sustainability

MDPI

Article

Integrated Multi-Criteria Decision-Making Approaches for Sustainable Forklift Selection with a Real-Life Application in Turkey

Selin Çabuk

Department of Industrial Engineering, Faculty of Engineering, Çukurova University, Sarıçam, 01330 Adana, Turkey; selincabuk@cu.edu.tr

Abstract

Sustainable forklift technologies have become essential in modern industrial logistics due to increasing environmental regulations, rising energy costs, and heightened occupational safety requirements. Given the complexity and variety of sustainable forklift options, selecting the most appropriate one has become a critical multi-criteria decision-making (MCDM) problem for companies. This study aims to determine the most appropriate sustainable forklifts by considering multiple qualitative and quantitative criteria that play a critical role in the forklift selection process of companies. To this end, meetings are conducted with managers possessing expertise in sustainability and logistics at companies operating in Turkey. Based on these insights, ten forklift alternatives and six evaluation criteria are identified. This is the first time, in this study, sustainability criteria such as sustainability in occupational health and safety, sustainability in agility, sustainability in ergonomics, durability and material sustainability, sustainability in load lifting capacity and sustainability in price are incorporated into the evaluation. To the best of our knowledge, no study in existing literature has specifically focused on sustainable forklift selection, incorporating the comprehensive sustainability-oriented criteria considered in this study. The Analytic Hierarchy Process (AHP) is employed to determine the weight of each criterion. Subsequently, forklift alternatives are ranked using the Multi-objective Optimization by Ratio Analysis (MOORA) ratio approach, the Additive Ratio Assessment (ARAS), and the Elimination and Choice Translating Reality (ELECTRE) methods. Moreover, weights derived based on different subjective and objective weighting schemes, specifically FUCOM, BWM, and Entropy, as well as the resulting ranking outcomes are comparatively examined to assess the impact of varying weighting structures on the robustness and consistency of the final decision results. The proposed methodology is applied within manufacturing and logistics companies in Turkey to assess its practical effectiveness. As a result of this study, the most appropriate sustainable forklifts for the companies are identified. Furthermore, the outcomes of the applied methods yield consistent/similar results. The results emphasize that managers should place greater importance on the criteria of sustainability in occupational health and safety—identified as the most critical factor—followed by durability and material sustainability, and sustainability in load lifting capacity when selecting forklifts. Sensitivity analyses indicate that the method yields consistent and effective results. Moreover, it demonstrates the robustness and accuracy of the forklift evaluations. In this context, this study serves as a guided reference for companies in the selection of sustainable forklifts.

Check for updates

Academic Editors: Mario Fargnoli, Ming Liu and Giada La Scalia

Received: 24 January 2026
Revised: 22 April 2026
Accepted: 24 April 2026
Published: 27 April 2026

Copyright: © 2026 by the author. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

Keywords: sustainable forklift selection; MCDM; AHP/BWM/FUCOM/entropy; ARAS; MOORA; ELECTRE; durability and material sustainability; occupational health and safety; sustainability in load lifting capacity; sustainability in ergonomics

1. Introduction

Internal logistics involves the transportation of materials within warehouses or between different storage locations within a company, making the selection of material handling equipment (MHE) a critical aspect of logistics operations. In many industrial sectors, particularly in logistics, internal transportation refers to the movement of materials either within a warehouse or between warehouses. The selection of appropriate material handling equipment plays a vital role in ensuring the efficient, economical, and safe transport of materials.

MHE selection is increasingly recognized as a complex MCDM problem, influenced by numerous factors that affect the decision process. Selection of the appropriate MHE is crucial for improving the productivity and efficiency of industrial organizations operating in the global market. Choosing the most suitable MHE for a specific engineering application is often a costly and time-consuming process due to the large number of candidate alternatives available on the market [1].

Forklifts are vital components for the transportation of materials within the industrial and logistics sectors, particularly in internal logistics processes involving the transfer of goods between warehouses or production facilities. Among various types of MHE, forklifts are the most commonly used in industrial warehousing and transportation. In most company operations, forklifts are utilized continuously, and logistics processes are hardly feasible without them. Therefore, selecting a suitable forklift is essential for ensuring their optimal performance and service to the organization. In real-time industrial settings, the analysis and selection of the most appropriate forklift represent a complex decision-making problem that must be addressed using an effective analytical model [2]. Various parameters must be considered during forklift selection. In other words, forklift selection involves multiple criteria and thus necessitates the use of MCDM methods [3].

Sustainable material handling equipment is designed and operated to minimize environmental impact while maintaining and improving operational efficiency. These systems integrate energy-efficient technologies, low-emission power sources, durable and recyclable materials, and smart control architectures that optimize material flow with reduced resource consumption. In modern logistics and manufacturing environments, sustainable material handling equipment has become a critical component of sustainable supply chain and logistics strategies.

