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From AGVs to AMRs: A Decision-Driven Framework for the Selection and Implementation of Autonomous Transport Systems in Intralogistics.

Master thesis in Management Engineering

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Abstract

The transition toward automated material handling solutions is increasingly pursued as an urgent necessity in modern intralogistics, yet many manufacturing companies find themselves unprepared and lack of awareness regarding the exact process required to execute it. While various autonomous transport technologies, such as Automated Guided Vehicles (AGVs) and Autonomous Mobile Robots (AMRs), are available, industrial decision-makers are often unaware of structured methodologies to evaluate and compare vehicle suitability against their operational requirements. This makes it difficult to assemble fragmented pieces of knowledge scattered across literature and industry practice. The present study addresses this bottleneck by providing a structured decision-support framework and guidelines for the preliminary implementation of the selected fleet. Using a mixed-methods approach, a qualitative parameters prioritization matrix was developed to synthesize key vehicle and process characteristics. This qualitative tool is integrated with a Total Cost of Ownership (TCO) model; rather than providing rigid quantitative data, the TCO highlights overlooked operational variables that translate into financial advantages. The framework was calibrated and validated through industrial field insights, involving a prominent automated transport systems supplier and a large-scale manufacturing end-user within the automotive sector. The findings demonstrate that a successful automation path depends on balancing environmental dynamics with system predictability: while AMRs excel in highly flexible configurations, AGVs remain a critical, reliable solution that should not be underestimated where operational consistency is crucial. The resulting framework offers logistics managers a holistic, replicable guide to streamline knowledge, reduce implementation risks and evaluate the hidden economic benefits of autonomous transport adoption.

Keywords: Intralogistics Automation, Automated Guided Vehicles (AGV), Autonomous Mobile Robots (AMR), Decision-Support Framework, Total Cost of Ownership (TCO), Technology Selection

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Francesca Grigolato

During the drafting of this thesis, the author used AI-based language models (specifically Google Gemini) exclusively for linguistic revision and the formatting of interview transcriptions. These tools were employed purely to improve the grammatical accuracy and readability of the manuscript. The conceptual framework, data collection, TCO modeling and all critical analyses were independently developed and remain entirely the original work of the author.

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1. Introduction

This first chapter provides the essential context for the study by outlining its background, purpose and limitations. It explores the current complexities companies face when integrating AGV (automated guided vehicle) and AMR (autonomous mobile robot) systems into their internal processes, framing this research as a strategic response to such operational challenges. Following this analysis, the chapter defines the core purpose of the study and the boundaries that delineate its scope.

1.1 Background

The spread of digitalization and automation in intralogistics has shown significant gaps regarding data collection and selection. Understanding which data is relevant and how it should be organized remains one of the main challenges regarding this topic. Indeed, having well-structured and interoperable data is the first step to ensure an informed and competitive decision. This is the context where SARDINIA project (Smart digital infrastructure for increased value of automation in manufacturing intralogistics) was born, with a focus on the manufacturing and automotive industries.

These sectors struggle to cope with the dynamics and complexity of the environment by means of an automated solution that is also flexible and cost-effective. Nevertheless, AGVs and AMRs provide concrete benefits such as reduction in lead time, cost optimization, error minimization, increased efficiency and safety in the processes (Kubasáková et al., 2026; Grover and Ashraf, 2024). The success of this transition, however, relies on careful planning. As demonstrated by Zuin et al. (2020), a change in the implementation results in a significantly higher expense compared to a change in the planning phase. Moreover, the authors highlight that working in such dynamic conditions complicates the entire process, from selection to implementation planning.

In conclusion, a well standardized infrastructure can prevent those expenses from happening and let companies simulate and predict the AGVs/AMRs performance. However, while SARDINIA project is currently focusing on creating a framework to collect and structure data, a work that supports decision-making process and the preliminary implementation planning is still missing. Having the data is not enough if companies don't know how to use it. Considering different perspectives from the beginning is the key for successful technology selection.

1.2 Purpose

This thesis will develop in parallel with the first phase of the SARDINIA project. While the project is now focusing on the creation of a digital infrastructure, this research connects the work to concrete applications. The aim is to develop a decision-driven framework to support the selection and implementation planning of AGVs and AMRs. Consequently, this framework provides a structured methodology, pragmatic tools and actionable guidelines to evaluate automation investments within complex industrial environments.

The analysis will combine process parameters such as transport frequency, payload and distance among stations, with technical and environmental constraints, like aisle width, sensors detection range and system interoperability. Specifically, the objective is to identify operational thresholds and optimal performance ranges to determine the conditions under which an AMR outperforms an AGV and vice versa. These findings will then be validated through semi-structured interviews with industry experts to verify if the defined parameters are sufficient to support the selection process and the preliminary design of the implementation phase, ensuring that the framework is robust and aligned with real-world industrial requirements.

To address these objectives and guide the analysis, the research will answer the following questions:

- RQ1: What are the key parameters and technical constraints for technology selection and implementation planning for automated material handling solutions, specifically AGVs and AMRs?
- RQ2: How can these factors shape the design of a decision-supporting tool that assists both the selection and the implementation planning in such a complex environment?

1.3 Limitations

As the thesis will be developed in a 20-week period, it faces some limitations. Due to this time constraint, the decision-supporting model will focus mainly on parameters related to the processes; technical infrastructure requirements, such as Wi-Fi stability, IoT systems and AI algorithms used in the vehicles, will be treated as background constraints, but not further developed. Furthermore, among all the available technologies, the scope will be limited to the comparison between AGVs and AMRs.

A second limitation is associated with the specificity of the research sector. While the model is designed to fit the manufacturing and automotive industries, its applicability to other sectors may be limited. Lastly, the framework will be validated through a qualitative approach rather than a quantitative one. Instead of a multi-company empirical test, the model relies on the expert judgment of a single case company, a leading European heavy-duty commercial vehicle manufacturer, to verify its logic and practical relevance. While this ensures high industrial alignment within the SARDINIA project context, it implies that the results are based on the subjective experience of professionals and the existing literature, rather than empirical statistical testing.

2. Theoretical background and state of the art

This chapter presents the theoretical foundation of the study, beginning with the definition of its core operational context: intralogistics. “Intralogistics refers to the control, execution, and optimization of internal processes and material flows within self-contained company sites such as factory plants, warehouses, and large distribution centers” (Lackner et al., 2024).

2.1 Production logistics and material handling

In this framework, production logistics represents the key link between procurement and distribution, ensuring that the right materials reach the right workstation at the right time. Therefore, effective material management and handling are essential to minimize waste and bottlenecks. In the transition toward Industry 4.0, automation has evolved from a choice to a necessity. As Fragapane et al. (2021) highlight, modern production environments require high flexibility and operational agility to cope with uncertainty. Accordingly, the adoption of automated solutions is becoming the key to competitiveness, as they provide systems capable of adapting to real-time changes where traditional ones fail.

2.2 Material handling tools

The selection of material handling tools depends on a wide array of operational factors, including the specific application, plant layout, and the required degree of autonomy. Among these alternatives, AGVs and AMRs are the most relevant solutions. An Automated Guided Vehicle (AGV) is a centralized transportation system that navigates autonomously along fixed paths to move materials in industrial environments (Fragapane et al., 2021). On the other hand, an Autonomous Mobile Robot (AMR) is a decentralized, infrastructure-free vehicle that uses onboard sensors and simultaneous localization and mapping (SLAM) technology to navigate, select the optimal route and avoid obstacles.

Understanding the technical specifications and the navigation logic of both systems is crucial for identifying the most suitable solution for a given layout; therefore, a comprehensive review of their functional characteristics is presented below.

2.2.1 Automated Guided Vehicle (AGV)

AGV is a term related to vehicles that can navigate without human intervention. They are essentially transportation systems, created to move autonomously materials inside a plant or a warehouse. For this type of vehicle, a central unit takes control decisions such as routing and dispatching for all AGVs (Fragapane et al., 2021). According to Ullrich and Albrecht (2019), the first implementation of an automated transport vehicle happened in 1953 in America, when the human on a towing wagon was replaced with an automated machine. The following year, the first AGV was used as a towing train that covered long distance transportation. Nowadays the main area of application for AGVs is intralogistics.

There are different types of AGVs according to the purposes and the criteria of the application, such as the size and weight of the materials, the complexity of the system, the operating conditions and so on (Ullrich & Albrecht, 2019). A classification of the most common AGV configurations based on their load-handling capabilities is provided in Table 2.1.

Table 2.1 - AGV load types and configurations

Load Type	**Naming**	**Typical Load**
Heavy Loads & Pallet	Forklift AGV, Piggyback AGV, Heavy Duty AGV	1 t (Heavy Duty up to 35 t)
Small Parts Handling	Mini AGV, Underrun AGV	0.5 - 1 t
Trailers	Towing Tractor	5 t
Various & Special Applications	Assembly AGV, Outdoor AGV, Special Design AGV	1 - 3 t

Adapted from (Ullrich & Albrecht, 2019), Table 2.6

2.2.2 Navigation

AGV systems utilize a variety of navigation procedures, all of which require a supporting infrastructure. This infrastructure can range from physical tracks to laser and radio guidance systems, or even rely on "natural" environmental features within the facility. The following sections examine the five primary navigation methods currently employed in industrial environments (Ullrich & Albrecht, 2019).

2.2.2.1 Physical track guidance

Physical track guidance systems rely on a fixed infrastructure installed on or within the floor. There are many types, but the most common are presented below.

Active-inductive track. This system utilizes a conductor positioned in the ground and powered by an alternating current. A sensor antenna, mounted under the vehicle, measures the intensity of the resulting magnetic field to determine its position. Based on the distance from the conductor, the field induces a voltage in two coils inside the antenna; if the vehicle deviates from the track, the resulting differential voltage serves as a signal for the motor to correct the steering. A significant advantage of this technology is its robustness, as the alternating magnetic field is not affected by road conditions or weather.

Magnetic guidance track. In this system, a metal or magnetic strip is taped directly to the floor. A sensor mounted under the vehicle detects the magnetic field changes based on any deviation from the center of the strip. Similar to the inductive method, this deviation is used as a control signal for the steering motor to adjust the vehicle's path.

Optical guidance track. This method relies on a colored line with a clear contrast to the ground, which is painted or applied to the floor. The line is detected by a camera positioned under the vehicle through edge detection algorithms. By calculating the lateral deviation from the center of the line, the system generates the signals necessary to correct the steering. Additionally, the camera can evaluate the AGV's exact position by scanning barcodes or QR code labels placed alongside the track. Even if advanced systems can identify even partially damaged lines, this technology remains unsuitable for environments with dirty or greasy floors.

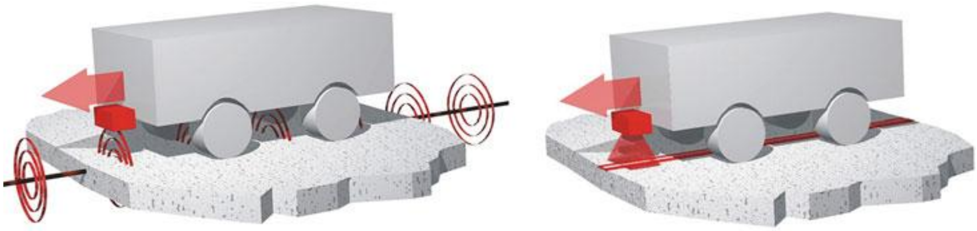

Figure 2.1 - Principle sketch for inductive and optical track guidance
(Source: Götting KG)

2.2.2.2 Base point guidance

To overcome the disadvantages associated with physical track guidance, such as limited flexibility and high implementation and maintenance costs, base point navigation (also known as grid navigation) represents a valid alternative. The system works with artificial markers positioned in or on the ground along the path. Within this grid, vehicles navigate using a combination of dead reckoning and direction finding (bearing).

The markers employed for this purpose can include QR code, RFID transponders or permanent magnets. In the case of magnetic systems, the magnets are positioned in drilled holes and secured to the floor, with their quantity and placement determined by the AGV manufacturer. Once installed, onboard sensors, such as a magnetic sensor bar, convert the magnetic field into a voltage proportional to the field strength, allowing the vehicle to establish its exact position.

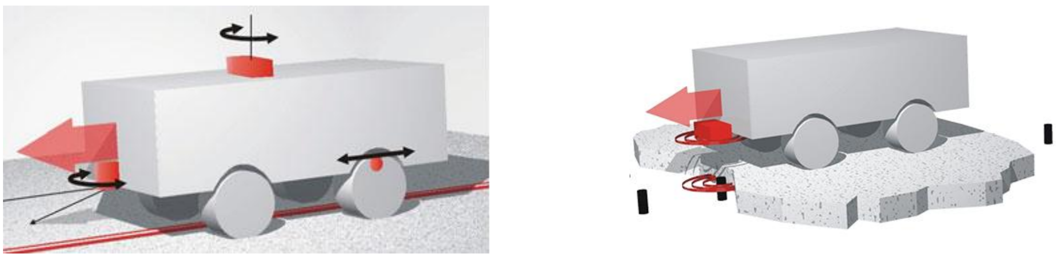

Figure 2.2 - Priciple sketch for dead reckoning (left) and for magnet navigation (right)
(Source: Götting KG)

2.2.2.3 Laser navigation

The most common form of free navigation is laser navigation (specifically, laser triangulation or localization). This technology is implemented by mounting retroreflective markers on walls, machines, or pillars, typically above the height of employees and obstacles. A rotating laser scanner fixed to the top of the vehicle detects at least two or three markers simultaneously to calculate their precise coordinates through triangulation.

Since the location of these markers is independent of the vehicle's actual path, the route remains entirely virtual. This provides a high degree of flexibility, as routes can be easily modified through software without requiring any changes to the physical infrastructure of the plant. However, the successful implementation of this system requires a constant, clear line of sight to a sufficient number of markers from any position, as well as the technical possibility of mounting the laser sensor at an adequate height on the AGV.

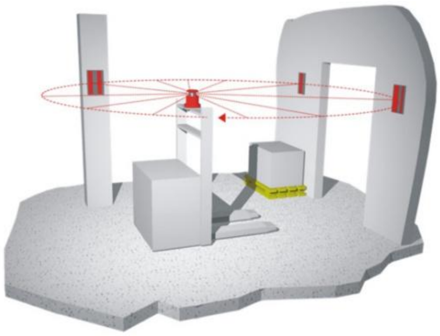

Figure 2.3 - Principle sketch for laser navigation with retroreflectors on walls and columns
(Source: Götting KG)

2.2.2.4 Natural navigation

Contour navigation is a type of navigation that uses natural, fixed and unchangeable marks, such as walls, doors and pillars, to guide the vehicle. In this system, the laser scanner mounted on the AGV scans its surroundings to measure the distance from these static objects. The onboard software then matches the detected environment with a previously stored map of the building to calculate the exact location and orientation of the vehicle. Furthermore, it compares this current position with the target destination, the system provides the necessary driving directions.

However, this method faces a significant limitation: since sensors are typically mounted only 10-15 cm above the floor, temporary obstacles like pallets or other objects can obstruct the view, making it difficult for the software to accurately match the environment with the stored map. To overcome this restriction, some systems employ ceiling navigation. In this configuration, the laser scanner is directed upwards to scan the ceiling, which, unlike the floor level, rarely presents obstacles that could interfere with the navigation process.

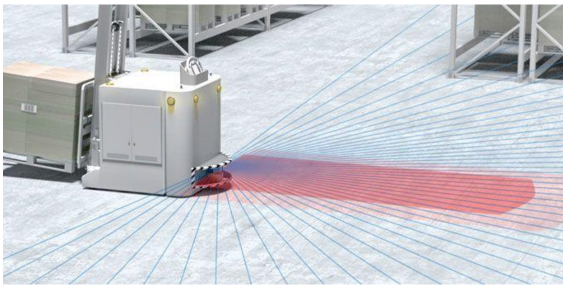

Figure 2.4 - Principle sketch for contour navigation
(Source: Leuze Electronic)

2.2.2.5 Radio localization

Last navigation method for an AGV is radio localization, also called indoor GPS. The vehicle exchanges radio signals with fixed antennas (anchors) positioned in the building to calculate the time-of-flight, therefore its position. A great advantage of the system is that radiofrequency can pass through obstacles, meaning a clear line of sight is not required. On the other hand, this method has a much lower accuracy (around ±30 cm) compared to laser navigation, making it unsuitable for applications that require high precision.

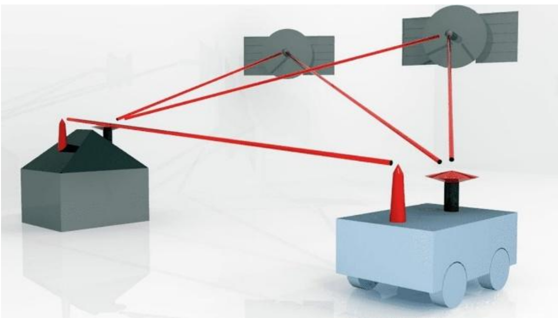

Figure 2.5 - Principle sketch for navigation using GPS
(Source: Götting KG)

2.2.3 Autonomous Mobile Robot (AMR)

AMRs are transportation vehicles capable of making autonomous decisions regarding path planning, dispatching and obstacle avoidance. As described in the literature review by Lackner et al. (2024), the first patent for an AMR was registered in 1987. While an AGV must follow fixed paths, an AMR can navigate autonomously, collision-free and without the need for physical infrastructure. These vehicles are equipped with onboard laser scanners and additional sensors, such as depth cameras, to reach any point within a given area.

From a structural perspective, a robot is composed of a wheel-based mobile platform with differential steering, whose size and shape vary based on the application. The platform usually supports either an active manipulator or a unit for passive transportation tasks. Sensors are another fundamental element of the system; their type and number depend on the AMR's specific degree of movement. In particular, optical laser scanners and 3D depth cameras are critical for safety, as they enable both navigation and obstacle avoidance, while some models also feature tactile sensors to guarantee emergency stops.

From a software perspective, the system manages path-motion planning through AI algorithms. This process is divided into global and local planning: global planning involves the creation of the plant map, including charging stations, targets, sources and no-go zones; local planning instead processes real-time data from sensors during motion to avoid obstacles that are not present in the global map. Additionally, in advanced configurations, AMRs can localize themselves and map their surroundings simultaneously through SLAM technology. Finally, AI algorithms are employed to optimize tasks such as path planning, collision avoidance and resource scheduling.

2.2.4 Fleet management and system integration

According to Ullrich and Albrecht (2019), an AGV master control system is needed to integrate the vehicles into the operational environment, to coordinate them and to receive and processes transport orders. Vehicles are connected to this central controller via a Wireless Local Area Network (WLAN). The architecture is hierarchical; therefore, an AGV "acts intelligently, not autonomously" and does not communicate directly with the rest of the fleet. Decisions are made by a higher-level host computer connected to the master controller through a Local Area Network (LAN). This host system can include material flow control for production, Production Planning Systems (PPS), or Warehouse Management Systems (WMS). Additionally, a remote diagnosis service is typically available via a VPN (Virtual Private Network) over a standard phone line.

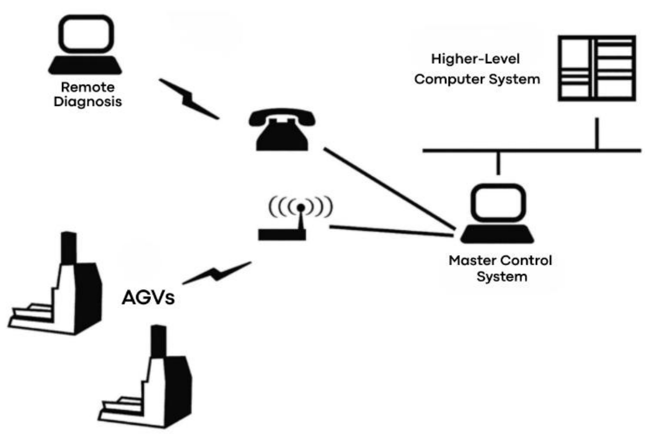

Figure 2.6 - The system architecture of a simple AGV system according to VDI 4451-7
(Adapted from Ullrich et al., 2019)

In contrast, the management of AMRs follows a different logic. As highlighted by Fragapane et al. (2021), these robots can communicate and negotiate directly with other resources, such as machines and Enterprise Resource Planning (ERP) systems, allowing them to make decisions autonomously. The enablers of this decentralized mechanism are AI algorithms, which make the vehicles more flexible and reactive to environmental changes. This approach ensures rapid implementation within the operational system and allows for the continuous optimization of the robots' performance.

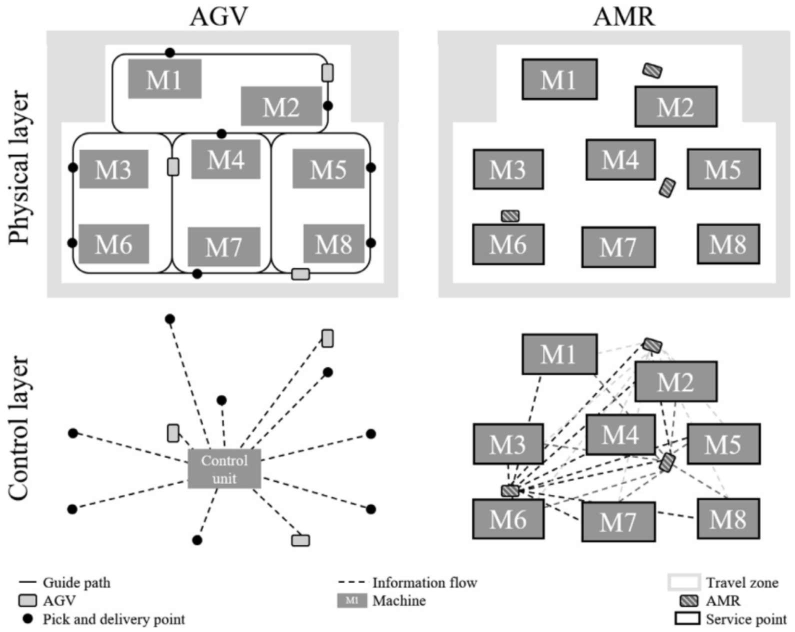

Figure 2.7 - Comparison between centralized control (AGV) and decentralized control (AMR)
(Source: Fragapane et al., 2021)

2.2.5 Core tasks

To operate efficiently in complex environments, the control system of an automated transport system must perform several key functions. Following the framework proposed by De Ryck et al. (2020), these functions can be divided into five main core tasks, as presented in Figure 2.8. These phases represent the entire workflow of a vehicle, from order reception to vehicle maintenance. In the following sections, each component will be discussed to comprehend how these technologies operate and differ.

