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# EVALUATING FACTORS OF ADOPTING AUTONOMOUS MACHINERY IN DISTRIBUTION CENTRES USING ANALYTICAL HIERARCHY PROCESS

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**ABSTRACT**

The rapid growth of logistics in Malaysia, particularly in Selangor, has increased the demand for more efficient and technologically advanced Distribution Centres (DCs). Autonomous machinery offers significant potential to enhance operational efficiency, reduce labour dependency, and improve accuracy in logistics operations. This study investigates the key factors influencing the adoption of autonomous machinery in distribution centres in Selangor by applying the Analytic Hierarchy Process (AHP) method. Data were collected through purposive sampling of 10 experts with at least three years of experience in logistics and automation. The AHP analysis structured the decision problem into a three-level hierarchy, followed by pairwise comparisons to determine weightings and priorities. The results reveal that operational factors are the most influential, accounting for 55% of the decision weight, with infrastructure readiness and workplace safety ranked as the top sub-factors. Internal factors, particularly maintenance costs and return on investment, ranked second, highlighting the importance of financial sustainability. External factors, such as data security and market scale, were found to be less influential but remain relevant for long-term adoption strategies. The study concludes that successful implementation of autonomous machinery requires balancing technological readiness, financial justification and workforce adaptation. Limitations of this study include the small sample size and short time frame, which restrict generalisability. Nonetheless, the findings provide actionable insights for policymakers, managers and industry stakeholders to strengthen Malaysia's logistics competitiveness in alignment with Industry 4.0 initiatives.

## Introduction

A Distribution Centre (DC) is a facility where products from various suppliers are collected and sometimes assembled for delivery to consumers (Mayadunne *et al*., 2024). DCs are vital to the retail industry, as they reduce operational costs, enhance flexibility and customer responsiveness, and improve network productivity. This is particularly relevant in omnichannel and multichannel (OC/MC) settings, where retailers provide multiple fulfillment options, such as online purchases, in-store pickup and home delivery. However, these options create a complex operational environment. To address these challenges, the deployment of autonomous machinery has been increasingly considered, as it can enhance the efficiency of handling complex operations (Tagashira, 2022). Such machinery includes automated storage and retrieval systems (AS/RS), vertical lifts, conveyors, automated guided vehicles (AGVs), mini-load systems, picking robots and other advanced picking technologies. These systems integrate mobile, autonomous and collaborative capabilities, streamlining processes and accelerating the movement of goods.

DCs play a critical role in ensuring that goods are efficiently processed, stored, and delivered to meet the needs of both manufacturing facilities and end-users. Traditional models of DCs often assume that demand and cost parameters are precisely known. In practice, however, these factors are subject to uncertainty due to market fluctuations, supply chain disruptions and unpredictable consumer behaviour (Ayid *et al*., 2024). Historically, DCs have evolved through several generations of warehouse systems. First-generation systems relied on manual models, such as picker-to-part, where workers retrieved items from parallel-aisle warehouses. Second-generation systems introduced semi-automated methods, including batching, zoning, scattered storage and order consolidation, which increased efficiency but continued to depend heavily on human labour. The most recent generation involves robotised systems that significantly reduce labour requirements while improving speed, accuracy and scalability. These advanced systems enable modern DCs to operate continuously and meet the rising demands of global supply chains (Boysen & de Koster, 2024).

In Malaysia, logistics and distribution form a core component of the national economy, particularly in Selangor, one of the country's largest industrial and commercial hubs. The integration of autonomous technologies into DCs offers solutions to emerging challenges, such as labour shortages, rising operational costs, high risks of human error and growing customer expectations for speed and accuracy in deliveries. In line with global trends in logistics innovation, automation enhances efficiency, accuracy and scalability within DC operations. This is particularly significant in Malaysia's context, as leveraging advanced technologies can help bridge current operational gaps and provide actionable insights to ensure that the nation's supply chain remains competitive regionally and globally.