MHE accounts for approximately one-third of the energy consumed in material handling operations; therefore, the adoption of environmentally efficient forklifts can be an effective solution for reducing energy consumption. As one of the most critical material handling equipment, forklifts must be designed with well-developed safety and ergonomic features to prevent workplace accidents. Approximately 75 to 100 workers lose their lives each year in forklift-related accidents, corresponding to an annual average of 87 fatalities. Notably, this figure has increased by nearly 30% over the past decade. According to the most recent estimates reported by the Occupational Safety and Health Administration (OSHA), forklift-related incidents also result in approximately 35,000 to 62,000 injuries annually.

Sustainable forklift technologies play a critical role in reducing environmental impacts, enhancing economic efficiency, and strengthening occupational health and safety within industrial logistics operations. Energy-efficient power systems, low-emission profiles,

durable materials, and recovery practices significantly decrease carbon footprints and resource consumption throughout the equipment's life cycle. Additionally, ergonomic designs and smart sensor technologies improve working conditions and support social sustainability. In this regard, sustainable forklifts have become strategic assets in modern supply chains, enhancing operational performance while aligning with environmental and corporate sustainability objectives.

1.1. Motivation

Forklifts play a central role in industrial operations, particularly in material handling activities such as transportation, loading, and unloading within and between warehouse facilities. In contemporary production, warehousing, and logistics operations, sustainable forklifts have become increasingly important for enabling organizations to meet both environmental responsibilities and operational performance objectives. The expansion of green supply chain practices, rising energy costs, and stricter occupational health and safety regulations have transformed sustainable forklift technologies from optional solutions into strategic necessities. However, selecting the most suitable sustainable forklift is a complex decision-making problem that involves multiple, interrelated, and often competing criteria, including environmental, economic, and social considerations. Despite this complexity, existing decision-making practices in industrial contexts are often based on limited criteria or intuitive judgments, which may lead to suboptimal or unsustainable investment decisions.

In this regard, the motivation behind this study arises from the need to develop a structured and sustainability-oriented decision-making framework that can systematically evaluate alternative forklift options. By integrating sustainability principles with multi-criteria decision-making approaches, this study aims to support organizations in making more informed, transparent, and consistent forklift selection decisions aligned with both operational and sustainability objectives.

1.2. Research Gap and Contribution

Sustainability theory emphasizes the need to simultaneously consider environmental, social, and economic dimensions in decision-making processes. However, translating these multidimensional sustainability principles into practical decision-making frameworks remains a significant challenge, particularly in complex industrial contexts such as material handling equipment selection. This difficulty primarily arises from the fact that sustainability inherently involves multiple criteria with trade-offs that must be evaluated simultaneously. In this regard, MCDM methods provide a structured and analytical approach for operationalizing sustainability by enabling the systematic evaluation of such interrelated and competing criteria. Therefore, MCDM methods serve as an essential bridge between sustainability theory and practical decision-making applications.

Although numerous MCDM models have been proposed for general material handling equipment [MHE] selection, the literature on forklift selection remains relatively fragmented and limited. Several studies have examined forklift selection using different MCDM approaches; however, these studies primarily focus on operational and economic criteria. The integration of sustainability-oriented criteria into the forklift selection process remains relatively limited and fragmented in the existing literature. To the best of our knowledge, aspects such as occupational health and safety sustainability, ergonomics, agility, durability, and material sustainability have not been simultaneously addressed within a comprehensive forklift evaluation framework. Furthermore, studies employing integrated approaches that combine AHP, BWM, FUCOM, Entropy with ranking methods such as ELECTRE, ARAS, or MOORA in the context of sustainable forklift evaluation remain scarce. Comparative analyses examining the performance and consistency of mul-

tiple ranking methods within the same decision framework are also rarely reported. In addition, existing studies generally rely on a single weighting method, and comprehensive comparative analyses incorporating multiple subjective and objective weighting techniques remain limited. This study aims to address these gaps by proposing a hybrid decision-making framework that integrates multiple weighting methods—including AHP, BWM, FUCOM, and Entropy—with three different ranking methods—ARAS, MOORA (ratio approach), and ELECTRE—for the evaluation and selection of sustainable forklift alternatives. Through this approach, both the impact of different weighting schemes and the consistency of ranking results across multiple MCDM methods are systematically examined, thereby enhancing the robustness and methodological diversity of the decision-making framework. Another important aspect of this study lies in the incorporation of sustainability-oriented evaluation criteria. In this respect, this study not only applies the MCDM techniques, but also contributes to bridging the gap between sustainability theory and practical decision-making. In particular, criteria such as sustainability in occupational health and safety, agility, ergonomics, durability and material sustainability, sustainability in load lifting capacity, and price are considered simultaneously within a unified evaluation framework. While some of these criteria have been individually discussed in related studies, their combined consideration within the context of sustainable forklift selection remains limited. Moreover, the identification of the evaluation criteria and forklift alternatives is carried out in collaboration with experts in sustainability and logistics, which strengthens the practical relevance and applicability of the proposed framework. The results of the analysis also reveal that sustainability in occupational health and safety represents a highly significant factor in the forklift selection process.

