64]

Incorporating grey numbers into the TOPSIS method improves its ability to handle uncertainty and imprecision in decision-making. Grey numbers, by definition, represent ranges rather than precise values, which allows for more flexible and realistic modeling of uncertain information. Ogonowski et al. explain how this is particularly useful when decision criteria are not strictly quantitative or when exact data is difficult to obtain. This was a predominant reason we decided to use grey numbers within our TOPSIS approach. Ultimately, this improved our ability to reflect the known uncertainty present in these real-world automation design scenarios. Ogonowski et al. specifically highlight how this approach provides a more robust and reliable decision-making framework.[65]

TOPSIS relies on a set of weights for the attributes. The weighting system output from the chosen decision model, in our case from the AHP analysis, allowed us to determine the ideal solution. This highlights the compatibility with the previously defined AHP method for weight assessment and how it is uniquely compatible with this proposed method. Our decision to use grey numbers further ensures that the decision-making process remains applicable. The supporting documentation presents the case for the application of this method in our study.**aassari\_role\_2012**

## 4.4 Data Collection

We have now established an extensive review of our preferred MCDM considerations to support a comprehensive evaluation of warehouse operation. Before fully implementing our selected MCDM methods, we first needed to establish a data set against which to deploy these techniques. This data collection effort took the form of a survey response

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<sup>4</sup>These elements show how vital the different criteria are concerning one other. The correlations between the observed items and the factor dimensions are called eigenvectors. An eigenvalue of a matrix having the largest absolute magnitude is called its principal eigenvalue. The scaling factor of the related eigenvector is the scalar in a linear transformation that the matrix provides

<sup>5</sup>When a matrix multiplies a non-zero vector, the result is a scalar multiple of the original vector. The AHP normalizes the principal eigenvector such that the total of its components equals one. The values of its constituent parts show the relevant standards or possibilities being considered.

<sup>6</sup>A full demonstration of the TOPSIS process can be found in Appendix B.

initiative. As with any survey, it was critical to design it to ensure the reliability and validity of the results, thus supporting the research objectives. To achieve this from the collected responses, we first needed to build a strong sense of the demographics of our target focus group. The survey deployment strategy focused on using various resources to improve the setup of such surveys. This included identifying a desired background in our target respondents that we believe to be the best suited to support our desired responses. These categories were based on the attributes of job function, industry experience, and familiarity with warehouse automation. From these identifiers, we establish further necessary screenings in the responses (see Table 4.4). This supported the collection in the study of a desired focus group.<sup>7</sup> The survey deployment was developed and administered using the Qualtrics platform. The primary information collected was focused on the necessary pairwise comparison of the AHP method on the predetermined decision criteria and the establishment of range in the ranking of the automation integration methods.

## Data Collection Process

Our survey collection strategy initially focused on an open network distribution strategy through focus email groups, such as the System Design & Management (SDM) alumni network, and through LinkedIn. In addition, channels were used to reach active practitioners within the warehouse and logistics communities. However, as insurance in the field study, we also used additional resources through a survey collection agency, Centiment. This supported us in collecting the essential number of viable survey responses necessary to complete our investigation. This approach helped protect our study from poor response quality or the high rate of incomplete responses frequently associated with collecting survey data from an open platform. Additional benefits were found to be higher quality in our respondents and built-in consistency in demographics for the targeted respondents.

As a level of assurance in the deployment of the survey, we implemented a "soft launch" protocol to ensure that the results were received as expected. In our case, this involved releasing a targeted survey to a small subset of the target respondent group in focus. Within this testing period, we were able to verify the health of our survey design by verifying the completion times, which we held to a shorter than 10-minute limit, and by identifying questions that produced inconsistency in response or confusion from the respondents. After validating our survey design through a beta testing phase, we opened the survey for live collection. The responses collected used a phased approach over a three-week period. This phased or "start-and-stop" strategy used in the release was a recommendation of the provider Centiment. This approach had been found to help ensure the successful collection of survey results and to improve participation rates in our more specialized respondent group.

In total, the survey focused on three main areas. These included demographics, pairwise collection focus, and a section for ranking in automation integration methods. As expected, this design complements directly our MCDM methods. Respondents received a survey reference guide to support understanding of the criteria in review. This improved participation in the survey questions and its structure, helping us to meet the survey expectations and maintain quality from the collected data. As a final measure of validation,

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<sup>7</sup>It is essential to note that all responses collected within this field study will be anonymous and carry the COUHES exemption (Exempt ID: E-5998). This applies to studies that use surveys, interviews, educational tests, or watching how adults or children act in public, and sharing the subjects' answers outside of the study could not reasonably put subjects at risk of criminal or civil liability or harm their finances, ability to get a job, academic progress, or reputation.

a consistency ratio (CR) was calculated for each respondent’s pairwise comparison matrix. The literature detailing the AHP analysis noted that responses with a CR greater than 0.1 should be flagged and consulted to improve consistency. Due to the anonymous nature of our survey, we could not further consult with the respondents about their ratings. A method from our literature provided us with an approach to handle these more inconsistent scores: the response result would be thrown out if the CR value could not be lowered below 0.1 after three rounds of changes to the top three inconsistent judgments were made in the included pairwise categories. This technique from the literature was a crucial step in maintaining the validity of the AHP analysis by ensuring adequate consistency in the results.[60]

## Demographic Attributes in Focus

Here, we identify the targeted demographic factors we included in our study to help us understand the varied backgrounds and experiences we were tapping into from the respondents who participated. We received a diverse range of responses collected from these selected demographics, which we will detail later. In these areas of categorization, the information captured from the respondents contributed to the research and provided a wide range of information. Table 5.2 explains the demographic categories we considered in the field study and will be presented further in the results.

Table 4.3: Core Demographic Categories and Descriptions

Category	Description
<b>Experience</b>	Captures the number of years the respondent has been in their respective field.
<b>Age</b>	Segments respondents into age groups to understand generational differences.
<b>Education</b>	Categorizes respondents based on their educational attainment.
<b>Company Size</b>	Reflects the respondent’s understanding of the scale for their organizations. This was requested to be reflected as an estimated company value in total revenue and assets or market capitalization for publicly traded companies.
<b>Industry</b>	Classifies respondents in association with the industry they work in.
<b>Familiarity</b>	Measures respondents’ familiarity with automation systems.
<b>Role</b>	Captures the respondent’s roles within their organizations.
<b>Adoption</b>	Reflects the respondent’s attitudes toward adopting robotic automation into their operations.

We will later find in our results how, by examining these select demographic factors, the field study successfully established significant insights from the respondents. These elements in the data collection brought significant correlations to the respondent’s overall recommendations for a preferred method to implement automation. We found that demographic segmentation played an important role in the analysis and helped establish the varied influences each respondent profile had on their responses.

## Quality Control in Data Collection

One critical area of quality control we found useful was the selection of survey respondents, which involved a series of screening questions that allowed them to self-identify their domain knowledge around automation and support a higher probability of having the necessary background when providing information for our study. As Table 4.4 indicates, this screening criterion refers to four main areas. For additional quality control in the responses, we relied on our third-party service provider (Centiment) to facilitate the collection of survey responses using a project management approach. This offering involved an assigned resource and a series of features in the platform that directly supported improved data quality when conducting survey-based data collection. These services helped to ensure that the data received was as verified as possible during the collection period. These features include IP verification for geography-based profiling, proxy detection to reduce VPN interference, a ReCaptcha factor to prevent bot interference, fraud scoring that identifies disengagement from respondents, and duplication prevention.

Criterion	Description
#1	Respondents must indicate that they are involved in one of the related industries (Warehousing/Logistics, Shipping/Distribution, Manufacturing, Food/Beverage).
#2	Respondents were required to have some familiarity with the technology associated with robotic automation. Respondents indicating no familiarity were excluded from the study.
#3	Respondents must indicate that their company uses or plans to use automation in (1-3 years).
#4	Respondents must indicate that they are involved in their organization’s decision-making for the implementation of robotic automation.

Table 4.4: Survey screening criteria for respondents included in the study.

Through this means of quality control, we maximized our ability to find sufficient results to adequately capture the sentiments of the respondents and demonstrate the effectiveness of the proposed methodology. Combining these quality control measures provided a more guaranteed panel of respondents and greater precision in data collection.

## 4.5 Analysis Approach

### Deriving Quantitative from Qualitative Analysis

Our study consisted of a qualitative survey that focused on measurable criteria. We used our literature review and qualitative analysis to identify these measurable elements. This qualitative review summarized the 'state of practice' through informal discussions with industry contacts, participation in industry seminars and forums, and field visits to factories. We conducted two field trips to Locus Robotics and Hronis Inc. during our research period. These illustrated, on the one hand, the Robot-as-a-Service (RaaS) service model and, on the other, a standard storage facility looking to incorporate automation

into its warehouse. These field visits supported a tangible understanding of how industry practitioners are finding a need for automation.<sup>8</sup> Another complementary engagement was attending the MIT CTL omnichannel roundtable seminar, Omnichannel Revolution: Navigating the Future of E-Commerce. These collective engagements led to targeted follow-up interviews with some of the stakeholders<sup>9</sup> we met during the study. The outcome of the information collected ensured that further identification of the present correlations across the reviewed criteria was possible. Without this coupling of these themes in our research, our analysis would be limited in providing a complete understanding of how decision makers view the integration challenge and what the dominant hypotheses and concepts are for the study.

## Sensitivity Analysis

Sensitivity analysis is a valuable tool to identify the limits and robustness of an evaluation under specific conditions. In this study, we conducted a sensitivity study from the collected responses to help identify the level of resilience seen in a set rank for the three desired implementation methods (purchase, lease, and RaaS). This additional layer in the study helped us determine a relationship between the variations of the assigned weight in the associated decision criteria and the affect it had on the final choice of the optimal implementation method. We completed this by adjusting the weights and tracking the resulting TOPSIS C+ rank variations for the three alternatives. This helped us identify the variables most significantly affecting the decision-making process. This information provides us with the criteria groups and weights most likely to change the evaluation outcome and demonstrated how the framework can improve confidence in decision making. This assessment enables us to provide grounds for scenario management exercises and further exhibits the capabilities of the decision framework. In practice, we expect this to help teams identify the decision criteria that have the greatest impact on the decision and where additional information could be useful to reduce uncertainty in the decision.

## Cluster Analysis

As noted, when groups make judgments, MCDM methods are found to be extremely useful. Although combining individual input to obtain a group output is logical, we have found it advisable to examine the results using a consensus indicator to gauge group member alignment. To achieve this, we performed a cluster analysis on the results we collected from our AHP results, incorporating the Shannon entropy method.<sup>10</sup>

Klas D. Goepfle extensively discusses how to apply the Shannon entropy method. This method is a well-established method in biology for measuring biodiversity. In our case, we

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<sup>8</sup>These trips were instrumental in helping us to understand the potential application of RaaS in the warehouse. The principal attributes defined in these engagements were the advantages of scalability and the ability to handle seasonal demand fluctuations and improve operational efficiency as a direct benefit and practicality.

<sup>9</sup>An interview with an industry professional representing a major retail firm revealed a qualitative assertion that the robotic automation industry is highly fragmented. Even on their scale, there is a noted challenge in reliability issues due to the need for service providers to be directly involved in hardware. There are no "one-size-fits-all" or "turnkey" providers. This fragmentation often leads to "blocky" implementations that lack a singular ontology for an end-to-end system. This stresses the complexity of the automation integration process.

<sup>10</sup>See Appendix D for details on the Shannon entropy method and how it is being used.

exercised its ability to measure the entropy of a system against the pairwise evaluations of our respondents.[66]

This approach allowed us to determine the level of consensus among the group. We calculated this consensus indicator for all possible pair combinations in the decision maker pool. The summary of these results then populated a similarity matrix with off-diagonal values that indicate the various levels of consensus. We then used a 'threshold clustering' approach. By setting a threshold of 75%, we counted the number of elements exceeding this threshold in each row of the similarity matrix. The row with the highest count determined the first cluster.

## Establishing Decision Maker Profiles

This clustering approach directly supports abstract group decision making exercises, such as ours, and allows us to build on the input of the individual respondents. We identified that this additional measure improved our understanding of the similarity of the respondents in the survey. The outcome of this algorithm also supported our ability to segment the respondent pool into distinct groupings or Decision Maker Profiles.

Using common statistical methods such as Multiple Correspondence Analysis (MCA) and the Chi-square test, we were able to draw out tangible associations in the demographic variables and provide further support in establishing what present correlations exist among the groups. Using MCA analysis within our analysis helped reduce the dimensionality of our demographic data while preserving the variance of the dataset. MCA enables one to examine the relationships of numerous categorical dependent variables. When the variables examined are categorical rather than quantitative, a generalization of the principal component analysis can also be considered. Technically, MCA is derived by applying a standard correspondence analysis to an indicator matrix, that is, a matrix whose elements are 0 or 1. The interpretation of the correspondence analysis of the distances between points must be adjusted, and the percentages of explained variance must be updated. A set of observations defined by a set of nominal variables is analyzed using MCA, in which every nominal variable consists of numerous levels, and each of these levels is assigned a binary coding.[67] From the completed MCA analysis, we conducted a chi-square test. For a categorical dataset such as ours, the Chi-square test was found to be an appropriate statistical instrument that can be used to determine whether the observed frequencies deviate significantly from the expected frequencies. This helps determine whether the observed data distribution diverges from what was anticipated, hence revealing links between categorical variables. To evaluate the relevance of variations, this test gathers observed data, determines expected frequencies based on a theoretical model, and then generates the chi-square statistic.[68] Together, these statistical measures helped identify the distinctive characteristics of each group of groups.