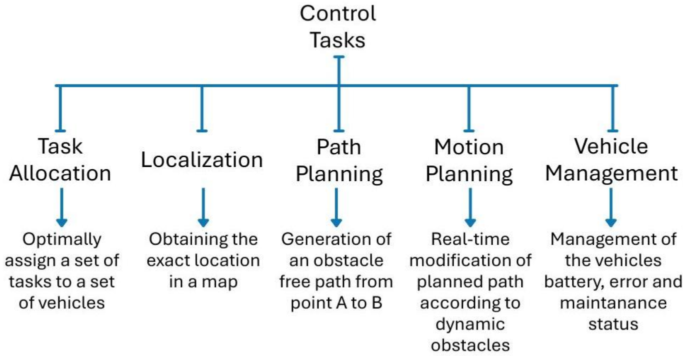

Figure 2.8 - Overview of the five core AGV/AMR tasks
(Source: De Ryck et al., 2020)

2.2.5.1 Task allocation

Task allocation is one of the most challenging tasks for the system and is typically performed by means of an optimization algorithm. The aim is to assign the transport order, such as moving an object from location A to location B inside the factory, to the most suitable vehicle. While the main objective is to maximize the use of resources by efficiently distributing the workload, additional optimization objectives may include total costs (measured in travel time, energy, or distance) and task priority based on urgency. In centralized systems the allocation is performed by the master controller, while in decentralized environments it is managed by autonomous negotiations between the vehicles.

2.2.5.2 Localization and path planning

Through the localization process the vehicle can obtain its position inside the working area. As already mentioned, this activity can be based on physical infrastructures or virtual maps. Once the position is established, the system must manage the fleet's movements through specific control logic. Typically, there can be centralized and decentralized approaches to manage the fleet. According to Pratissoli et al. (2024), centralized approaches generally perform better, but as the number of vehicles increases, the computational side becomes impractical. On the other hand, in decentralized approaches, robots communicate with surrounding equipment to estimate the global performance and take local control decisions.

Even if it is computationally less demanding, decentralization presents some disadvantages, such as obtaining a sub-optimal solution or generating non-feasible paths due to deadlocks, situations where a group of vehicles (or tasks) becomes interlocked in such a way that they cannot complete their tasks. Furthermore, the system must constantly prevent collisions, defined as two robots attempting to occupy the same position at the same time. In their paper the authors present a method that aims to overcome those limitations using a multi-level algorithm, however this remains a wide area of study.

This ongoing complexity is one of the main reasons why many companies still prefer to adopt AGVs, as rigidity and predictability often outweigh theoretical optimization. The takeaway, already discussed by (Fragapane et al., 2021) is that the solution lies in the negotiation process, seen not just as a way to avoid collisions by deciding which vehicles have priority and which must wait, slow down or stop, but also as a way to optimize the entire performance of the system.

2.2.5.3 Motion planning and safety

Unlike path planning, the motion planning process ensures real-time route changes to avoid collision with dynamic obstacles and prevent deadlocks. These situations, where a group of vehicles becomes interlocked and unable to move, are typically addressed through two main strategies: deadlock detection, which identifies and resolves a stall after it occurs and deadlock avoidance, which uses preventive algorithms to ensure the system never enters an interlocking state.

The approach to obstacle avoidance and safety, however, varies significantly between different technologies. Since vehicles and staff members share the same space, predictability is the key. As stated by Ullrich and Albrecht (2019), when an AGV encounters an obstacle, such as a pallet or an employee, it slows down until it reaches a complete stop and waits until the path is clear to move again. This high level of predictability, combined with a low operating speed (around 1 m/s for safety reasons), ensures staff members are aware of an AGV's behavior and trajectory. In dynamic environments, conversely, the motion planner of an AMR can generate a new path if the selected one is no longer feasible due to an obstacle (Fragapane et al., 2021). Yet, the possibility of avoiding an obstacle is strictly related to the plant layout: this feature requires sufficient clearance to allow the robot to maneuver around the object. As a result, in scenarios with tight layouts, such as a narrow corridor or aisle, the vehicle is forced to stop and wait as a traditional AGV, neutralizing one of its main advantages.

Moreover, unlike the uniform cycle time of AGVs, the flexibility of AMRs introduces variability in path and travel times, as their speed and route are constantly adjusted based on real-time environmental changes. This implies that even if autonomy is usually seen as an advantage, it introduces a relevant trade-off in the operation of the vehicle: when a system is too safe, it becomes inefficient. If the AMR continuously recalculates the path to avoid obstacles, it can create "phantom bottlenecks", leading to a drop in productivity. Furthermore, human operators may find it difficult to predict the robot's next move due to this erratic behavior.

Nevertheless, it has been proven that the use of automated technologies reduces the number of accidents caused by human errors, increasing the safety in the implementation of intralogistics activities (Dabić - Miletić and Raković, 2023). Safety remains a critical aspect and one of the main areas of ongoing research, as system reliability depends also on the perception accuracy of their surroundings. The primary tool for environmental detection is the LiDAR, a laser scanner that can rotate 360 degrees and thus distinguish static objects from dynamic ones based on the time-of-flight of the emitted laser beam (Aizat et al., 2023).

However, LiDAR alone is often insufficient. This system is usually paired with 3D or depth cameras to classify the detected objects (Lackner et al., 2024). The integration of these sensors is necessary to meet the requirements of international safety standards, such as ISO 3691-4 (2023). The document, updated in June 2023, defines the specifications for obstacle detection and safety zones, to ensure seamless integration between vehicles and human operators.

This integration is deeply rooted in the path following approach. While an AGV is predictable, because it follows predefined rules to complete a task, an AMR can navigate autonomously in a dynamic environment. AI techniques are the key feature enabling problem solving in complex real-world situations; without AI, all AMRs would react to obstacles in the same way (Fragapane et al., 2021). This implies that AGVs perform better in static surroundings with predefined obstacles, while AMRs can determine the optimal path to take in dynamic conditions by elaborating data collected from repeating the route many times (Aizat et al., 2023).

2.2.5.4 Vehicle management

As previously mentioned, while the control system is a key element for fleet performance, individual vehicle management is equally critical. According to De Ryck et al. (2020), this task involves monitoring the battery, error log and maintenance, all of which directly affect the vehicle's availability. Modern AGVs and AMRs are powered by onboard rechargeable batteries, making energy management a fundamental constraint.

The authors highlight once again the distinction between centralized and distributed control for energy management. The first one, knowing that the battery capacity is low, will send the vehicle to a charging station or will assign the task to another one. Conversely, in a distributed control system, the vehicle monitors itself and if it notices that the State of Charge (SoC) is insufficient, autonomously heads to a charging station while dispatching the mission to another robot to avoid waiting time.

The paper then presents three different charging schemes: opportunity charging, where the vehicle exploits the idle time to charge; automatic charging, where the vehicle waits for the battery to drop below a certain limit; and combination charging, which is a hybrid of the two. Moreover, the charging process can consist of battery swapping, with the vehicle autonomously replacing an empty battery with a full one, or the use of a standard charging station. Either way, a flawless charging strategy increases the productivity of these technologies significantly. However, even if battery management has a high impact on the performance, the literature is lacking deep research regarding the topic.

2.2.6 Interoperability and scalability

A critical challenge in fleet management is the interoperability among heterogenic vehicles. As highlighted by Ullrich and Albrecht (2019), a standardized interface is fundamental to operate with a unique master control system, overcoming the limitations of proprietary solutions. This standardization allows vehicles from different manufacturers to communicate with each other within the same environment. The VDA 5050 protocol was specifically developed for this purpose, aiming to integrate both AGVs and AMRs into a single operational framework. This protocol also supports the decentralized communication and negotiation processes discussed by Fragapane et al. (2021), where many resources must interact dynamically to optimize the overall system performance. Building on this foundation, recent studies have proposed models and tools to facilitate the implementation of VDA 5050; Kaven et al. (2022), for instance, developed a digital twin model to enable the comparison and synchronization of heterogeneous robots. While digital twins represent the future for an easier integration of AGVs and AMRs, they still face significant challenges regarding real-time data synchronization and mapping accuracy.

Another deal breaker for the selection and implementation of these technologies is system scalability. Thanks to their decentralized nature, AMRs are easier to scale, since the introduction of a new robot typically requires only a software update (Fragapane et al., 2021). However, increasing the fleet dimension in limited spaces can introduce uncertainty in cycle times, due to continuous route negotiations among vehicles (Lackner et al., 2024). On the other hand, AGVs offer a deterministic path planning, ensuring fixed cycle times, but require expensive infrastructural changes whenever the fleet size or layout needs to be adjusted.

2.2.7 Sustainability and impact

In conclusion, the adoption of automated solutions results in significant benefits. Primarily, AGVs and AMRs contribute to the creation of a sustainable supply chain through electric-powered engines and the development of more ergonomic working environments. As stated by Dabić - Miletić and Raković (2023), employees' movements are curtailed and process safety is enhanced by reducing the frequency of accidents and damages associated with human errors. Moreover, material handling and transportation efficiency are optimized and, even with high initial capital expenditures, automation potentially cuts labor costs by over 60%, offering a more cost-effective alternative in the long run.

Nevertheless, these technologies still present some limitations. AGVs often face challenges related to path rigidity and the need for human intervention AMRs frequently require additional specialized equipment to autonomously manage material handling at loading and unloading stations. Beyond these technical constraints, the significant initial investment remains a hurdle. Consequently, a comprehensive planning phase is essential to fully exploit the benefits and effectively counterbalance the drawbacks of each technology.

2.2.8 Comparative analysis and summary

To provide a clear overview of the technical and operational differences analyzed in the previous sections, a summary comparison is presented in Table 2.2. This synthesis highlights how the choice between AGVs and AMRs is not merely a matter of hardware, but a strategic decision that affects the entire logistics workflow, from infrastructure requirements to system scalability and human-machine interaction.

Table 2.2 - Comparison between AGV and AMR features

Feature	AGVs	AMRs
Infrastructure	Physical one required	Not required: virtual maps and natural obstacles
Navigation	Fixed paths (magnetic, wire, optical, laser, radio)	Free navigation (SLAM, LiDAR)
Decision & Path Planning	Managed by control system	Up to the vehicle
Control System	Centralized	Decentralized
Deadlocks/Collisions Frequency	Rare, thanks to predictable behavior	More frequent, causing delays
Obstacle Avoidance	Stop and wait	Actively avoid it generating a new path
Employee Perception	Safe behavior, easy to predict	Slightly erratic behavior
Energy Management	Centralized	Distributed
Flexibility	Low: require infrastructure changes	High: software-based mapping
Scalability	Difficult and expensive: need infrastructural changes	Easy: usually require just a software update
Time to Complete Tasks	Constant, deterministic	Shorter, but variable
Best Use Case	Stable and repetitive environment	Dynamic and complex environment

2.3 Multicriteria selection methods

The selection of the most suitable automated material handling system is a strategic problem that cannot be addressed through a single-objective approach. As stated by (Taherdoost & Madanchian, 2023), decision-making is a complex mental process and a problem-solving program aimed at determining a desirable result by considering different aspects and solving potential problems. In the context of intralogistics, the choice between AGVs and AMRs involves a wide set of factors, such as investment costs, flexibility, safety requirements and system throughput, that typically present trade-offs. This complexity places the research within the field of Multi-Criteria Decision Making (MCDM), also known as Multi-Criteria Decision Analysis (MCDA).

In their paper, the authors highlight that MCDM approach provides a structured framework for evaluating multiple conflicting objectives. This is particularly relevant when comparing the superior adaptability of AMRs with the deterministic nature and predictable cycle times of AGVs. The core of an MCDM problem lies in the interaction between a finite set of alternatives, represented in this study by the different vehicle technologies, and their measurable attributes, which are the measurable technical characteristics used for evaluation.

The use of MCDM methods allows for the integration of both quantitative data and qualitative insights derived from expert judgment. This is achieved by assigning different weights to the criteria based on their relative importance in the specific industrial case. Practically, this approach is used to handle the formulation and planning steps to reach an optimal solution based on the decider's preferences. Therefore, developing a decision-supporting framework based on these principles is essential to navigate the technical uncertainties of Industry 4.0 and ensure that the selected technology aligns with the company's strategic goals.

3. Methodology

This chapter explains the methodology that was applied during the project, starting with the literature review and concluding with the data analysis. The following section presents an overview rather than a detailed step-by-step procedure, as this will be better discussed in the subsequent chapters.

3.1 Research strategy

The research was conducted adopting an abductive approach. According to Charles Peirce, abduction begins with an existing result (in this study represented by the strategic need to implement automated transport systems in industrial settings), that was used to analyze which rule could explain the research problem and, finally, confirmed through observation. Following this logic, the project was articulated in four main phases.

First, a data collection phase was carried out, involving an extensive literature review to identify a wide range of potential parameters and technical constraints influencing technology selection. Simultaneously, preliminary interviews were conducted for both the thesis and the SARDINIA project; this allowed for the analysis of the information gathered and its integration through direct correspondence with experts and technology providers.

In the second stage, the collected data were organized and reviewed to filter the parameters' list by selecting the most relevant for the industry. This led to the framework creation, alongside the definition of operational thresholds, optimal performance ranges for technology selection and the identification of requirements for preliminary implementation planning.

Subsequently, the model was validated through a qualitative analysis, involving a semi-structured interview with an expert from the case company, to verify its logic and practical relevance. The last phase involved the critical analysis of these findings and the final presentation of the results.

3.2 Literature review

"In order to contribute to the development of knowledge in an area, we need to know which knowledge already exists" (Säfsten and Gustavsson, 2020). Defining the state-of-the-art of knowledge is important; thus, the first phase of the project consisted of a literature review conducted using a hybrid approach.

The first step involved a systematic keyword search through scientific platforms such as Google Scholar, Scopus, Elsevier and IEEE Xplore. In the second step, a backward snowballing approach was adopted to analyze also relevant papers mentioned in these works. Backward snowballing means using the reference list to identify new papers to include (Wohlin, 2014).

This method ensured a solid foundation for the research. Specifically, this review was employed to define the current state-of-the-art of AGVs and AMRs, to analyze multi-criteria selection methods and, finally, to obtain the list of parameters and constraints that were subsequently refined and validated during the qualitative phase of the study.

3.3 Data collection

In addition to the literature review, the data collection was articulated in several steps to integrate theoretical information with industrial practice. The first stage involved the consultation of technology suppliers' websites, technical datasheets and official video demonstrations. This method allowed for the gathering of technical specifications and operational constraints that are often not detailed in scientific papers. These data, together with the literature, constituted the foundation for the decision-making logic, the definition of optimal operational ranges and the identification of implementation guidelines.

Subsequently, semi-structured interviews were conducted online. "A primary benefit of the semi-structured interview is that it permits interviews to be focused while still giving the investigator the autonomy to explore pertinent ideas that may come up in the course of the interview" (Adeoye-Olatunde & Olenik, 2021). This flexibility was essential to understand the main challenges and the industry's "as-is" situation.

The expert consultation followed a specific progression: an interview was first carried out with a specialist from Supplier A to validate the technical information previously collected and to gather useful insights into the implementation guidelines. Following this, the model was validated through a further interview with Expert B from an industrial end-user. This discussion was fundamental to verify the logic and practical relevance of the framework, ensuring its alignment with real-world industrial requirements. To ensure ethical research standards, all the data and company information were handled according to the confidentiality guidelines provided by the partners involved.

3.4 Model development

The development of the decision-supporting framework was articulated in three main stages, adopting a mixed-methods approach to handle both qualitative and quantitative data.

The first step involved the extraction of the most relevant criteria from scientific literature. These criteria were then verified and weighted through the information collected during the expert consultations, to identify which factors are truly critical in the real world. In this stage, data were mainly qualitative; therefore, the most suitable method was the thematic analysis, which enabled the identification of recurrent patterns across literature and the interview to select the key information.

The second phase consisted of the determination of thresholds and optimal performance ranges through the available literature and technical specifications provided by suppliers. Comparative analysis, together with descriptive statistics and normalization, were used in this stage to deal with quantitative data. This synthesis was fundamental for mapping the relevant factors, defining the related critical values and establishing the optimal performance ranges for both technologies.

Finally, these parameters and values were translated into a decision-supporting logic in the form of a comparison matrix. This tool enables a direct comparison of quantitative vehicle specifications, supporting the selection between AGVs and AMRs while providing preliminary guidelines for the implementation phase.

3.5 Implementation guidelines development

In the final stage of the research, a set of implementation guidelines was developed to complement the selection framework. These guidelines represent a synthesis of best practices identified through the triangulation of different sources.

Specifically, the literature review provided the theoretical basis for project management and change management in automation. This was integrated with practical insights from suppliers' websites and technical documentation, which highlighted common operational limitations and technical requirements. Finally, the consultation with the expert from Supplier A played a crucial role in refining these findings, adding strategic industrial perspectives on integration challenges and system scalability. This comprehensive approach ensured that the guidelines are not only theoretically consistent but also aligned with current industrial standards and provider expectations.

3.6 Model validation and analysis

Once the model was developed, it had to be validated. The model was validated through a qualitative approach rather than a quantitative one. The validation was carried out through a semi-structured interview with an expert from a leading vehicle manufacturer. During the session, the framework's structure, the identified parameters and the decision-making logic were presented and discussed to ensure their consistency and practical relevance.

This qualitative review allowed for the verification of the tool's reliability from an industrial perspective. By comparing the theoretical results derived from literature with the feedback provided by the expert, it was possible to identify potential discrepancies and refine the model to better reflect industrial reality. This final step ensured that the outcome was realistic and that the framework could effectively support a company's future decisions on automated intralogistics and its related implementation.

3.7 Research quality

To ensure the quality of the research, the study employed data triangulation, combining scientific literature, technical documentation from suppliers and expert interviews. This multi-source approach provided a more comprehensive understanding of the parameters and their industrial application. In addition, continuous feedback from the supervising professors and transparent documentation of each research step guaranteed the reliability of the process. Lastly, to validate the framework for further applications, the theoretical solutions were compared with the professional insights provided by the industry experts, ensuring that the final model is both robust and practically applicable.

4. Data gathering and parameter identification

This chapter presents the empirical and quantitative foundation required to build the framework. To bridge the gap between theory and industrial reality, data was gathered from literature, supplier specifications and direct expert validation. The chapter begins with the identification of as many parameters and constraints as possible mentioned in the academic papers analyzed, organized in a list of 101 technical, operational and economic variables to map both vehicle capabilities and process-facility interactions. These parameters are then translated into practice by analyzing 9 global automation leaders to build a dataset of 35 different AGV and AMR models. To integrate the financial layer, cost benchmarks covering CAPEX, OPEX and integration complexity are presented to establish a financial baseline. The dataset is further refined through a semi-structured interview with a senior expert from a leading automation supplier to validate technical parameters and calibrate the criteria weighting based on practical operational trade-offs. Finally, fleet simulation dynamics and traffic vulnerabilities from literature are analyzed to help design the final implementation guidelines.

Together, these sections combine empirical data and industry insights to provide the exact inputs, constraints and cost factors evaluated by the decision-support framework developed in Chapter 5.

4.1 Parameter list

The final list counts 101 parameters, which were categorized to reflect both the technology and its integration into the working environment. This classification represents a fundamental step in the systematization of the attributes required for the decision-making process.

Initially a distinction between vehicle (v) and process (p) parameters was made: the formers describe the technical capabilities of the unit, such as battery life or navigation type, while the latters focus on how the system interacts with the facility, including factors like aisle dimensions, layout constraints and floor conditions.

Subsequently, to better handle the complexity of the decision, these parameters were classified into three main clusters: technical, operational and economic. This organization was fundamental to go beyond a simple technical comparison and to identify the factors that really impact implementation planning and overall costs. This structured approach ensures that the decider's preferences can be evaluated against a comprehensive and balanced set of criteria. The complete list of the 101 identified parameters, including their categorization, is provided in **Appendix A**.

4.2 Supplier selection and market overview

To bridge the gap between scientific literature and industrial reality, several solution manufacturers were analyzed. Consulting their websites and technical datasheets was essential to move from the abstract definition of parameters to the collection of concrete values. This process led to the creation of a dataset covering 35 different vehicle models, which serve as the alternatives for the proposed decision framework.

It is important to highlight the specific scope of this selection: only AGVs and AMRs designed for production and assembly areas were considered, deliberately excluding solutions strictly intended for warehousing. This focus ensures that the collected data, such as operating ranges and performance thresholds, reflect the specific constraints of manufacturing environments and provide a set of homogeneous attributes for comparison. Due to the extent and level of detail of these comparisons, the resulting technical tables are provided in **Appendix B**.

4.2.1 Selected supplier's overview

To ensure the robustness of the framework, the data collection covered a diverse group of global leaders in automation. These companies were selected to represent different technological approaches, from traditional AGVs to the latest generation of AMRs, including both historical industrial giants and specialized pioneers. This broad selection was essential to define a comprehensive set of alternatives, ensuring that the data, covering 35 different vehicle models, reflects the full spectrum of the market: from robust, lane-guided tradition to flexible, sensing-driven autonomy. This variety allows for a realistic evaluation of the attributes and performance thresholds currently available, providing a solid empirical foundation for the framework.

Group 1: established material handling leaders

Toyota Material Handling (SE): Toyota follows the principles of the Toyota Production System (TPS) and the Toyota Service Concept (TSC). Their focus is on streamlining internal material handling, providing a global benchmark for reliability and standardized automation.

STILL: since its foundation in 1920 (Hamburg), STILL has evolved from a forklift manufacturer into a provider of smart integrated solutions. Their expertise in combining warehouse machinery with sophisticated maintenance services is vital for understanding long-term operational stability.

ABB: with Swedish and Swiss roots dating back to the 19th century (ASEA and BBC), ABB represents the leading authority in electrification and robotics. Their long history of technology leadership and strategic acquisitions makes them a key reference for high-end automation and power management.

Group 2: AGV and automated systems specialists

AGVE Group: founded in 1985 in Sweden, AGVE is a leading specialist in both standard and customized AGVs. Their dual focus on vehicles and control systems provides essential data on how tailored solutions impact implementation flexibility.

MAX AGV: based in Gothenburg with over 35 years of experience, MAX AGV offers a complete in-house approach, from initial analysis to aftermarket support. Their local expertise is particularly relevant for the Swedish industrial context analyzed in this research.

DS AUTOMATION: since 1984, this company has focused on simplifying processes, particularly in the automotive industry. Today, they are among the world's leading suppliers, bridging the gap between traditional AGVs and autonomous mobile robotics.

Group 3: AMR and sensing pioneers

Mobile Industrial Robots (MiR): established in 2013 in Odense, Denmark, MiR pioneers a specialized AMR philosophy. Their focus on optimizing global logistics through collaborative robots easy-to-deploy was essential for defining the thresholds of infrastructure-free navigation.