While global research increasingly explores automation and autonomous technologies in logistics, there remains limited empirical evidence on the specific factors that influence the adoption of autonomous machinery within DCs in Malaysia, particularly in high-activity regions such as Selangor. Although the literature highlights the benefits of autonomous machinery, such as improved efficiency, scalability and error reduction (M. Bonini *et al*, 2015; T. Machado *et al*, 2021; Görçün, Ö.F, 2022), there is insufficient localised research that accounts for Malaysia's industrial structure, leaving a gap in methodological approach for prioritising adoption factors. This gap limits industry stakeholders' ability to make evidence-based technology investment decisions that align with national Industry 4.0 goals.

The primary objective of this study is to investigate the key factors influencing the adoption of autonomous machinery in distribution centres in Selangor, within the broader context of Malaysia's expanding logistics sector and alignment with Industry 4.0 initiatives. Specifically, the study seeks to identify factors that shape adoption decisions. By addressing this objective, the research contributes to the existing literature on advanced logistics technologies and provides practical insights to support Malaysia's transition towards Industry 4.0.

## Literature Review

### *Background of Distribution Centres in Selangor*

A DC is a strategically located facility designed to ensure efficient service to beneficiaries by enabling the rapid movement of goods. Beyond basic storage functions, DCs undertake value-added activities, such as receiving, sorting, storing and preparing goods for timely delivery to retailers, wholesalers or end consumers (Vivek Kumar Dubey & Dharmaraj Veeramani, 2024). Unlike conventional warehouses, distribution centres in Selangor — a key logistics hub in Malaysia — prioritise supply chain optimisation by shortening cycle times and improving inventory management. These facilities are critical to the operations of manufacturers, importers, exporters and transportation companies, and are typically located within industrial zones close to major highways, seaports and airports to enhance accessibility.

The emergence of distribution centres is historically linked to surging trade demands, which necessitated more efficient storage and transportation policies. In Selangor, rapid industrial expansion and its strategic position in the Greater Klang Valley have accelerated the development of advanced distribution facilities. Modern centres increasingly incorporate technologies, such as warehouse management systems (WMS), automation and smart inventory tracking, to enhance efficiency. Historically, during the Industrial Revolution, storage facilities became more specialised, often situated near railway stations and ports to facilitate transport. Similarly, Selangor's distribution centres are strategically located near Port Klang, Kuala Lumpur International Airport (KLIA) and major expressways, reinforcing the state's role as a national and regional logistics hub.

Recent distribution operations in Selangor demonstrate significant levels of automation. Technologies, such as forklifts, conveyor systems, robotic order-fulfillment solutions, pallet racking systems, heavy-duty shelving and Automated Guided Vehicles (AGVs), are widely used to improve speed, accuracy and space utilisation. These innovations represent a marked departure from traditional practices, which were heavily manual and labour-intensive, relying on pulley systems and manual sorting. Today, many facilities are designed from the ground up with technology-driven infrastructure to support the efficient management of large-scale inventory. The integration of smart technologies has given rise to "Smart Distribution Centres", which are increasingly being adopted in Selangor to meet growing logistics demands (Kai *et al*., 2024).

### *Autonomous Machinery*

Autonomous machinery in distribution centres refers to self-operating robots and systems that perform material handling, transportation and order-fulfillment tasks with minimal or no human intervention. These technologies are designed to enhance operational efficiency, reduce labour costs, and optimise warehouse performance (Boysen & de Koster, 2024). Several types of autonomous machinery have gained prominence in recent years:

1. Automated Guided Vehicles (AGVs) outperform traditional manual methods of material handling in terms of speed, precision and safety. They can operate continuously, enabling warehouses to process larger volumes of goods while reducing reliance on manpower. AGVs are typically programmed to follow predetermined pathways, thereby minimising the risk of collisions and accidents (Boysen *et al.,* 2019) (Figure 1).

Figure 1: Automated Guided Vehicles (AGVs)

2. Conveyor and sortation systems are some of the most established forms of automation in distribution centres. These systems, controlled by sensors and sorting mechanisms, transport parcels, cartons and other items to designated destinations. Barcode scanners and RFID readers determine item destinations based on labels or zip codes, after which diverters, tilt trays or cross-belt sorters direct items accordingly. This reduces the need for manual intervention, accelerates the sorting process, improves accuracy and minimises order-fulfillment errors (Chen *et al*., 2021) (Figure 2).