Our further examination of these groups led to different decision outcomes. This better understanding of the group results produced identifiable themes in consideration of the decision criteria associated with the feedback of the actual respondents in the decision-making process. Furthermore, this method complemented the AHP analysis we performed. By identifying the highest-valued decision criteria in the identified clusters, we could address where additional information could reduce uncertainty for each group. If applied in practice, this would, in turn, provide valuable information to conduct scenario management activities and lead to improved confidence in the decision-making process. Figure 4.2 further illustrates our plan to perform a post-field study analysis.

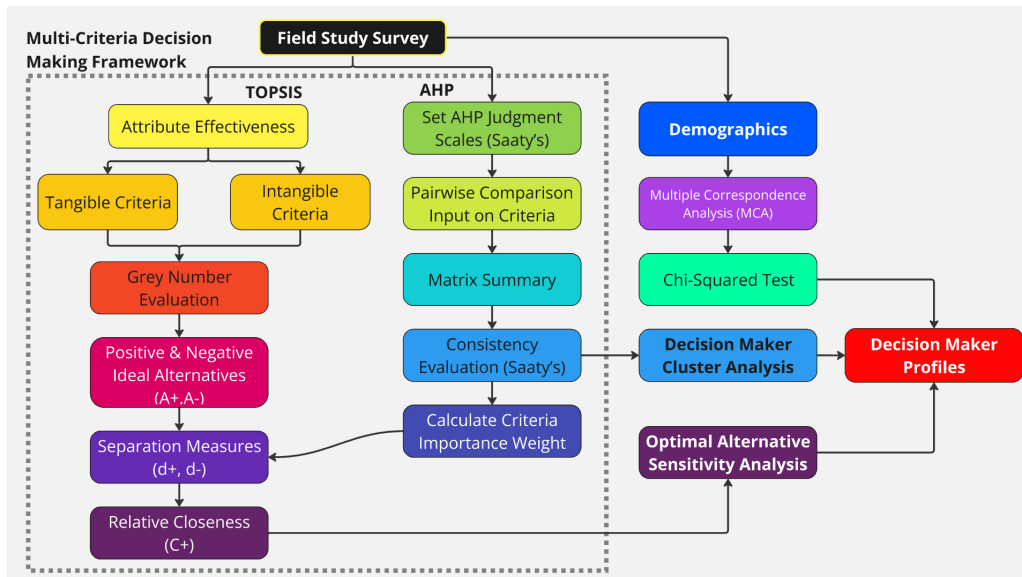


Figure 4.2: Framework for evaluating decision-makers' preference for automation integration options. The sequence and progression summarize how the previous analysis enabled us to produce a "Decision Maker Profile" from the field study.

## Summary

This section outlines our plan for using an MCDM framework that incorporates AHP and TOPSIS. Our goal was to move from these two traditional MCDM approaches and provide analysis to better understand the preferences of decision makers in the alternatives provided. With this intention, we further establish our approach using sensitivity, cluster analysis, and statistics to enable the analysis to produce new insights associated with a common set of decision criteria. This approach to methodology allowed us to conduct a refined analysis of the collected responses to establish different grouping and decision-making profiles from the fielded respondent pool. Chapter 5 presents these results and discusses how this enables us to deliver on the research objectives.

# Chapter 5

## Results

To open this section, we briefly recap our objective and the research question in focus. This helps us recall the nature of one of the main challenges we identified when implementing robotic automation in the warehouse. This specifically focused on the business capacity to assess the most relevant strategies available to implement a desired automation system. Our results demonstrate how to support this challenge and the underlying themes of the study. Furthermore, this section will now use what our literature review and methodology sections previously discussed. In presenting this, we will confirm the use of the identified decision criteria and cement the capabilities of our associated MCDM decision framework.

**RQ:** *What are the prevailing decision criteria considered when adopting warehouse automation, and how do decision makers consider these criteria in their ranking as a preferred method of implementing a desired automation system?*

We intend to follow the order outlined in Chapter 4 as we present the main findings of our analytical process and the most critical observations collected. This will demonstrate how decision makers, familiar with their decision environments, prioritized the identified decision criteria. Through this process, our results will show how we have connected the priority of the respondents in the criteria with their preferred integration methods. Together, we highlight the tangible benefits of using the approach developed from our research and the contribution of meaningful connections of active practitioners provided by the associated respondents in the field study.

### 5.0.1 Observed Participation in Field Study

Focusing on those meaningful connections, our field study used a Qualtrics survey platform and generated more than 290 responses. Initially, to field completed surveys, we focused on open platforms to collect the desired responses. However, these initial efforts proved challenging as we tried to rely on data collection through targeted email lists, LinkedIn, and other social media platforms. During our initial three weeks of collection, the survey received fewer than 100 responses, with less than 10% considered viable for inclusion in the study. We made several strategy adjustments, from multiple release phases to other recommended methods to stimulate participation. Unfortunately, it became apparent that the survey lacked an incentive for respondents to participate. Therefore, we decided to conduct the study in mid-July through a self-contracted survey provider, Centiment. This significantly improved our ability to collect the necessary data and allowed the study

to proceed. Figure 5.1 shows the speed with which survey responses were collected during the initial and final sections of its collection.

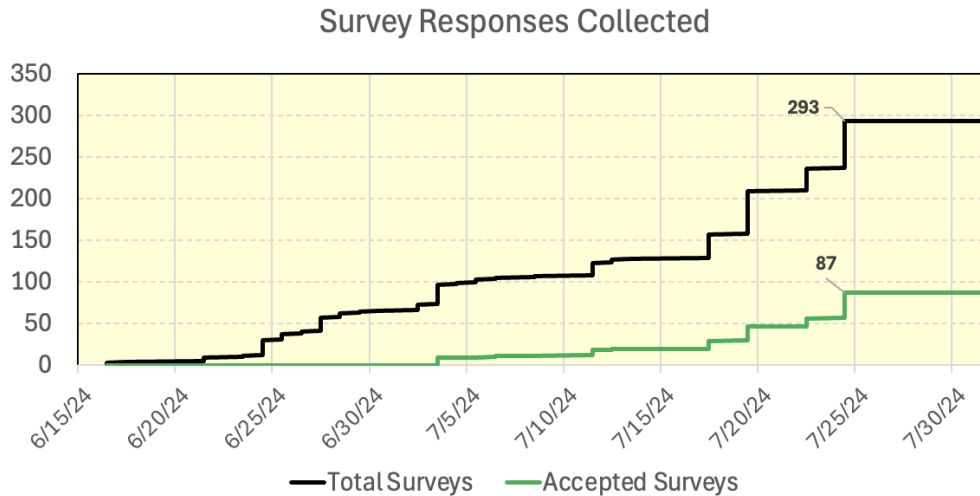


Figure 5.1: Phases of implementation and rate of accepted surveys over the collection period.

At the end of the collection period, the study had received 87 viable surveys, 31% of the total field survey pool. As expected, there were some common characteristics of poor participation in the responses to our survey, which led to the need to omit 69% of the results obtained. The predominant reason was an incomplete submission, in which the respondent initiated the survey but did not complete it. Another common source of omission was surveys collected with an unrealistic completion time, indicating that a respondent sped through the submission without focusing on the content. The typical response time was 8-9 minutes, further confirmed by our initial estimates from the Qualtrics platform. Surveys found to be completed in an unreasonable short period of time, less than 4 minutes, were considered insufficient to provide accurate information and excluded from the study. Among several other quality assurance checks, these supported the collection of healthy data sets. Our high tolerance for the quality of the submission was critical for our ability to produce the tangible results that we now present from the study.

### 5.0.2 Observed Demographics Found in the Study

We first break down our results by reviewing the demographic profile collected from our respondents to adequately contextualize the insights generated from these results. The demographic data collected exhibited a normal distribution in most categories. These initial findings and the responses received supported the assertion that the collected information had provided a sufficient concentration of respondents to support our targeted research question. Establishing these demographic measurements confirmed the diversity of the data collected in the sample of respondents on which our findings are based. Our review confirmed that the study had successfully sourced information from various backgrounds and experiences. This helped us identify correlations among decision makers, contributing to a set of profiles and grounds for further review and future research.

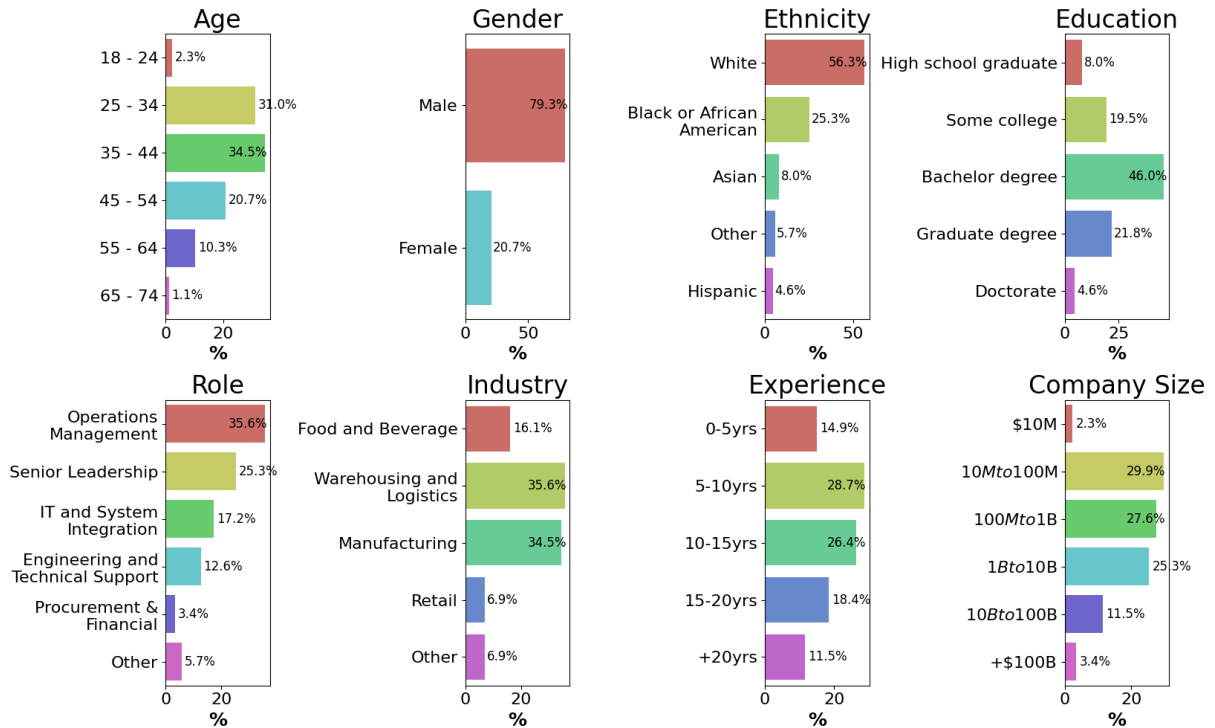


Figure 5.2: Demographics chart illustrating a diverse range of respondents across several categories.

Some of the main demographic focus areas of the survey were categories such as firm size, industry knowledge, and company roles. Figure 5.2 shows the various domains in which the survey requested information. This is not specifically highlighted here but later presented in our results, which shows how our demographic diversity allowed us to investigate possible correlations and links between these elements and the ranking of implementation strategies and criteria from the individual respondents. Figure 5.2, we note that our response group was sourced mainly, more than 50%, from respondents in the age group between 25 and 34 years and between 35 and 44 years. We also see that 29% of the respondents reported having (5 to 10 years) experience and 26% (10 to 15 years) experience, respectively. The combination of this information suggests that the study probably sourced more than 50% of our responses from an early to mid-career group of professionals in the industry. Further exploration of this information shows a primary

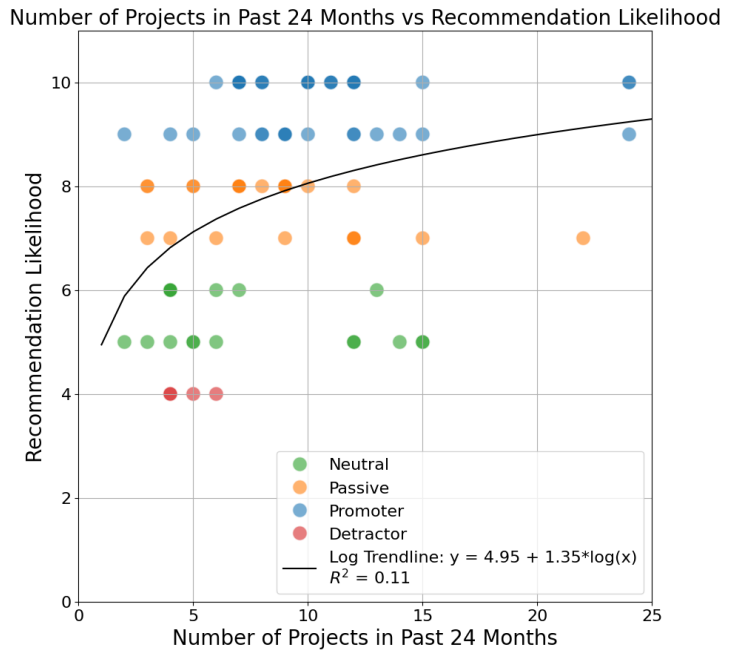


Figure 5.3: The plot illustrates the relationship between the number of projects completed in the past 24 months and the likelihood of recommending automation.

representation in our survey of people working in companies between \$10 million and <\$10 billion in company value. This information finds that <15% of our respondents represented large corporations of greater than \$10 billion in company value.