OMRON: from its 1933 origins in Kyoto (Japan), OMRON has evolved from a small factory into a global leader in sensing and control. Their contribution to this study is centered on the intelligence of robots, specifically how advanced sensing components influence safety and fleet autonomy.

KNAPP: founded in 1952 in Austria, KNAPP is a family-owned business that has become a leader in digitalization and robotics. Their customized software and sophisticated automation solutions represent the upper limit of system complexity and performance in this framework.

4.3 Economic estimates and data

To complete the quantitative foundation of the framework, a collection of economic data was performed. This phase focused on identifying the typical investment ranges (CAPEX) and the recurring operational expenditures (OPEX) associated with both AGV and AMR technologies. Due to the high variability and confidentiality of industrial pricing, these estimates were derived from a comprehensive market analysis provided by a specialized supplier, which aggregates industry data to establish a functional benchmark. The resulting dataset, detailed in **Appendix C**, categorizes costs into vehicle acquisition, infrastructure requirements, software licensing, and integration complexity.

A preliminary analysis of these figures reveals a significant divergence between the two technological paths. Traditional AGVs generally involve a lower unit cost for the vehicle itself but require substantial investments in physical infrastructure (e.g., magnetic tapes, reflectors, or floor markers), which can range between $5,000 and $20,000 depending on the facility.

Conversely, AMRs represent a higher initial investment in vehicles, especially for heavy-duty models, but offer the elimination of fixed infrastructure investments and costs regarding physical layout changes, making them more attractive for dynamic manufacturing environments.

Furthermore, the data collection highlighted the impact of integration depth. Moving from a light integration of basic tasks to a deep synchronization with ERP/MES systems, can more than double the implementation costs, regardless of the vehicle type. These findings underscore that the Total Cost of Ownership (TCO) is heavily influenced by the software and facility readiness rather than just the hardware. In the context of the proposed framework, these averages provide the baseline economic attributes necessary to evaluate the long-term feasibility of each alternative.

4.4 Validation interview

Among the previous suppliers it was possible to conduct a semi-structured interview with a leading provider of automated logistics solutions operating in the Nordic region. The conversation with a senior expert from the company was essential to verify the collected data and to gain deeper professional insights. The interview took place online with a solution design engineer who provided a perspective shaped by nearly 30 years of industry experience. The full transcript of this interview is available in **Appendix F** - Interview transcript.

The discussion provided a practical validation of the technical parameters and highlighted that, while vehicle hardware is increasingly standardized, the primary differentiator in modern intralogistics lies in the control software. The expert emphasized that the ability to manage large-scale fleets and the availability of digital twins for layout testing are critical attributes for ensuring long-term scalability. Regarding navigation, the interview clarified that while SLAM is highly effective for general movement, millimeter precision in specific zones still requires secondary systems like reflectors or cameras. Furthermore, it was noted that environmental challenges, such as greasy or wet floors, impact AMRs and AGVs equally due to the physical constraints of braking distances, debunking common myths about technological superiority in harsh conditions.

Discrepancies in battery data were explained through the philosophy of opportunity charging, where short power boosts during work cycles eliminate the need for dedicated charging downtimes. Significant insights also emerged regarding operational efficiency and the human factor. The expert pointed out that system disruptions are rarely technical but are primarily linked to human-machine interaction, such as obstacles left in paths or staff resistance during the initial implementation phase. From an economic standpoint, the dialogue shifted the focus beyond simple labor savings toward the importance of damage control. Automated systems drastically reduce costs associated with human errors and collisions, a factor that often justifies the significant initial investment and the varying payback periods observed in the market. These professional insights were fundamental to refine the criteria weighting within the framework. This ensures that the decision-logic reflects real-world operational complexities and the typical trade-offs found in automation projects.

4.5 Literature insights for implementation guidelines

In addition to the expert interview, the study by Silva et al. (2024) provides essential technical insights that are often not fully detailed in suppliers' datasheets. This study is particularly relevant for the subsequent definition of the implementation guidelines, as it focuses on fleet performance and system stability.

The authors conducted a simulation to investigate the performance of an autonomous vehicles' fleet. Specifically, three different tests were performed to compare different fleet sizes and different solutions. The case of a single vehicle showed that AMRs completed the task faster than AGVs. The same scenario appeared in the test of a five vehicles fleet: AMRs were faster, but a collision happened in two different simulations. Finally, the third test was conducted with a fleet of ten vehicles. The robots outperformed the AGVs, however, in eight cases out of ten one or more collisions happened, against zero in the case of AGVs. To further evaluate the performance of the fleet, the map was modified to remove any choke points between the start and end points resulting in a more open space for navigation. The same mission was performed with fleets of five and ten robots and was successfully completed without any collision.

This study highlighted the fact that by increasing the size of an AMR fleet, the probability of collisions rises, while the predictability and stability of AGV completely avoids this situation. On the other hand, this rigidity of AGVs can increase the mission time up to 60% in restricted spaces, against a 20% for AMRs.

If the process requires the transportation of heavy and constant loads, AGV could be the right alternative, while if flexibility and speed are the key requirements, AMRs could be a better solution. For a detailed reference of these simulation outcomes, the full data tables are reported in **Appendix G**.

5. Data elaboration

This chapter translates the data previously presented into a functional decision-support tool, evaluating the technical and economic feasibility of transitioning from manual to automated intralogistics. To achieve this, the chapter begins with a Total Cost of Ownership (TCO) analysis that expands the economic evaluation beyond initial capital expenditures to critical hidden costs within a Swedish manufacturing context. To integrate operational constraints, the initial list of 101 variables is processed through a filtering logic and mapped onto a Data Availability-Importance matrix. This matrix serves as a visual tool to highlight the most critical parameters and expose key information gaps, while separating main differentiating factors from standard industry prerequisites. These economic findings and parameter rankings are then synthesized into a final table, which establishes the mathematical averages, operational thresholds and site-dependent variables for both AGV and AMR solutions. Finally, to ensure the practical viability of the model, the chapter outlines preliminary implementation guidelines divided into five strategic areas, mapping out network, layout, socio-technical and simulation prerequisites. The chapter concludes with a visual flowchart that demonstrates how to use the framework as a concrete resource during corporate decision-making.

By aligning these distinct phases, the chapter provides a cohesive methodology, demonstrating how financial calculations and parameter selections directly define the implementation guidelines and the expected savings.

5.1 Total Cost of Ownership (TCO)

Since the initial purpose was to consider all the perspectives of AGVs and AMRs, it is fundamental to discuss the economic dimension through a TCO approach. TCO goes beyond the initial advertised price, which is often the only figure considered during planning, to include CAPEX, representing the capital expenditure for the initial investment, and OPEX, which covers the ongoing operating costs. Furthermore, this approach accounts for indirect and hidden costs that emerge throughout the product's life cycle, such as integration complexity and maintenance, which are frequently overlooked but significantly impact long-term viability.

It is important to clarify that, given the high variability and confidentiality of industrial pricing, certain simplifications were made and average indicative values were used throughout the calculations. The primary objective of this model is not to provide absolute financial figures, but rather to highlight the key cost-saving drivers and demonstrate the significant impact that hidden costs can have when all other parameters remain constant. In the context of a MCDM approach, these figures function not as fixed prices, but as the baseline economic attributes necessary to evaluate the relative feasibility of each technological alternative.

5.1.1 Model assumptions

To quantify these dynamics, a comparative model was developed for a hypothetical scenario involving 5 vehicles operating over two shifts in a Swedish manufacturing context. The model compares manual baseline against unit-load AGV and AMR solutions. To ensure a robust comparison, the following assumptions were adopted:

- *Vehicle substitution ratio*. A 1:1 replacement ratio is assumed for the transition from manual to automated vehicles, leveraging the deployment capabilities and operational logic discussed by Zhao and Chidambareswaran (2023).
- *Pricing basis*. Vehicle costs are calculated using the median value of the price ranges provided in the market analysis.
- *Labor-efficiency ratio*. In the manual baseline, a dedicated operator is assigned to each vehicle. For the automated scenarios, the model adopts an operator replaced by robot ratio of 1:1.67. This value was selected as a representative average, bridging the benchmarks observed for established providers such as TOYOTA, MiR and OMRON (1:1.5) and high-efficiency systems like KNAPP and (STILL, 2025) (1:1.8).
- *Labor costs*. Based on the Swedish labor market, the hourly employee rate is estimated between 25 and 30 $/h; a mean value of 27$/h was adopted for all calculations.
- *Battery lifecycle*. The expected battery lifespan is estimated at 3-5 years. Consequently, the model accounts for one full battery replacement within the analyzed five-year period.
- *Charging infrastructure*. The system layout assumes a ratio of three charging stations for every five vehicles (3:5) to ensure operational continuity.
- *Software*. Fleet management and operational software are treated as Software as a Service (SaaS), incorporating annual subscription fees.
- *OPEX*. Estimates for OPEX (Operating Expenses) are derived from the technical benchmarks and data provided by (Novus Hi-Tech, 2025).

Table 5.1 - TCO dataset

	AGV	AMR	MANUAL
Number of vehicles	5	5	0
Vehicle price (unit load) [$]	35.000	45.000	0
Working hour per day	16	16	16
Working days per year	250	250	250
Operators per shift	3	3	5
Employee cost [$/h]	27	27	27
New battery (LiFePo4) [$]	4.000	4.000	0
Moderate case integration [$]	14.000	14.000	0
Charging station [$]	3.000	3.000	0
Physical infrastructure [$]	12.000	0	0
Network infrastructure [$]	9.000	9.000	0
Software [$]	1.500	3.500	0
Layout change [$]	10.000	750	1.000
Safety certification per robot [$]	3.500	3.500	0

5.1.2 Hidden costs

Typical manufacturing uptime is commonly reported in the range of 85-92%, corresponding to downtime levels of approximately 8-15%, although these values depend on system configuration and measurement methods. These figures are consistent with widely reported Overall Equipment Effectiveness (OEE) benchmarks, which typically place overall efficiency in the 55-75% range depending on the level of automation and process type.

Based on these ranges, a conservative downtime rate of 10% was adopted for the manual case, while a reduced value of 7% was assumed for the automated scenario. As noted by the expert, although automation increases process predictability, the system remains subject to external factors such as human-machine interaction and the initial operational learning curve.

$$Downtime_{AGV,AMR} = \left(C_h \times H_d \times D_y \times N_o\right) \times 7\%$$

$$Downtime_{AGV,AMR} = (27 \times 16 \times 250 \times 3) \times 0.07 = 22{,}680\ \$$$

$$Downtime_{Manual} = \left(C_h \times H_d \times D_y \times N_o\right) \times 10\%$$

$$Downtime_{Manual} = (27 \times 16 \times 250 \times 5) \times 0.10 = 54{,}000\ \$$$

C_h: Hourly employee cost [$/h]
H_d: Working hours per day [h/day]
D_y: Working days per year [day]
N_o: Number of operators per shift

The cost of hiring and training was estimated based on data from the Society for Human Resource Management (SHRM, 2022), which reports an average cost-per-hire of approximately \$4700-\$5500 depending on role and industry. Based on these figures, an average cost of \$5,000 per employee was selected for the calculation, assuming an annual employee turnover rate of 15%. This choice ensures a realistic yet cautious approach, especially considering that total turnover costs can range from 30% to over 100% of an employee's annual salary according to SHRM estimates. By incorporating these factors, the model captures the recurring economic impact associated with workforce variability, which may be partially mitigated under more automated operating conditions.

$$Hiring\ \&\ Training = N_o \times N_s \times HT \times T$$

$$Hiring\ \&\ Training_{AGV,AMR} = 3 \times 2 \times 5000 \times 0.15 = 4500\ \$$$

$$Hiring\ \&\ Training_{Manual} = 5 \times 2 \times 5000 \times 0.15 = 7500\ \$$$

N_s: Number of shifts
HT: Hiring and training cost [\$]
T: Turnover

Material damage cost data were based on the framework proposed by Vijayakumar et al. (2022), which models damage-related costs as the combination of inspection costs, direct material losses and related opportunity costs. Based on the cost structure proposed in the study, an average value of \$50 per damage event was assumed for the calculation. The frequency of damaged materials was estimated at 1-3% per transport mission in the manual scenario, while a significantly lower rate of 0.1% was considered for the automated case, reflecting improved handling consistency. Consequently, the first step is to estimate the number of missions per year, knowing that the average mission time is 10 min:

$$M_y = \frac{H_d \times D_y}{t_m}$$

$$M_y = \frac{16 \times 250}{10/60} = 24000$$

The second step is evaluating the cost of a failed mission:

$$C_{fail} = M_y \times C_d$$

$$C_{fail} = 24000 \times 50 = 1{,}200{,}000\ \$$$

Finally, the error percentage can be introduced, obtaining two different values.

$$Material\ Damage = C_{fail} \times e_d$$

$$Material\ Damage\ _{AGV,AMR} = 1{,}200{,}000 \times 0.1\% = 1200\ \$$$

$$Material\ Damage\ _{Manual} = 1{,}200{,}000 \times 2\% = 24{,}000\ \$$$

M_y: Missions per year
t_m: Mission time [h]
C_{fail}: Cost of failed mission [$]
C_d: Damage cost [$]
e_d: Damage percentage [%]

To quantify the economic impact of safety, the cost associated with safety accidents was estimated using incidence statistics from Eurostat, European Statistics on Accidents at Work (ESAW, 2026). While the manufacturing sector reports an average of 1.7 non-fatal accidents per 100 employees annually, for this calculation the focus is mainly on manual operations. Given that manual material handling typically carries a higher risk profile than the sector average, a conservative assumption of 3.5 cases per 100 employees (0.035 per worker-year) was adopted. For the baseline scenario of 10 operators, this translates to an expected frequency of 0.35 injuries per year.

The cost per injury is assumed to be $50,000, based on international benchmark values from the National Safety Council (NSC, 2024). This figure is further supported by European macroeconomic estimates from (Tompa et al., n.d.), which indicate comparable orders of magnitude when aggregating productivity losses, medical costs, and administrative burdens. However, a 90% reduction in injury incidence was assumed for the automated scenario due to the strong decrease in direct operator exposure to manual hazardous tasks.

$$Safety\ Accidents_{AGV,AMR} = (N_a \times C_a) \times (1 - 90\%)$$

$$Safety\ Accidents_{AGV,AMR} = (0.35 \times 50000) \times 0.1 = 1750\ \$$$

$$Safety\ Accidents_{Manual} = N_a \times C_a$$

$$Safety\ Accidents_{Manual} = 0.35 \times 50000 = 17{,}500\ \$$$

N_a: Number of accidents per year
C_a: Cost of an accident [$]

Rework and line stoppage costs were modeled following the framework proposed by Vijayakumar et al. (2022), which highlights the impact of human factors on operational disruptions. The study emphasizes that error rates are highly context-dependent, influenced by task complexity and the level of automation. Based on this, a conservative human error rate of 10-15% was assumed for manual operations, while significantly lower rates were assigned to automated systems to reflect their superior process consistency and reduced human intervention.

In addition, rework costs were estimated assuming that errors can lead to an increase of 3 to 10 times the cost of the original operation, reflecting the reprocessing and interruption expenses typical of industrial engineering. This aligns with the findings from the Expert A interview, which identified damage control and the mitigation of human-induced errors as one of the possible primary economic drivers for automation, often outweighing simple labor savings. Consequently, the associated cost can be calculated as:

$$C_e = 6.5 \times (t_m \times C_h)$$

$$C_e = 6.5 \times (10/60 \times 27) = 29.25\ \$$$

Considering now the number of errors as failed missions, it is possible to estimate the cost.

$$Rework = M_y \times C_e \times e_r$$

$$Rework_{AGV} = 24000 \times 29.25 \times 1.5\% = 10{,}530\ \$$$

$$Rework_{AMR} = 24000 \times 29.25 \times 0.5\% = 3510\ \$$$

$$Rework_{Manual} = 24000 \times 29.25 \times 12.5\% = 87{,}750\ \$$$

C_e: Error cost [$]
e_r: Rework percentage [%]

Last element is the cost of energy. Typical power demand for AGV/AMR systems in industrial intralogistics is reported in the range of approximately 0.6-1 kW in technical literature and industry specifications. An average value of 0.8 kW was therefore assumed for energy consumption calculations.

$$E_y = H_d \times D_y \times P_v$$

$$E_y = 16 \times 250 \times 0.8 = 3200\ kWh$$

Considering 90% of battery efficiency and 70% of time usage for the vehicle, the amount of energy needed becomes:

$$E_e = \frac{P_y \times t_v}{\eta_b}$$

$$E_e = \frac{3200 \times 70\%}{90\%} = 2489\ kWh$$

Regarding energy consumption, the model uses electricity price statistics for non-household consumers in the EU provided by (Eurostat, 2026a). While industrial prices vary across member states and consumption levels, an average value of approximately 0.2 $/kWh (≈0.18 €/kWh) was adopted for this study, a figure consistent with the reported European range.

$$Energy = E_e \times p_e \times N_v$$

$$Energy = 2489 \times 0.2 \times 5 = 2489\ \$$$

P_y: Annual needed energy [kWh]
P_v: Power of a vehicle [kW]
E_e: Annual effective energy consumption [kWh]
t_v: Time of vehicle usage [%]
η_b: Battery efficiency [%]
p_e: Energy price [$/kWh]
N_v: Number of vehicles

Data analysis indicates a significant performance gap, with automation demonstrating an average ten percentage points increment compared to manual handling baselines.

Table 5.2 - Hidden costs

	AGV	AMR	MANUAL
Downtime cost [$]	22.680	22.680	54.000
Hiring and training [$]	4.500	4.500	7.500
Material damage cost [$]	1.200	1.200	24.000
Safety accidents [$]	1.750	1.750	17.500
Rework or line stoppage cost [$]	10.530	3.510	87.750
Energy consumption [$]	2.490	2.490	0
Productivity	85% – 95%	85% – 95%	70% – 85%

5.1.3 CAPEX, OPEX, labor cost and savings

The next phase of the calculation involves the evaluation of CAPEX, OPEX, labor cost and yearly savings. The TCO was estimated over a 5-year period. Manual system CAPEX are excluded from this model as the existing equipment is assumed to be fully depreciated. This study, in fact, focuses on the marginal impact and the economic viability of replacing the current manual operations with automated solutions.

CAPEX refer to the initial investment costs, specifically in the case of automated solutions are the one-time purchases and costs associated with physical and network infrastructure:

$$CAPEX = (p_v \times N_v) + C_{int} + C_{inf} + C_{net} + \left(C_{charg} \times 3\right) + (C_{cert} \times N_v)$$

$$CAPEX_{AGV} = (35000 \times 5) + 14000 + 12000 + 9000 + (3000 \times 3) + (3500 \times 5) = 236{,}500\ \$$$

$$CAPEX_{AMR} = (45000 \times 5) + 14000 + 0 + 9000 + (3000 \times 3) + (3500 \times 5) = 274{,}500\ \$$$

p_v: Vehicle price [$]
C_{int}: Integration cost [$]
C_{inf}: Physical infrastructure cost [$]
C_{net}: Network infrastructure cost [$]
C_{charg}: Charging infrastructure cost [$]
C_{cert}: Safety certification cost [$]

OPEX represent the yearly costs associated with the operation of the equipment and include maintenance, energy consumption, software licenses, safety accidents, downtimes, damage and reworks:

$$OPEX = C_{soft} + Downtime + Material\ Damage + Safety\ Accidents + Rework + Energy$$

$$OPEX_{AGV} = 1500 + 22680 + 1200 + 1750 + 10530 + 2490 = 40{,}150\ \$/year$$

$$OPEX_{AMR} = 3500 + 22680 + 1200 + 1750 + 3510 + 2490 = 35{,}130\ \$/year$$

Manual OPEX are basically the same, but don't contain software and energy costs:

$$OPEX_{Manual} = Downtime + Material\ Damage + Safety\ Accidents + Rework$$
$$OPEX_{Manual} = 54000 + 24000 + 1200 + 17500 + 87750 = 183{,}250\ \$/year$$

C_{soft}: Yearly software cost [$]

Labor yearly cost was calculated in the same way for both manual and automated scenarios:

$$Labor = \left(H_d \times D_y \times N_o \times C_h\right) + Hiring\ \&\ Training$$

$$Labor_{AGV,AMR} = (16 \times 250 \times 3 \times\ 27) + 4500 = 328{,}500\ \$/year$$
$$Labor_{Manual} = (16 \times 250 \times 5 \times 27) + 7500 = 547{,}500\ \$/year$$

Yearly savings are calculated as the difference between the total OPEX and labor costs of the manual baseline versus those of the AGV or AMR scenarios. The calculations for the automated scenarios needed to include also the battery cost, since the assumption was one replacement every 3-5 years, and the layout change cost. For AGVs the adopted yearly factor is $5000 to reflect high costs of physical layout changes ($10k per event) and hardware-dependent navigation maintenance. In the case of AMRs, the factor is $2500 due to the virtual mapping flexibility and lower intervention costs during operational shifts. Both include a prorated share of the battery replacement cost over its expected lifespan. The final formula eventually is:

$$Savings_{AGV} = (OPEX_{Manual} + Labor_{Manual}) - (OPEX_{AGV} + Labor_{AGV} + 5000)$$
$$Savings_{AGV} = (183250 + 547500) - (40150 + 328500 + 5000) = 357{,}100\ \$/year$$

$$Savings_{AMR} = (OPEX_{Manual} + Labor_{Manual}) - (OPEX_{AMR} + Labor_{AMR} + 2500)$$
$$Savings_{AMR} = (183250 + 547500) - (35130 + 328500 + 2500) = 364{,}620\ \$/year$$

Table 5.3 - CAPEX, OPEX, Labor, Savings

	AGV	AMR	MANUAL
CAPEX [$]	236.500	274.500	0
OPEX [$]	40.150	35.130	183.250
LABOR COST	328.500	328.500	547.500
YEARLY SAVINGS	357.100	364.620	-

5.1.4 TCO assessment

The TCO calculation in five years can follow two different directions related to the layout changes. In scenario A, there are different layout changes depending on the technology type: AGV systems will face a lower number of changes due to their dependence on the physical infrastructure, while in the AMR and manual will be introduced a greater number of smaller changes. Scenario A represents the logic of conscious technological constraints. By choosing an AGV system, the company is aware of the limited flexibility regarding layout changes due to the physical infrastructure. This scenario assumes that if the primary goal had been higher adaptability, the company would have opted for an AMR solution instead. Therefore, the lower number of changes for the AGV is not an oversight, but a deliberate trade-off between system stability and flexibility. Scenario B, instead, compares an identical number of changes across all three cases. The choice of a normalized number of changes is used as sensitivity analysis, evaluating the economic impact if the AGV system were forced to undergo the same frequency of modifications as the more flexible AMR and manual systems.