Figure 2: Conveyor and sortation systems

3. Drones have recently been adopted in warehouse inventory management, offering advantages beyond traditional floor-based systems. Their ability to move freely in three-dimensional space allows them to scan barcodes and RFID tags at various heights, including those not easily accessible from the floor. This functionality enables more efficient inventory strategies, such as the First-Expired, First-Out (FEFO) approach, which is particularly important for reducing waste in perishable goods management. By integrating with automated identification (AutoID) technologies, such as barcodes and RFID tags, drones facilitate inventory automation with minimal human intervention (Kapoor *et al*., 2024) (Figure 3).

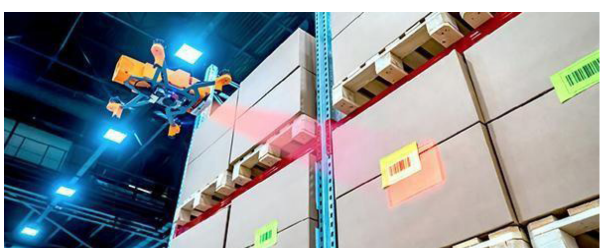

Figure 3: Drones and RFID tags for inventory management

### *Factors that Influence the Adoption of Autonomous Machinery*

To identify the factors influencing the adoption of autonomous machinery, a literature review was first conducted to consolidate the determinants commonly discussed in prior studies. To strengthen the conceptual grounding of these factors, the analysis is guided by the Technology-Organisation-Environment (TOE) framework proposed by Tornatzky and Fleischer (1990). The TOE framework has been widely applied across diverse innovation studies to explain firm-level adoption decisions (Nguyen *et al*., 2025). The TOE framework is well suited for this purpose because it provides a comprehensive structure, integrating technological, organisational and environmental dimensions that collectively shape innovation decisions. This structure aligns naturally with the types of factors found in the literature: Internal, external and operational factors.

*1. Internal factors*

Internal factors are controllable aspects within a DC that directly influence decision-making and the successful application of autonomous machinery. These include financial outcomes, technical readiness and human resource dynamics arising from the organisation's operations, systems and personnel (Gursoy & Swanger, 2007). The three key internal factors considered here are maintenance costs, return on investment and employees' perception, which may be further disaggregated into sub-factors affecting the overall financial and organisational impact (Simic *et al*., 2023).

Maintenance costs refer to the total annual expenditure required to service and repair automated devices, vehicles and robotic systems within a DC. Next, return on investment (ROI) is a crucial consideration, as it measures the efficiency and profitability of adopting automation, helping organisations assess whether the investment yields sufficient benefits (de Souza *et al*., 2011). Finally, employees' perception — including safety concerns, job security and adaptability — plays an important role in shaping adoption outcomes. Resistance may arise if employees fear job loss or lack confidence in using new technologies. Therefore, effective training programmes and transparent communication are essential for easing the transition (Filippi *et al*., 2023).

*2. External factors*

External factors are those beyond an organisation's direct control but remain critical for the successful adoption of autonomous machinery in DCs (Efthymiou & Ponis, 2021). In particular, three external factors require consideration: market scale, industry trends and data security and privacy. Market scale determines whether automation investments align with market demand, ensuring that resources are not over- or under-committed. Industry trends show a growing adoption of automation across companies seeking to stay competitive, meet e-commerce demands and reduce labour dependency (Javaid *et al*., 2021). Data security and privacy are also central concerns, as autonomous machinery often relies on digital networks and interconnected systems. Safeguarding sensitive information against cyber threats while complying with regulatory requirements is essential to maintaining customer trust (Sun *et al*., 2024). Addressing these factors allows organisations to implement automation more effectively, adapt to evolving expectations and build long-term resilience.