A less profound but exciting finding from our demographic data set is shown in Figure 5.3, which shows a link between the number of projects they have worked on in the last 24 months and the likelihood that they would recommend implementing robotic automation in operations. As shown as a black line in the figure, a logarithmic correlation that links these variables can be loosely identified. A somewhat intuitive and notable result is that respondents who reported an increase in the number of finished projects also tended to report an increase in their likelihood of proposing automation. This simple validation is helpful, as it supports the higher likelihood that the survey received attentive engagement from the involved respondents.

This series of observations demonstrates how the results collected allow for a more reflective analysis in developing a respondent's profile relative to their preference for specific decision criteria. We will later show how we used these attributes from the respondents and isolate unique similarities in the respondent groups. We reserve for Chapter 6 our discussion on how these profiles support establishing our decision framework. With our demographics now understood, our evaluation will continue to build on this and apply our outlined methodology.

### 5.0.3 Results of the Pairwise Evaluation in AHP Analysis

The field study was specifically designed to facilitate the pairwise evaluation portion of an AHP analysis. This method was only intended to provide us with weights of significance for the individual decision criteria. We now examine the results of the field studies on this and how the information collected allowed us to accomplish this. Figure 5.4, the heatmap, shows the aggregated average of the summary of this pairwise comparison, which was asked of the respondents.<sup>1</sup> This is visible across the seven criteria they evaluated. The color gradient from purple to yellow represents the intensity of these preferences. Darker shades indicate lower values, and brighter shades indicate higher values. This shows the aggregate rank for the pairwise comparisons and the corresponding inverse values. To more fully detail how we interpret this table, we can focus on the intersection of "System Usability" and "Project Duration." We see, for example, that the respondents valued the "System Usability" two times more than the "Project Duration" when asked to directly compare the two criteria. However, one of the main takeaways from the details in this set of results is confirmation of our ability to successfully incorporate the pairwise assessment of the AHP framework. What is most notable in the matrix is the stark contrast in the criteria of "Provider Reputation"; it was found that this specific criterion had lower typical importance values for the respondents. This is evident from the lower values on the left side of the diagonal in the pairwise matrix table. Figure 5.5 captures the graph of the final weights of the seven criteria of the AHP method conducted.<sup>2</sup>

Table 5.1 shows the AHP weight assessment, which presents the Required Infrastructure criterion as the highest value criterion at 0.195. The significance of this is somewhat

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<sup>1</sup>We find the highest-rated pairwise comparison and the reciprocal values represented here. It is important to note that seeing values greater than one on the left of the diagonal indicated (such as system usability versus project duration) that respondents saw a reverse preference in the criteria coupling reviewed here.

<sup>2</sup>The details of how this calculation was conducted can be seen in Appendix A.

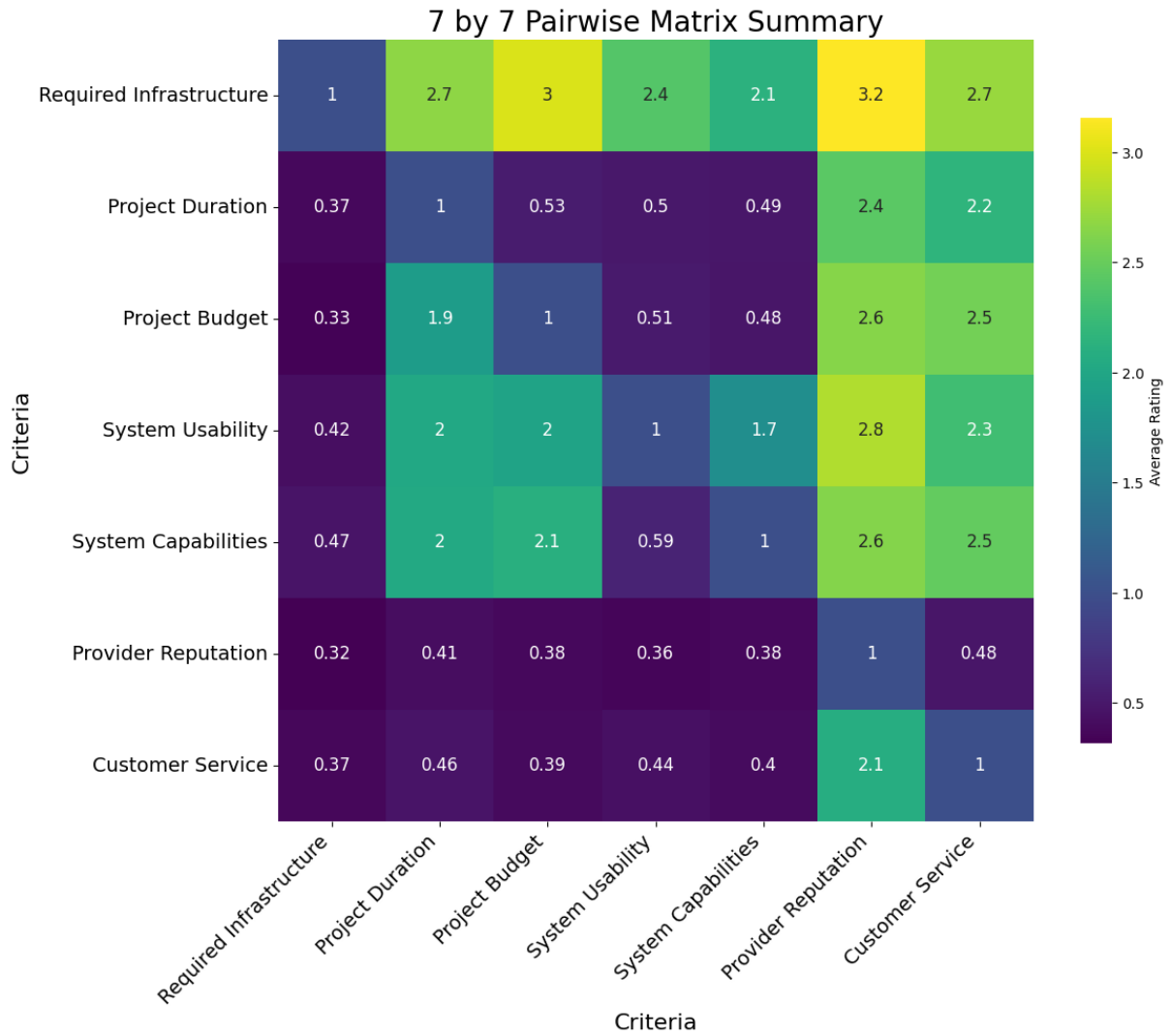


Figure 5.4: Pairwise matrix heatmap provides a clear visual representation of how the seven different criteria were prioritized among the fielded responses.

intuitive, but the information derived from our research in these criteria could suggest that our response pool generally saw the feasibility of upgrading or modifying existing infrastructure as a primary concern when considering the adoption of robotic automation. In contrast, our lowest criterion was 'Provider Reputation', with a value of 0.097. This would suggest that respondents were generally less focused on the reputation of a particular vendor and more focused on the tangible aspects of the robotic system. Considerations like this demonstrate a more comprehensive view of the factors that influence the decision of the respondents, which is now available. With these weights established, the evaluation must first confirm their consistency and then consider their impact on the preferred integration method of this group of decision makers.

Criteria	Average Value
Required Infrastructure	<b>0.195</b>
Project Duration	0.134
Project Budget	0.140
System Usability	0.152
System Capabilities	0.155
Provider Reputation	0.097
Customer Service	0.126

Table 5.1: Consolidated results of the AHP weights for the seven evaluated criteria.

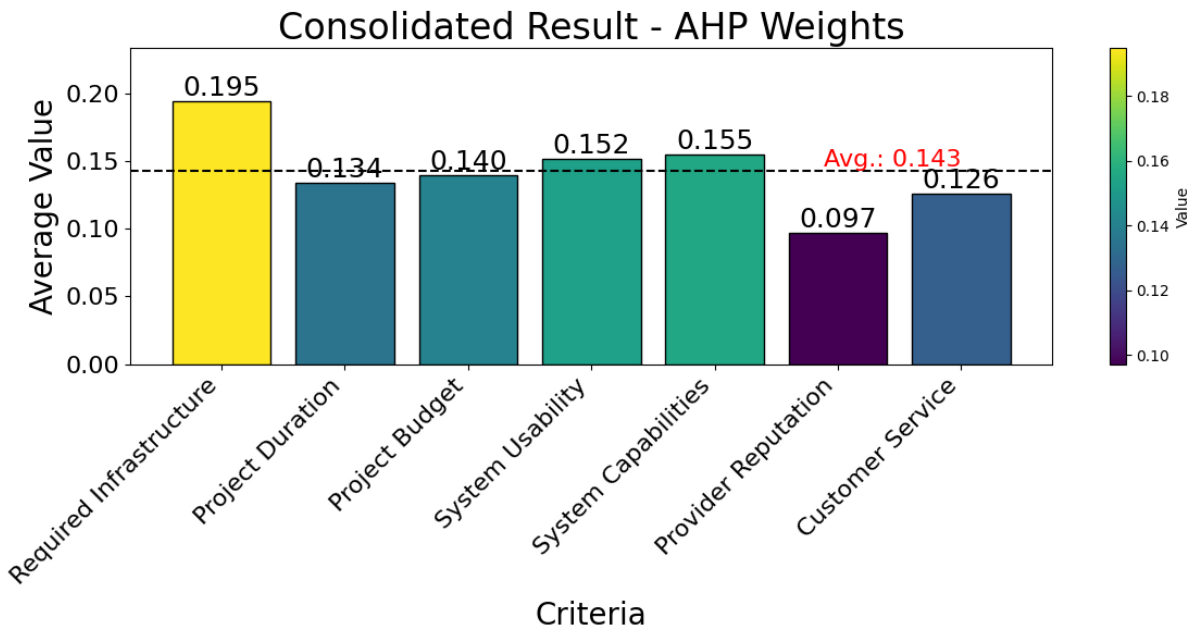


Figure 5.5: The relative importance of each criterion across all respondents as determined by the AHP analysis.

### 5.0.4 Consistency Analysis

One main means of validation for the AHP analysis is the Consistency Index (CI) calculation. Figure 5.6 presents a series of box plots.<sup>3</sup> These values represent the core components of the calculation as further confirmation of the AHP process. The most notable aspect is a detailed view of the eigenvector values of the analysis, which are used to derive the corresponding consistency index and ratio defined. The red dashed line is shown at the Consistency Ratio (CR) threshold value of 0.1, indicating the acceptable consistency level for AHP calculations. The analysis highlights areas of inconsistency that may need further attention. Essentially, this confirms that the comparisons made by a decision maker are logical or coherent. The reasons for the incoherence are not always known and can result from decision-making bias or general incorrect assignment of matrix values in the pairwise model.[60] Ultimately, here, the figure serves primarily as confirmation of the assurance that our analysis is correct in collecting pairwise evaluations. This validation enables us to review the assessment, knowing that it was captured in a consensus-bound

<sup>3</sup>The normalized eigenvector values along with the Consistency Index (CI) and Consistency Ratio (CR) are critical values to identify the health in the pairwise analysis.

prioritization of the set criteria.

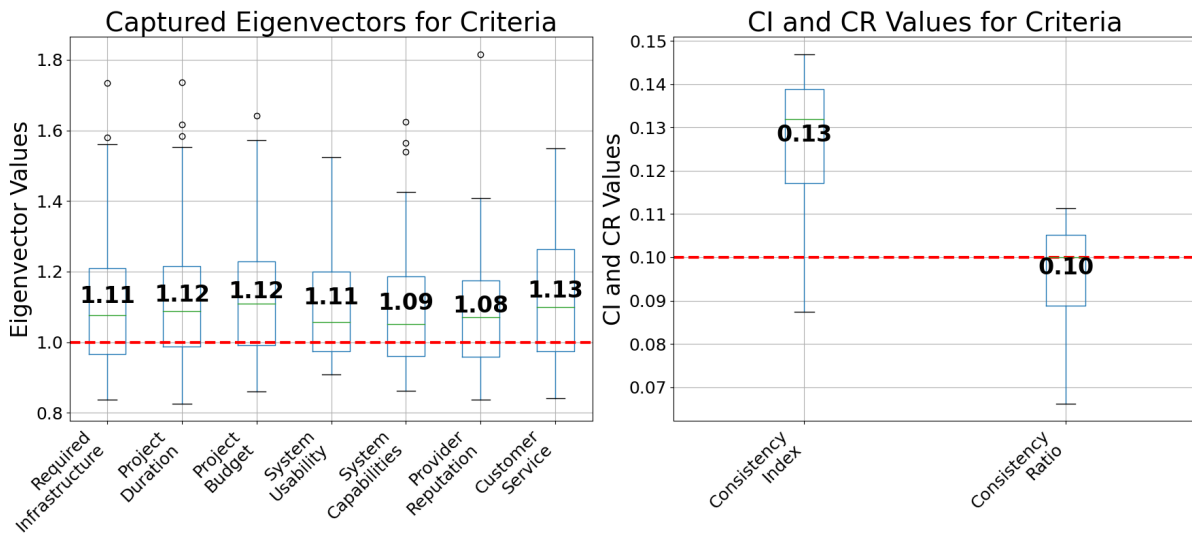


Figure 5.6: This box plot illustrates the distribution of normalized eigenvector values for our criteria in focus.