Number wise, for scenario A, 2 layout changes were chosen for AGVs and 10 for AMRs and manual systems. Scenario B sees 10 layout changes per system.

Scenario A:

$$TCO = CAPEX + 5\ years \times (OPEX + Labor) + C_b + (N_l \times C_l)$$

$$TCO_{AGV} = 236500 + 5 \times (40150 + 328500) + 4000 + (2 \times 10000) = 2{,}103{,}750\ \$$$

$$TCO_{AMR} = 274500 + 5 \times (35130 + 328500) + 4000 + (10 \times 750) = 2{,}104{,}150\ \$$$

$$TCO_{Manual} = 0 + 5 \times (183250 + 547500) + (10 \times 1000) = 3{,}663{,}750\ \$$$

Scenario B:

$$TCO = CAPEX + 5\ years \times (OPEX + Labor) + C_b + (10 \times C_l)$$

$$TCO_{AGV} = 236500 + 5 \times (40150 + 328500) + 4000 + (10 \times 10000) = 2{,}183{,}750\ \$$$

$$TCO_{AMR} = 274500 + 5 \times (35130 + 328500) + 4000 + (10 \times 750) = 2{,}104{,}150\ \$$$

$$TCO_{Manual} = 0 + 5 \times (183250 + 547500) + (10 \times 1000) = 3{,}663{,}750\ \$$$

C_b: Battery replacement cost [$]
N_l: Number of layout changes
C_l: Layout changes cost [$]

Table 5.4 - Final TCO values

		AGV	AMR	MANUAL
A	**TCO in 5 years**	2.103.750	2.104.150	3.663.750
B	**TCO in 5 years**	2.183.750	2.104.150	3.663.750

5.1.5 Payback Period (PBP)

Another relevant parameter is the payback period (PBP), i.e. the amount of time required for an investment to generate sufficient cash flow to recover its initial cost. There are many formulas to estimate it, but in this calculation the one adopted was:

$$PBP = \frac{CAPEX}{Savings}.$$

The results were: 0.7 for AGVs and 0.8 for AMRs, corresponding to roughly eight and a half and nine and a half months, respectively.

To further validate the impact of the previously discussed parameters, the PBP was also estimated by excluding hidden costs. In this simplified version, OPEX is limited to software licenses and energy consumption for automated scenarios, while remaining null for the manual baseline. Removing these factors results in a longer period to recover the initial investment, as the yearly savings are reduced. Using the logic from Scenario A, the results for this comparison are presented in the table below.

Table 5.5 - OPEX, Savings, PBP without hidden costs

	AGV	AMR	MANUAL
OPEX without hidden costs	3.990	5.990	0
Savings without hidden costs	220.010	215.510	
PBP without HIDDEN COSTS	**1,1**	**1,3**	

5.2 Parameter selection and prioritization

Following the identification of the 101 parameters discussed in the previous section, a filtering process was applied to select the most relevant ones for the study. To make this selection, each parameter was weighted from 1 to 5 based on its importance and the availability of data. In specific cases, a score of zero was assigned to exclude parameters that were either nonessential to the current operational scope or lacked any reliable data. This evaluation was fundamental to identify the main information gaps and distinguishing the primary drivers from factors that were not as relevant for this analysis. The complete list of the 101 parameters, now updated with their respective scores for strategic importance and data availability, is presented in **Appendix D**. This detailed mapping provides a transparent overview of the prioritization logic used to move from the initial comprehensive identification to the final focused analysis.

5.2.1 Parameter selection and exclusion logic

The next step involved selecting a subset of these parameters to finalize the analysis and represent them graphically. The selection was not based strictly on high importance scores. Instead, it aimed to capture a diverse range of importance and data availability levels. A key criterion was to exclude parameters that have become industry standards or essential prerequisites for these technologies. For instance, factors such as Wi-Fi stability (a necessary condition for system implementation), speed limitations for safety, battery type (now predominantly Li-ion) and battery life were omitted. Since these features are consistently provided across all analyzed models, they offer no added value in differentiating solutions or guiding the final selection process. However, to ensure a comprehensive understanding of the technical requirements, the full list and detailed definitions of all selected parameters are provided in the glossary in **Appendix E**.

5.2.2 Data availability - Importance matrix

To visualize the results of the filtering process, the selected parameters were mapped into a prioritization matrix (displayed below) based on importance for selection process and data availability. This approach allows for an immediate understanding of the variables driving the study, distinguishing the core parameters, high-impact factors like carrying capacity, navigation type and vehicle cost, from the critical gaps. The latter represent relevant variables, such as operating costs and reliability, where data is scarce and requires careful assumptions.

Furthermore, the matrix highlights standard parameters, such as battery replacement cost, which act as necessary data but offer low differentiation between models. Finally, the low priority quadrant includes those factors with a marginal influence on the overall decision-making process, such as Global Warming Potential or infrastructure maintenance. This parameter is considered low priority under the assumption that periodic facility maintenance is already standard practice within the company, regardless of the specific technology implemented, thus not representing a differentiating cost driver for this study.

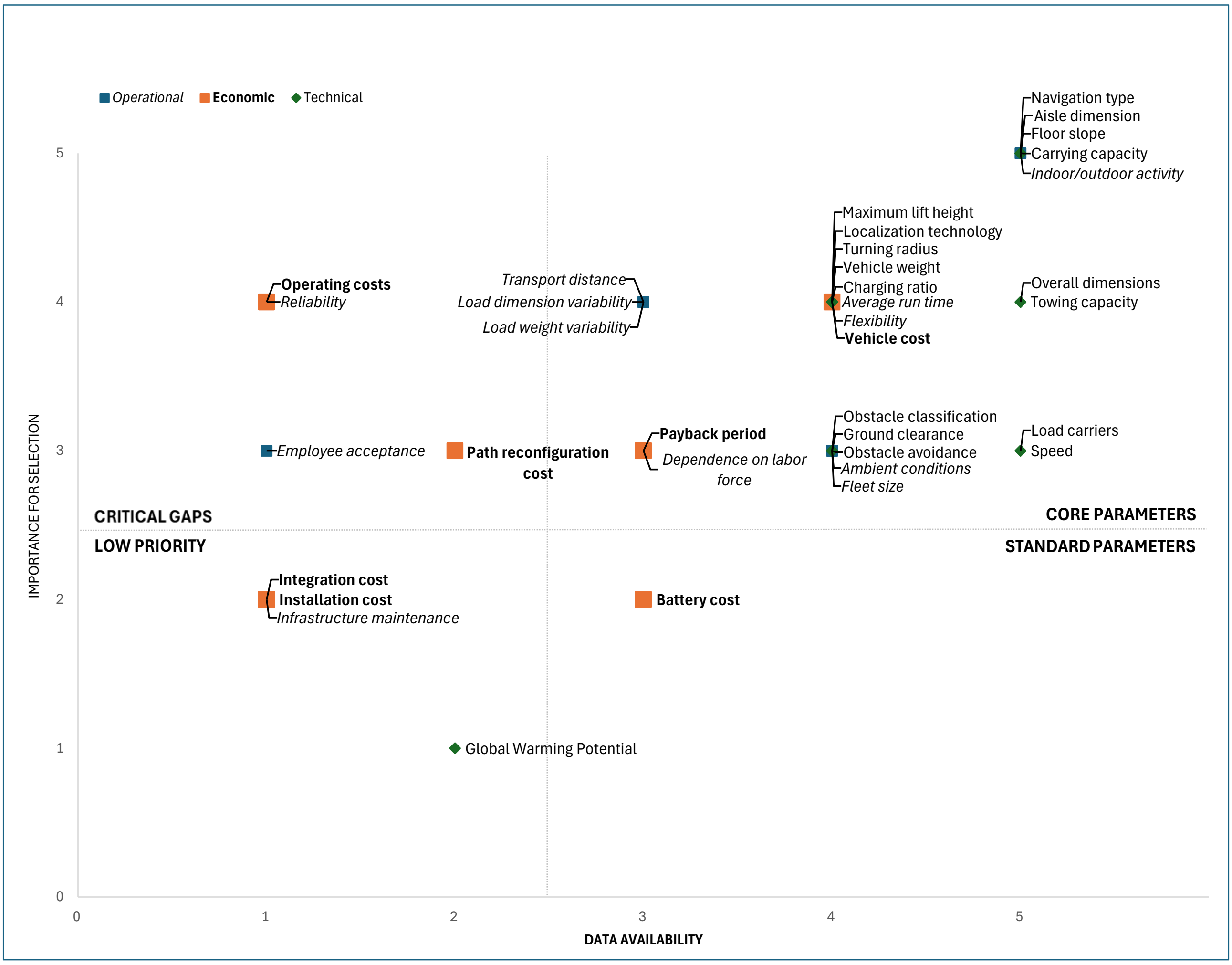

Figure 5.1 - Data Availability-Importance matrix

5.2.3 Data limitations and key evaluation lens

The integration of the TCO analysis and the prioritization matrix leads to a necessary reflection on the transition from manual to automated logistics. In a real-world industrial context, manual labor represents a significant and predictable cost, yet many companies may feel constrained by the initial budget required for digital transformation. However, the findings suggest that the evaluation should not be limited to CAPEX alone, but must consider the broader complexity of the operational reality.

It is fundamental to recognize that obtaining absolute and precise estimates for operating costs is extremely challenging prior to actual implementation. For this reason, the framework relies on industry benchmarks which indicate that OPEX is significantly lower than the potential savings, especially when hidden costs are included in the calculation. Moreover, within this scenario, the reliability of the entire system is not a static value, but a dynamic variable depending on the synergy between software quality, operator readiness and the efficiency of the physical system itself.

Given the difficulty of predicting absolute performance in advance, the aim of this study is to identify the optimal ranges and technical requirements needed to prepare the ground for subsequent phases. From this perspective, tools such as digital twin simulations, as suggested by Expert A, become essential to predict system behavior and validate performance before the final investment, transforming estimated uncertainty into a concrete operational strategy.

5.3 Final parameters list: ranges and thresholds

Once the final parameter list was established, the optimal operative ranges and thresholds were estimated to complete the framework. Starting with data coming from suppliers' datasheets, every range or number was calculated as the mathematical average of the data collected in the previous section (see **Appendix B**). All analyzed vehicles were classified by type, allowing for a robust distinction of ranges and results. As data were gathered from multiple company databases, the source "suppliers' datasheets" refers to the supplier list presented in the previous chapter.

In the case of qualitative data, a thematic analysis was performed to assess the frequency of each variable, with the most relevant ones reported in the following table in an order reflecting their frequency. For economic estimates, the sources follow those presented previously; however, the entire range was included in the table, as it provides a more accurate representation than a single average value. The table also includes two assessments based on supplier data and scientific literature requirements: dependence on labor force and infrastructure maintenance. Although the performance of these factors is largely the responsibility of the company implementing the system, it is still possible to provide an estimate for them thanks to the analyzed sources.

Furthermore, the PBP ranges have been estimated based on real case studies presented on supplier's websites. Finally, certain parameters have been intentionally identified as site-dependent. These represent critical process variables that cannot be standardized, as they rely exclusively on the user's internal facility conditions. For these entries, the framework acts as a diagnostic tool, indicating that an internal mapping or assessment is required by the user to complete the evaluation.

The resulting framework, consolidating these optimal ranges and technical thresholds into a structured reference tool, is presented in the next page.

Table 5.6 - Decision-support framework

Parameter	Type	AGV Underride Value	AGV Forklift Value	AMR Underride Value	AMR Top-Load Value	AMR Tugger Value	Source
Carrying capacity	Technical	1 t	1.76 t	0.75 t	0.78 t	-	Suppliers datasheets
Maximum lift height	Technical	-	-	-	-	-	Suppliers datasheets
Towing capacity	Technical	-	-	-	-	from 1 to 10 t	Suppliers datasheets
Overall dimensions	Technical	1480 x 775 x 285 mm	2425 x 925 x 2010 mm	1180 x 765 x 335 mm	1265 x 940 x 400 mm	1510 x 645 x 660 mm	Suppliers datasheets
Navigation type	Technical	QR code, Magnetic, Laser, Natural	Laser, Natural, Magnetic, Optical	SLAM, QR code, RFID, Laser	SLAM	Magnetic, RFID, SLAM, Laser	Suppliers datasheets
Minimum aisle dimension [a]	Technical	1610 mm	2160 mm	1480 mm	1715 mm	1650 mm	Suppliers datasheets
Floor slope tolerance	Technical	2 - 3%	5 - 6%	3%	3 - 4%	2 - 3%	Suppliers datasheets
Indoor/outdoor activity [b]	Operational	*Site-dependent*	*Site-dependent*	*Site-dependent*	*Site-dependent*	*Site-dependent*	To be defined by user
Vehicle cost	Economic	$25,000 - $80,000	$60,000 - $120,000	$20,000 - $90,000	$20,000 - $90,000	$50,000 - $95,000	Novus Hi-Tech Robotic Systemz
Localization technology	Technical	QR code, Reflector Navigation, Hybrid	Reflector Navigation, Hybrid	Natural Localization, LiDAR SLAM	Natural Localization, LiDAR SLAM	Natural Localization, LiDAR SLAM	Suppliers datasheets
Average run time	Operational	8 h	9 h	7 h	8 h	9 h	Suppliers datasheets
Turning radius	Technical	670 mm	1630 mm	440 mm	0 mm	870 mm	Suppliers datasheets
Vehicle weight	Technical	370 kg	1760 kg	186 kg	390 kg	400 kg	Suppliers datasheets
Charging ratio [c]	Technical	from 1:5 to 1:10	from 1:3 to 1:10	from 1:5 to 1:12	from 1:8 to 1:12	1:6 on average	Suppliers datasheets
Speed (max)	Technical	1.6 m/s	2.1 m/s	1.7 m/s	1.6 m/s	1.5 m/s	Suppliers datasheets
Load carriers	Technical	Pallets, Trolleys	Pallets	Pallets, Trolleys, Boxes	Pallets, Containers, Boxes	Trolleys, Wagons	Suppliers datasheets
Fleet size [d]	Operational	*Site-dependent*	*Site-dependent*	*Site-dependent*	*Site-dependent*	*Site-dependent*	To be defined by user
Flexibility to layout changes	Operational	Medium - High	Medium - High	High	High	High	Suppliers datasheets
Obstacle avoidance	Technical	Depending on the model	Yes	Yes on average	Yes	Yes	Suppliers datasheets
Obstacle classification	Technical	Depending on the model	Yes on average	Yes	Yes	Depending on the model	Suppliers datasheets
Ground clearance	Technical	25 mm	35 mm	25 mm	30 mm	25 mm	Suppliers datasheets
Load dimension variability [e]	Operational	*Site-dependent*	*Site-dependent*	*Site-dependent*	*Site-dependent*	*Site-dependent*	To be defined by user
Load weight variability [e]	Operational	*Site-dependent*	*Site-dependent*	*Site-dependent*	*Site-dependent*	*Site-dependent*	To be defined by user
Transport distance	Operational	Short - Medium	Medium - Long	Short - Medium	Short - Medium	Medium	Suppliers datasheets
Ambient conditions [f]	Operational	*Site-dependent*	*Site-dependent*	*Site-dependent*	*Site-dependent*	*Site-dependent*	To be defined by user
Dependence on labor force	Operational	Medium	Medium	Low	Low	Low	Assessment based on the autonomous exception management capabilities as stated in the suppliers' technical datasheets
Payback period	Economic	1.5 - 2.5 years	2 -3 years	1 - 1.5 years	1 - 1.5 years	1.5 - 2 years	Values based on suppliers' case studies and TCO estimations
Path reconfiguration cost	Economic	$5,000 - $15,000	$5,000 - $15,000	$0 - $1,500	$0 - $1,500	$0 - $1,500	Novus Hi-Tech Robotic Systemz
Reliability [g]	Operational	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	Internal assessment required
Operating costs	Economic	$800 - $2,500	$800 - $2,500	$1,000 - $3,000	$1,000 - $3,000	$1,000 - $3,000	Novus Hi-Tech Robotic Systemz
Employee acceptance [h]	Operational	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	Internal assessment required
Battery cost (Li-ion)	Economic	$3,000 - $5,000	$3,000 - $5,000	$3,000 - $5,000	$3,000 - $5,000	$3,000 - $5,000	Novus Hi-Tech Robotic Systemz
Installation cost	Economic	$5,000 - $20,000	$5,000 - $20,000	$0	$0	$0	Novus Hi-Tech Robotic Systemz
Infrastructure maintenance	Operational	Medium - High	Medium	Low	Low	Low	Assessment derived from the hardware installation requirements specified in the AGV/AMR system integration manuals and scientific literature
Integration cost (average)	Economic	$8,000 - $20,000	$8,000 - $20,000	$8,000 - $20,000	$8,000 - $20,000	$8,000 - $20,000	Novus Hi-Tech Robotic Systemz
Global Warming Potential	Technical	from 851 to 1174 kg Co2 eq	from 851 to 1174 kg Co2 eq	from 889 to 1112 kg Co2 eq	from 889 to 1112 kg Co2 eq	from 889 to 1112 kg Co2 eq	Stefanini et al. (2025) [i]

[a] Minimum aisle dimension: with AGVs forklift sometimes it needs to be bigger to have active obstacle avoidance (possibility of performing maneuvers).

[b] Indoor/Outdoor: the average standard operating temperature is between 5 and 40° C. Alternatives that can operate in colder environment exist but are associated with a higher price.

[c] 1:12 ratio means that 10 minutes of charge corresponds to 2 running hours, while 1:3 ratio stands for 30 minutes of work per 10 minutes of charge.

[d] Fleet size is up to the company, since suppliers can guarantee that their software can coordinate a very high number of vehicles simultaneously. However, the topic will be discussed in the next paragraph, with the guidelines for the implementation.

[e] Load and dimension variability are relevant especially because they have an impact on the aisle dimension and obstacle avoidance strategy. Objects much bigger than the vehicle require an extra clearance space to allow for maneuvers and emergency brake distance.

[f] The ambient conditions concern mainly dust, grease, light, operating temperature and other disturbances. Dirty floors are not suited for technologies with an infrastructure on the ground, such as labels or tapes, while reflectors for the laser navigation could be light sensitive.

[g] It is very difficult to estimate the reliability of a system that has not been implemented yet. Anyway, many suppliers offer nowadays the possibility of simulating system performance with digital twins.

[h] Employee acceptance is an element often underestimated. An operator that is against the technologies will interfere with the work of a robot, decreasing the efficiency of the system. This can usually be solved with the training activities provided by the suppliers.

[i] (Stefanini et al., 2025)

5.4 Guidelines for preliminary implementation

Once the selection is completed, the next critical phase is system implementation. Among all the activities that need to be performed, it is possible to identify five main areas to help the navigation through this process.

5.4.1 Infrastructure assessment

One of the primary prerequisites for seamless system implementation is the quality and stability of the wireless network infrastructure. As indicated in the technical requirements of suppliers and papers such as Fragapane et al. (2021) and De Ryck et al. (2020), autonomous vehicles rely on constant communication with the fleet management system to receive missions and update their positioning. A lack of Wi-Fi coverage or delays in transmission can lead to system deadlocks or emergency stops. Therefore, it is essential to ensure signal stability and minimize communication lags. This prevents unexpected operational downtime and guarantees that the system meets the safety standards required to work alongside humans.

As shown in the suppliers' technical datasheet, floor conditions are a relevant constraint. With such a limited slope tolerance and ground clearance, holes and bumps cannot be present in the working area. Additionally, the presence of dust and grease must be carefully monitored, as they can compromise the robot's performance by reducing traction and interfering with sensor precision. Although expert insights from Supplier A suggest that different wheel types can be selected to compensate for specific environmental conditions, this is not always a viable path. Dimensional constraints or budget limitations may prevent the adoption of specialized components, making the maintenance of a clean and regular floor surface the most cost-effective and reliable solution for the system stability over its lifecycle.

5.4.2 Operational layout

Battery management is a crucial aspect of system performance, as the runtime of vehicles can only be maximized through a correct charging strategy. To effectively implement automatic or opportunity charging (De Ryck et al., 2020), the positioning of charging stations becomes a critical factor for maintaining high system availability. As observed in the charging ratios analyzed in the previous section (ranging from 1:3 up to 1:12), charging spots should be strategically located along the main operational flows or near buffer areas. This placement minimizes non-productive travel time and allows vehicles to recharge during natural pauses in the workflow. By integrating these spots into the existing layout without causing bottlenecks, the system can ensure continuous operation and productivity levels estimated in the TCO analysis table.

Moreover, a core requirement for safety and efficiency is the definition of no-go zones and the management of narrow corridors. While AMRs offer flexibility by means of obstacle avoidance, narrow aisles significantly increase the risk of deadlocks or collisions. As indicated by (Silva et al., 2024), with an increase in fleet density, the probability of interference rises, making the virtual mapping of restricted areas essential to preserve the system's overall throughput.

Another aspect related to the layout is cross pathing. Intersections where multiple vehicle paths cross require a specific coordination strategy. As discussed by (Sperling et al., 2023), the complexity of layout topologies and the orientation of flow paths significantly influence the risk of congestion. Beyond the technical capability of the sensors, the fleet manager must prevent vehicles from freezing in a mutual block. Therefore, the implementation guidelines must include a preliminary simulation of these high-traffic nodes to ensure that the physical layout supports the software's coordination logic.

5.4.3 Socio-technical integration

The success of the implementation depends on the seamless integration of the technology into both the digital and human ecosystems of the facility. From a technical perspective, adopting the VDA 5050 protocol is a primary requirement, as it enables standardized communication between vehicles and the central control system (Ullrich & Albrecht, 2019). This interoperability is essential for managing mixed fleets and ensuring that the software can effectively coordinate the hardware. However, technical compatibility alone does not guarantee performance. Employee acceptance has been identified as a leading cause of failure in reaching operational targets. Insights from the expert interview (Supplier A) reveal that resistance to change can manifest in intentional disruptions, such as operators intentionally obstructing vehicle paths. Furthermore, a lack of deep software knowledge among staff often prevents the system from reaching its full potential. To mitigate these risks, the implementation must include training programs and a clear change management strategy. Educating the workforce not only on how to use the software but also on the benefits of the transition is essential to transform potential resistance into collaboration.

5.4.4 Simulation

Before physical implementation, testing the system through a digital twin is a fundamental step to reduce investment risks. As analyzed by Kaven et al. (2022), simulation allows for the verification of the integration between proprietary systems and communication standards in a virtual environment. The importance of this phase was also confirmed during the interview with Expert A, who highlighted how their software allows for the preventive simulation of system performance. Using a digital twin is not only useful for identifying potential bottlenecks, but it is essential to validate whether the chosen fleet and layout can reach the established throughput targets, ensuring that the transition to physical reality is as smooth as possible.