The main contributions of this study can be summarized as follows:

1. Proposing a sustainability-oriented evaluation framework for forklift selection that integrates operational, economic, and sustainability-related criteria.
2. Developing an integrated MCDM framework combining AHP with ARAS, MOORA (ratio approach), and ELECTRE methods for the evaluation of sustainable forklift alternatives.
3. Comparing different criteria weighting approaches, including both subjective (AHP, BWM, FUCOM) and objective (Entropy) methods, in order to analyze the consistency of criteria weights and their influence on the decision results.
4. Providing a comparative analysis of multiple ranking methods within the same decision-making environment to examine the consistency and robustness of alternative rankings.
5. Identifying evaluation criteria and alternatives through expert consultations in logistics and sustainability.

Overall, the findings contribute to the literature by providing a structured decision-support framework for sustainable forklift selection and by offering comparative insights into the performance of different integrated MCDM approaches.

The rest of the paper is organized as follows: In Section 2, the literature on MHE selection with MCDM methods and forklift selection with MCDM methods are separately reviewed. In Section 3, the methods used in this study are described in detail. Section 4 dedicates to real-life implementation of this study. In Section 5, sensitivity analysis is provided to validate the model (results of the methods) used in this study. Spearman's rank correlation analysis is done to examine the consistency among rankings obtained from the MCDM methods in Section 6. Section 7 provides a comprehensive comparison of weighting methods (AHP, BWM, FUCOM, and Entropy) and the corresponding ranking results. Section 8 presents the results of Kendall's coefficient of concordance. Section 9

discusses the managerial implications of the findings. The conclusions of this study are presented in Section 10.

2. Literature Review

2.1. Studies on MHE Selection with MCDM Methods

Many studies have been conducted on the selection of MHE, which encompasses a wide range of equipment types, including forklifts, turret trucks, reach trucks, side loaders, as well as port and outdoor cranes. These studies typically focus on developing MCDM models to evaluate and select the most suitable MHE for specific industrial applications. The following section summarizes selected studies related to MHE selection.

Chakraborty and Banik [4] employed AHP to identify the optimal MHE alternative. Tuzkaya et al. [5] developed an integrated fuzzy MCDM approach based on fuzzy sets, ANP, and PROMETHEE. The methodology is applied in a real manufacturing company, demonstrating its feasibility for MHE selection. Mousavi et al. [6] applied a fuzzy grey group compromise ranking approach and performed a comparative analysis with the VIKOR method under uncertainty. Khandekar and Chakraborty [7] used fuzzy axiomatic design principles for selecting the most appropriate MHE. Chakraborty and Prasad [8] used a QFD-based approach for selecting the best industrial truck. Nguyen et al. [9] present an integrated MCDM model based on fuzzy AHP and fuzzy ARAS for conveyor evaluation and selection. Saputro and Rouyendegh [10] used the entropy-based hierarchical fuzzy TOPSIS method and Multi-Objective Mixed Integer Linear Programming to select the best MHE. Varun et al. [11] used AHP to evaluate the material transportation systems used in a steel manufacturing industry. Nayal et al. [12] compared the outcomes of TOPSIS, VIKOR, and SAW in the context of tower crane selection. Ulutaş et al. [13] used the correlation coefficient and the standard deviation method and the indifference threshold-based attribute ratio analysis method for weighting criteria. They employed the MARCOS method to evaluate the MHE alternatives. Mohamadghasemi et al. [14] used Gaussian interval type-2 fuzzy sets and the fuzzy weighted average (FWA) approach to weight criteria and sub-criteria. The ELECTRE III method was employed to select the best conveyor. Goswami and Behera [1] investigated conveyor systems, automated guided vehicles (AGVs), and robotics selection problems. They used the Entropy method for weighting the criteria, followed by the ARAS and COPRAS methods for evaluating their performance. Hornakova et al. [15] applied the AHP to select appropriate handling equipment in a specific industrial facility for final product movement. Ulutaş [16] proposed a new MCDM model consisting of the MEREC method and the WISP-S methods for pallet truck selection in a textile workshop. Veskovic et al. [17] developed a model that included Fuzzy FUCOM (Full Consistency Method), Fuzzy MARCOS (measurement of alternatives and ranking according to the compromise solution), and the Fuzzy Bonferroni Mean (BM) operator to select the best reach stacker. Fulzele et al. [18] proposed a decision framework incorporating AHP, TOPSIS, VIKOR, and Deng's similarity-based approach for conveyor system selection. Zolfani et al. [19] introduced an extended hybrid model combining the FUCOM and WASPAS methods, supported by fuzzy Dombi aggregation operators. Goswami and Behera [20] proposed a new COPRAS-ARAS hybrid model for industrial robot selection. Yu et al. [21] used the Best–Worst Method (BWM) and Pythagorean hesitant fuzzy VIKOR methods to evaluate container cranes. Görçün et al. [22] proposed an intuitionistic fuzzy consensus-based complex proportional assessment model (IF-c-COPRAS) to determine the best crawler crane.

2.2. Studies on Forklift Selection with MCDM Methods

Although many studies focus on the MHE selection, the literature on forklift selection, which represents one of the most commonly used MHE types, remains relatively limited. Below is a summary of studies specifically addressing forklift selection and the methods used.