### 5.0.5 Range Found in Tangible Criteria

When establishing the necessary components for our TOPSIS analysis, gray numbers collection was planned for our study. This section reviews the results of tangible criteria specifically within our framework. To this point, only two tangible criteria were addressed concerning the project budget and duration. The project duration was defined as the time between the start of the project and the time when the automation system was fully operational. The project budget was defined as the total cost of ownership of the system, which includes the integration of automation into the facility and the additional cost required to support the automation system over a predefined lifecycle of 5 years. The summary of this data collection is shown in Figure 5.7.<sup>4</sup> These values represent the normal range of the respondents in the project duration and the budget of the three integration methods on which they were asked for feedback.

From the results of this information, we found that respondents generally represented the budget and duration ranges of the three systems to occupy distinctly different regions. For example, RaaS systems tend to cluster between \$7.09 million and 7.6 months for the project cost and duration. There are notable ranges for the other systems, as seen in Figure 5.7. With this collection of responses representing only a fraction of active practitioners and projects across the industry, likely, the captured relationships may not be an accurate empirical representation of the cost and duration of any automation project. However, the study does establish a set range that our respondents gave from the survey results, directly correlated with their preference for the methods they desired to implement those systems. An interpretation of this series of concentrations may lead us to believe that the respondents take a graduated approach to incorporating these distinct methods for integrating their desired automation solution. This means that this group of decision makers is likely to have typically seen the use of RaaS as a preferred method when handling smaller, more time-bound integrations. Compared to lease- and purchase-based systems, it is seen as a more advanced or complicated integration effort that requires time

<sup>4</sup>This relationship likely captures how respondents identified the progressive nature of incorporating these three distinct methods into their efforts to implement robotic automation into their facilities.

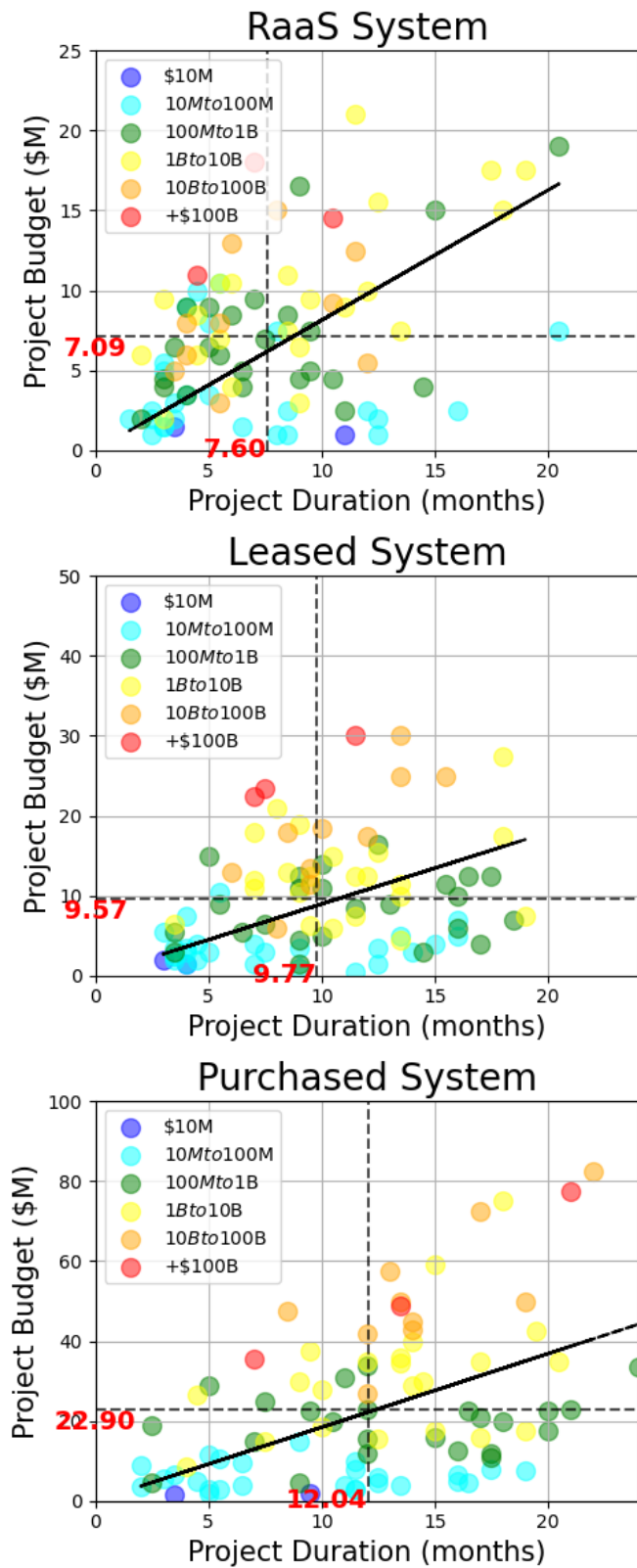


Figure 5.7: The respondents' recorded typical range in duration and budget for the three implementation systems.

and budget. Ultimately, this evaluation confirms that these ranges are adequate for our TOPSIS evaluation.

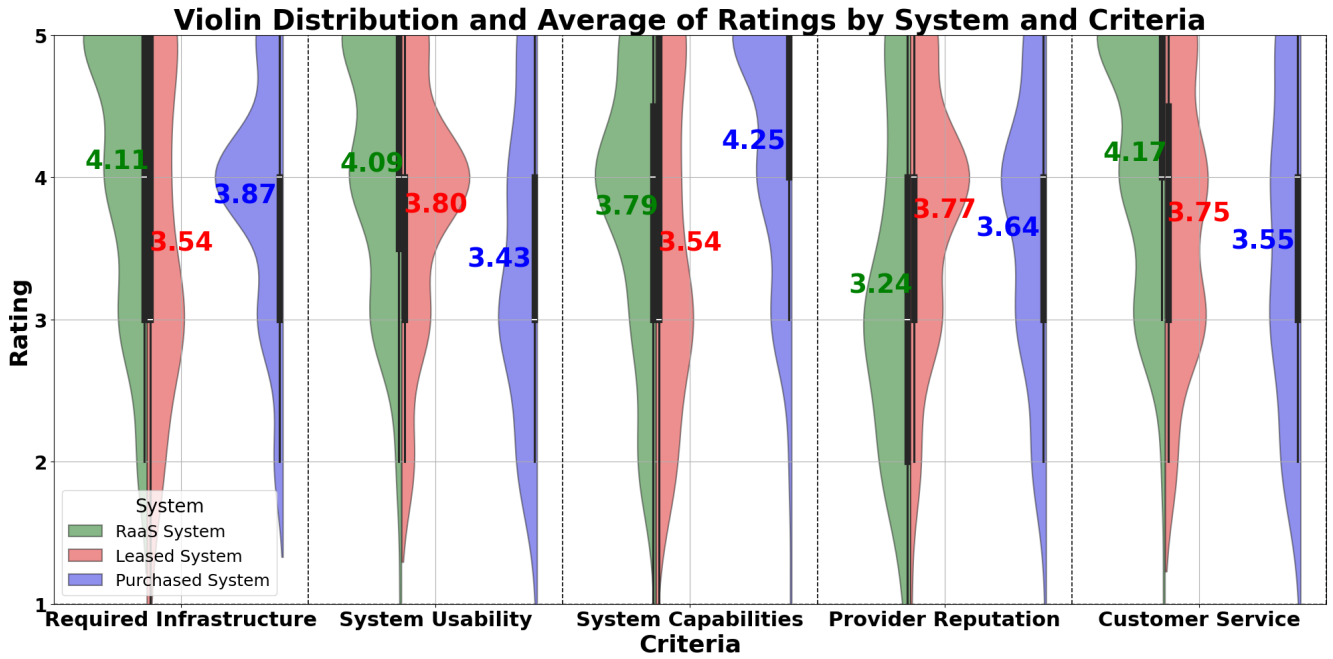


Figure 5.8: Displays a violin chart illustrating three systems’ reported average rating and distribution across the five criteria.

#	Criteria	RaaS System	Leased System	Purchased System
1	Required Infrastructure	4.11 *	3.54	3.87
2	System Usability	4.09 *	3.80	3.42
3	System Capabilities	3.79	3.54	4.25 *
4	Provider Reputation	3.24	3.77 *	3.64
5	Customer Service	4.17 *	3.75	3.55

Table 5.2: The numerical average values from Figure 5.8 for each criterion, with a (\*) indicating the highest rank system in the row-level comparison.

### 5.0.6 Range Found in Intangible Criteria

We now review the remaining five intangible decision criteria. The violin charts in Figure 5.8 have labels that indicate the average levels of performance reported by the respondents associated with these five criteria when considering the three integration methods. The violin plot reveals nuanced insights into the distribution for the three different systems.<sup>5</sup> This performance was evaluated on a one-to-five Likert scale. From these results, we can observe the combined sentiment of the entire field of respondents across all our intangible criteria.

For example, we observe that the RaaS system performs best with respect to the required infrastructure. When considering how easily an automation system can be inte-

<sup>5</sup>Further description in these categories can be found in Appendix E.

grated with a facility’s existing infrastructure, the respondents see a RaaS system as the most accommodating. From this compiled view of all responses, we also see RaaS being rated as highest in both system usability and customer service as well. These results highlight that customers generally see the as-a-service model as a superior form of integration to deliver user-friendly systems with strong technical support for automation equipment.

Another conclusion from this is that the respondents found that when considering system capabilities, a purchased system was seen as having the highest capacity to deliver functionality from the automation system to its users. This likely captures that respondents prefer to use purchased-based integration for more custom-designed automation implementations that provide a higher degree of capability to their operation. Then we see that the lease system is most highly regarded for its provider reputation. This is interesting as this may relate to the general familiarity respondents have with leasing providers through their experience.

Together, we can also take the view that the high and more uniform rating distribution for RaaS suggests a more consistent and generally favorable view of the method. This uniformity may result from a lower variability in the use cases of the method by respondents. In contrast, the Lease and Purchase systems appear to have more varied distribution indicating mixed experience, possibly due to a wider range of context in the implementation.

From the initial review, much can be hypothesized further about the implications of these captured results. However, these results are presented here to establish how respondents identified strength in the targeted criteria and how they saw the advantages of using Lease, Purchase, or RaaS as options to acquire automation. In practice, this exercise would be implemented to capture the positions of the unique target group in focus.

In Table 5.2, we see a more numeric representation of the previous table. These results confirm that the study adequately measured all the decision criteria in scope and established the fundamental reference values needed for our TOPSIS analysis.

Now that the respondents have established all the criteria of interest in an appropriate range, we can confirm the preferred method for implementing the desired system. Furthermore, analysts can now begin to understand the implications of these criteria against the three integration methods in focus. These are both core elements of our overall research objective.

### 5.0.7 TOPSIS Analysis

With the decision matrix laid out and our consistency confirmed, the results will now be presented on the TOPSIS evaluation performed. As previously established, our process will now incorporate the established gray numbers. The set criteria’s upper and lower maximum limits were found and then converted to normalized values using the representative positive and negative ideal values to produce a normalized range for all requirements. This summary is shown in Figure 5.9, along with the associated ideal solutions  $A^+$  and negative ideal  $A^-$  for each category.<sup>6</sup>

The values in  $d^+$  represent the positive distance from the ideal solution, and in  $d^-$  represent the negative distance to the ideal solution, as seen in Figure 5.10. Finally, Figure 5.10, shows the relative proximity to the ideal solution  $C^+$ . This value ranges from 0 to 1. From this scale, the highest value  $C^+$  is considered the best option because

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<sup>6</sup>Further details of this calculation are available for reference in Appendix B.

Criteria	Weight	RaaS Sys. (Norm.)	Leased Sys. (Norm.)	Purchased Sys. (Norm.)	A+	A-
Infrastructure	0.195	(0.6, 1.0)	(0.6, 1.0)	(0.6, 0.8)	1	0.6
System Usability	0.134	(0.7, 1.0)	(0.6, 0.8)	(0.6, 0.8)	1	0.6
System Capabilities	0.14	(0.6, 0.9)	(0.6, 1.0)	(0.8, 1.0)	1	0.6
Provider Reputation	0.152	(0.5, 1.0)	(0.75, 1.0)	(0.75, 1.0)	1	0.5
Customer Service	0.155	(0.8, 1.0)	(0.6, 0.9)	(0.6, 0.8)	1	0.6
Project Duration	0.097	(0.078, 0.287)	(0.124, 0.426)	(0.202, 1.0)	0.078	1
Project Cost	0.126	(0.2, 0.6)	(0.314, 0.757)	(0.4, 1.0)	0.2	1

Figure 5.9: AHP weights and grey numbers used to determine the ideal and negative-ideal solutions.

System	d+	d-	C+
RaaSSystem	0.26	0.43	0.62
LeasedSystem	0.29	0.38	0.57
PurchasedSystem	0.38	0.32	0.46

Figure 5.10: This table summarizes our study’s separation measures from the TOPSIS analysis. Based on the responses, the RaaS System has the highest  $C^+$  value of 0.62, making it the closest to the ideal solution among the three systems.

the value represents the alternative closest to the ideal solution and thus farthest from the negative ideal solution. In conjunction with this assertion, it is observed that respondents were more likely to recommend the RaaS method over a lease-and-purchase alternative. The final rank collected from the respondents considered RaaS at 0.62 out of 1 as their ideal solution when considering their perspectives and criteria areas in the decision.