5.4.5 Pilot project

The final recommendation for the implementation process is the launch of a pilot project. deploying the technologies within a single process allows for the monitoring of real-world results and validation of the TCO assumptions before scaling, ensuring that the projected Return On Investment (ROI) remains accurate under operating conditions. If the pilot results are positive, the system can then be scaled; however, this expansion must be handled carefully. As highlighted in the previous analysis of fleet performance (Silva et al., 2024), increasing the number of vehicles can lead to a higher probability of collisions and deadlocks if the layout contains choke points. Starting with a pilot allows management to identify these physical constraints early and make necessary corrections before the final investment. This phased approach ensures that the system scales effectively while maintaining the required safety and throughput standards.

5.5 Flowchart

To support managers in navigating the outcomes of this research, the figure below outlines the practical, step-by-step application of the decision-support framework. This flowchart operates as a sequential guide to convert the gathered data into an effective investment choice.

First, the user maps internal facility constraints and prioritizes key parameters using the matrix. Second, these specific company requirements are screened against the framework's technical thresholds to immediately discard non-compliant vehicle categories. Third, a detailed Total Cost of Ownership calculation is performed on the remaining alternatives to weigh the financial impact of hidden expenses against expected savings. Finally, the selected fleet configuration is validated through the preliminary implementation guidelines to ensure that all critical operational, structural and socio-technical risks are addressed prior to physical deployment.

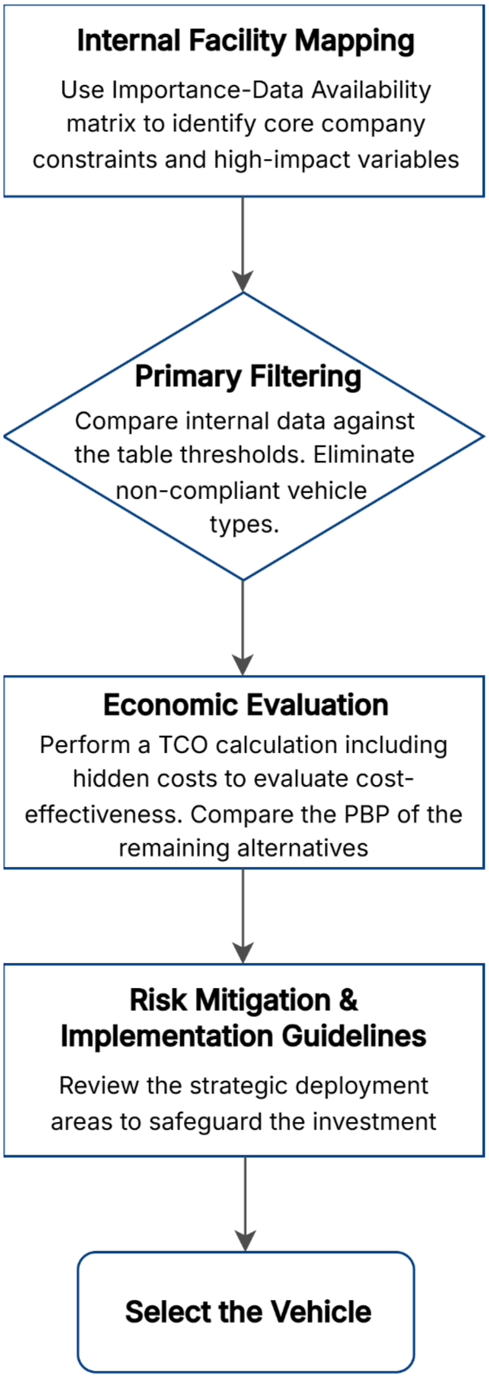

Figure 5.2 - Framework application flowchart

6. Model validation

To ensure the reliability and industrial applicability of the proposed decision-supporting framework and implementation guidelines, a qualitative validation phase was conducted. The objective of this stage is to verify whether the identified parameters and operational thresholds accurately reflect the actual challenges of industrial logistics processes.

The validation is based on a semi-structured interview with an industry expert, selected from professionals with direct experience in AGV/AMR fleet management, system integration and internal logistics. This method was chosen for its ability to explore not only technical data accuracy but also the operational nuances that rarely emerge from technical literature alone.

The interview followed a structured protocol divided into four key areas: process analysis, parameter matrix validation, economic factors verification and strategic insights.

The flexible nature of the interview (available in full in **Appendix H**) allows for the collection of qualitative insights based on expert judgment, focusing on the structural logic of the framework rather than the verification of empirical technical thresholds, which are already grounded in verified supplier documentation. The results of this validation phase have been used to calibrate the final framework, ensuring that the recommendations provided to the case company are not only theoretical but also operationally sustainable.

6.1 Validation of Data Availability-Importance matrix

The first core element submitted for validation was the prioritization matrix (Figure 5.1). Expert B, coming from extensive experience in large-scale automotive automation projects, provided a critical review of how operational, technical, and economic parameters are mapped.

Regarding the core parameters quadrant (high importance, high data availability), the expert strongly confirmed that navigation type, vehicle safety features, and shop floor dimensions are the primary constraints analyzed during procurement. However, some divergences emerged.

First, the expert argued that installation costs should be shifted from the core parameters into the critical gaps quadrant. From an industrial perspective, these costs are highly important but exceptionally difficult to estimate accurately during the preliminary phases of a project, representing a major data gap for buyers. Furthermore, the expert emphasized that integration costs are consistently underestimated. While suppliers provide a standard baseline quote, any subsequent operational modification later in the project generates substantial extra expenses, a risk that must be mapped early in the selection process.

Second, the expert pointed out a missing parameter in the current framework: the dual nature of physical-to-digital Integration. This factor represents the intersection between mechanical tolerances and software execution. For instance, before a fleet management system can trigger a mission, the vehicle must achieve millimeter mechanical precision to align with fixed racks or docking stations. Without a reliable physical interface, software integration inevitably fails, making this physical-to-digital coordination a strict prerequisite for the selection matrix.

Finally, a minor context-specific distinction emerged regarding vehicle speed and load carriers. Although the framework classifies these as core parameters where data might represent a gap for some buyers, the perspective within a large-scale corporate environment is slightly different. Since the case company operates within regulated and standardized facilities, internal safety and operational rules already dictate strict maximum speed baselines and standardized pacing profiles across the plant. Therefore, for highly structured manufacturers, this information is already defined internally, meaning that the supplier’s specifications do not represent a critical information but rather a baseline that must comply with pre-existing internal constraints.

Specifically, to reflect these operational adjustments, installation and integration costs have been assigned higher importance ratings, shifting their coordinates into the critical gaps quadrant due to the high financial uncertainty of early-stage estimations. Similarly, the newly introduced parameter, software integration (taking into account the double nature mentioned earlier), has been positioned at the top-left boundary of the matrix, emphasizing its role as a strict operational prerequisite. The parameter is in fact assigned maximum importance because any failure in mechanical alignment causes the software to pause, disrupting the entire automated workflow. At the same time, data availability is low because this specific information cannot be retrieved from standard supplier catalogs or scientific literature; it represents a blind spot that the company can only uncover by conducting specific internal studies on its own infrastructure tolerances.

To visually capture these adjustments, a calibrated version of the prioritization matrix has been developed (Figure 6.1), illustrating the relocated cost parameters and the introduction of physical-to-digital integration as a core prerequisite.

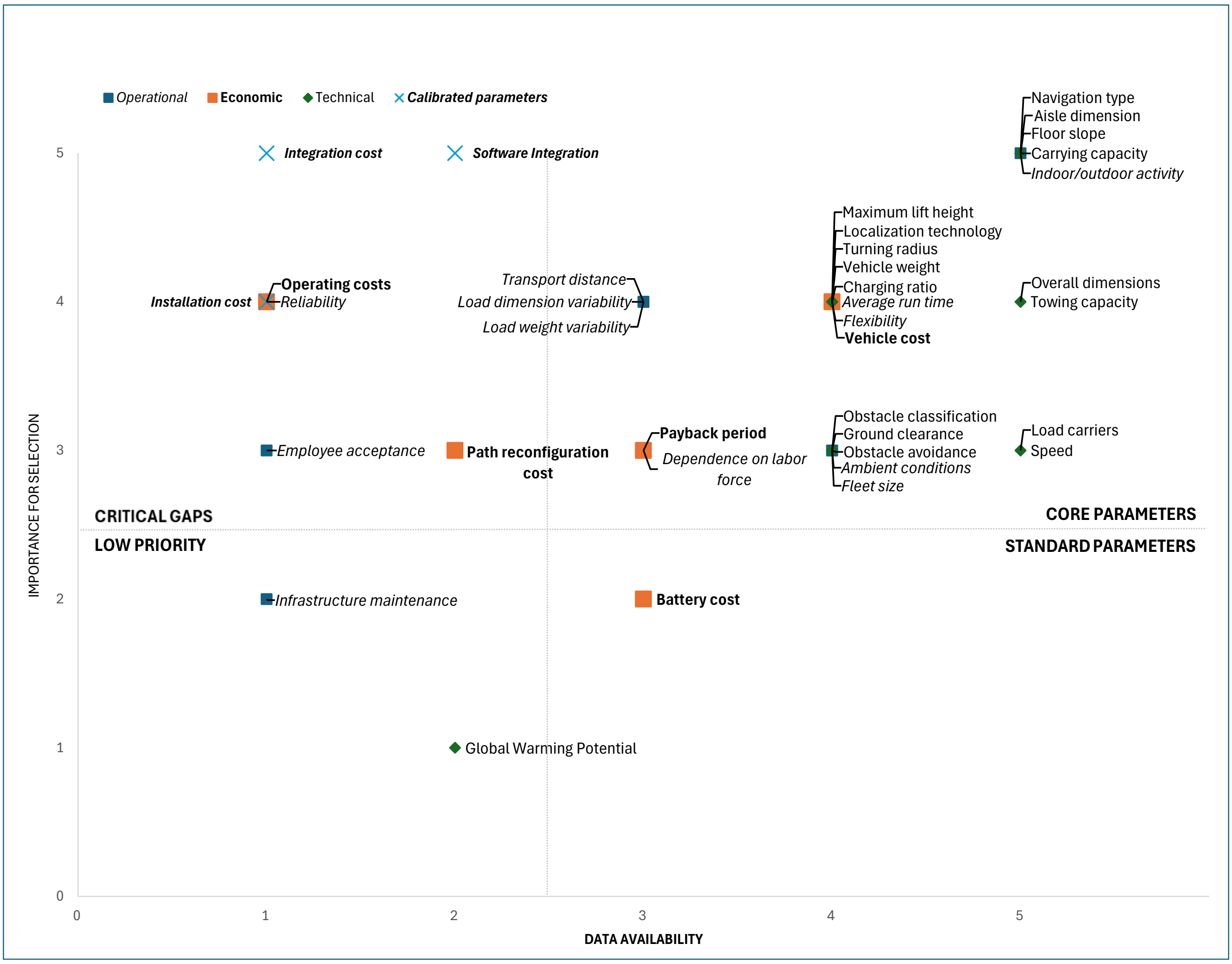

Figure 6.1 - Calibrated Data Availability-Importance matrix

6.2 TCO validation

The economic dimensions of the framework, specifically regarding labor cost reductions and hidden financial benefits, were subsequently evaluated by the expert.

A consensus emerged regarding the reduction of operational labor expenses. Expert B validated that a substantial reduction in labor costs is realistic and achievable in high-labor-cost environments, such as the Swedish market, providing a reliable baseline for calculating operational savings. However, this feasibility is strictly tied to process stability, where automated vehicles operate within continuous, standardized flows with highly repetitive tasks. Furthermore, the expert agreed with the inclusion of hidden costs within the financial model, confirming that capturing these non-apparent variables is essential to fully grasp the long-term ROI.

Despite this alignment, a significant contextual variance emerged concerning the PBP. While the preliminary calculations of the framework estimated a PBP of under one year for very small fleets due to the integration of hidden benefits, the case company's investment plan for a fleet of roughly ten automated vehicles indicates a longer payback period, ranging between 2 and

2.5 years. This discrepancy is explained by two main operational factors. First, the framework's initial estimate was modeled on an extremely limited fleet size, where the low initial capital expenditure (CAPEX) naturally shortens the recovery timeline. When scaling the fleet to around ten vehicles, the initial investment increases significantly, which extends the baseline PBP before accounting for external savings. Second, the expert provided a refinement on how hidden financial benefits actually materialize, emphasizing that operational safety is the absolute highest priority and the primary driver for securing project approval from management. Within confined or high-risk production areas, minimizing manual forklift traffic is a critical necessity that justifies the automation investment regardless of the strict payback timeline. Furthermore, within their operational environment, direct material scrap resulting from human errors is secondary and does not significantly lower the PBP. Instead, the true hidden financial advantage stems from preventing infrastructure and facility damage. Manual forklift operators frequently collide with fixed structures, such as factory gates, permanent racks, and building pillars. Therefore, the structural logic of the developed TCO framework is validated: balancing physical infrastructure repair costs with strict operational safety requirements represents the actual driving force that accelerates the financial model, rather than the savings from the transported goods themselves.

6.3 Industrial insights for implementation guidelines

Beyond the matrix and financial calibrations, Expert B provided some recommendations based on real-world deployment challenges. These field insights offer valid integration for the implementation guidelines previously developed.

Process standardization was highlighted as a foundational step. The expert explicitly stated that automation cannot be successfully integrated into a process that is not fully mapped or stable. In industrial logistics, rushing into a technological selection, such as choosing between an AGV and an AMR, before settling the underlying material flow logic is a critical error. Operational standardization must always precede any technological implementation.

In second place, a strict warning emerged regarding the independent validation of supplier simulations. This perspective directly refines the concepts addressed in the framework’s simulation phase (5.4.4 Simulation). While suppliers utilize simulation tools to estimate the required fleet size for a specific throughput, the expert strongly advised against relying entirely on external calculations. Buyers must execute internal verification studies and run independent throughput calculations, as the internal engineering team possesses a deeper and more accurate understanding of specific shop-floor layers and operational anomalies that external suppliers inevitably overlook.

The concept of the “babysitting phase” was the final insight introduced by Expert B to define the initial pilot deployment (5.4.5 Pilot project). During the first months of controlled field trials, the system frequently experiences operational stoppages. Rather than treating these halts as technical system failures, the case company performs a continuous root cause analysis directly on the shop floor. If data tracking reveals that an interruption was triggered by human interference or an operator obstructing the vehicle's path, a targeted, on-the-job training session is immediately deployed to correct the behavior. This iterative approach ensures that socio-technical alignment is managed dynamically based on real-time data rather than theoretical assumptions.

6.4 Final recommendations

To conclude the validation phase, is worth mentioning that Expert B highlighted also the cross-functional nature of automated vehicle projects and provided a systematic approach to managing information gaps during the early deployment stages.

Indeed, large-scale automation initiatives cannot be relegated to a single department; they demand the continuous alignment of process engineering, logistics, IT, maintenance, safety, and procurement. The project timeline heavily depends on this synchronization. For instance, within the case company, implementing a small-scale fleet of 10 to 12 vehicles requires less than a year, whereas a large-scale deployment of 200 to 300 units extends the timeline to 1.5 or 2 years.

When facing critical information gaps, the expert recommended adopting a parallel execution methodology rather than a traditional sequential workflow. By deploying immediately stable and standardized process components while concurrently developing complex software interfaces, the engineering team can protect the project timeline and mitigate data deficiencies without lagging behind key milestones.

Finally, the socio-technical factor emerged once again. Based on the expert's experience, a major operational challenge frequently underestimated during the planning phase is the co-existence of automated fleets with manual forklifts and human operators. To prevent unnecessary protective stops and operational bottlenecks in mixed-traffic environments, companies must establish strict and visible operational boundaries. Defining dedicated routing logics and minimizing physical interactions between automated and manual workflows is a fundamental requirement. This sharp strategic focus is what ultimately guarantees high fleet utilization and secures the expected return on investment.

7. Result discussion

The discussion chapter evaluates the developed framework from four different perspectives: generalizability, socio-technical trade-offs, implications for managers and limitations combined with future research directions.

The validation of the structural logic of both the selection matrix and the TCO model by a leading automotive manufacturer demonstrates the industrial relevance of the developed framework. Despite variations in the payback period due mainly to fleet size, the focus on safety and infrastructure protection aligns with real-world investment criteria.

Furthermore, this alignment highlights the robustness of the study's circular validation. By building the framework upon established literature insights, validating technical data and specifications with a technology supplier (Supplier A) and ultimately verifying the overarching logic with an industrial end-user, the research achieves a balanced perspective. This triangulation ensures that the final decision-driven model is not only grounded in academic theory and supplier capabilities but is also calibrated against the practical, cross-functional demands of manufacturing environments.

7.1 Framework generalizability

One of the limitations presented in the methodology was the scope specificity. The framework was developed using data derived primarily from the automotive and manufacturing sectors, with a specific focus on the Swedish industrial environment. In Sweden, the high labor cost makes automation exceptionally attractive, representing the primary source of direct financial savings.

In countries with lower average wages, however, the economic justification shifts. While both experts validated operational safety and infrastructure damage prevention as critical advantages of automation, these factors would become even more decisive in low-wage environments. In such contexts, where labor cost reductions alone may not be enough to justify the initial investment (CAPEX), the avoidance of facility repair costs, operational downtime, and safety risks ceases to be a secondary benefit. Instead, these elements emerge as the primary strategic and financial drivers required to secure project approval and accelerate the investment recovery timeline.

Another critical aspect to evaluate within the framework is the scale of the project. When introducing a very small fleet (e.g., 1 to 3 vehicles), the PBP can be extremely short due to the low initial CAPEX and straightforward deployment. However, scaling up the number of vehicles not only extends this recovery period but also introduces unexpected operational and technical complications that must be thoroughly assessed before the implementation phase.

As the fleet size increases, infrastructure constraints become more severe. Financially, large-scale deployments extend the payback period significantly due to high integration and infrastructure costs. Issues such as fleet management software bottlenecks, traffic congestion, docking station availability and the co-existence with manual forklifts scale exponentially rather than linearly. Therefore, it is up to project managers to conduct a careful and comprehensive evaluation of these factors. To mitigate these risks, the selection and implementation process cannot be relegated to a single department; it requires the active involvement of a cross-functional team, encompassing logistics, process engineering, IT safety, and maintenance, to ensure that the facility's physical and digital infrastructure can support a larger automated deployment without generating unforeseen downtime or bottlenecks.

7.2 Socio-technical trade-offs

Automation is not just a combination of software and hardware, but it is deeply dependent on human factors. Because automated vehicles and manual operators share the same shop-floor environment, investing time and resources into socio-technical integration is fundamental. As highlighted by Expert A, human interference, whether intentional or unintended, represents the primary risk for unexpected fleet stoppages.

This challenge extends beyond safety compliance. Training programs must focus on increasing operator awareness and system acceptance to foster a productive work environment. For these reasons, the "babysitting" phase and the root cause analysis mentioned by Expert B are critical operational steps. Eventually, implementation success does not rely solely on technical performance, but on the organization's capability to systematically manage the interaction between human personnel and automated systems.

7.3 Managerial implications

It is common to think that AMRs are always the best solution due to their flexibility and advanced technology. However, in contexts like the automotive industry, which features stable layouts, the stability and consistency of an AGV represent a great advantage. Indeed, the first step in any automation project must be a meticulous process study and analysis. Only with full knowledge of the process undergoing the transition is it possible to assess the potential of these technologies and exploit their advantages. Therefore, managers must prioritize studying their own internal processes.

Moreover, companies must be fully aware of integration costs. Once a supplier is selected, the buyer loses bargaining power. For this reason, it is critical to study the process beforehand, create simulations and leverage tools like digital twins along with the resources of all departments to reduce the risk of unexpected cost increases. Additionally, managers should consider the complexity of connecting the new fleet software with pre-existing systems (WMS or ERP) during initial budgeting rather than treating it as a post-procurement detail. As established in the theoretical chapters, planning remains the most critical stage of the entire implementation process.

7.4 Limitations and future research

Some of the main limitations of this framework include the data gaps regarding system installation and software integration costs. Moreover, the TCO and PBP estimations are not absolute numbers, but rather a method to support the logic behind the decision-making process and to prove that automation brings many advantages that are usually overlooked, which are sometimes even more relevant than labor cost savings. In the framework, specific data regarding the user's processes are intentionally omitted because they are highly context specific. It is not possible to give predefined indications regarding these aspects, since every manufacturing process and every facility is unique.

Additionally, the AGV and AMR landscape are subject to continuous change and technological development. Therefore, the data and specifications presented in this framework will need to be updated or cross-checked in the coming years. Future research should monitor these technological shifts, as new advanced transport solutions will likely emerge together with new digital tools to further support companies during the planning and selection phases.

8. Conclusions

The primary objective of this thesis was to provide manufacturing companies with a set of tools and actionable guidelines to successfully navigate the selection and implementation planning of AGVs and AMRs. By combining insights from literature, technical input from a technology supplier and validation from a leading automotive manufacturer, the research highlights how economic drivers, technological constraints and operational readiness simultaneously influence the investment decision.

8.1 Research questions

Based on the findings, the answers to the formulated research questions are presented below.

RQ1: What are the key parameters and technical constraints for technology selection and implementation planning for automated material handling solutions, specifically AGVs and AMRs?

The selection and implementation planning of automated guided vehicles and autonomous mobile robots depend on a multi-criteria intersection of operational, technical and economic parameters. The research identifies that the primary condition for any automated intralogistics project is the physical configuration and stability of the plant layout. Meticulous evaluation of floor conditions, specifically floor slope tolerances, alongside aisle dimensions represent strict technical constraints that dictate vehicle maneuverability and braking safety zones. While physical attributes such as carrying capacity and towing capacity differentiate models based on load requirements, the choice between AGV and AMR navigation logic is governed by environment dynamics. Stable and repetitive manufacturing architectures favor the deterministic path planning and fixed cycle times of infrastructure-based AGVs, whereas complex and evolving surroundings leverage the infrastructure-free flexibility of AMRs.

From an implementation and economic planning perspective, the framework highlights that while labor cost savings represent the most direct and quantifiable financial driver within the TCO, the evaluation must include operational factors that heavily influence the actual payback period. Industrial validation emphasizes that installation and software integration costs constitute major data gaps that are frequently underestimated during the preliminary phases. Furthermore, successful planning requires balancing technical performance with socio-technical readiness, where human factors, operator training and system acceptance are as critical as hardware specifications to prevent unexpected fleet stoppages. Finally, the analysis demonstrates that cost avoidances related to operational safety, facility damage protection and the reduction of human-induced errors act as crucial secondary drivers. These factors safeguard investment and, in environments with different wage structures or high operational risks, can become decisive strategic criteria to justify the initial capital expenditure.