*3. Operational factors*

Operational factors relate to day-to-day procedures, systems and practices that influence how efficiently a distribution centre functions. While internal in nature, they differ from strategic or financial aspects, as they focus on executional elements in logistics and automation environments (Popović *et al*., 2021). Key operational factors include infrastructure readiness, workplace safety and integration capabilities. Infrastructure readiness refers to whether existing warehouse layouts and equipment can support new automation systems, or whether upgrades are necessary (Ardiansyah *et al*., 2024). Automation also contributes to workplace safety by reducing heavy lifting and repetitive tasks, thereby minimising accidents and human errors (Lavender *et al*., 2025). Finally, integration capabilities determine how seamlessly new technologies interact with existing systems, ensuring smooth and unobstructed operations. Through these operational factors, maximum effectiveness of autonomous machinery and sustained productivity improvement are expected.

### *The Analytical Hierarchy Process Technique*

The Analytical Hierarchy Process (AHP) was developed by Saaty (1980) as a decision-making tool for addressing complex problems in economics and the social sciences. According to Taylor (2004), the AHP technique is particularly valuable when decision-makers must evaluate and rank multiple alternatives to identify the most preferred option. In logistics and shipping industries, AHP has been widely applied for ranking factors and prioritising strategies, including in the maritime sector, where it supports decision-making under conditions of complexity and uncertainty (Karim *et al*., 2018).

AHP is one of the most widely used multi-criteria decision-making (MCDM) methods, as it enables the consideration of multiple variables simultaneously. Unlike linear decision-making systems, AHP employs a non-linear approach that allows both deductive and inductive reasoning, without relying on strict syllogistic logic. The method structures decision problems into a hierarchy of goals, criteria and alternatives, enabling the systematic comparison of factors through pairwise judgments. These judgments generate numerical values that represent relative priorities, allowing for a synthesis that leads to the final decision.

At its core, AHP is a theory of relative measurement that addresses complex decision problems involving multiple criteria. Its strength lies in integrating both quantitative data and qualitative insights. As Marenco-Porto *et al*. (2023) highlight, AHP provides a procedure that captures the experience and knowledge of stakeholders, not merely the available data. This makes it particularly useful in contexts where expert judgment is critical. Ultimately, AHP produces a prioritisation and weighting scale based on decision-makers' assessments, thereby offering a structured and transparent framework for making well-informed decisions.

Prior studies have demonstrated the suitability of the AHP for evaluating technology adoption factors. In the context of mobile services, AHP has been applied to identify the most relevant services for consumers and to prioritise the factors driving adoption decisions (Nikou & Mezei, 2013; Lotfi *et al*, 2020). Similarly, Sepasgozar and Davis (2018) employed AHP as a benchmarking tool to support companies in evaluating the adoption of new construction technologies. These studies highlight AHP's strength in structuring complex decision problems and systematically comparing multiple criteria. Given that the adoption of autonomous machinery in DCs also involves balancing diverse technological, organisational and environmental considerations, AHP provides an appropriate methodological approach. It enables the prioritisation of factors based on expert judgment and supports a hierarchical evaluation of the factor adoptions.

The decision to adopt such technologies involves multiple dimensions, including internal, external and operational factors, each with varying levels of importance. AHP allows these factors to be structured hierarchically and compared through pairwise evaluations, producing quantifiable priority weights. This approach makes it possible to balance tangible considerations, such as financial costs and infrastructure readiness, with more qualitative aspects, including employee perception and industry trends. In doing so, AHP enables a comprehensive evaluation of adoption drivers and provides decision-makers in Malaysia's logistics sector with clearer insights into where resources and strategies should be directed.

## Methodology

### *Research Design and Data Collection*

This study employed a quantitative research design to examine the factors influencing the adoption of autonomous machinery in Distribution Centres (DCs) in Selangor. The process began with a literature review of existing research to identify potential factors relevant to the utilisation of autonomous machinery in DCs. Data were collected using a purposive sampling method through questionnaires distributed to participants with relevant knowledge and experience in logistics operations and autonomous technologies. Ten experts from DCs in Selangor were engaged to perform pairwise comparisons for each main factor and sub-factor affecting adoption. The selection of experts was based on their professional positions and industry experience, with a minimum requirement of three years, as summarized in Table 1.