### 5.0.8 Sensitivity Analysis

To further improve our ability to provide a practical framework, a sensitivity assessment was applied to the study based on the previously established foundation in the findings and the original preferences set across the focus criteria. Including this technique in the analysis helped clarify which criteria most likely influence this general decision based on the extreme weight of one criterion over the others.

The results of this sensitivity analysis, observed in Figure 5.11, highlight a one-at-a-time approach in this analysis. Recall the normalized range from Figure 5.9; From this we see the limits in producing the profiles evident in this analysis. Each plot shows how the value of  $C^+$  changes as the weight assigned to a particular criterion varies from 0 to 1. What is most evident in this is how the adjustment changes the condition of the alternative method order preference when subjected to extremes in weight for each tested criterion. These results allow for a full spectrum of possible rankings to be presented across extremes in the prioritization of decision-makers. This evaluation enables a deeper dialogue in considering the implications of these conditions as decision makers look to make sense of what hypothetical environment they likely represent. For example, consider when different options have crossovers in their calculated ranks. This is an area of significant consideration in the scenario that would create this tipping point for the preferred alternative. Thus, it would be important to focus attention on that area to ensure that slight shifts in weight do not significantly change a major project decision. Ultimately, our observations of this analysis begin to identify the characteristics of the three alternatives rooted in the original evaluation of the seven criteria. This exercise is found to be strong at highlighting potential challenging conditions for a decision.

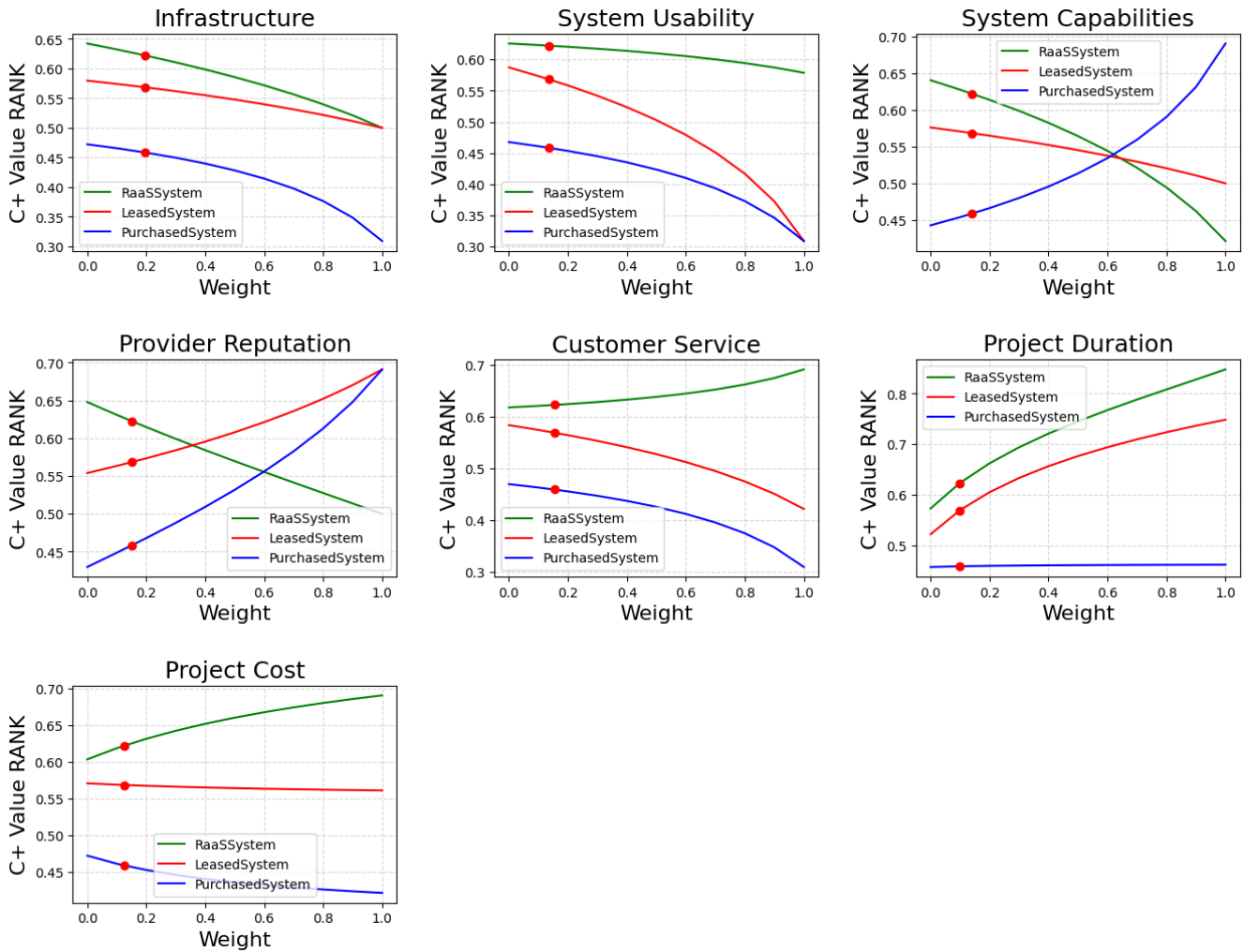


Figure 5.11: The sensitivity analysis of the  $C^+$  or alternative rank values for three systems across different criteria. The red dots indicate the original weights and  $C^+$  values (seen in Figure 5.10) using the original weights noted in Figure 5.9.

The results of our research offer a comprehensive breakdown of the main factors that influence the choice of automation in warehouse activities. These findings support the body of knowledge that we made available from our review of the literature in association with warehouse automation. This review will also offer industry decision makers a helpful template to structure similar analyses.

### 5.0.9 Cluster Analysis

Cluster analysis was performed using the AHP results previously covered, allowing a better understanding of the degree of similarity between the respondents collected during the study. Here, we demonstrate the use of the Shannon entropy method.<sup>7</sup> This method allows us to build on the opinions of the individual responders. It directly aids abstract group decision making, as we have done. This method can determine the degree of consensus among the groups to help divide the response pool into distinct groups and

<sup>7</sup>We cite Klas D. Goeple as our source for demonstrating the use of the Shannon entropy method, which we reference for this analysis. A detailed breakdown of this approach can be found in Appendix D.

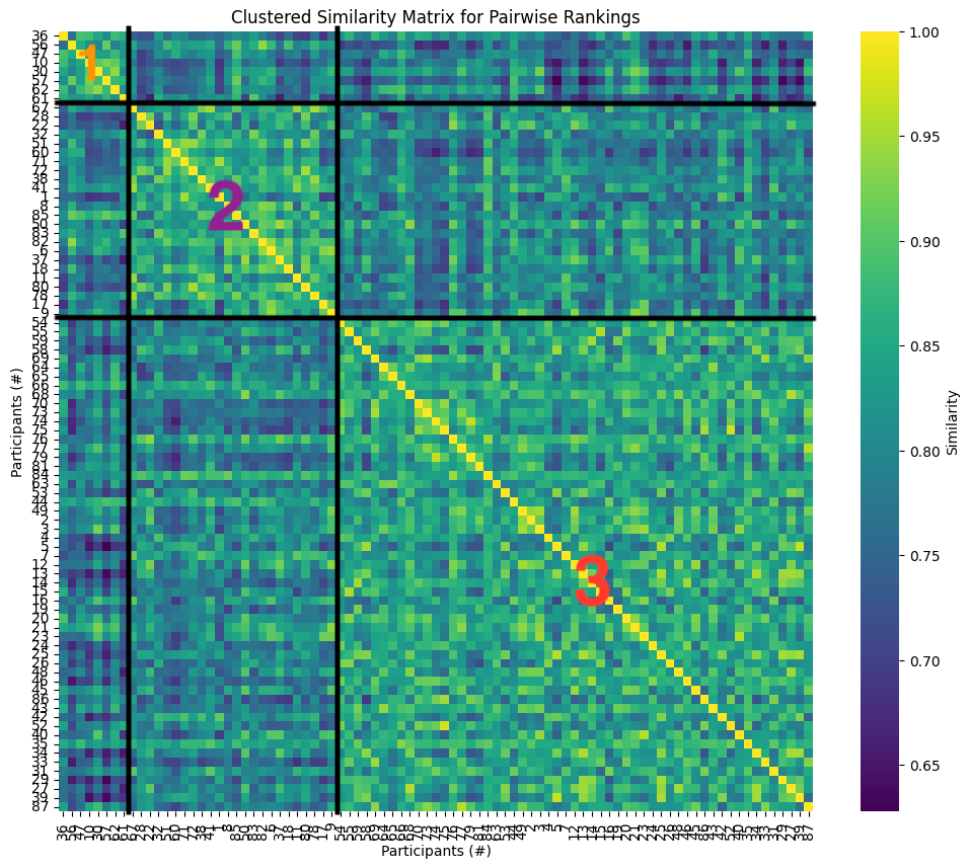


Figure 5.12: The heatmap is a one-to-one matrix, capturing the calculation of similarity among respondents in their AHP pairwise rankings. Clusters were established with a 75% similarity threshold limit.

further establish how such distinctions can consider decision criteria differently from our initial findings. This helps us better grasp the group results and the related tranches in the criterion preference for the decision-making process.

Figure 5.12 summarizes the similarity calculations among the respondents for pairwise comparisons. The most notable aspect of this evaluation is the observed clusters, indicated with the black borders. The indicated clusters are defined around group participants who exhibit similar preferences in the pairwise review of the decision criteria. Three notable groupings from this analysis were identified using a similarity limit of 75%. Lowering the threshold produces further subdivisions in the cluster groups. Figure 5.13 illustrates the clustering process of comparative evaluations of respondents with lower levels of similarity, showing how this analysis can identify specific patterns in the relationship within the data.

However, for our analysis, lowering the threshold further below 75% is not necessary, as it would result in an excessive number of less meaningful clusters. This would only further complicate the analysis without providing additional significant insights. Because of this, we maintain our focus on the three original groupings. These groupings, shown in Figure 5.12 & 5.13, are the respective groups assigned for all future evaluations. A significant takeaway from this section of our analysis is the three cluster groups identified.

Three valuable insights can be determined by examining the clusters. The first is the ability to gauge the level of consensus. As we have observed, the tighter the size of the cluster and the higher the average value of similarity, the greater the overall consensus in the group. Cluster Group 1 is found to have the highest consensus among the three

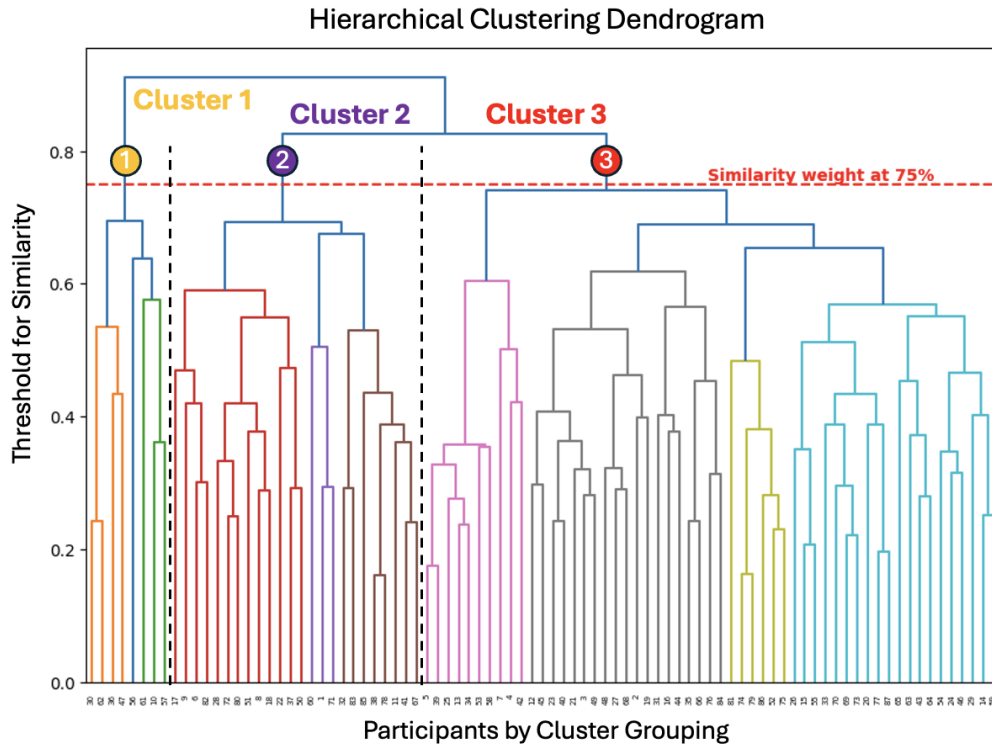


Figure 5.13: The Hierarchical Clustering Dendrogram provides a visual representation of the clustering process applied to the participants' data. Each vertical line represents a participant, and the horizontal lines indicate the merging of clusters.