Atanaskovic et al. [23] employed the Delphi and VIKOR methods to select the optimal forklift unit for warehouse operations. Prusa [24] used the TOPSIS method for forklift truck selection, while Pamucar and Cirovic [25] utilized MABAC and compared it with other methods, such as SAW, COPRAS, TOPSIS, MOORA, and VIKOR, under the same conditions. Fazlollahtabar et al. [26] applied FUCOM and WASPAS methods for evaluating forklift alternatives. Mahmutagić et al. [27] introduced a forklift selection model combining DEA, FUCOM, and MARCOS. Ulutaş et al. [28] used fuzzy BWM to define the criteria weights and proposed a new fuzzy MCDM approach, the fuzzy MCRAT method, for forklift ranking. Their study also compared fuzzy MCRAT outcomes with fuzzy ARAS and fuzzy MARCOS, showing close similarities. Dua [3] adopted COCOSO and PIV methods for forklift evaluation and combined them with Entropy and MEREC weighting techniques, providing four separate ranking outputs that consistently identified the same best and worst alternatives. Huskanović et al. [29] applied the CRITIC method to derive criteria weights and used MARCOS for evaluating forklifts in internal transport processes. Chakraborty and Saha [2] determined criteria weights using FUCOM and conducted forklift ranking using the MOORA ratio approach.

3. Methodology

In this section, the AHP, MOORA, ELECTRE, and ARAS methods employed in this article are described in detail. The research methodology applied in this study is shown in Figure 1:

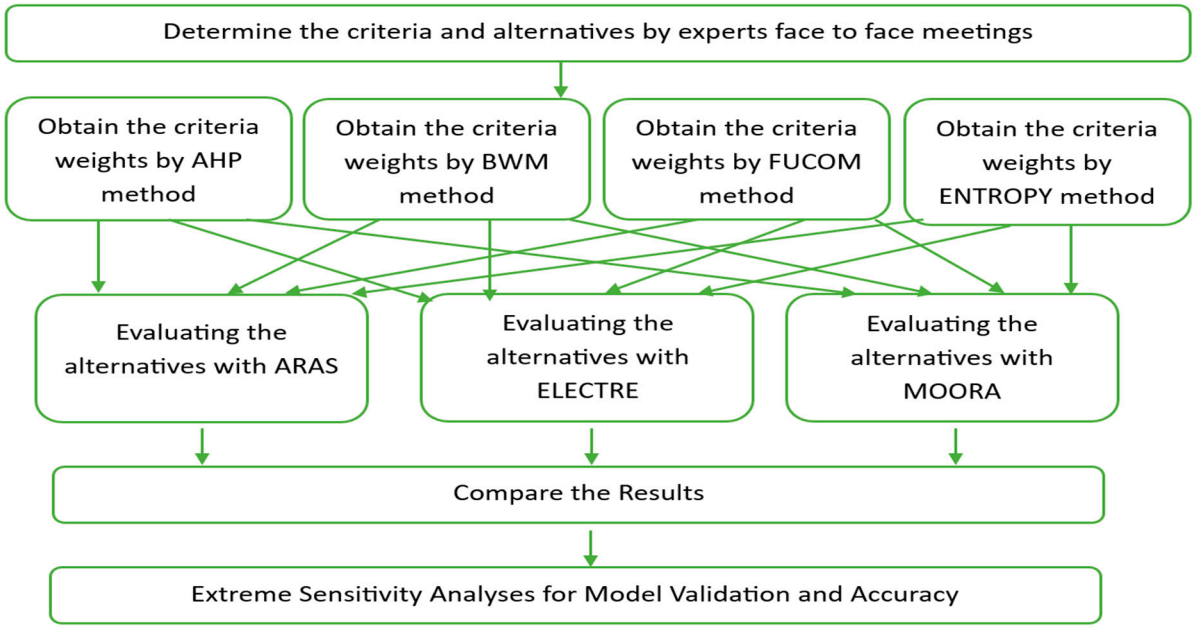


Figure 1. Research methodology.

Within the research methodology presented in Figure 1, the weights of the criteria influencing sustainable forklift selection are first determined using the AHP method. Subsequently, the rankings of the forklift alternatives are obtained using the ARAS, ELECTRE,

and MOORA methods. Finally, the effects of the criterion weights derived from the FUCOM, BWM, and Entropy weighting methods on the sustainable forklift rankings are examined.