RQ2: How can these factors shape the design of a decision-supporting tool that assists both the selection and the implementation planning in such a complex environment?

To navigate the complexity of intralogistics automation, these factors dictate that a decision-supporting tool cannot rely on a single, isolated method, but must instead feature a multi-staged, sequential and interconnected design. The research demonstrates that the tool must be structured into two primary, interdependent modules: a qualitative technological selection matrix and a quantitative TCO model. The first stage shapes the tool by using the physical plant constraints and environmental dynamics as strict filtering parameters. By mapping attributes like layout stability, floor conditions and clearance dimensions, the tool screens out incompatible transport technologies at the earliest stage. This qualitative layer ensures that managers do not waste resources evaluating solutions that are physically or operationally unfeasible for their specific shop-floor conditions, effectively narrowing down the choice between AGVs, AMRs, or manual alternatives based on deterministic requirements.

Once technological feasibility is established, the operational and socio-technical factors shape the second stage of the tool, which shifts the focus toward quantitative implementation planning through the TCO and PBP module. Rather than treating financial evaluation as a simple calculation of hardware purchasing costs, the tool must incorporate the broader economic realities of integration. This is achieved by combining specific fields for integration and installation costs, while ensuring that the financial model reflects the actual investment recovery timeline based on the selected fleet size. Furthermore, the tool's design must reflect both direct and indirect financial drivers; while labor cost reductions form the baseline of the savings model, the tool integrates risk-mitigation factors, such as safety improvements and facility damage prevention, as core variables. This comprehensive architecture ensures that the final decision-supporting tool does not function as a static theoretical exercise, but as a dynamic framework that bridges the gap between technological capabilities and long-term financial viability.

8.2 Academic and industrial contributions

This research contributes to both theory and practice by bridging the gap between academic literature and real-world industrial application. By integrating theoretical insights with empirical technical data from technology suppliers and validating the final logic with industrial end-users, the study provides a comprehensive, triangulated framework. Academically, it expands the understanding of intralogistics automation by treating technology selection as a multi-criteria process rather than a simple hardware choice. Industrially, it provides project managers with a tool and actionable guidelines to evaluate the operational realities, integration complexities and financial trade-offs of automation investments.

8.3 Final remarks

The future of intralogistics automation will likely be driven by an increasing need for operational resilience, flexibility and tighter software integration. As technologies like AGVs and AMRs continue to evolve, the distinction between rigid and flexible automation will decrease, allowing facilities to deploy adaptive hybrid fleets. However, technological advancement alone will not guarantee project success. The long-term viability of automated material handling solutions will ultimately depend on a company's ability to fully analyze its internal processes and properly budget for integration complexities from the very beginning. Within this context, structured decision-supporting tools will remain essential instruments to transform technology selection from a capital risk into a predictable and strategic industrial investment.

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10. Appendix

Appendix A - Comprehensive parameters list

This appendix contains the complete list of the technical, operational, and economic parameters identified throughout the study. These variables form the baseline of the decision-supporting framework, categorized by vehicle or process reference.

Table A.1 - Complete and categorized list of 101 parameters for AGVs and AMRs selection

Process / Vehicle	Type	PARAMATERS
p	Operational	Aisle dimention
p	Operational	Slope and ramps
p	Operational	Indoor/outdoor activity
p	Operational	Material handling system design (AS-IS)
p	Operational	Floor conditions
p	Operational	Layout topology
p	Operational	Station operation frequency
p	Operational	Number of stations
p	Operational	Path segregation from operators
p	Operational	Flow path orientation
p	Operational	Fleet size
p	Operational	Load dimension variability
p	Operational	Load weight variability
p	Operational	Transport distance
p	Operational	Ambient conditions
p	Operational	Task structure
p	Operational	Traffic density
p	Operational	Number of path crossing
p	Operational	Possibility of mistakes
p	Operational	Sensitivity of the warehouse system
p	Technical	Speed limitation for safety
p	Technical	WiFi stability
v	Economic	Vehicle cost
v	Economic	Path reconfiguration cost
v	Economic	Software license cost
v	Economic	Operating costs
v	Economic	Battery replacement cost
v	Economic	Mapping cost
v	Economic	Reconfiguration cost
v	Economic	Installation cost
v	Economic	Training cost
v	Economic	Integration cost
v	Economic	Spare part holding cost
v	Economic	Transportation cost
v	Economic	Payback period
v	Economic	Vehicle insurance
v	Operational	Accuracy
v	Operational	Reliability
v	Operational	Flexibility
v	Operational	Productivity
v	Operational	MTBF
v	Operational	MTTR
v	Operational	Average run time
v	Operational	Software reliability
v	Operational	Localization error
v	Operational	Pick and drop times
v	Operational	Labor saving ratio
v	Operational	Dependence on labor force
v	Operational	Training activities for operators
v	Operational	Operators required to manage obstacles
v	Operational	Employee acceptance
v	Operational	Energy consumption
v	Operational	Spare parts availability
v	Operational	Tasks' success rate
v	Operational	Blocking time
v	Operational	Number of collisions
v	Operational	Number of re-routings
v	Operational	Deadlock frequency
v	Operational	Infrastructure maintenance
v	Operational	Cleaning frequency required
v	Technical	Carrying capacity
v	Technical	Navigation type
v	Technical	Safety standards compliance
v	Technical	Navigation system level
v	Technical	Slope/gradient capacity
v	Technical	Working temperature range
v	Technical	Maximum lift height
v	Technical	Overall dimensions
v	Technical	Towing capacity
v	Technical	Manual override
v	Technical	Localization technology
v	Technical	Turning radius
v	Technical	Vehicle weight
v	Technical	Speed ranges of the vehicle
v	Technical	Load carriers
v	Technical	Sensor range and field of view
v	Technical	Minimum aisle clearance
v	Technical	Floor quality requirements
v	Technical	Obstacle avoidance
v	Technical	Obstacle classification
v	Technical	Integration time with existing WMS/ERP
v	Technical	Ground clearance
v	Technical	Operating humidity range
v	Technical	Installation complexity
v	Technical	Clearance zone/positioning tolerance
v	Technical	Transfer station height
v	Technical	Blind spots
v	Technical	Charging time
v	Technical	Battery type
v	Technical	Charging ratio
v	Technical	Battery life
v	Technical	Charging current / voltage
v	Technical	Charging method
v	Technical	Charging station size
v	Technical	Battery degradation rate
v	Technical	Diagnostic remote access availability
v	Technical	HNI (Human Machine Interface)
v	Technical	Map update frequency
v	Technical	Light sensitivity
v	Technical	Sound level during operation
v	Technical	Global Warming Potential

Appendix B - Technical benchmarking data for automated vehicles

This appendix contains the technical data collected from the suppliers' datasheet. These parameters support the direct comparison between AGV and AMR solutions based on vehicle and process capabilities.

Table B.1 - Physical dimensions and mechanical performance

Supplier	Model	Type	Flexibility	Playload (t)	Towing capacity (t)	Max lift height (mm)	Optimal transfer station height (mm)	Vehicle dimensions l,w,h (mm)	Vehicle weight (kg)	Speed loaded (m/s)	Speed empty (m/s)
STILL	AXH 10 iGo	AMR (underride)	High	1	-	-	280 / 300	1440 x 634 x 222	170	2,2	2,2
STILL	ACH 10 iGo	AGV (underride)	Medium-High	1	-	-	330 / 320 480 530 730	1180 x 832 x 260	230	1,2	1,5
STILL	ACH 15 iGo	AGV (underride)	Medium-High	1,5	-	-	331 / 320 480 530 730	1181 x 832 x 260	235	1,2	1,5
STILL	OPX iGo neo	AGV (forklift)	High	2	-	700	0 - 700	3700 x 720 x 1300	1100	3,3	3,8
AGVE	A2	AGV (forklift)	Medium-High	1	0,5 - 1	1700	0 / 800	1500 x 800 x 2100	550 800	1 1	1,5 1,2
AGVE	A4	AGV (forklift)	Medium-High	2	2 - 3,5	6000	0 / 600 / 900	1900 x 1000 x 2300	1050	1,5	2
AGVE	A6	AGV (forklift)	Medium-High	1,5	3 - 5	6000	0 / 600 / 900	2400 x 1000 x 2300	2500	1,5	2
KNAPP	Open shuttle 100	AMR (top-load)	High	0,1	-	1500	500 / 1000	800 x 600 x 350	200	1,2	1,5
KNAPP	Open shuttle 600	AMR (top-load)	High	0,6	-	1500	500 / 900	1300 x 900 x 400	500	1,2	1,5
KNAPP	Open shuttle 1500	AMR (top-load)	High	1,5	-	1500	400 / 700	1600 x 1100 x 500	900	1	1,2
MAXAGV	CX12	AGV (underride)	Medium-High	1	0,5 - 1	310	310	1600 x 800 x 1400	600	1,5	1,7
MAXAGV	CX15	AGV (straddle)	Medium-High	1,5	1,5	900	400 - 900	2350 x 1600 x 1380	850	1,3	1,5
MAXAGV	FX15	AGV (forklift)	Medium-High	2	-	6000	85 - 6000	2600 x 1100 x 2200	1400	1,2	1,5
TOYOTA	LAE250	AGV (forklift)	Medium-High	2,5	-	210	0	1850 x 780 x 1500	1200	2	2,2
TOYOTA	SAE160	AGV (forklift)	Medium-High	1,6	-	4700	0 - 4500	1950 x 850 x 2300	1700	1,8	2,2
TOYOTA	TAE500	AGV (tugger)	Medium-High	-	0,5	-	-	1100 x 600 x 1300	450	1	1,2
DS AUTOMATION	SALLY	AMR (underride)	High	0,1	-	-	550	720 x 580 x 550	110	1,4	1,6
DS AUTOMATION	CAREY trike	AGV (underride)	High	0,5	1	410	330	1968 x 638 x 333	420	1,4	1,6
DS AUTOMATION	FLEXIMOVER trike	AGV (assembly line)	Medium	0,8	1,5 - 3	Optional	350	1800 x 600 x 400	750	1	1
DS AUTOMATION	ARNY mono	AGV (forklift)	Medium-High	1,5	-	1500	0 - 1500	3500 x 1150 x 2100	4600	1,5	1,8
Mobile Industrial Robots	MiR250	AMR (underride)	High	0,25	0,5	380	340 / 390	580 x 800 x 300	94	2	2
Mobile Industrial Robots	MiR1350	AMR (underride)	High	1,35	6	476	370 / 450 / 600	1350 x 910 x 322	244	1,2	1,2
Mobile Industrial Robots	MiR1200	AMR (forklift)	High	1,2	-	1140	0 - 850	1934 x 820 x 2120	750	1,5	1,5
ABB	Flexley Tug T701	AMR (tugger)	High	-	1,5	-	260	1420 x 500 x 230	250	1	1,2
ABB	Flexley Tug T702	AMR (tugger)	High	-	2	-	130 - 180	2104 x 500 x 230	330	1,5	1,7
ABB	Flexley Tug T901	AMR (tugger)	High	-	10	-	200 - 350	1424 x 980 x 880	585	1,7	2
ABB	Flexley Mover P304	AMR (underride)	High	0,6	-	472	400	1202 x 780 x 352	185	1,9	1,9
ABB	Flexley Mover P404	AMR (underride)	High	1	-	472	400	1202 x 835 x 352	215	1,8	1,8
ABB	Flexley Mover P604	AMR (underride)	High	1,5	-	430	410	1953 x 885 x 250	320	1,7	1,7
ABB	Flexley Stack F602	AMR (forklift)	Medium-High	1,6	-	1800/4800/6000	80 - 6000	2055 x 830 x 2751	2400	1,7	1,7
OMRON	LD-250	AMR (top-load)	High	0,25	-	487	450 - 600	969 x 697 x 380	148	1,2	1,2
OMRON	MD-650	AMR (top-load)	High	0,65	-	472	80 -120 / 450 - 600	1194 x 1194 x 370	220	2,2	2,2
OMRON	MD-900	AMR (top-load)	High	0,9	-	472	80 -120 / 450 - 600	1194 x 1194 x 370	250	1,8	1,8
OMRON	HD-1500	AMR (top-load)	High	1,5	-	715	80 -120 / 450 - 600	1800 x 900 x 450	506	1,8	1,8
OMRON	OL-200	AMR (underride)	High	0,2	-	315	80 -120 / 450 - 600	1000 x 700 x 350	150	1,2	1,5

Table B.2 - Energy systems and charging specifications

Supplier	Model	Type	Battery type	Run time (h)	Charging ratio	Battery life (cycles)	Charging voltage (V)	Charging station size (mm)	Charging method supported
STILL	AXH 10 iGo	AMR (underride)	Lithium-ion battery	5	1:5	2500 - 4000	48	830 x 788 x 288	Automatic, Opportunity
STILL	ACH 10 iGo	AGV (underride)	Lithium-ion battery	5	1:5	2500 - 4000	48	560 x 543 x 686	Automatic, Opportunity
STILL	ACH 15 iGo	AGV (underride)	Lithium-ion battery	5	1:5	2500 - 4000	48	560 x 543 x 686	Automatic, Opportunity
STILL	OPX iGo neo	AGV (forklift)	Lithium-ion battery	8-10	1:3	2500 - 4000	24	600 x 400 x 300	Automatic, Opportunity
AGVE	A2	AGV (forklift)	Lithium-ion battery VRLA Gel Battery	8 7	1:12 1:1	3000 - 5000 500 - 1000	24	600 x 400 x 300	Automatic, Opportunity Automatic
AGVE	A4	AGV (forklift)	Lithium-ion battery	10	1:10	3000 - 5000	48	600 x 400 x 300	Automatic, Opportunity
AGVE	A6	AGV (forklift)	Lithium-ion battery	12	1:8	3000 - 5000	48	600 x 400 x 300	Automatic, Opportunity
KNAPP	Open shuttle 100	AMR (top-load)	Lithium-ion battery	8	1:12	3000 - 5000	24	400 x 300 x 600	Automatic, Opportunity
KNAPP	Open shuttle 600	AMR (top-load)	Lithium-ion battery	8	1:10	3000 - 5000	48	600 x 400 x 1200	Automatic, Opportunity
KNAPP	Open shuttle 1500	AMR (top-load)	Lithium-ion battery	8	1:8	3000 - 5000	48	800 x 500 x 1400	Automatic, Opportunity
MAXAGV	CX12	AGV (underride)	Lithium-ion battery	10	1:10	3000 - 5000	24	600 x 600 x 1800	Opportunity
MAXAGV	CX15	AGV (straddle)	Wet Lead Acid / Gel / Lithium Ion	7 - 10	1:1 - 1:10	1200 - 1500 / 3000 - 5000	48	400 x 300 x 600 / 600 x 600 x 1800	Opportunity, Battery swap
MAXAGV	FX15	AGV (forklift)	Wet Lead Acid / Gel / Lithium Ion	7 - 10	1:1 - 1:10	1200 - 1500 / 3000 - 5000	48	400 x 300 x 600 / 600 x 600 x 1800	Opportunity, Battery swap
TOYOTA	LAE250	AGV (forklift)	Lithium-ion battery	8 - 12	1:8	4000 - 5000	24	600 x 400 x 1200	Automatic, Opportunity
TOYOTA	SAE160	AGV (forklift)	Lithium-ion battery	7 - 10	1:6	4000 - 5000	48	600 x 400 x 1200	Automatic, Opportunity
TOYOTA	TAE500	AGV (tugger)	Lithium-ion battery (std)	6 - 9	1:10	2500 - 3500	24	400 x 300 x 800	Automatic
DS AUTOMATION	SALLY	AMR (underride)	Lithium-ion battery	10	1:12	3000 - 500	24	300 x 200 x 500	Automatic, Opportunity
DS AUTOMATION	CAREY trike	AGV (underride)	Lithium-ion battery / Lead gel	12	1:10	3000 - 5000	24	400 x 300 x 800	Automatic, Opportunity
DS AUTOMATION	FLEXIMOVER trike	AGV (assembly line)	Lithium-titanate battery	24	1:15	15000 - 20000	48	600 x 300 x 20	Flash Charging
DS AUTOMATION	ARNY mono	AGV (forklift)	Lead gel / Lithium-ion battery	9	1:8	4000 - 5000	48	600 x 400 x 1200	Automatic, Opportunity
Mobile Industrial Robots	MiR250	AMR (underride)	Lithium-ion battery	13	1:16	3000 - 5000	48	622 x 237 x 287	Automatic, Opportunity
Mobile Industrial Robots	MiR1350	AMR (underride)	Lithium-ion battery	8	1:12	3000 - 5000	48	622 x 237 x 287	Automatic, Opportunity
Mobile Industrial Robots	MiR1200	AMR (forklift)	Lithium-ion battery	10	1:14	3000 - 5000	48	621 x 340 x 187	Automatic, Opportunity
ABB	Flexley Tug T701	AMR (tugger)	Lithium-ion battery	10	1:6	3000 - 5000	48	450 x 250 x 250	Automatic, Opportunity
ABB	Flexley Tug T702	AMR (tugger)	Lithium-ion battery	10	1:6	3000 - 5000	48	500 x 250 x 300	Automatic, Opportunity
ABB	Flexley Tug T901	AMR (tugger)	Lithium-ion battery	8 - 10	1:6	3000 - 5000	48	400 x 200 x 300	Automatic, Opportunity
ABB	Flexley Mover P304	AMR (underride)	Lithium-ion battery	9	1:6	3000 - 5000	48	400x400x250	Automatic, Opportunity
ABB	Flexley Mover P404	AMR (underride)	Lithium-ion battery	9	1:6	3000 - 5000	48	400x400x250	Automatic, Opportunity
ABB	Flexley Mover P604	AMR (underride)	Lithium-ion battery	8	1:5	3000 - 5000	48	600x600x300	Automatic, Opportunity
ABB	Flexley Stack F602	AMR (forklift)	Lithium-ion battery	8	1:6	3000 - 5000	48	811 x 503 x 1656	Automatic, Opportunity
OMRON	LD-250	AMR (top-load)	Lithium-ion battery	10	1:6	2000	48	349 x 369 x 315	Automatic, Opportunity
OMRON	MD-650	AMR (top-load)	Lithium-ion battery	8	1:8	3000	48	1200 x 350 x 500	Automatic, Opportunity
OMRON	MD-900	AMR (top-load)	Lithium-ion battery	8	1:8	3000	48	1200 x 350 x 500	Automatic, Opportunity
OMRON	HD-1500	AMR (top-load)	Lithium-ion battery	9	1:9	8000	48	1500 x 350 x 500	Automatic, Opportunity
OMRON	OL-200	AMR (underride)	Lithium-ion battery	10	1:10	2000 - 3000	48	350 x 370 x 315	Automatic, Opportunity

Table B.3 - Navigation, localization and operational requirements

Supplier	Model	Type	Minimum aisle width (mm)	Turning radius (mm)	Transport distance	Pick and drop time (s)	Navigation type	Localization	Sensors range	Load carriers
STILL	AXH 10 iGo	AMR (underride)	2948	1592	Long	min 45	SLAM	Natural Localization / LiDAR SLAM	360°	Trolley, Pallet
STILL	ACH 10 iGo	AGV (underride)	1897	618,5	Short-Medium	min 35	QR code	QR Codes / Tag	180°	Loading platform, Pallet
STILL	ACH 15 iGo	AGV (underride)	1897	618,5	Short-Medium	min 35	QR code	QR Codes / Tag	180°	Loading platform, Pallet
STILL	OPX iGo neo	AGV (forklift)	2500	2200	Medium-Long	min 10	Laser	Hybrid (LiDAR + 3D Vision)	360°	Pallet
AGVE	A2	AGV (forklift)	1500	1200	Short	min 35	Laser, Magnetic	Reflector Navigation	270°	Trolley, Pallet
AGVE	A4	AGV (forklift)	1700	1600	Medium-Long	min 50	Laser, Optical	Reflector Navigation	360°	Unit loads, Pallet
AGVE	A6	AGV (forklift)	1800	1950	Medium-Long	min 50	Laser, SLAM	Reflector Navigation	360°	Heavy loads, Pallet
KNAPP	Open shuttle 100	AMR (top-load)	1100	0	Short-Medium	min 15	SLAM	Natural Localization / LiDAR SLAM	360°	Boxes
KNAPP	Open shuttle 600	AMR (top-load)	1500	0	Medium-Long	min 20	SLAM	Natural Localization / LiDAR SLAM	360°	Pallet
KNAPP	Open shuttle 1500	AMR (top-load)	1700	0	Long	min 30	SLAM	Natural Localization / LiDAR SLAM	360°	Heavy loads, Pallet
MAXAGV	CX12	AGV (underride)	1350	1450	Short-Medium	min 20	Laser, Natural	Reflector Navigation	360°	Trolley, Pallet
MAXAGV	CX15	AGV (straddle)	1900	1700	Medium-Long	min 25	Laser, Natural	Reflector Navigation	360°	Pallet, Containers
MAXAGV	FX15	AGV (forklift)	1600	1600	Long	min 45	Laser, Natural	Reflector Navigation	360°	Pallet, Containers
TOYOTA	LAE250	AGV (forklift)	2600	1500	Long	min 20	Laser, Natural	Reflector Navigation	360°	Pallet
TOYOTA	SAE160	AGV (forklift)	2800	1600	Medium	min 25	Laser, Natural	Reflector Navigation	360°	Pallet
TOYOTA	TAE500	AGV (tugger)	2500	1000	Short-Medium	-	Laser, Magnetic	Reflector Navigation	270°	Wagons
DS AUTOMATION	SALLY	AMR (underride)	1000	600	Short-Medium	min 10	Laser, Natural, SLAM	Hybrid	360°	Trolley, Boxes
DS AUTOMATION	CAREY trike	AGV (underride)	1300	1100	Medium-Long	min 20	SLAM, Magnetic	Hybrid	360°	Trolley, Containers
DS AUTOMATION	FLEXIMOVER trike	AGV (assembly line)	1500	1000	Short	min 15	Magnetic, Optical, Inductive	Magnetic spot/Tape	180°	Trolley, Assembly kit
DS AUTOMATION	ARNY mono	AGV (forklift)	2800	1400	Medium-Long	min 25	Laser, Natural, Magnetic	Reflector Navigation	360°	Pallet
Mobile Industrial Robots	MiR250	AMR (underride)	1450	493	Short-Medium	min 15	SLAM	Natural Localization / LiDAR SLAM	360°	Trolley, Boxes
Mobile Industrial Robots	MiR1350	AMR (underride)	1800	815	Medium-Long	min 20	SLAM	Natural Localization / LiDAR SLAM	360°	Heavy loads, Pallet
Mobile Industrial Robots	MiR1200	AMR (forklift)	2350	1950	Medium-Long	min 20	SLAM	Natural Localization / LiDAR SLAM	360°	Heavy loads, Pallet
ABB	Flexley Tug T701	AMR (tugger)	1500	600	Short-Medium	min 20	Magnetic, RFID	Natural Localization / LiDAR SLAM	270°	Trolley
ABB	Flexley Tug T702	AMR (tugger)	1100	600	Short-Medium	min 15	SLAM, Magnetic, RFID	Natural Localization / LiDAR SLAM	360°	Trolley
ABB	Flexley Tug T901	AMR (tugger)	1500	1270	Long	min 15	SLAM, Magnetic, RFID	Natural Localization / LiDAR SLAM	360°	Trolley
ABB	Flexley Mover P304	AMR (underride)	950	0	Short-Medium	min 4	QR code	Natural Localization / LiDAR SLAM	360°	Trolley, Pallet
ABB	Flexley Mover P404	AMR (underride)	1050	0	Short-Medium	min 5	QR code	Natural Localization / LiDAR SLAM	360°	Trolley, Pallet
ABB	Flexley Mover P604	AMR (underride)	1250	0	Short-Medium	min 5	SLAM, Magnetic, RFID	Natural Localization / LiDAR SLAM	360°	Heavy loads, Pallet
ABB	Flexley Stack F602	AMR (forklift)	2100	1683	Medium	min 10	Laser	Reflector Navigation	360°	Pallet, Containers
OMRON	LD-250	AMR (top-load)	1200	0	Short	min 20	SLAM	Natural Localization / LiDAR SLAM	360°	Boxes
OMRON	MD-650	AMR (top-load)	2000	0	Short-Medium	min 25	LiDAR SLAM	Natural Localization / LiDAR SLAM	360°	Pallet, Containers
OMRON	MD-900	AMR (top-load)	2000	0	Short-Medium	min 25	LiDAR SLAM	Natural Localization / LiDAR SLAM	360°	Pallet, Containers
OMRON	HD-1500	AMR (top-load)	2500	0	Medium	min 30	LiDAR SLAM	Natural Localization / LiDAR SLAM	360°	Heavy loads, Pallet
OMRON	OL-200	AMR (underride)	1400	0	Short-Medium	min 20	LiDAR SLAM	Natural Localization / LiDAR SLAM	360°	Trolley, Pallet