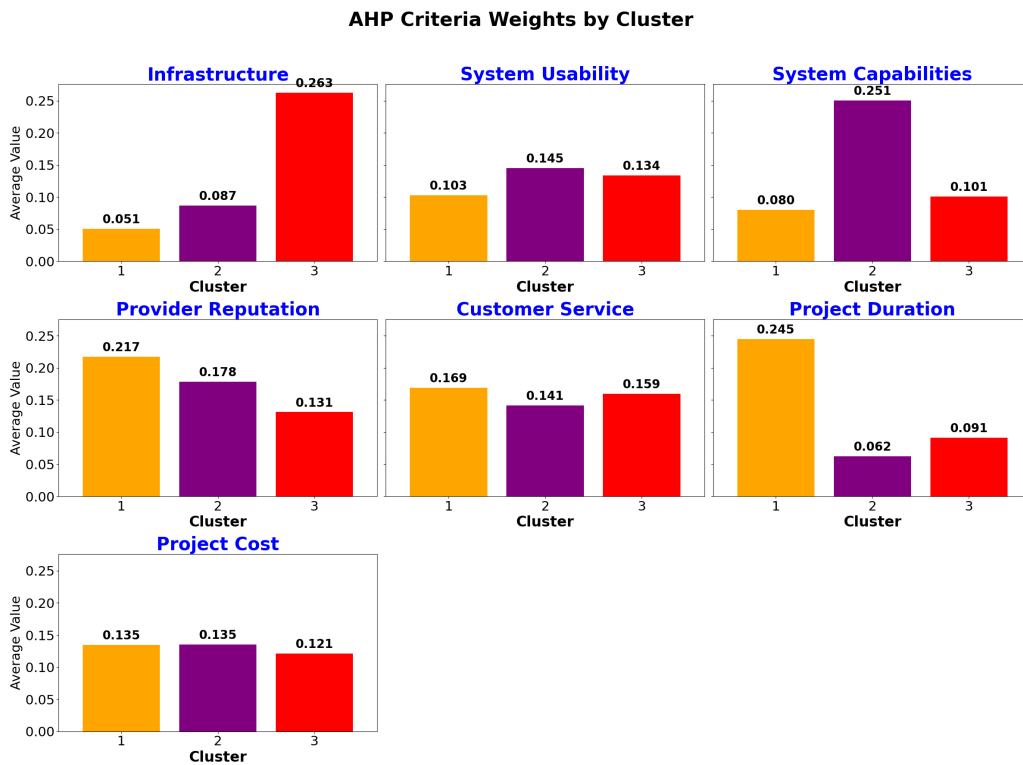


Figure 5.14: From these presented AHP criteria weights by cluster we capture a more comprehensive understanding of the cluster groups.

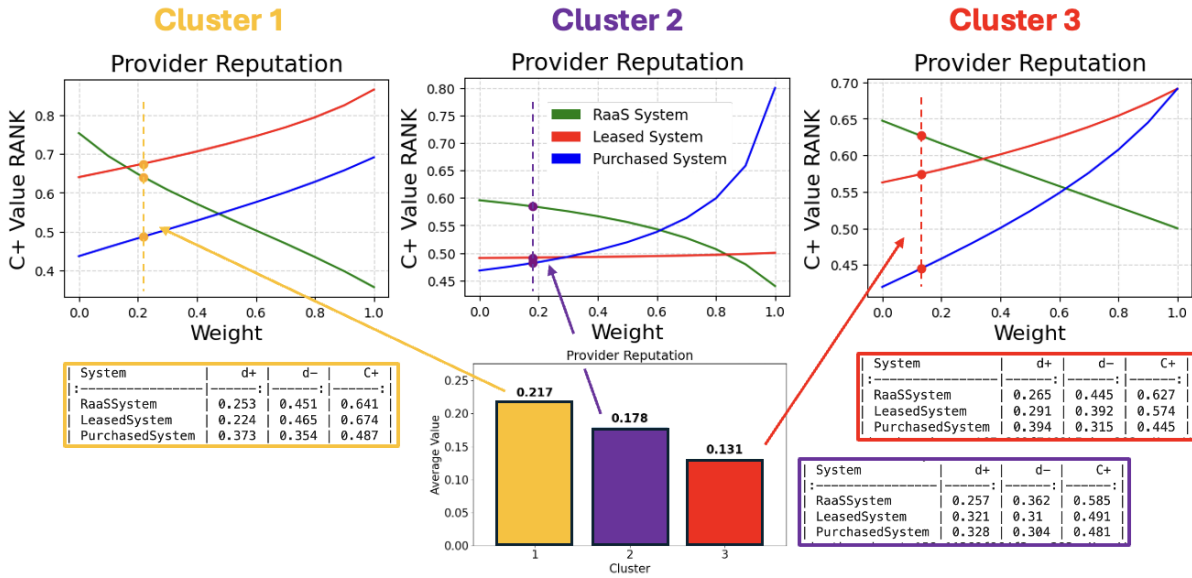


Figure 5.15: Performing the sensitivity analysis on the individual cluster groups, there are new behaviors that emerge from the changing of weights and ranges of the associated criteria for each group.

groupings, as seen in Figure 5.12. Next, we can identify divergence and diversity in the preference for the decision criteria for the cluster groups. This is accomplished by taking these cluster grouping assignments and applying the previously defined weight assessment through the AHP process. These results are shown in Figure 5.14, which summarizes the set of re-evaluated weights of the three groups of groups across the seven defined criteria.

Our analysis provides further distinctions that can be established in the diversity of cluster groups. For example, all three groups have significantly different weights for several categories. We can further examine these results to reassess their impacts on the sensitivity analysis previously performed for additional information, as shown in Figure 5.15.<sup>8</sup> This analysis captures a section of the results that helps identify how the cluster groups exhibited unique sensitivity profiles based on the weights assigned to the seven criteria reviewed. Figure 5.15 shows the sensitivity analysis of each group's 'Provider Reputation' criterion. As highlighted, the weights assigned to this criterion differ significantly among the clusters. The graphs show how changes in the Provider Reputation weight affect the C+ value ranks of each group's three systems (Leased System, Purchased System, RaaS System). These values are recalculated for each cluster again using the TOPSIS method. The recalculated values of d+, d-, and C+ (shown in the figure) for each group provide additional information on decision-making preferences. These calculations show the importance of identifying these groups and their impacts on the overall decision-making process.

The preceding results and analysis lead to a better understanding of the varying priorities and concerns of the respondents across these groupings. Upon conducting this analysis, we observe that a series of themes in these groupings are beginning to appear, as shown for the three groups in the list below and as derived from Figure 5.14.

<sup>8</sup>This highlights the comparison of "Provider Reputation". The tables in each group provide detailed values of C+, d+ and d- for the systems, while the graphs reinforce the superiority of each system relative to a changing set of weights.

**Cluster 1** A difference in the preference of the criteria is indicated around the importance of “Project Duration” and “Provider Reputation.” This difference in criteria weights may suggest that these respondents see higher pressure on the time component of implementing an automation system and, therefore, are also risk-averse with their service providers. This relates to the fact that these respondents likely find that the lower the provider’s reputation, the more likely this lower service level leads to complications of the integration effort, ultimately impacting the project timeline.

**Cluster 2** The indicated weights are significantly different and place a higher value on “System Capability” and “System Usability” criteria. This may indicate that the respondents in this group are looking for reliable and user-friendly systems in their decisions.

**Cluster 3** The indicated weights primarily reflect the previously defined weights from the original analysis. This makes sense as this grouping is the largest in overall size and would carry the highest likelihood of resembling the original weights in the decision criteria. From this, we can infer that the respondents in this group are very attentive to the requirements for how a new system can be integrated into existing facilities. Thus, this grouping may likely see the importance of customer service as of higher value in their decision.

### 5.0.10 Statistical Analysis

Having established the different cluster groups and their basis in the prioritization of the criteria by the respondents, we will present the results to further substantiate these clustering groups using statistical analysis. This leads us to the final of the three primary distinctions that can be extracted from the cluster analysis, the demographic profiles among the groupings. This was achieved using the statistical methods of applying PCA and chi-square tests. Together, the combined evaluation and results provide validation of the demographic and decision-making differences between these cluster groups.

Figure 5.16 shows the distribution of the stacked chart of the demographic categories. We can see a distinction in Experience between the three groups. Participants in group 1 tend to have more experience, with a notable concentration in the range of 15-20 and +20 years of experience. Other areas, such as education, were found to be somewhat consistent between the groups, with a strong concentration on a bachelor’s degree level of education. After further review, we begin to see a segmentation of our original demographics, which provides us with some of our initial views on how the groups exhibit distinct profiles from their respondents. This begins to identify areas with a pattern in the respondents’ background and preference in the decision in a wide sample of individuals.

This is an effective review of individual variables; however, the method does not allow for a greater understanding of the combined effects of multiple demographic factors. The MCA analysis allows for a more extensive review of this collective distinction in the variables. Figure 5.17 shows the result of our MCA analysis. The first two calculated multiple correspondence components explain approximately 25% of the variance in the data set. This confirms that the included components explain the most significant variance observed in the dataset. However, we can choose to visualize as many MCA components as needed. We show only the first two components of MCA in Figure 5.17, because they capture the most variance in the data. Figure 5.17 shows three distinctions in

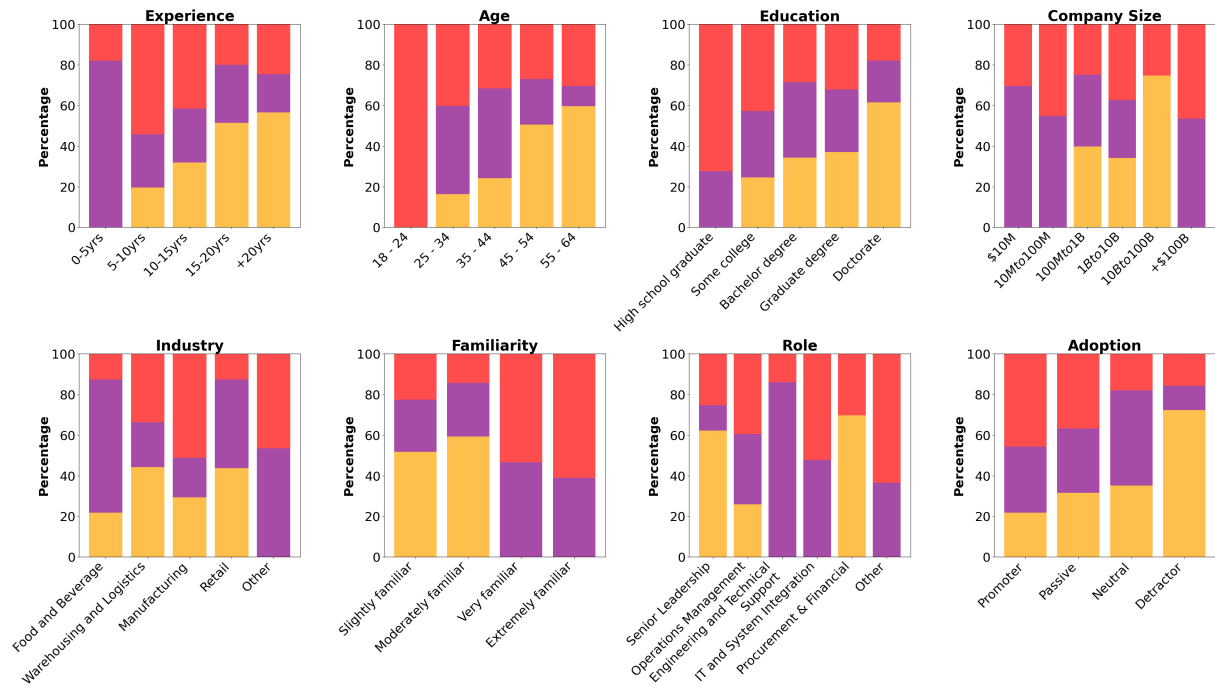


Figure 5.16: Illustrates the demographic distribution across three clusters for various categories. This helps to identify the distinct differences in each group.

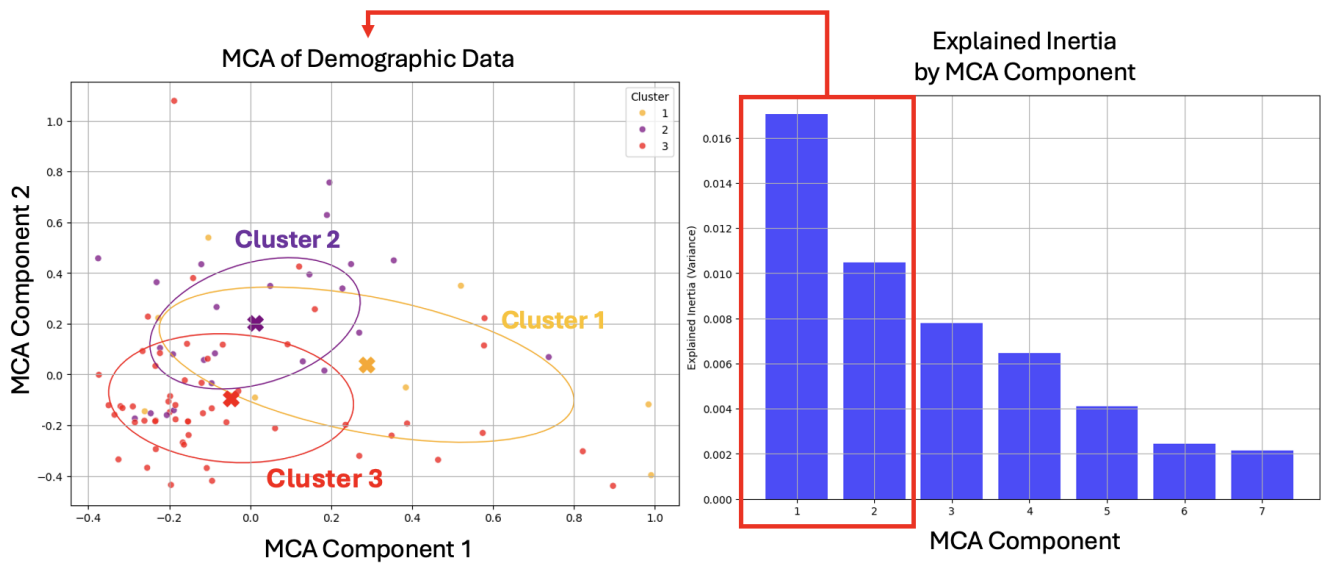


Figure 5.17: The data points projected onto the first two MCA components. Each point represents an individual, colored by cluster membership. The ellipses and centroids indicate the areas of highest concentration for each cluster.

the MCA plot. This shows that demographic data were an effective source for further identification of the unique characteristics of groups. Ultimately, MCA helped successfully reduce the complexity of our demographic dataset, revealing clear clusters with distinct characteristics.