Method Selection

In this study, a classical yet robust hybrid decision-making framework consisting of AHP–ARAS, AHP–MOORA, and AHP–ELECTRE is adopted as a deliberate methodological choice. The AHP method is selected due to its ability to derive consistent and systematic criteria weights from expert judgments in complex decision-making problems. By integrating AHP with different ranking methods, the same set of criteria weights is tested separately using ARAS, which is based on an additive and compensatory utility approach; MOORA, which relies on a benefit–cost balance logic; and ELECTRE, which is founded on a non-compensatory outranking relationship. Employing these classical methods within a hybrid and comparative structure enabled the analysis to go beyond evaluations based on a single decision philosophy, allowing the consistency and robustness of the results to be examined across different decision logics. Consequently, without resorting to data-intensive modern methods, a highly interpretable and methodologically sound evaluation process is established in accordance with the data structure of the decision problem. Moreover, the integration of multiple weighting schemes and ranking algorithms enables the evaluation of the decision problem from complementary methodological perspectives and provides additional validation for the robustness and credibility of the obtained results. Therefore, weights are derived based on different subjective and objective weighting schemes, specifically FUCOM, BWM, and Entropy, and the resulting ranking outcomes are comparatively examined to assess the impact of varying weighting structures on the robustness and consistency of the final decision results.

Explanations of the methods are given in Appendix I.

4. Implementation of Integrated Methods

In this study, various types (brands) of forklifts that international companies operating in Turkey find difficult to choose during the purchasing process are identified through meetings conducted with twenty experienced and field expert professionals (experts) responsible for internal logistics and sustainability. Subsequently, the same experts are asked about the criteria they consider when selecting these forklifts, and they are requested to evaluate these criteria.

As a result of face-to-face meetings conducted by sector experts—based on their professional experience and knowledge of the relevant literature—the evaluation criteria and alternatives are determined. These industry experts include 20 managers who are university graduates, have at least 15 years of professional experience, and are competent in the fields of sustainability and internal logistics. Their areas of expertise are sustainability and internal logistics.

The expert evaluations are obtained from twenty professionals working in industries where forklift operations are widely used. These experts hold managerial roles related to logistics, supply chain management, warehouse operations, and sustainability. Their professional experience ranges from 15 to 24 years, ensuring a high level of expertise in material handling and equipment selection. Detailed expert descriptions are provided in Appendix A (Table A1).

To obtain reliable expert evaluations, a total of 20 professionals with substantial experience in logistics, material handling, and sustainability practices are included in this study. Previous studies in the multi-criteria decision-making (MCDM) literature indicate that expert panels ranging from 10 to 20 participants are sufficient to provide consistent and reliable judgments. Therefore, the inclusion of twenty experts ensures both diversity of

professional perspectives and sufficient expertise to support the decision-making process. Only experts directly involved in logistics operations, warehouse management, equipment procurement, or sustainability practices are included in this study. Several experts participating in this study are directly involved in material handling equipment (MHE) evaluation, forklift fleet management, and equipment procurement decisions within their organizations. This ensures that the expert judgments reflect practical knowledge related to forklift selection and logistics operations.

The expert selection protocol is outlined below.

The experts are selected based on the following criteria: (i) having at least 15 years of professional experience in the fields of logistics and sustainability, (ii) holding a position related to logistics and sustainability, and (iii) being directly involved in strategic or operational decision-making processes concerning the evaluation and selection of alternatives and criteria in the relevant field.

These selection criteria are established to ensure that the evaluations are conducted in a knowledge-based, consistent, and reliable manner. The expert team consists of experienced professional managers in the fields of sustainability and logistics working in international companies operating in Turkey. The experts are selected according to their industry roles, professional experience, and areas of expertise.

4.1. Evaluation Procedure

In this study, the evaluations of alternatives and criteria are conducted by domain experts using a structured evaluation protocol. First, an environment is established, in which the experts can perform independent scoring without being influenced by one another. Prior to the evaluation process, the experts are provided with a 1–10 rating scale for scoring, along with its detailed explanation, as presented in Table 1. On this scale, 1 represents the lowest level of importance, while 10 indicates the highest attainable importance level of the corresponding criterion. The intermediate values between 1 and 10 indicate progressively increasing levels of importance, as illustrated by the 1–10 rating scale presented in Table 1. In addition, the experts are instructed on how to use this scale during the scoring process.

Table 1. 1–10 rating scale.

Numerical Value	1	2	3	4	5	6	7	8	9	10
Expression (Importance Level)	Extremely Low	Very Low	Low	Slightly Low	Moderate	Slightly High	High	Very High	Extremely High	Absolute/ Maximum

Each expert individually scored the alternatives with respect to each criterion. The individual scores provided by the experts are then aggregated by calculating the arithmetic mean for each criterion. As a result, the final decision matrix is obtained. This approach reduces the influence of individual biases and reflects a collective expert judgment.

To ensure methodological consistency throughout this study, the same panel of 20 experts participated in all stages of the evaluation process. Specifically, the experts were involved in identifying and defining the decision criteria, determining the relevant forklift alternatives, evaluating the importance of the criteria, and scoring the alternatives with respect to the established criteria. Maintaining a consistent expert panel across these stages ensured that the evaluations are conducted based on a shared understanding of the decision framework and the operational context of the problem. This approach also minimized potential inconsistencies that could arise from involving different evaluators at different

stages and enhanced the reliability and coherence of the aggregated expert judgments used to construct the decision matrix for the subsequent multi-criteria decision-making analysis.