Table 1: Expert's position and years of experience

| Expert | Position | Experiences |
|---|---|---|
| 1 | Warehouse Supervisor | 7 years |
| 2 | Warehouse Supervisor | 9 years |
| 3 | Senior Distribution Clerk | 8 years |
| 4 | Logistic Executive | 3 years |
| 5 | Senior Distribution Operator | 6 years |
| 6 | Distribution Operator | 3 years |
| 7 | Fulfillment Operator | 4 years |
| 8 | Fulfillment Operator | 5 years |
| 9 | Distribution Operator | 6 years |
| 10 | Distribution Manager | 15 years |

### *Data Analysis*

The Analytic Hierarchy Process (AHP) was applied to rank and weigh the most important factors influencing the potential adoption of autonomous machinery in DCs in Selangor. A flow chart depicting the sequential steps of the methodology is shown in Figure 4, which illustrates the calculation process used in this study.

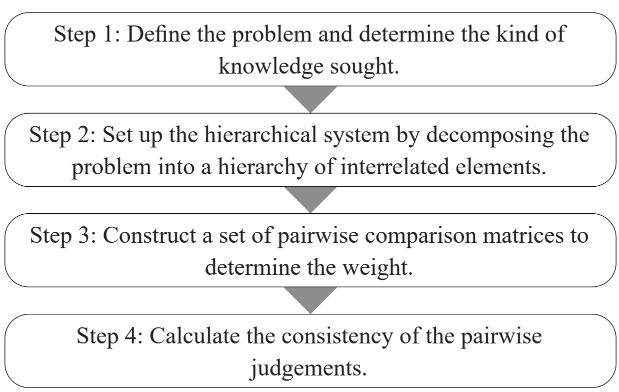


Figure 4: Flow of the Analytic Hierarchy Process in this research.

*Step 1: Define the problem and determine the kind of knowledge sought*

The first step involves defining the unstructured problem. Decision analysis requires a clear understanding of the issue under investigation, as insufficient understanding or inaccurate information may distort the entire problem structure.

*Step 2: Set up the hierarchical system by decomposing the problem into a hierarchy of interrelated elements*

The decision-making problem was structured into a hierarchical model consisting of three levels: Goal (L1), criteria (L2), and sub-criteria (L3). The goal represents the main objective of this research, while the criteria specify the factors influencing the adoption of autonomous machinery in DCs. Each criterion may further contain sub-criteria for deeper analysis. This hierarchical decomposition ensures that all relevant factors are systematically considered before conducting the pairwise comparisons in the next stage of AHP.

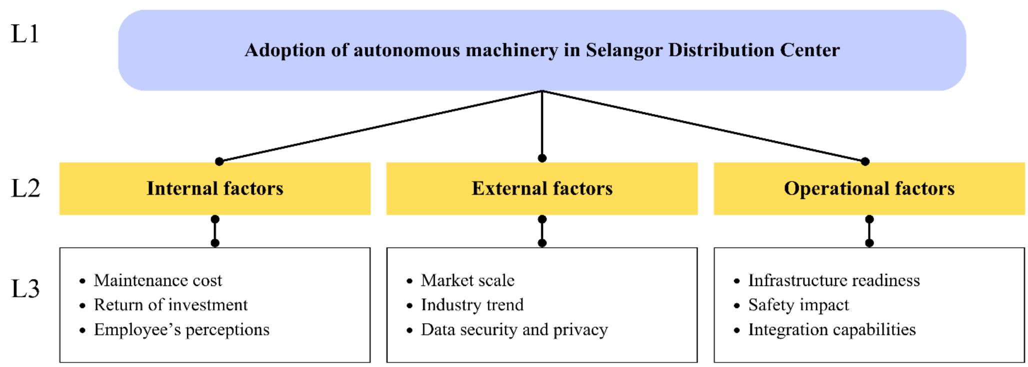


Figure 5: Hierarchy structure model for this research

*Step 3: Construct a set of pairwise comparison matrices and calculate the weight*