From this, we conducted a further statistical review using the Chi-square test to validate the visual patterns observed in the MCA analysis. This method helped us determine whether a significant association existed between the categorical variables in focus. Figure

5.18 shows these results and the variables that were found to be statistically significant. Each bar represents a different attribute and, on the x-axis, the associated chi-squared value. As typically defined, we indicate the “significant” vs. “not significant” with any attribute seeing a p-value <0.05. Each attribute aligns directly with the demographic we discussed previously in our segmentation of the cluster groups.

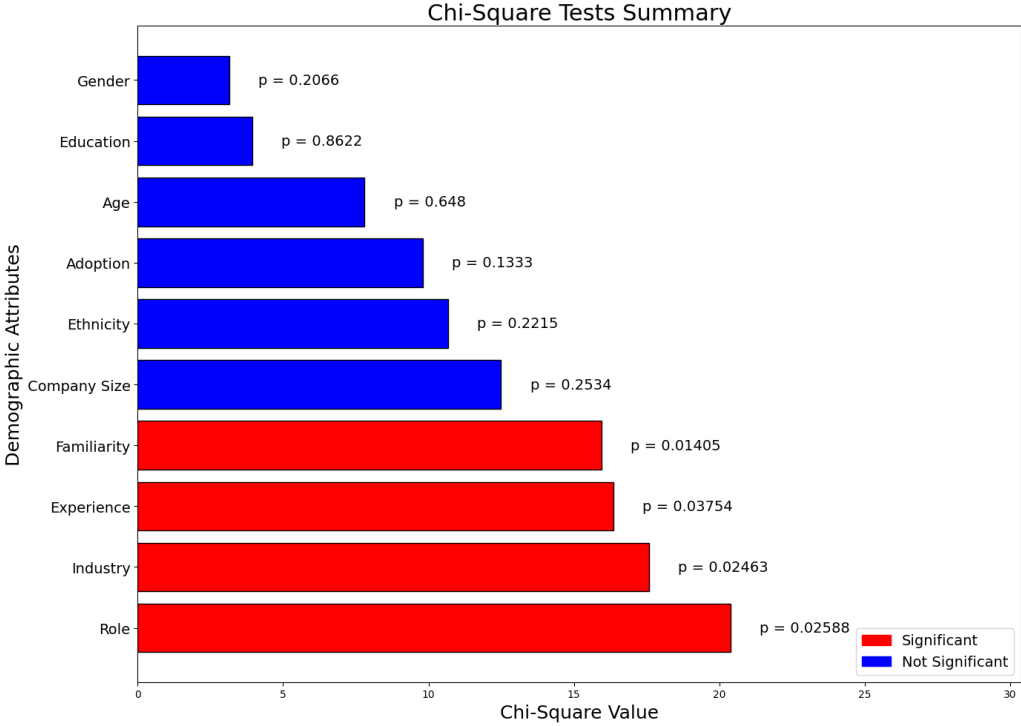


Figure 5.18

The numerical p-value we obtained from this analysis is another way to show which variables were statistically significant compared to the three cluster groups: Familiarity, Experience, Industry, and Role. All of these were identified as influencing the membership of the group we identified. This suggests that these factors influence the weight that we previously associated with these groupings. Interestingly, the other categorical variables included did not have significance. From this, we will further identify strategies based on these significant factors to support possible adjustments to be more inclusive of these specific needs and the characteristics of the identified groups. This set of results has led us to a direct association of variables on which to focus to improve communication in the decision-making process in the context of adopting robotic automation.

# Chapter 6

## Discussion & Conclusion

### 6.1 Summary of Findings

Here, we present the implications that can be derived from the results of our study. Our description of the findings has revealed significant information about the decision-making process. This reflects a real snapshot of various industry professionals on automation in warehouse operations or related industries. We identified three key areas in our findings:

- 1 - Identification of the preferred decision criteria, for which we identified the key criteria and an overall consensus from a field of respondents on the priority of these criteria.
- 2 - Established a decision framework to specify a preferred integration method. With this, we could convert the placed value of respondents in the systems and preferences in the decision-making process to demonstrate specific strengths for a preferred method.
- 3 - Finally, we identify specific decision-maker profiles from our field group of respondents; we revealed three distinct groups based on similarity in the pairwise evaluation from our field study.

The results from this indicated that demographic attributes statistically impacted decision-making. These identified demographic clusters were found to exhibit unique preferences and priorities, which we can now reflect on.

**Cluster 1:** Respondents within this group value the provider's reputation and customer service mostly highly among all groups. The demographics of this group were found to be less familiar with automation overall but had more industry experience, which were identified as statistically significant variables. This cluster was found to represent larger firms and senior-level participants. Finally, the group's weight on project duration indicates a higher preference for faster implementations. From this, it is determined that the group usually prefers dependable and quick-implementable solutions. Together, this assessment in profile supports the inclination of this decision group to focus on trust and support for the automation solution.

**Cluster 2:** This group measured priorities in the decision criteria and highly valued system capabilities and usability overall. As the group was found to have a more

balanced age and experience, this cluster likely represents a wider array of experienced decision makers. There is an indication that this group held a preference for more advanced but user-friendly systems. The fact that this finding was less concerned with project duration may suggest they are willing to invest more time for better capabilities in a solution.

**Cluster 3:** This group primarily values a dominating importance for the required infrastructure of a system. This indication aligns with a focus on robust and scalable systems such as those offered through a RaaS platform. This grouping places a strong emphasis on system usability. From this, it is likely that the decision makers here represent companies that prioritize strong infrastructure and usability to support complex operations. As this cluster group was by far the largest, it likely reflects a more common profile of decision makers. From these inferences, we can suggest that the cluster group finds a more significant need for systems that are easy to use and integrate into existing operations.

These insights confirm that a one-size-fits-all approach to automation adoption is insufficient. Instead, solutions must be tailored to the specific needs and priorities of different demographic groups to enhance adoption success and evaluation efficiency. We have underlined the relevance of understanding the unique priorities, particular needs, and preferences of the possible subgroups present within these decisions. Understanding these different profiles will improve communication and customized decision-making plans to properly use automated solutions.

## 6.2 Key Contributions

**Development of a Decision-Support Framework:** A comprehensive Multi-Criteria Decision-Making (MCDM) framework was developed to assist decision-makers in evaluating various automation implementation strategies. This framework integrates the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The strength of this method allowed us to objectively evaluate the imperfect data in the provided ranges from respondents associated with their experience with automation projects and associate this with their desired integration method.

**Empirical Validation Through Field Study:** The proposed decision-support framework was tested empirically through a field study involving verified industry professionals. The study collected responses from a statistically verified distribution of participants. This opened a possibility for future application in the framework and demonstrated its robustness in performing the intended assessment of the respondents.

**Insights into Decision-Maker Priorities:** From our research, we identified and analyzed the prevailing decision criteria reflective of the "state of practice" for automating warehouse operations. We then produced an understanding of the preferences and priorities of decision makers regarding these criteria. This established valuable insights into common factors that can impact the selection of integration systems for adopting automation.

**Cluster Analysis of Decision-Maker Profiles:** Our decision to leverage recognized approaches in cluster analysis and combine this with other common statistical methods

helped the study identify distinct profiles among decision-makers. This differentiation laid out a tailored approach in recommending automation solutions. This contribution opens further research and works around improving the ability to ensure the specific needs and preferences of different decision maker clusters, which can improve the ability to implement an automated solution.

**Framework for Future Research and Practice:** The contributions of this thesis have laid out a path for application in the discussed methods. However, we feel that this framework supporting decision making could be extended to a more broad range of use cases and industries. Through follow-up research, we could more fully understand how demographic elements affect decision-making changes over time. This can be particularly useful in observing changes as new technologies emerge and the workforce demographics shift. We could look at how various decision criteria and certain demographic elements correlate. We feel this would improve the ability to facilitate more dynamic and effective automation proposals.

### 6.3 Managerial Implications of Findings

The managerial implications in this thesis highlight numerous factors necessary to efficiently apply warehouse automation technologies to operations. The research underscores the importance of identifying the requirements and preferences of various demographic groups to better align with a preferred method to implement automation systems. The lesson is that companies focusing on these decision-making profiles and their specific needs will probably improve their success and efficiency in using automation. Realizing that a one-size-fits-all solution is inadequate helps them to develop more informed and successful decision-making processes by personalizing.

These findings further demonstrate the need to know the preferences and priorities of various decision-maker profiles obtained by cluster analysis. A comprehensive MCDM framework that combines AHP with TOPSIS offers an effective means of objectively evaluating several automation implementation strategies. Since our study is validated by actual field research, this framework shows its usefulness and stability when evaluating respondents' preferences and decision criteria.

The study's sensitivity analysis offers a helpful overview of the flexibility of the evaluation in particular settings, thus establishing the most effective decision criteria and identifying areas where more data could help reduce uncertainty. This study supports scenario management activities, increasing decision makers' confidence in selecting the best approach to implement automation.

In the end, the consequences of this thesis imply that companies should concentrate on creating specialized automation options that satisfy the particular requirements and preferences of various decision-making profiles. By doing this, businesses can improve communication, decision-making efficiency, and the general effectiveness of adopting automation. This change in practice would, therefore, produce more efficient and customized marketing plans from providers and identify offers that meet the special needs of the target customer.

## 6.4 Limitations And Future Work

Although this study is extensive, some design constraints must be acknowledged. First, we identify the potential for bias introduced by data collection. We depend on self-reported information from survey participants that cannot be eliminated or ignored. Furthermore, although sufficient for preliminary research, we acknowledge that the current

collected sample size could represent only a portion of the industry. It is therefore recommended that the sample size be expanded and other choice criteria be investigated to help future studies overcome these restrictions. Second, the study concentrated on a limited set of criteria. Although these criteria were well researched and supported, they may not adequately reflect all the subtleties of decision making in many organizational environments. Lastly, the data collected reflect the decision-making landscape at a specific time. Changes in technology and market conditions can influence the relevance of the findings over time.

## 6.5 Conclusion

Finally, this study emphasizes the intricate interaction among several research areas that influence decision making about the acceptance of automation systems in warehouse operations. We have provided a structure that can direct both theoretical studies and actual implementations by identifying and evaluating the main criteria and preferences of decision makers. The results highlight the need for automation solutions customized to the particular requirements of various decision-making profiles, therefore supporting better informed and successful industry decision-making procedures.

# Appendix A

## Warehouse KPI Evaluation

**Economic Aspects-**[45] Performance metrics in this area can be grouped into general, time-related, cost-related, and information systems.

The general areas of metrics look at things like how much a system can do and how it is used? They involve throughput, or what is the numerical capacity of parts going through the system? How much space does the system take up? How much space can be increased or decreased? Can the space flex from one operation to the next? What is the system used for and for what period?

Cost and time are reported to have the most significant impact on the overall economics of a warehouse operation. A cost analysis should be used to identify the breadth and depth of an operation. Many different cost factors must be considered, which we will detail in later sections. Time is also an essential factor. What are the cycle times? How much time is wasted? Can it be reduced?

Finally, performance indicators of warehouse information systems typically include assessing their efficiency and effectiveness.

**Environmental Aspects-**[45] The "Environmental KPIs" section provides an overview of the standard measurements used to assess the impact of operational activities, products, and services on the environment. For instance, by examining these measurements, one may analyze an organization's emissions and identify a reason for the change. In addition, these metrics are further noted to help support the ability to review a product or service's life cycle assessment. An interesting point highlighted in the report identifies how measuring these metrics could be more helpful. Upon reviewing this section, the authors identify how, when you look at these operational measures in the context of the trade-offs involved in an organization's critical processes, you start to understand the costs and potential harms associated with various activities.

**Social Aspects-**[45] The Social KPIs section considers the interaction between the operations and various social entities. The few existing that are noted in this segment touch mainly on the interaction between human labor and automation. Importantly, it is noted that these indices will likely tend to focus on indices on operator safety. The literature notes that this grouping is largely based on social sustainability activities and ISO 26000 guidelines. Examples in this KPIs measure such as human utilization, human error, work safety, human activity time, machine safety, noise levels, activity automation, and the number of operators per area.