4.2. Defining and Scoring the Criteria and Alternatives

Based on the face-to-face meetings conducted by sector experts' meetings, 10 alternative forklift alternatives and 6 evaluation criteria were identified. During the expert meetings, consensus-based decisions were reached regarding the evaluation process. Initially, the weights of these criteria were determined using the AHP method. Subsequently, the 10 alternatives were evaluated with respect to the six criteria by employing the ARAS method, the MOORA ratio approach, and the ELECTRE method. Accordingly, the values assigned to CRT1, CRT3, CRT4, and CRT5 were determined using a standardized 1–10 rating scale (as seen in Table 1), where 1 denotes the lowest and 10 the highest performance level. The explicit definition of the 1–10 rating scale and its provision to the experts for use in the evaluation process demonstrate the transparency and reproducibility of this study. In contrast, for CRT2 and CRT6, real-world quantitative data corresponding to these criteria are collected from the experts (by manufacturers' technical specifications) and directly assigned, thereby enhancing objectivity and reproducibility.

The decision matrix comprises both quantitative and qualitative criteria. Quantitative criteria are obtained directly from manufacturers' technical specifications and incorporated into the matrix using their original numerical values. Qualitative criteria are evaluated by experts using a 1–10 scale, and the individual expert assessments are aggregated by calculating their arithmetic mean to obtain a single representative value for each alternative–criterion pair. The arithmetic mean is used exclusively for evaluations considered qualitative; quantitative criteria, being single, directly measured values, are not subjected to any aggregation procedure.

For criteria such as Agility (CRT5) and Ergonomics (CRT3), technical indicators specified in Appendix D—(Table A4)—such as turning radius, aisle width, vibration level, and noise level (dB)—are obtained from manufacturers and incorporated into the evaluation process. However, these parameters alone cannot fully capture the multidimensional and experience-based nature of forklift performance under real operational conditions. Operational agility and ergonomic suitability depend not only on isolated technical specifications but also on application-specific factors such as operator comfort, maneuverability in confined spaces, field of vision, usability of the control layout, and perceived safety. These dimensions are largely contextual and cannot be adequately represented by single quantitative measures.

Accordingly, in many multi-criteria decision-making (MCDM) studies in the fields of equipment selection, logistics systems, and ergonomic assessment, expert-based scoring approaches (e.g., a 1–10 scale) are widely employed to enable a holistic evaluation that integrates both measurable and experiential components. Consistent with these established practices, the present study adopts an expert judgment-based holistic scoring method for the assessment of the aforementioned criteria. CRT1 and CRT4 criteria are evaluated using the same procedure. This approach allows decision-makers to systematically incorporate their practical experience and domain expertise into the evaluation process, thereby providing an analytical framework that more accurately reflects real operational performance rather than relying solely on fragmented technical data.

Consequently, several criteria considered in this study (e.g., ergonomics, agility, and occupational health and safety) cannot be directly quantified using standardized numerical indicators, as they do not possess standardized measurable metrics due to their multidimensional and context-dependent nature (e.g., operator comfort, maneuverability in confined spaces, field of vision, usability of control layout, perceived safety, and application-specific

experiential factors such as the presence or absence of certain equipment features). Therefore, the use of a structured expert-based scoring approach is not only appropriate but also necessary to ensure a meaningful and comparable evaluation across alternatives.

Expert-based scoring: the use of structured rating scales based on expert judgment is a widely adopted practice in multi-criteria decision-making (MCDM) studies, particularly in equipment selection and logistics system evaluations where certain performance attributes cannot be fully represented through standardized quantitative indicators. In such contexts, expert-based scoring enables the integration of experiential knowledge and operational insights into the evaluation process. Previous studies in the MCDM literature have similarly employed rating scales (e.g., 1–10 or 1–9 scales) to assess qualitative or semi-quantitative criteria under conditions of limited or heterogeneous data availability.

To reduce potential subjectivity associated with expert scoring, several precautions are implemented. First, the evaluation scale is explicitly defined and provided to the experts prior to the assessment process. Second, evaluations are conducted through structured meetings involving experienced sector professionals, allowing consensus-based discussions. Third, individual expert scores are aggregated using the arithmetic mean to obtain representative values for each alternative–criterion pair, thereby reducing individual bias and increasing the reliability of the assessment process.

The forklift alternatives in this study are denoted as FLT1, FLT2, FLT3, FLT4, FLT5, FLT6, FLT7, FLT8, FLT9, and FLT10. Additionally, the criteria and their descriptions are presented in Table 2.

Table 2. Criteria definitions.