In this study, each factor was evaluated based on its relative importance through pairwise comparisons using the AHP framework. A preference scale ranging from 1 to 9 was employed, where a value of 1 indicates equal importance between two factors, and a value of 9 indicates that one factor is extremely more important than the other. The complete scale is presented in Table 2. A pairwise comparison matrix (n × n) was then constructed to quantify the judgments, illustrating the relative preference of one factor over another. This approach is widely recognised in multi-criteria decision-making (MCDM) for its effectiveness in structuring and analysing complex decision problems.

Table 2: The ratio scale of pair-wise comparison

| Numerical assessment | Linguistic meaning |
|---|---|
| 1 | Equally important |
| 3 | Weakly important |
| 5 | Strongly important |
| 7 | Very strongly important |
| 9 | Extremely important |
| 2,4,6,8 | Intermediate values between the two adjacent judgements |

The qualified judgments on pairs of attributes $A_i$ and $A_j$ are presented by an n × n matrix A. The entries $a_{ij}$ are defined by entry rules as follows (Saaty 1980; Mohd Salleh *et al.* 2014):

- Rule 1: If $a_{ij} = \alpha$, then = $1/\alpha$, $\alpha \neq 0$
- Rule 2: If $A_i$ is judged to be of equal relative importance as $A_j$, then $a_{ij} = a_{ji} = 1$.

A=$(a_{ij})$ [1 $a_n \ldots a_{1n}$ $1/a_n$ $1 \ldots a_{2n}$ $1/a_{1n}$ $1/aa_{2n} \ldots$ 1 ]

(1)

where $i,j$=1,2,3,…,$n$ and each $a_{ij}$ is the relative importance of attribute $Ai$ to attribute $Aj$.

For a matrix of order $n$, $(n\times(n-1)/2)$ comparisons are required. According to Pam (2010), the weight vector indicates the priority of each element in the pair-wise comparison matrix in terms of its overall contribution to the decision-making process. A weight value of W can be calculated by using Equation 2 as follows:

$$W_k = \frac{1}{n} \left[\sum_{i=1}^{n} \square \left(\frac{a_{kj}}{\left[\sum_{i=1}^{n} \square a_{ij}}\right) \quad (k=1,2,3,\ldots n) \qquad (2)$$

Where $a_{ij}$ stands for the entry of row i and column j in a comparison matrix of order n.

This study uses group decision-making. Therefore, the judgments of all experts will be combined. It has been proven that the geometric mean, not the frequently used arithmetic mean, is the only way to combine the judgments of the group of experts (Saaty, 2008).

$$GM=(A1 \text{ x } A2 \ldots An) \qquad (3)$$

where A1 is the first number, A2 is the second number and n is the number of entries. The arithmetic mean of a set of $\frac{1}{n}$ data is found by taking the sum of the data and then dividing the sum by the total number of values in the set. A mean is commonly referred to as an average.

*Step 4: The calculation of the consistency of the pairwise judgments.*

This involves carrying out a consistency measurement to screen out the inconsistency of responses. Comparisons made by this method are subjective, and the AHP tolerates inconsistency through the amount of redundancy in the approach. If the consistency index fails to reach a required level, then answers to comparisons may be re-examined. The weight values obtained in the pair-wise comparison matrix are checked for consistency using a Consistency Ratio (CR). The CR value is computed using the following equations (Saaty, 1990):

$$CR=\frac{CI}{CR} \qquad (4)$$

$$CI=\frac{\lambda max\text{-}n}{n\text{-}1} \qquad (5)$$

$$\lambda max\text{-}n=\frac{\left[\sum_{j}^{n} \square 1 \frac{\sum_{k}^{n} \square = 1 w_k a_{jk}}{w_j}}{n} \qquad (6)$$

where $n$ is the number of items being compared, $\lambda max$ is the maximum weight value of the $nx$ $n$ comparison matrix, RI stands for average random index (Table 3) and CI stands for consistency index.