# Appendix B

## Steps to Leverage the Analytic Hierarchy Process (AHP)

The Goepel, K.D. (2018) documentation further supports the implementation of this part of the AHP method which we will follow further.[60] As we have established the AHP process uses a pairwise comparison matrix (A) below to compare how important each of n criteria is. The matrix A is defined as follows:

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \quad (\text{B.1})$$

### Step 1: Normalize the Matrix

From this we then normalize the matrix by dividing each element by the sum of its column:

$$A_{\text{normalized}} = \begin{bmatrix} \frac{a_{11}}{\sum_{i=1}^n a_{i1}} & \frac{a_{12}}{\sum_{i=1}^n a_{i2}} & \cdots & \frac{a_{1n}}{\sum_{i=1}^n a_{in}} \\ \frac{a_{21}}{\sum_{i=1}^n a_{i1}} & \frac{a_{22}}{\sum_{i=1}^n a_{i2}} & \cdots & \frac{a_{2n}}{\sum_{i=1}^n a_{in}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{a_{n1}}{\sum_{i=1}^n a_{i1}} & \frac{a_{n2}}{\sum_{i=1}^n a_{i2}} & \cdots & \frac{a_{nn}}{\sum_{i=1}^n a_{in}} \end{bmatrix} \quad (\text{B.2})$$

### Step 2: Calculate the Row Averages

We take this and then calculate the row averages to obtain the eigenvector:

$$\text{Eigenvector (unnormalized)} = \begin{bmatrix} \frac{\sum_{j=1}^n a_{1j}}{n} \\ \frac{\sum_{j=1}^n a_{2j}}{n} \\ \vdots \\ \frac{\sum_{j=1}^n a_{nj}}{n} \end{bmatrix} \quad (\text{B.3})$$

### Step 3: Normalize the Eigenvector

This sets us up to then normalize the eigenvector so that the sum of its components equals 1:

$$\text{Eigenvector (normalized)} = \frac{\text{Eigenvector (unnormalized)}}{\sum_{i=1}^n \text{Eigenvector (unnormalized)}_i} \quad (\text{B.4})$$

**Step 4:** Here we find the principal eigenvalue. Simply multiply the original matrix by the normalized eigenvector and then divide each element by the corresponding element of the normalized eigenvector:

$$A \times \text{Eigenvector (normalized)} = \lambda_{\max} \times \text{Eigenvector (normalized)} \quad (\text{B.5})$$

The principal eigenvalue is the average of the resulting values.

**Step 5:** Calculate the Consistency Index (CI)

The AHP method offers a way to check how much sense a set of direct comparison judgments makes with respect to their consistency. The key to this idea is to say whether the comparisons made by a decision maker are logical or coherent. We use a measure called the Consistency Index (CI). This value indicates whether or not we should reevaluate our direct comparison judgments because of what they imply about the appropriateness of our model. The reasons for the incoherence can be decision-making bias or an inappropriate assignment of matrix values in the model.[60]

The consistency index is calculated as:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (\text{B.6})$$

**Step 6:** Calculate the Consistency Ratio (CR)

Use the linear fit for the calculation of the consistency ratio:

$$CR = \frac{\lambda_{\max} - n}{2.7699n - 4.3513 - n} \quad (\text{B.7})$$

where:

- $\lambda_{\max}$  is the maximum eigenvalue of the judgement matrix
- $n$  is the order of the matrix (number of criteria)

When completing this analysis, the supporting authors recommend finding and reviewing the top inconsistent judgments if the consistency ratio  $CR$  is more than 10%. [69] To account for this suboptimal value  $CR$  in the analysis of the decision matrix  $d_{ij}$ , the author proposes to build the inconsistency matrix based on the calculated weights  $w_i$  and  $w_j$  as

$$e_{ij} = \frac{d_{ij} \cdot w_j}{w_i} \quad (\text{B.8})$$

and determine the highest  $e_{ij}$ . Decision makers can then make the necessary changes to raise the inconsistency score by highlighting pairs of comparisons that match.[61]

# Appendix C

## Steps Integrating TOPIS into our AHP results

**Step 1:** Construct the Decision Matrix: The following decision matrix with  $m$  options linked to  $n$  characteristics (or criteria) is evaluated using the TOPSIS approach.

$$D = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \end{bmatrix} \quad (\text{C.1})$$

where  $d_{ij}$  is the performance of alternative  $i$  on criterion  $j$ .

**Step 2:** Normalize the Decision Matrix: Through the attempt to convert the different attributes into non-dimensional characteristics, comparison among the attributes is made possible.

$$R = \begin{bmatrix} \frac{d_{11}}{\sqrt{\sum_{i=1}^m d_{i1}^2}} & \frac{d_{12}}{\sqrt{\sum_{i=1}^m d_{i2}^2}} & \cdots & \frac{d_{1n}}{\sqrt{\sum_{i=1}^m d_{in}^2}} \\ \frac{d_{21}}{\sqrt{\sum_{i=1}^m d_{i1}^2}} & \frac{d_{22}}{\sqrt{\sum_{i=1}^m d_{i2}^2}} & \cdots & \frac{d_{2n}}{\sqrt{\sum_{i=1}^m d_{in}^2}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{d_{m1}}{\sqrt{\sum_{i=1}^m d_{i1}^2}} & \frac{d_{m2}}{\sqrt{\sum_{i=1}^m d_{i2}^2}} & \cdots & \frac{d_{mn}}{\sqrt{\sum_{i=1}^m d_{in}^2}} \end{bmatrix} \quad (\text{C.2})$$

**Step 3:** Construct the Weighted Normalized Decision Matrix:

$$V = R \cdot W \quad (\text{C.3})$$

where  $W$  is the diagonal matrix of weights derived from AHP.

$$V = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1j} & \cdots & v_{1n} \\ \vdots & \vdots & & \vdots & & \vdots \\ v_{i1} & v_{i2} & \cdots & v_{ij} & \cdots & v_{in} \\ \vdots & \vdots & & \vdots & & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mj} & \cdots & v_{mn} \end{bmatrix} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_j r_{1j} & \cdots & w_n r_{1n} \\ \vdots & \vdots & & \vdots & & \vdots \\ w_1 r_{i1} & w_2 r_{i2} & \cdots & w_j r_{ij} & \cdots & w_n r_{in} \\ \vdots & \vdots & & \vdots & & \vdots \\ w_1 r_{m1} & w_2 r_{m2} & \cdots & w_j r_{mj} & \cdots & w_n r_{mn} \end{bmatrix} \quad (\text{C.4})$$

**Step 4:** Determine the Ideal and Negative-Ideal Solutions:

$$A^+ = \left\{ (\max_i v_{ij} \mid j \in J), (\min_i v_{ij} \mid j \in J') \mid i = 1, 2, \dots, m \right\} \quad (\text{C.5})$$

$$= \{v_1^*, v_2^*, \dots, v_j^*, \dots, v_n^*\}$$

$$A^- = \left\{ (\min_i v_{ij} \mid j \in J), (\max_i v_{ij} \mid j \in J') \mid i = 1, 2, \dots, m \right\} \quad (C.6)$$

$$= \{v_1^-, v_2^-, \dots, v_j^-, \dots, v_n^-\}$$

where  $J = \{j = 1, 2, \dots, n \mid j \text{ associated with benefit criteria}\}$

$$J' = \{j = 1, 2, \dots, n \mid j \text{ associated with cost criteria}\}$$

Then it is assured that the two produced alternatives, A+ and A-, represent the ideal solution, which is the most preferred option, and the least desirable solution, which is the negative-ideal solution.

**Step 5:** Calculate the Separation Measures: Euclidean distance in n dimensions is a measure of the distance between each possibility.

$$S_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2}, \quad | i = 1, 2, \dots, m \quad (C.7)$$

$$S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2}, \quad | i = 1, 2, \dots, m \quad (C.8)$$

**Step 6:** Calculate the Relative Closeness to the Ideal Solution:

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-} \quad 0 < C_i^* < 1 \quad | i = 1, 2, \dots, m \quad (C.9)$$

**Step 7:** Rank the Alternatives: The alternatives are ranked on the basis of the relative proximity to the ideal solution, with higher values indicating better alternatives.

# Appendix D

## Group Consensus Cluster Analysis

### Shannon Entropy Calculation

This section provides a step-by-step demonstration of the Group Consensus Cluster Analysis algorithm using Shannon Alpha- and Beta-Entropy. This is referenced from the algorithm described in Klaus D. Goepel's paper, "Group Consensus Cluster Analysis using Shannon Alpha- and Beta-Entropy." [66]

#### Step 1: Shannon Entropy for Individual Decision-Makers

Shannon entropy  $H$  is calculated as:

$$H = - \sum_{i=1}^n w_i \ln(w_i)$$

where  $w_i$  are the relative weights of the categories.

#### Step 2: Alpha and Beta Entropy

**Gamma Entropy** Gamma entropy  $H_\gamma$  for the group is:

$$H_\gamma = - \sum_{i=1}^n w_{i,\text{avg}} \ln(w_{i,\text{avg}})$$

where  $w_{i,\text{avg}}$  is the average weight for category  $i$ :

$$w_{i,\text{avg}} = \frac{1}{k} \sum_{j=1}^k w_{ij}$$

**Alpha Entropy** Alpha entropy  $H_\alpha$  for a group of  $k$  decision-makers is the average Shannon entropy of all individual decision-makers:

$$H_\alpha = \frac{1}{k} \sum_{j=1}^k \sum_{i=1}^n -w_{ij} \ln(w_{ij})$$

**Beta Entropy** Beta entropy  $H_\beta$  is calculated as the difference between gamma entropy and alpha entropy:

$$H_\beta = H_\gamma - H_\alpha$$

### Step 3: Diversity Measures

**Alpha Diversity** Alpha diversity  $D_\alpha$  is the exponential of alpha entropy:

$$D_\alpha = \exp(H_\alpha)$$

**Gamma Diversity** Gamma diversity  $D_\gamma$  is the exponential of gamma entropy:

$$D_\gamma = \exp(H_\gamma)$$

**Beta Diversity** Beta diversity  $D_\beta$  is the ratio of gamma diversity to alpha diversity:

$$D_\beta = \frac{D_\gamma}{D_\alpha}$$

### Step 4: Consensus Indicator

The consensus indicator  $S$  is the reciprocal of beta diversity:

$$S = \frac{1}{D_\beta} = \frac{D_\alpha}{D_\gamma}$$

This is transformed to a relative index of homogeneity:

$$S = \frac{\frac{1}{D_\beta} - \frac{1}{n}}{1 - \frac{1}{n}}$$

## Similarity Matrix

### Matrix Construction

Calculate the consensus indicator  $S_{ij}$  for all pairs of decision-makers  $i$  and  $j$ :

$$\mathbf{M}_S = \begin{pmatrix} 1 & S_{01} & \cdots & S_{0k} \\ S_{10} & 1 & \cdots & S_{1k} \\ \vdots & \vdots & \ddots & \vdots \\ S_{k0} & S_{k1} & \cdots & 1 \end{pmatrix}$$

## Cluster Algorithm

### Initial Threshold

Set an initial threshold  $th$  (e.g., 75%) and count the number of elements in each row of  $\mathbf{M}_S$  exceeding this threshold.

## Clustering

Identify the row with the highest count to determine the first cluster. Lower the threshold if no clusters are found and repeat.

## Optimal Clustering

Repeat the process to find optimal clustering by minimizing the number of clusters and dissociated decision-makers:

minimize  $(m_{cl} + m_{uc})$  with conditions  $m_{cl} > 1$  and  $m_{uc} < 3$

# Appendix E

## Pairwise Attribute Descriptions

### List of Attributes Asked For Pairwise Evaluation

#### **Required Infrastructure**

Refers to how well automation systems can be integrated with a facility's technological infrastructure. Poor integration can cause malfunctions and increase operational costs. Since automation systems are used across different departments, combining the authorization and authentication systems is crucial for the success of the automation project.

#### **Project Duration**

This refers to how well the automation project timeline aligns with the facility's needs. Simply, it shows the time between the project's start and when the automation system is fully operational. The project duration includes activities such as installing and configuring hardware and software, training staff, designing and implementing the system, migrating from previous systems, testing, and going live with the automation system.

#### **Project Budget**

This refers to the total cost of integrating automation into the facility. This includes initial expenses for purchasing hardware and software, installation costs, and ongoing support and maintenance. The budget criterion also covers implementation costs and any additional costs required to support the automation system over its lifecycle.

#### **System Usability**

This is crucial for the acceptance of a new automation system. If users find it difficult to operate the system, their attitude may change, leading to project failure. In facility automation, usability refers to the system's ease of use, including critical functionalities like intuitive interfaces, straightforward operation procedures, and efficient error-handling capabilities.

#### **System Capability**

This refers to the functionalities that the automation system provides to its users. These can include built-in, directly available functions, optional features that can be added as needed, and custom-developed solutions for specific requirements. To test the system's capabilities, a pilot project can be conducted to evaluate its performance and suitability for the facility's needs.

### **Provider Reputation**

Refers to the company responsible for implementing the automation project. Beyond software criteria, the competencies and reputation of the service provider are crucial in the selection process. To ensure an accurate evaluation, the company's references should be checked, and previous projects should be reviewed. This information provides insight into the vendor's capabilities and potential to complete the project successfully.

### **Customer Service**

Integrating automation into a facility refers to the availability of support options and channels for the customer. Lack of technical support can cause system malfunctions, leading to various adverse outcomes. Components of this criterion include system usage manuals, commercial support and training, and ongoing system development and updates.

## **Robotic Automation Implementation Approaches**

### **Lease Agreement**

A contract to use equipment for a specified payment period without owning the asset.

### **Purchase**

Buying and owning the equipment outright, with full responsibility for maintenance and upkeep.

### **Robot-as-a-Service (RaaS)**

A service model where robotic automation is rented on a subscription basis, including maintenance and updates, without ownership responsibilities.

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