Criteria	Criteria Definitions
Occupational Health and Safety (CRT1)	This criterion evaluates the extent to which the design, operational features, and technological configuration of forklifts contribute to long-term operator safety and workplace health by minimizing risks to the operator and the surrounding environment. The degree to which sustainable forklift systems incorporate occupational health and safety-oriented protective mechanisms and sensor-based designs, as well as their environmentally friendly and human-centered characteristics, may vary significantly during the design process. Automatic collision-avoidance sensors and emission-free or low-noise electric drive systems substantially enhance both operator comfort and environmental sustainability. Advanced safety systems also improve operational efficiency by reducing accident-related costs, equipment failures, and insurance expenses. Given that firms place high importance on employee health, safety, and the sustainability of these factors, this criterion holds considerable significance in forklift procurement decisions.
Load Lifting Capacity(kg) (CRT2)	Since forklifts are lifting and stacking vehicles, they are equipped with forks or attachments whose specifications depend on lift height, fork or attachment length, and the hydraulic system. As the lifting capacity of a forklift varies according to the weight of the load, this criterion becomes highly significant. In sustainable forklift selection, load-lifting capacity is not merely a performance indicator but also a determining factor for energy efficiency and system longevity. Selecting a forklift with a capacity that matches actual operational requirements prevents energy waste, reduces component wear, and extends the service life of the vehicle, thereby promoting resource efficiency and lowering emissions throughout its life cycle. In sustainable forklift systems, load-lifting capacity represents the balance among performance, safety, and energy optimization. Sustainable designs focus on adaptive hydraulic systems that recover energy during lifting or lowering, intelligent load sensors, and regenerative braking technologies.

Table 2. *Cont.*

Criteria	Criteria Definitions
Ergonomics (CRT3)	In sustainable forklift systems, ergonomics refers to human-centered design and represents an integrated structure in which physical comfort, cognitive ease, and environmental responsibility converge. As a concept that examines proper human–machine interaction and the correct use of the human body, ergonomics is essential for ensuring operator compatibility in forklift operations. Modern sustainable forklifts incorporate features such as intelligent seat-occupancy sensors, adaptive steering systems, noise-insulated cabins, digital displays, ergonomic cabin layouts, vibration- and noise-reduction technologies, and posture-supporting suspension seats, thereby integrating not only energy efficiency but also human health and safety into the scope of sustainability. Ergonomic efficiency indirectly reduces energy consumption and emissions by decreasing operational errors and unnecessary waiting times. Forklifts that are ergonomically optimized lower absenteeism rates, reduce workplace accidents, and enhance productivity, ultimately improving overall operational cost effectiveness. This criterion also evaluates the noise level generated during forklift movement and lifting operations. Forklifts with low noise levels enhance worker comfort while reducing stress and fatigue. Furthermore, they help prevent noise pollution in warehouses and in facilities located near residential areas.
Durability and Material Sustainability (CRT4)	This criterion examines the durability, recyclability, and environmental friendliness of the materials used in forklift manufacturing. Long-lasting, reusable, and recyclable materials reduce waste generation and raw material consumption. Durable design extends the operational lifespan of the forklift, decreases maintenance frequency, and enhances resource efficiency.
Agility (CRT5)	Agility in forklifts refers to acceleration performance, angular turning speeds, and vehicle responsiveness to the operating surface. Beyond these elements, it also encompasses the concept of intelligent motion control, which optimizes energy use, reduces accident risks, and enhances overall workflow efficiency. Sustainable forklifts are equipped with smart driving systems, adaptive steering, and regenerative braking technologies that maintain balance while delivering agility and enabling energy savings. These features prevent unnecessary idling, excessive acceleration, and abrupt braking, thereby improving both safety and environmental performance. The lift mast and fork movements must be designed to operate at proportional speeds, neither excessively rapid and sharp nor overly slow and time-consuming. Extremely fast or slow movements increase the likelihood of accidents and load-handling failures. The forklift's ability to maneuver efficiently within the stacking area—lifting, lowering, or side-shifting a load at an optimal level of agility—is essential for effective use of the equipment. As agility determines a forklift's maneuverability and contributes to time savings and operational efficiency, it constitutes a critical sustainability criterion. Modern sustainable forklifts are equipped with electric power steering, proportional hydraulic control, traction-control systems, and AI-assisted stability sensors. These technologies not only enhance maneuverability in confined spaces but also reduce energy consumption and operational risks, thereby supporting broader sustainability objectives.
Price (€) (CRT6)	This criterion assesses not only the initial purchase price of a forklift but also the energy, maintenance, repair, spare parts, battery replacement, and disposal costs incurred throughout its entire service life. Rather than emphasizing short-term expenses, it highlights long-term total economic efficiency. A low life-cycle cost is one of the fundamental indicators of sustainable investments. Although forklifts designed to be energy efficient, low-emission, or manufactured from recyclable materials may require higher upfront expenditures, they reduce operating costs over time, minimize environmental impacts, and generate economic benefits. In sustainable forklift selection, price represents a strategic investment value. Decision-makers should employ life-cycle costing approaches that take into account fuel or electricity consumption, maintenance needs, battery replacement, and end-of-life recycling potential. By doing so, organizations that embrace sustainability align their financial decisions with environmental and social objectives, targeting economic efficiency, durability, and a low total cost per operation. Specifically, the aggregated life-cycle cost includes initial purchase price, energy consumption cost, maintenance and repair costs, spare parts expenses, average battery replacement cost considering replacement frequency, end-of-life disposal, and recycling costs.

Sustainability is a multidimensional concept that encompasses environmental, economic, and social aspects. In addition to environmental considerations, social dimensions such as occupational health, safety, and ergonomics play a critical role in sustainable product design [30]. These factors are essential components of social sustainability, as they directly influence worker well-being, reduce accident risks, and enhance overall system reliability and long-term productivity.