Table B.4 - Environmental standards, safety features and compliance

Supplier	Model	Type	Sound pressure level db(A)	Min operating temperature (°C)	Max operating temperature (°C)	VDA5050 compatible	Obstacle avoidance	Obstacle classidication	Clearance zone* (mm)	Ground clearance (mm)	Max slope with load
STILL	AXH 10 iGo	AMR (underride)	< 70	5	45	yes	yes	yes	300	30	3%
STILL	ACH 10 iGo	AGV (underride)	< 75	5	45	no	no	no	variable	30	3%
STILL	ACH 15 iGo	AGV (underride)	< 75	5	45	no	no	no	variable	30	3%
STILL	OPX iGo neo	AGV (forklift)	< 70	5	45	wip	yes	yes	variable	30	8%
AGVE	A2	AGV (forklift)	< 70	0	40	yes	yes	yes	50	20	2%
AGVE	A4	AGV (forklift)	< 70	0	45	yes	yes	yes	100	40	5%
AGVE	A6	AGV (forklift)	< 70	0	45	yes	no	yes	100	50	6%
KNAPP	Open shuttle 100	AMR (top-load)	< 65	5	40	yes	yes	yes	400	15	0%
KNAPP	Open shuttle 600	AMR (top-load)	< 70	5	40	yes	yes	yes	400	25	2%
KNAPP	Open shuttle 1500	AMR (top-load)	< 70	5	40	yes	yes	yes	600	30	2%
MAXAGV	CX12	AGV (underride)	< 70	0	40	yes	yes	yes	100	25	2%
MAXAGV	CX15	AGV (straddle)	< 70	0	40	yes	yes	yes	200	35	3%
MAXAGV	FX15	AGV (forklift)	< 70	0	40	yes	no	yes	500	45	5%
TOYOTA	LAE250	AGV (forklift)	< 70	0	40	yes	yes*	no	200	35	10%
TOYOTA	SAE160	AGV (forklift)	< 70	0	40	yes	yes*	no	200	30	5%
TOYOTA	TAE500	AGV (tugger)	60 - 65	5	40	yes	no	no	50	25	2%
DS AUTOMATION	SALLY	AMR (underride)	< 60	5	40	yes	yes	yes	150	15	2%
DS AUTOMATION	CAREY trike	AGV (underride)	< 65	10	35	yes	yes	yes	200	20	2%
DS AUTOMATION	FLEXIMOVER trike	AGV (assembly line)	< 65	5	40	yes	yes	yes	50	25	2%
DS AUTOMATION	ARNY mono	AGV (forklift)	< 70	0	40	yes	yes	yes	150	30	5%
Mobile Industrial Robots	MiR250	AMR (underride)	< 70	5	40	yes	yes	yes	50	28	5%
Mobile Industrial Robots	MiR1350	AMR (underride)	< 75	0	50	yes	yes	yes	50	27	3%
Mobile Industrial Robots	MiR1200	AMR (forklift)	< 77	0	40	yes	yes	yes	250	30	0%
ABB	Flexley Tug T701	AMR (tugger)	< 80	0	40	yes	no	no	30	25	2%
ABB	Flexley Tug T702	AMR (tugger)	< 70	5	40	yes	yes	yes	50	25	3%
ABB	Flexley Tug T901	AMR (tugger)	< 70	5	40	yes	yes	yes	200	30	2%
ABB	Flexley Mover P304	AMR (underride)	< 70	5	40	yes	no	yes	20	25	1%
ABB	Flexley Mover P404	AMR (underride)	< 70	5	40	yes	no	yes	20	25	1%
ABB	Flexley Mover P604	AMR (underride)	< 70	5	40	yes	yes	yes	50	30	1%
ABB	Flexley Stack F602	AMR (forklift)	< 70	0	40	yes	no	no	50	30	5%
OMRON	LD-250	AMR (top-load)	< 70	5	40	yes	yes	yes	50	40	3%
OMRON	MD-650	AMR (top-load)	< 70	5	40	yes	yes	yes	50	35	8%
OMRON	MD-900	AMR (top-load)	< 70	5	40	yes	yes	yes	50	35	8%
OMRON	HD-1500	AMR (top-load)	< 70	5	40	yes	yes	yes	80	35	8%
OMRON	OL-200	AMR (underride)	< 70	5	40	yes	yes	yes	80	35	8%

*Clearance Zone: defined by the relationship between the nominal pick-up point (A) and the actual location of the target object (A+x), the clearance zone represents the maximum tolerance (x) within which the system can still correctly identify the load and execute the mission. Essentially, it quantifies the system's ability to compensate for positioning misalignments during the pick-up phase.

The following table outlines the official documentation, corporate portals, and supplementary sources utilized for the data collection and benchmarking of the analyzed AGV and AMR models, ensuring the full reproducibility and verifiability of the research dataset.

Table B.5 - Technical sources, documentation references and accessibility status for the AGV and AMR dataset

Brand	**Model**	**Source**	**Note**
STILL	AXH 10 iGo / ACH 10 iGo / ACH 15 iGo	ACH iGo/AXH iGo Datasheet & Corporate Website	Publicly Available
STILL	OPX iGo neo	OPX Datasheet & Corporate Website	Publicly Available
AGVE	A2 / A4 / A6	"Automated Guided Forklifts" Technical Product Specifications & Corporate Website	Technical Datasheets available upon request / Publicly Available
KNAPP	Open shuttle 100 / Open shuttle 600 / Open shuttle 1500	"Open Shuttle" Official Technical Datasheet, Official Demonstration Videos & Corporate Website	Publicly Available (via Supplier Website registration)
MAXAGV	CX12 / CX15 / FX15	Official Technical Product Specifications & Corporate Website	Technical Datasheets available upon corporate request / Publicly Available
TOYOTA	LAE250 / SAE160 / TAE500	Official Application Videos, Corporate Website & Market-Average Parametric Estimation	Publicly Available / Estimated
DS AUTOMATION	Sally / Carey trike / Fleximover trike / Arny mono	Product Pages & Technical Datasheets	Publicly Available
MiR	MiR250 / MiR1350 / MiR1200	Corporate Website & Technical Datasheets	Publicly Available (via Supplier Website registration)
ABB	Flexley Tug T701 / Flexley Tug T702 / Flexley Tug T901	Corporate Website & Official Technical Product Manuals	Publicly Available
ABB	Flexley Mover P304 / Flexley Mover P404 / Flexley Mover P604	Corporate Website & Official Technical Product Manuals	Publicly Available
ABB	Flexley Stack F602	Corporate Website & Official Technical Product Manuals	Publicly Available
OMRON	LD-250 / MD-650 / MD-900 / HD-1500	Technical Product Portals, Official Case Study Videos & Cross-Model Synthesis	Publicly Available / Derived
OMRON	OL-200	OL-450S Series" Official Technical Datasheet & Corporate Website	Publicly Available

Appendix C - Economic baseline and cost estimates

The figures represent estimated market ranges based on system complexity. Reductions in hidden costs are evaluated against a manual labor baseline to highlight the benefits of automation.

Table C.1 - Cost breakdown and operational impact comparison for AGV and AMR systems

		AGV	AMR
VEHICLE COST [$]	**Unit Load**	25,000 - 50,000	20,000 - 60,000
	Tugger	40,000 - 70,000	50,000 - 95,000
	Pallet Truck	40,000 - 80,000	50,000 - 90,000
	Forklift	60,000 - 120,000	70,000 - 150,000
	Heavy Duty	80,000 - 250,000+	100,000 - 250,000+
PHYSICAL INFRASTRUCTURE [$]		5,000 - 20,000	None
MEDIUM SIZE Li-ion BATTERY COST [$]		3,000 - 5,000	3,000 - 5,000
FLEET MANAGEMENT SOFTWARE per robot [$]	One-time license	5,000 - 15,000	3,000 - 10,000
	Yearly subscription	1,000 - 2,000	3,000 - 4,000
INTEGRATION COST [$]	**Light** (basic tasks)	2,000 - 5,000	2,000 - 5,000
	Moderate (WMS, scanners)	8,000 - 20,000	8,000 - 20,000
	Deep (ERP, MES)	20,000 - 50,000+	20,000 - 50,000+
SINGLE DOCK CHARGING INFRASTRUCTURE [$]		1,000 - 5,000	1,000 - 5,000
NETWORK INFRASTRUCTURE [$]		3,000 - 15,000	3,000 - 15,000
MEDIUM-SCALE LAYOUT CHANGE [$]		5,000 - 15,000	0 - 1,500
OPEX - OPERATING COSTS per robot [$]		800 - 2,500	1,000 - 3,000
SAFETY CERTIFICATION per robot [$]		2,000 - 5,000	2,000 - 5,000
HIDDEN COSTS (compared to manual labor)	Downtime Cost During Manual Movement	▼ 30 - 50%	▼ 30 - 50%
	Material Damage	▼ 70 - 90%	▼ 70 - 90%
	Hiring & Training	▼ 90 - 100%	▼ 90 - 100%
	Safety Incidents	▼ 85 - 95%	▼ 85 - 95%
	Rework / Line-Stoppage Costs	▼ 80 - 90%	▼ 80 - 90%

Source: Novus Hi-Tech (2025)

Note: OPEX figures include an annualized allowance for preventive maintenance, software upgrades, battery replacements (prorated over a 3-5 year lifespan) and occasional spare parts.

Appendix D - Parameters' strategic importance and data availability

This appendix contains the scores assigned to each parameter regarding its data availability and strategic importance, along with the legend explaining the criteria for each score.

Table D.1 - Scoring criteria definitions for parameter prioritization

SCORE	IMPORTANCE FOR THE SELECTION	DATA AVAILABILITY
5	5: constraint	5: always available
4	4: critical for the selection	4: usually available
3	3: affects the performance	3: easy to estimate
2	2: to take into account	2: complex estimation
1	1: low relevance	1: difficult to find

Table D.2 - Parameter list containing the data availability and importance scores

Process / Vehicle	Type	PARAMATERS	DATA AVAILABILITY	IMPORTANCE
p	Operational	Aisle dimention	5	5
p	Operational	Slope and ramps	5	5
p	Operational	Indoor/outdoor activity	5	5
p	Operational	Material handling system design (AS-IS)	4	5
p	Operational	Floor conditions	4	4
p	Operational	Layout topology	4	4
p	Operational	Station operation frequency	4	4
p	Operational	Number of stations	5	3
p	Operational	Path segregation from operators	4	3
p	Operational	Flow path orientation	4	3
p	Operational	Fleet size	4	3
p	Operational	Load dimension variability	3	4
p	Operational	Load weight variability	3	4
p	Operational	Transport distance	3	4
p	Operational	Ambient conditions	4	3
p	Operational	Task structure	3	3
p	Operational	Traffic density	3	3
p	Operational	Number of path crossing	2	2
p	Operational	Possibility of mistakes	1	2
p	Operational	Sensitivity of the warehouse system	1	1
p	Technical	Speed limitation for safety	4	3
p	Technical	WiFi stability	2	4
v	Economic	Vehicle cost	4	4
v	Economic	Path reconfiguration cost	2	3
v	Economic	Software license cost	2	3
v	Economic	Operating costs	2	4
v	Economic	Battery replacement cost	2	2
v	Economic	Mapping cost	2	2
v	Economic	Reconfiguration cost	1	3
v	Economic	Installation cost	1	2
v	Economic	Training cost	1	2
v	Economic	Integration cost	1	2
v	Economic	Spare part holding cost	1	2
v	Economic	Transportation cost	1	1
v	Economic	Payback period	3	3
v	Economic	Vehicle insurance	1	0
v	Operational	Accuracy	4	4
v	Operational	Reliability	1	4
v	Operational	Flexibility	4	4
v	Operational	Productivity	3	4
v	Operational	MTBF	1	3
v	Operational	MTTR	1	3
v	Operational	Average run time	4	4
v	Operational	Software reliability	1	4
v	Operational	Localization error	3	4
v	Operational	Pick and drop times	4	3
v	Operational	Labor saving ratio	3	4
v	Operational	Dependence on labor force	3	3
v	Operational	Training activities for operators	3	2
v	Operational	Operators required to manage obstacles	2	2

Process / Vehicle	Type	PARAMATERS	DATA AVAILABILITY	IMPORTANCE
v	Operational	Employee acceptance	1	3
v	Operational	Energy consumption	3	1
v	Operational	Spare parts availability	1	3
v	Operational	Tasks' success rate	1	2
v	Operational	Blocking time	1	2
v	Operational	Number of collisions	0	0
v	Operational	Number of re-routings	0	0
v	Operational	Deadlock frequency	0	0
v	Operational	Infrastructure maintenance	1	2
v	Operational	Cleaning frequency required	2	0
v	Technical	Carrying capacity	5	5
v	Technical	Navigation type	5	5
v	Technical	Safety standards compliance	5	5
v	Technical	Navigation system level	5	4
v	Technical	Slope/gradient capacity	4	5
v	Technical	Working temperature range	4	5
v	Technical	Maximum lift height	4	5
v	Technical	Overall dimensions	5	4
v	Technical	Towing capacity	5	4
v	Technical	Manual override	5	4
v	Technical	Localization technology	4	4
v	Technical	Turning radius	4	4
v	Technical	Vehicle weight	4	4
v	Technical	Speed ranges of the vehicle	5	3
v	Technical	Load carriers	5	3
v	Technical	Sensor range and field of view	4	3
v	Technical	Minimum aisle clearance	3	4
v	Technical	Floor quality requirements	4	3
v	Technical	Obstacle avoidance	4	3
v	Technical	Obstacle classification	4	3
v	Technical	Integration time with existing WMS/ERP	3	4
v	Technical	Ground clearance	4	3
v	Technical	Operating humidity range	4	3
v	Technical	Installation complexity	3	3
v	Technical	Clearance zone/positioning tolerance	3	3
v	Technical	Transfer station height	3	3
v	Technical	Blind spots	4	2
v	Technical	Charging time	5	4
v	Technical	Battery type	5	3
v	Technical	Charging ratio	4	4
v	Technical	Battery life	4	4
v	Technical	Charging current / voltage	4	2
v	Technical	Charging method	4	2
v	Technical	Charging station size	3	2
v	Technical	Battery degradation rate	2	2
v	Technical	Diagnostic remote access availability	4	2
v	Technical	HNI (Human Machine Interface)	3	1
v	Technical	Map update frequency	1	2
v	Technical	Light sensitivity	2	1
v	Technical	Sound level during operation	4	0
v	Technical	Global Warming Potential	2	1

Appendix E - Glossary of parameters

This appendix contains the definitions for each technical, operational and economic parameter included in the matrix and final framework.

Ambient conditions	dust, grease, light, temperature, humidity of the working area
Average run time	expected duration the vehicle can operate on a single charge under normal load conditions
Battery cost	expense associated with the procurement, replacement, and disposal of a Lithium-ion battery
Carrying capacity	maximum weight the vehicle is designed to transport safely
Charging ratio	ratio between the time spent charging and the total operational time (1:X)
Dependence on labor force	level of human intervention required for daily operations
Employee acceptance	degree of workforce trust and readiness to interact with the new technology
Fleet size	total number of vehicles required to satisfy the material flow demand
Flexibility to layout changes	ability of the system to adapt to new routes, workstations, or facility reconfigurations
Floor slope tolerance	maximum gradient (incline or decline) the vehicle can navigate while maintaining stability
Global Warming Potential	environmental impact of the vehicle's lifecycle (CO_2 equivalent)
Ground clearance	minimum distance between the lowest point of the vehicle chassis and the floor
Indoor/outdoor activity	environment in which the robot has to work
Infrastructure maintenance	recurring cost of keeping the physical environment compatible with the fleet
Installation cost	one-time expense related to the physical deployment of the system, including setup, mapping, and hardware installation
Integration cost	cost associated with connecting the fleet management software with existing factory systems
Load carriers	type of interface used to hold the load
Load dimension variability	process parameter, referred the the variability of the size of objects that have to be transported
Load weight variability	process parameter, referred the the variability of the weight of objects that have to be transported
Localization technology	method used by the robot to calculate its coordinates within the map
Maximum lift height	highest vertical reach of the vehicle's lifting mechanism

Minimum aisle dimension	minimum width required for the vehicle to travel and perform maneuvers
Navigation type	method used by the vehicle to determine its path and position
Obstacle avoidance	system's ability to autonomously detect an object in its path and calculate a dynamic alternative route in real-time without stopping
Obstacle classification	ability to distinguish between static and dynamic objects to adapt the behavior
Operating costs	ongoing expenses required to keep the system running (OPEX)
Overall dimensions	external measurements of the vehicle (length, width, and height)
Path reconfiguration cost	total expense associated with changing a vehicle's route
Payback period	estimated time required for the cumulative savings generated by the system to equal the initial investment cost
Reliability	overall uptime of the system (software + hardware)
Speed	maximum velocity the vehicle can maintain under empty conditions
Towing capacity	maximum load weight that a vehicle can pull, rather than carrying it on board
Transport distance	total length of the mission path from the pick-up point to the drop-off location
Turning radius	minimum space required for the vehicle to execute a complete U-turn or navigate a curve
Vehicle cost	initial purchase price (CAPEX) of a single unit, excluding software and infrastructure
Vehicle weight	mass of the robot without any payload

Appendix F - Interview transcript: Expert A

This appendix contains the full interview transcript with Expert A from Supplier A, focusing on the validation of AMR and AGV technologies along with their selection criteria.

Company: Supplier A
Interviewee: Expert A
Position: Solution Design Engineer
Date: March 19, 2026
Topic: Validation of AMR/AGV technologies and selection criteria

Introduction

Interviewer: Before we begin, I would like to ask your permission to record this interview for data collection purposes. The aim is to validate information gathered online and gain new professional insights. Could you please state your name and position?

Expert A: Yes, you have my permission. As I mentioned, I work as a solution design engineer. I am happy to help; the market is in great need of people who understand this world, as there are still too few experts despite the popularity of AMRs.

Value proposition and software strength

Interviewer: How does your company differentiate its value proposition for AMRs and AGVs compared to competitors?

Expert A: That is a complex question because it depends on the customer's specific needs. However, our main differentiator is the software. While vehicle technology is somewhat standardized across the market, we are particularly strong on the software side and in our control systems. We can manage very large fleets, potentially hundreds of vehicles, using the same system. We also offer different types of AMRs: the open shuttle with forks for picking pallets from the floor, smaller units for cartons up to 50-100 kg, and our new Aerobot system, which combines racking with AMR technology for handling totes.

Navigation and precision

Interviewer: Is the software able to maintain SLAM navigation accuracy in high-density traffic environments with large fleets?

Expert A: Absolutely. We use the internal features of the room for SLAM navigation, which works very well. While SLAM alone might not be super precise in every spot, we add precision where needed through reflectors, cameras, or identification markers. Our vehicles are equipped with multiple cameras to identify various environmental elements, allowing them to be quite precise.

Impact of floor conditions

Interviewer: How do floor conditions impact SLAM navigation? Would an AGV be better for dirty or greasy floors?

Expert A: Honestly, there is not a significant difference between AMRs and AGVs regarding floor conditions; it depends more on the vehicle's physical design, such as the number, size, and material of the wheels (rubber or hard rubber). Normal industrial floors are usually fine. While big cracks or bumpy surfaces cause vibrations, they don't typically disrupt SLAM, especially since the vehicle slows down when approaching a load, reducing vibrations.

However, wet or greasy floors are a safety issue for both. Just like an AGV, an AMR traveling at 1.5 m/s on a greasy floor needs a longer distance to stop safely. This is pure physics, the weight of the machine and the load determine the stopping distance. Therefore, speed must be reduced in such conditions.

Battery and charging strategies

Interviewer: I noticed discrepancies in battery runtime data in your datasheets, ranging from 6 to 8 hours. Does this depend on the load or the charging strategy?

Expert A: It depends on the model. Our pallet machines use a 48V, 100Ah battery that can run for about 8 hours in a favorable environment. Smaller units, as the open shuttle 100, use a 27V, 50Ah battery and have less capacity. However, in practice, a vehicle rarely runs for 6 or 8 consecutive hours. In a fleet of 10, if a vehicle is idle, it goes to charge. Some systems use opportunity charging or power boosts, where the vehicle charges for 30 seconds every time it picks up or drops a load. With this philosophy, you technically never need to stop for a full charge. Otherwise we typically use wall-type chargers with steel contact plates, designed so they are safe to touch.