Table 3: Random Index (RI) values

| ***n*** | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| ***RI*** | 0 | 0 | 0.52 | 0.89 | 1.11 | 1.25 | 1.35 | 1.4 | 1.45 | 1.49 |

CR is designed in such a way that a value greater than 0.10 indicates an inconsistency in pairwise comparison. If CR is 0.10 or less, the consistency of the pair-wise comparisons is considered reasonable (Saaty, 1980). Tables 4, 5, 6, and 7 present the results of the pairwise comparison, weight value and CR for the criteria and sub-criteria.

Table 4: Pairwise comparison matrix and weights for the main criteria

| Criterion | IF | EF | OF | Weight Value |
|---|---|---|---|---|
| Internal Factors (IF) | 1.0000 | 2.2533 | 0.4094 | 0.2894 |
| External Factors (EF) | 0.4438 | 1.0000 | 0.3772 | 0.1649 |
| Operational Factors (OF) | 2.4426 | 2.6510 | 1.0000 | 0.5457 |
| **CR: 0.0575** | | | | |

Table 5: Pairwise comparison matrix and weights for the Internal Factors (IF)

| Sub-Criterion | MC | ROI | EP | Weight Value |
|---|---|---|---|---|
| Maintenance Cost (MC) | 1.0000 | 1.2723 | 2.5099 | 0.4616 |
| Return on Investment (ROI) | 0.7860 | 1.0000 | 1.6843 | 0.3443 |
| Employee's Perception (EP) | 0.3984 | 0.5937 | 1.0000 | 0.1940 |
| **CR: 0.0027** | | | | |

Table 6: Pairwise comparison matrix and weights for the External Factors (EF)

| Sub-Criterion | MS | IT | DS | Weight Value |
|---|---|---|---|---|
| Market Scale (MS) | 1.0000 | 0.8597 | 0.5119 | 0.2425 |
| Industry Trend (IT) | 1.1633 | 1.0000 | 0.5818 | 0.2800 |
| Data Security & Privacy (DS) | 1.9537 | 1.7188 | 1.0000 | 0.4775 |
| **CR: 0.0001** | | | | |

Table 7: Pairwise comparison matrix and weights for the Operational Factors (OF)

| Sub-Criterion | MS | IT | DS | Weight Value |
|---|---|---|---|---|
| Infrastructure Readiness (IR) | 1.0000 | 1.2785 | 0.8383 | 0.3408 |
| Safety Impact (SI) | 0.7822 | 1.0000 | 1.3653 | 0.3404 |
| Integration Capabilities (IC) | 1.1929 | 0.7325 | 1.0000 | 0.3188 |
| **CR: 0.0578** | | | | |

## Results and Discussion

The analysis of the selection criteria (Table 8) shows that the Operational Factor (0.5457) is the most important determinant of autonomous machinery adoption in DCs, followed by the Internal Factor (0.2894) and the External Factor (0.1649). The consistency ratio (CR) value for the main criteria is 0.0575, which is below the acceptable threshold of 0.10, indicating that the pairwise comparisons are consistent.

Table 8: Weight value for criterion and sub-criterion

| Criterion | Weigh Value | Sub-Criteria | Weight Value | Ranking |
|---|---|---|---|---|
| Internal Factors (IF) | 0.2894 | MC | 0.4616 | 1 |
| | | ROI | 0.3443 | 2 |
| | | EP | 0.1940 | 3 |
| | | **CR Sub-Criterion IF: 0.0027** | | |
| External Factors (EF) | 0.1649 | MS | 0.2425 | 3 |
| | | IT | 0.2800 | 2 |
| | | DS | 0.4775 | 1 |
| | | **CR Sub-Criterion EF: 0.0001** | | |
| Operational Factors (OF) | 0.5457 | IR | 0.3408 | 1 |
| | | SI | 0.3404 | 2 |
| | | IC | 0.3188 | 3 |
| | | **CR Sub-Criterion OF: 0.0578** | | |

Furthermore, the results indicate that operational considerations dominate, accounting for more than half of the total weight (55%). This finding emphasises the importance of day-to-day operational elements, particularly infrastructure readiness, workplace safety and system integration capabilities, in determining the feasibility of adopting autonomous machinery.

Within operational factors, infrastructure readiness (34%) and workplace safety (34%) are jointly ranked as the most critical. This suggests that experts place equal importance on preparing the physical environment for automation (e.g., warehouse layout, racking systems, connectivity) and ensuring that automation improves safety by reducing repetitive and physically demanding tasks. Integration capabilities (32%), while slightly lower, remain highly relevant, reflecting the necessity of seamless interaction between autonomous systems and existing warehouse management or enterprise resource planning platforms.

The internal factor (29%) ranks second, highlighting organisational considerations such as financial viability and employee response. Among these, maintenance cost (46%) emerges as the most influential sub-criterion, showing that decision-makers are highly attentive to long-term cost sustainability. Even if the initial investment is feasible, recurring expenses for repairs and servicing can deter adoption. Return on investment (35%) also carries significant weight, emphasising the need for automation to demonstrate tangible financial benefits over time. By contrast, employees' perception (19%) is the least influential, suggesting that, at least in the Selangor context, firms are initially more concerned with cost efficiency than workforce adaptation. However, neglecting employee acceptance could pose challenges later if not addressed through training and communication.

The external factor (16%) is considered least influential, although still relevant to decision-making. Here, data security and privacy (48%) stand out as the top concern, reflecting the risks posed by automation systems that rely on sensors, cloud platforms and real-time data exchange. Protecting sensitive operational and customer data is seen as critical to building trust and avoiding cyber vulnerabilities. Industry trends (28%) are next in importance, showing that organisations remain mindful of competitive pressures and sector-wide movements toward automation. Finally, market scale (24%) is rated lowest, suggesting that firms in Selangor currently prioritise technological and security considerations over market expansion potential. However, market size could grow in relevance as automation becomes more widespread and logistics demand continues to rise.

The findings contribute to the growing body of research on autonomous technologies in logistics. This helps clarify that the key driver of adoption is whether the DCs is technically and operationally prepared to use autonomous machinery. In practical terms, the results offer clear guidance for DCs in Malaysia. Since operational factors are the most important, companies should focus first on preparing their facilities, ensuring systems can work together and maintaining strong safety measures before adopting autonomous machinery. Organisations also need to provide support to help the processes transition smoothly to autonomous operations.

## Conclusions

This study evaluated the potential adoption of autonomous machinery in distribution centres by applying the Analytic Hierarchy Process (AHP) method. The findings provide key insights into the factors that decision-makers should consider prior to automation implementation. Among the main criteria, operational factors were identified as the most influential, with infrastructure readiness, workplace safety and integration capabilities emerging as critical determinants of adoption success. This highlights the importance of ensuring that physical facilities are well-prepared and that new systems can be seamlessly integrated into existing workflows. Internal factors, such as maintenance costs and return on investment, ranked second, underscoring the necessity of financial viability and organisational preparedness. Meanwhile, external factors, including market scale and data security, were found to be less influential in the short term but remain relevant for shaping long-term strategies. Overall, the findings suggest that successful adoption of autonomous machinery requires a balance between technological readiness, financial justification and workforce adaptation. These results highlight that successful implementation depends on strong facility preparation, system compatibility and organisational support. The insights offer both theoretical contributions to understanding adoption drivers and practical guidance for distribution canters planning to transition toward autonomous operations.

## Limitations

Several limitations of this study should be acknowledged. First, the use of purposive sampling may introduce bias, as the sample is not fully representative of the broader distribution centre workforce and may exclude certain perspectives. The study primarily targeted warehouse and distribution managers, as well as workers with at least three years of experience, which limits the diversity of viewpoints considered. Second, the relatively short time frame of the research constrained the number of responses collected, reducing the opportunity for broader generalisation. Future research should consider expanding the sample size, incorporating more varied stakeholders and adopting longitudinal designs to capture changes in adoption dynamics over time.

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## Conflict of Interest Statement

The authors declare that they have no conflict of interest.

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