Maintenance and common disruptions

Interviewer: In your experience, what is the most common cause of unplanned downtime?

Expert A: The biggest problem isn't the machine; it’s people. Because AMRs operate in open environments, people often leave pallets in the way or stand in the driving path. The second most common issue can be mechanical, drive technologies can be sensitive to dust, and movable parts suffer from wear and tear, especially on uneven floors. Software is rarely the cause of downtime, but any software issues are usually resolved during the commissioning and go-live phase. It is a common misunderstanding that automation is perfect from day one. In reality, it becomes perfect after two or three years, once the customer learns how to use and maintain the system properly.

Productivity and economic impact

Interviewer: Suppliers often claim increased efficiency, but does this apply immediately? What about the payback period?

Expert A: Not immediately. There is a learning curve. Initially, replacing manual forklifts with AMRs significantly reduces labor costs, which are high in our part of the world, and dramatically reduces damages caused by human error. This is a crucial point: manual forklift drivers often destroy things because they are under pressure to be quick. AMRs, while slower than a human-driven forklift due to safety protocols, do not drive into objects and can work up to 24 hours per day. In my experience, damage control itself can be the one of the primary reasons for a company to invest in these technologies. It represents a significant saving in terms of cost and management. However, machines are more strict and less flexible than humans, who can quickly decide to turn left instead of right. Productivity increases as the customer learns the system's limitations and possibilities.

Regarding payback, it is almost always more than a year. Smaller investments typically see a return in 1 to 3 years. For large-scale projects (10-20 million euros), we are looking at 5 to 10 years. Sometimes it's not just about saving money, but about increasing capacity without hiring more staff.

Connectivity and safety

Interviewer: What happens if the Wi-Fi goes down? Does the vehicle trigger an emergency stop?

Expert A: If Wi-Fi fails, the machine will perform a controlled stop, not an emergency stop. It remains safe. You can even complete a mission manually using a joystick. The main issue is that the fleet control system "freaks out" because it can no longer coordinate the vehicles or assign missions. Anyway, our machines use light signals to communicate status: green for okay/connected, and yellow for turning or indicating a reason for a stop. It is vital to be informative to the operators working near the machines.

Flexibility and digital twins

Interviewer: In the case of a layout change, how complex is the process of updating the maps?

Expert A: We offer training so customers can do this themselves. We use a Digital Twin. This allows the user to plan and test a new virtual path or a new route on a computer without affecting the live system. Once tested, the change is implemented with just a few clicks. It is a very flexible and open environment.

Selection criteria and market awareness

Interviewer: In your experience, what are the most important constraints or parameters to consider during the selection phase?

Expert A: The company must have a decent material flow to justify the investment. It makes the most sense for longer travel distances where manual forklifts are costly. Manufacturing companies with islands of production, like car manufacturers, are ideal candidates. But the selection phase actually starts with what I call the awareness stage. Before we as a supplier even get involved, the customer needs to be aware: do they have a suitable product and a real need for this? This is a crucial step. In today's market, there are probably 100 different AMR suppliers, and a customer can easily be flooded with information. That is why being visible on the internet and social media is so important for us; we need to be the go-to choice when a customer starts approaching a system.

Interviewer: On the opposite side, what is the primary reason why the introduction of these technologies might fail during or after implementation?

Expert A: The main reason for failure is often a lack of skill or understanding of automation on the customer's side. If the customer doesn't understand their responsibility, like keeping paths clear or training staff not to intentionally interrupt the machines, the project will fail. The selection phase is critical; customers must be aware of their needs before even approaching a supplier. My advice is to be curious: I have been doing this for 30 years and I still learn something new every day.

Interviewer: You mentioned that people often cause failures. Could you explain more about how operator behavior or the human element can disrupt or compromise the operational efficiency of an AMR system?

Expert A: This is a critical point: the most common problems are not caused by machines, but by people. Because AMRs operate using SLAM technology in open environments, meaning they are not fenced off, they must coexist with workers, forklifts, and pedestrians. Often, the disruption is unintentional: people might leave a pallet in the driving path or stand in a corridor chatting, not realizing they are blocking a vehicle that needs to pass. However, there is also a deeper, more intentional issue. Some employees do not like automation at all; they may perceive it as a threat to their jobs. In some cases, we see people deliberately trying to interrupt the machines or test them by stepping in front of them to force a stop, effectively sabotaging the system's efficiency. This is why the learning curve I mentioned isn't just for the software, but for the entire organization. If we fail to train the customers and their staff during the sales and commissioning phases, the risk of project failure is high. A system only reaches its full potential after two or three years, once the operators have moved past the initial resistance and have learned to treat the AMRs as predictable tools rather than obstacles or threats. Success depends on the customer's willingness to understand their responsibility in managing the human-machine interaction.

Appendix G - Fleet size simulation outcomes

This appendix presents the comprehensive data tables adapted from the simulation study by Silva et al. (2024). The data quantifies the operational trade-offs between mission speed and system stability for AGV and AMR fleets across different fleet sizes (1, 5 and 10 vehicles) and mission lengths (short, medium and long-distance). The simulation benchmarks evaluate performance under both constrained layouts featuring structural choke points and optimized open-space configurations.

The initial simulation phase evaluated a baseline scenario featuring a single vehicle performing short, medium, and long-distance missions from a starting point A to a destination point B. This test establishes the raw speed capabilities of each technology before fleet-level interactions or routing conflicts occur.

Table G.1 - Fleet performance and collision rates by mission distance

Missions	Average ToA for AMR	Average ToA for AGV
Short	00:35,41	00:40,38
Medium	00:46,38	01:02,70
Long	01:06,63	01:13,95

The second simulation phase involved a multi-vehicle scenario where a fleet of five robots was deployed simultaneously, with all units navigating from point A to point B. This configuration introduces the risk of localized traffic bottlenecks and interaction issues on the shop floor.

Table G.2 - Simulation results for a fleet of five AGVs (left) and AMRs (right)

Simulation	First robot's ToA	Last robot's ToA	Number of Collisions
1	01:23,15	02:38,38	0
2	01:29,83	**02:48,10**	0
3	**01:30,04**	02:40,86	0
4	01:15,67	02:44,52	0
5	**01:15,24**	02:30,35	0
6	01:16,34	02:41,02	0
7	01:16,23	02:36,44	0
8	01:17,42	**02:27,86**	0
9	01:16,86	02:30,82	0
10	01:24,35	02:43,96	0

Simulation	First robot's ToA	Last robot's ToA	Number of collisions
1	01:07,67	01:36,89	0
2	01:07,81	01:37,10	0
3	01:07,77	01:34,58	0
4	01:07,60	01:36,86	0
5	01:08,22	**01:41,55**	1
6	01:07,89	01:35,61	0
7	01:08,23	01:39,32	1
8	**01:08,36**	**01:31,74**	0
9	**01:07,18**	01:37,48	1
10	01:07,56	01:33,59	1

For the final phase of the standard layout testing, the fleet size was increased to ten robots. The mission objective remained identical: synchronized navigation from point A to point B, which significantly escalates layout congestion and tests the limits of the vehicles' routing logic.

Table G.3 - Simulation results for a fleet of ten AGVs (left) and AMRs (right)

Simulation	First robot's ToA	Last robot's ToA	Number of Collisions
1	01:21,85	**04:09,44**	0
2	01:24,64	04:16,58	0
3	01:26,34	**04:38,62**	0
4	**01:29,04**	04:35,75	0
5	**01:18,06**	04:15,07	0
6	01:27,07	04:11,01	0
7	01:22,54	04:21,08	0
8	01:23,79	04:33,83	0
9	01:26,72	04:27,80	0
10	01:21,30	04:23,26	0

Simulation	First robot's ToA	Last robot's ToA	Number of Collisions
1	00:54,64	**02:10,57**	1
2	**00:55,88**	01:57,94	1
3	**00:53,23**	01:57,51	3
4	00:55,74	01:59,37	1
5	00:54,16	**01:52,45**	0
6	00:54,39	01:57,55	0
7	00:54,16	02:01,77	2
8	00:55,31	02:03,68	2
9	00:55,33	02:05,83	3
10	00:54,51	02:02,01	5

To evaluate whether the operational bottlenecks were strictly dependent on infrastructure constraints, the environment map was modified to eliminate all physical choke points between the start and destination points. The identical transport missions were then repeated within this optimized, open-space layout using the fleets of five and ten robots.

Table G.4 - Simulation results for a fleet of five and ten AMRs in an open environment

AMR Fleet Size	First Robot's average ToA	Last robot's average ToA	Number of Collisions
5	00:58,95	01:09,13	0
10	00:51,77	01:26,23	0

Appendix H - Interview transcript: Expert B

This appendix contains the full interview transcript with Expert B from the industrial end-user, focusing on the industrial validation of the framework and operational applicability.

Company: Industrial end-user
Interviewee: Expert B
Position: Project Manager
Date: May 18, 2026
Topic: Industrial validation of the framework and operational applicability

Introduction

Interviewer: The objective of this interview is to validate a framework designed to assist companies in navigating the choice between AGVs and AMRs. During this session, I will present some data regarding a comparative graph and ask a few questions on related topics. Before we begin, could you please introduce yourself and briefly describe your current role within the company?

Expert B: Yes, certainly. I am currently working as a project manager for an international logistics and manufacturing project within the automotive sector, focusing primarily on the supply chain and logistics side. Specifically, my work is concentrated on a particular production unit, the Body in White (BiW) section. I spent two years abroad as a technical expert on this initiative and have recently returned to headquarters. Currently, one of the main projects on my agenda is the implementation of AGVs within our automated pressing and stamping department. The project is ongoing; we are actively discussing the technical requirements with global suppliers and expect to finalize our decision and procurement strategy with them shortly.

Project scope and bottlenecks

Interviewer: In your experience, which departments are typically involved in the selection and implementation of AGVs or AMRs, and how long does this entire process usually take depending on the project scope?

Expert B: When dealing with a wide project scope, for instance, implementing automation across an entire process, several functions are involved. These primarily include process engineering, logistics, IT, maintenance, safety, and procurement. Those are the key stakeholders heavily engaged throughout the project.

The timeline itself heavily depends on the scope. For a large-scale project involving roughly 200 to 300 AGVs, it can take approximately 1.5 to 2 years. On the other hand, for a smaller-scale implementation of around 10 to 12 AGVs, the timeline can be reduced to less than a year.

Interviewer: From your perspective, are there specific bottlenecks or challenges that frequently slow down the process?

Expert B: Yes, as you know, in the automotive industry we face significant challenges when process changes occur. Sometimes the project direction shifts mid-way, requiring adaptations. The main bottleneck arises when there is a lack of standardized process; without standardization, the implementation inevitably slows down.

Matrix validation and key selection parameters

Interviewer: I would now like to introduce the selection matrix. In this graph, several parameters and constraints critical to choosing between AGVs and AMRs are mapped and color-coded by category: orange for economic, blue for operational, and green for technical factors. Additionally, a distinction is made between vehicle-related and process-related factors.

The matrix evaluates these parameters along two axes: importance in the selection process (vertical axis) and data availability (horizontal axis). For instance, a factor such as navigation type is highly important, and the relevant information is readily accessible in supplier documentation. Consequently, the top-right quadrant presents the most critical factors guiding the final choice. These are parameters of high importance that do not suffer from a lack of data, as they are easily retrievable from supplier websites or datasheets. Conversely, other equally important parameters might be characterized by lower data availability. Given this framework, do you agree that this upper quadrant effectively captures the core parameters considered during selection, or do you believe other critical factors are missing?

Expert B: The framework is clear. Looking at the matrix, factors like navigation type and shop floor dimensions are undoubtedly significant. However, prior to considering these variables, establishing a standardized process is fundamental. Without a properly understood and standardized process flow, it is impossible to determine which AGV or AMR system to choose. The evaluation of navigation types and vehicle dimensions can only occur after the process has been clearly defined. Furthermore, introducing a perspective that differs slightly from the current graphical representation of the matrix, I believe that integration costs are exceptionally critical and frequently underestimated. Suppliers typically quote a standard baseline cost; however, any subsequent operational modification or additional request later in the project incurs substantial extra expenses. Once a supplier is selected, buyers lose leverage and cannot easily reject these variations. Therefore, comprehensively mapping integration costs early in the process is just as critical as evaluating technical specifications.

Interviewer: Understood. Moving instead to the critical gap quadrant in the top-left area: these represent parameters or constraints that are highly important for the selection process but suffer from low data availability in literature, supplier websites, or datasheets. Do you find this classification coherent, or are there other critical parameters where you frequently encounter a lack of data?

Expert B: Looking at what you mapped there, I believe installation costs should actually be shifted into the critical gaps quadrant, as they are highly important but difficult to estimate early on. On the other hand, going back to the previous quadrant, regarding load carriers and vehicle speed, your classification as core parameters is correct. However, in our specific case, the perspective is slightly different: because we operate within heavily standardized environments, internal and external speed limits are already predefined within our specific internal safety and operational regulations and are readily available. Therefore, we do not even need to look for this data from external suppliers as we already possess it internally.

Interviewer: Has it ever happened during a project that you had to evaluate a crucial parameter but faced a severe lack of data? If so, how did you solve that problem?

Expert B: Yes, this frequently happens with software implementation and integration. For instance, during the launch of a new process abroad, we lacked the necessary technical resources and specifications to handle the integration between our internal systems (like the WMS/MES) and the fleet management system. We realized these gaps gradually during the initial phase of the project. To avoid falling behind schedule and to protect our project timeline, we had to adopt a parallel working method. We identified what could be deployed immediately and handled the remaining process integrations concurrently. While we managed to stay on schedule, it did require some operational trade-offs. The key to mitigating the lack of initial data was executing these integration processes continuously and in parallel rather than sequentially, ensuring we did not lag behind our milestones.

Interviewer: Going back to the matrix, among all these parameters, or perhaps considering external factors, is there something that is frequently overlooked during the selection process which later creates significant issues during the implementation phase?

Expert B: Yes, definitely. The co-existence and integration of automated vehicles with manual forklifts and human operators is often underestimated. Ideally, we need the opportunity to evaluate these interactions in a real-world environment beforehand to fully grasp the safety parameters and potential risks of mixed traffic. We sometimes overlook these dynamics during the planning phase. To avoid issues, it is crucial to establish clear and strong operational boundaries, keeping a sharp focus on the specific routing and logic of the AGVs. Our primary goal is to ensure high utilization of the automated fleet to optimize our return on investment. If we fail to define these boundaries early on, successful implementation becomes extremely difficult, as the automated and manual workflows must be aligned in the same strategic direction.

Interviewer: As a final question regarding this matrix: in your opinion, is there any other highly important factor missing from the current framework?

Expert B: I see you have already included facilities and shop floor constraints, which is good. However, I would say that a parameter for software integration is missing. When we look at this aspect, it cannot refer strictly to the IT infrastructure; it must include physical-to-digital integration. For example, if an AGV needs to pick up a specific pallet and transport it to another location, that action requires both physical integration, ensuring the mechanical tolerances, docking station, and load carriers align perfectly, and software integration to trigger the mission. Physical integration is a strict prerequisite; it is exceptionally important because without a reliable physical setup, you cannot achieve proper software integration. This dual nature of integration is a critical point to highlight.

TCO, PBP and hidden costs

Interviewer: The next topic is the Total Cost of Ownership. Current literature suggests that adopting AGVs or AMRs can reduce labor costs by up to 60%. Based on your experience, do you consider this figure realistic, or could the actual reduction be even higher or lower?

Expert B: It heavily depends on the geographic location and the nature of the operation, for instance, in a high-labor-cost environment like Sweden, implementing AGVs in a continuous flow with highly repetitive tasks yields an excellent return on investment. If the process is standardized, the environment remains stable, and the vehicles move consistently from point A to point B, achieving a 60% reduction in operational labor expenses is definitely feasible due to the high level of automation.

Interviewer: Regarding the PBP for smaller fleets: my preliminary calculations for a limited number of vehicles indicate a payback period of under one year. In your experience, is it realistic for a small fleet, or does it typically take longer to recover the initial investment?

Expert B: In our current investment plan for the press shop, where we are implementing a small fleet of about 10 AGVs, our calculations show a payback period of approximately 2 to 2.5 years.

Interviewer: Did those calculations incorporate hidden costs, such as the reduction in safety accidents or minimized operational damage compared to manual operations? If we actually put a number on these factors, do you think it would shorten the calculated payback period?

Expert B: Yes, it would, but the impact depends heavily on which factors you quantify. Safety is always the absolute highest priority in our operations, and when presenting a project to the management team, the safety business case can be the primary driver. For example, the current environment in our press shop poses severe safety challenges; we want to deploy around 8 AGVs precisely because it is a confined area with a single access gate, making manual forklift operations highly problematic. These are the critical hidden operational factors that we always account for.

Regarding operational damage, if we look at it from the perspective of material scrap alone, the payback period would not decrease significantly, as the cost of damaged goods itself is often secondary. The real hidden financial benefit we observe comes from avoiding human error impacting on the surrounding facility infrastructure. Manual operators frequently collide with factory gates, fixed racks, or structural elements. Therefore, when looking at the financial model, avoiding infrastructure and facility damage, alongside the primary safety benefits, represents the true hidden financial advantage that impacts the return on investment, rather than just the direct cost of the material carried.

Fleet selection drivers and technology integration

Interviewer: The next topic concerns the specific fleet you are implementing within your facilities. When deciding between AGVs and AMRs for your plant, did you prioritize the flexibility of an AMR, the stability of an AGV, or were there other, more critical factors guiding this selection?

Expert B: In our production unit, we operate within a highly standardized process where materials are consistently transported from point A to point B. In this specific environment, layout changes are quite rare; it is not a situation where the shop floor setup changes from one day to the next. Because the environment is stable, we prioritized AGV technology. It offers an easier integration path for our fixed processes and is highly cost-effective under these stable conditions.

Interviewer: Earlier, you mentioned standardized vehicle limits. Is this pacing profile dictated entirely by pre-existing internal safety regulations, or did you have to adjust it dynamically to protect operators or increase environmental awareness along the vehicle's path?

Expert B: Our company provides a strict maximum speed baseline that we must follow as standard regulation. However, speed management is highly dependent on the specific operational environment, especially during load handling, such as picking, placing, or turning with a pallet on top of the vehicle. While there isn't a single low-speed rule, we must design specific deceleration zones. For instance, when traveling from A to B, the AGV can maintain standard speed, but as it approaches Point B to place the load onto a fixed rack, it must drop to an approach speed to execute the drop-off safely. We work closely with suppliers on the shop floor to map out these zones, adjusting the speed profiles based on the specific load type, whether we are handling a standard wooden pallet or a heavy steel bar. Safety during material placement is the ultimate factor that dictates how we modify the speed aspects across the layout.

Interviewer: You also mentioned earlier the integration of the fleet management software with the company's internal IT infrastructure. How critical is software compatibility with systems like the ERP or WMS during the selection process, and how heavily does this integration requirement weigh when choosing a supplier or a specific vehicle?

Expert B: Software integration is absolutely critical. Since AGVs operate autonomously without human intervention, their alignment with upper-level software is fundamental. However, this must run in parallel with physical flow optimization; when the physical layout and material flows are properly structured, the technical integration of the AGVs becomes significantly smoother. The fleet system must connect seamlessly with our core ERP system or any pre-existing database. To achieve this, I strongly recommend dedicated resources and a highly skilled technical team focused exclusively on bridging the gap between the internal ERP/WMS and the supplier's Fleet Management System.

Implementation recommendations and guidelines

Interviewer: To conclude, based on your extensive experience, could you share some key "Dos and Don'ts" or general recommendations to streamline the implementation process?

Expert B: My first and most critical recommendation concerns the process itself: it must be thoroughly standardized before introducing automation. Once you truly understand and lock down the process flow, you can deploy AGVs effectively.
Second, establish a clear cross-functional project team and organizational structure. You must define precisely who does what from the early stages. For example, IT is a massive domain; within a large corporate structure, you must integrate the fleet with numerous proprietary IT tools, legacy systems, and global ERP modules rather than just a single database. You need to identify the exact internal stakeholders responsible for these systems, bring them all under one roof, and align them immediately.
Third, ensure independent data validation. A supplier might simulate the system and claim, for instance, that you need exactly 10 AGVs for a specific throughput. While supplier simulations are helpful, you should never rely 100% on external estimates. You must conduct internal studies and run your own calculations because your internal team has a deeper, more accurate knowledge of the actual shop floor layers and process anomalies. Double-checking and validating supplier data internally is an absolute necessity.

Interviewer: In your opinion, is there a specific dealbreaker or a major error that could completely compromise the success of the fleet integration and should be avoided at all costs?

Expert B: I wouldn't say there is a single absolute dealbreaker, as every technical challenge in engineering has a solution if you follow the correct procedures. However, the closest thing to a failure point is neglecting the physical-environmental interface, specifically, how the AGV mechanically interacts with the fixed racks and docking stations within its working environment. The physical environment is the ultimate constraint; an automated vehicle only executes what it is programmed to do within a given space. If the physical infrastructure lacks precision or tolerates too much variance, the entire automated workflow breaks down. Precision in the physical environment is what guarantees the success of the system.

Employee acceptance, training and change management

Interviewer: Regarding the employees, if you have observed the system post-implementation or during the initial operator-vehicle interactions, how critical do you consider the human element? Specifically, how do operator acceptance and their technical understanding of the system impact internal logistics?

Expert B: It is highly significant. Operators must clearly understand what the AGV is doing and why it follows specific behavioral logics. Comprehensive operator training is essential to explain how the vehicles function, demonstrate their built-in safety mechanisms, and teach personnel how to interact with them properly. If the workforce is well-trained and possesses this knowledge, the automated process executes smoothly. On the other hand, without proper training, operators may inadvertently trigger unnecessary operational bottlenecks or protective stops by obstructing the vehicles, which ultimately incurs downtime costs for the company.

Interviewer: Did the implementation plan include dedicated investments or training sessions for the employees?

Expert B: Yes, although this process is primarily managed by the supplier, as we explicitly include these deliverables within our initial requirements. The contract accounts for a ramp-up support period, often referred to as a "babysitting" phase, lasting several months. During this phase, we run controlled trials to monitor vehicle behavior and analyze performance data. If the system encounters an obstacle and stops, we perform a root cause analysis on the shop floor. If the data shows that the interruption was caused by an operator blocking the path, we deploy targeted on-the-job training to correct the behavior, ensuring the process returns to a smoother, uninterrupted state.

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