Although criteria such as load capacity and agility are traditionally considered operational, they are directly linked to sustainability performance. Higher load capacity enables the transportation of more goods per cycle, thereby reducing the number of trips required and leading to lower energy consumption and improved resource efficiency. Similarly, agility enhances operational efficiency by minimizing idle time, unnecessary movements, and inefficient routing, which contributes to reduced energy use and improved system performance. In this respect, these criteria can be interpreted as indirectly contributing to environmental and economic sustainability through efficiency and resource optimization.

Agility is closely associated with energy recovery mechanisms, particularly through regenerative braking systems. During deceleration and load handling operations, energy that would otherwise be dissipated is partially recovered and reused, thereby improving overall energy efficiency and reducing environmental impact. High agility enables precise micromovements during load handling operations, reducing unnecessary micro-adjustments and repeated positioning attempts. This minimizes cumulative energy consumption at the operational level, which is often overlooked in traditional performance assessments. Agility also contributes to system-level sustainability by reducing congestion within warehouse environments. Improved maneuverability decreases traffic bottlenecks, shortens cycle times, and enhances overall flow efficiency, leading to lower indirect energy consumption across the entire logistics system. By enabling smoother acceleration, deceleration, and load handling, agile systems reduce mechanical stress on components such as tires, hydraulic systems, and drive units. This leads to lower maintenance requirements, extended equipment lifespan, and reduced material consumption over the product life cycle. Agility enhances human-centered sustainability by reducing operator fatigue and cognitive load. Improved responsiveness and intelligent control systems enable safer and more intuitive operation, which contributes to long-term workforce well-being and productivity. Higher load capacity reduces the number of trips required to transport goods, thereby decreasing total travel distance and associated energy consumption. This directly contributes to improved environmental performance. Increased load capacity can also contribute to better space utilization within warehouses, reducing the need for additional handling equipment and infrastructure. This supports resource efficiency and reduces the environmental impact of logistics operations. From an efficiency perspective, higher capacity improves the energy consumption per unit transported, allowing more goods to be handled with the same or lower energy input. This aligns with the principles of sustainable logistics and resource optimization. Higher load capacity also contributes to time efficiency and reduced labor intensity, supporting economic sustainability by lowering operational costs and improving overall productivity. Overall, both agility and load capacity extend beyond traditional operational performance metrics and play a critical role in sustainability. While agility enhances energy efficiency, system flow, and equipment longevity, load capacity improves transport efficiency and reduces resource consumption. Together, these criteria contribute to environmental, economic, and social sustainability dimensions, reinforcing their relevance within sustainable material handling systems.

4.3. Reproducibility of the Evaluation Process

The standardized scale definitions and documented evaluation protocol ensure that:

- The assessment process can be replicated by other researchers using the same criteria and expert profiles;
- The meaning and origin of the assigned 1–10 values are explicit and transparent;
- Subjectivity inherent in expert judgment is systematically controlled.

In the proposed MCDM framework, the evaluation criteria and alternatives are identified through face-to-face expert meetings involving all participating decision-makers, ensuring a common understanding of the problem scope and evaluation context. Subsequently, the scoring processes are conducted independently by each expert to avoid mutual influence and group bias. This two-stage approach enhances the objectivity and reliability of the expert judgments while preserving content validity in the decision model.

To enhance the replicability and transparency of this study, the technical specifications of all alternatives used as reference information in the expert evaluations are presented in Appendix C (Table A3). Appendix D (Table A4) provides the quantitative values among these specifications that are shared by manufacturers as measurable data. Therefore, the scoring process reflects a deliberate expert assessment based on objective technical data rather than solely on subjective judgments. Experts evaluated each alternative holistically and assigned scores ranging from 1 to 10 for the CRT1, CRT3, CRT4, and CRT5 criteria. The final values used in the decision matrix represent the arithmetic mean of the expert evaluations.

In this study, the decision matrix consists of quantitative criteria expressed in different units and scales (e.g., expert-based scores and real-life numerical values). Therefore, prior to applying ARAS, MOORA, and ELECTRE methods, a preprocessing procedure was conducted to ensure comparability among criteria.

First, all criteria are classified as benefit-type (the higher, the better) or cost-type (the lower, the better). Subsequently, cost-type criteria are transformed into benefit-type criteria using reciprocal transformation where necessary.

In the next step, normalization procedures specific to each method are applied. For the ARAS method, sum-based normalization is performed using Equations (A9) and (A10). For the MOORA method, vector normalization (square root normalization) is applied as given in Equation (A17). For the ELECTRE method, different normalization procedures are employed for cost and benefit criteria according to Equations (A20) and (A21).

These preprocessing steps ensured that all criteria are converted into dimensionless and comparable values prior to the application of the ranking algorithms. The detailed step-by-step procedures and numerical calculations are presented in Sections 4.5–4.7 and Appendix I.

4.4. AHP

Step-1: the pairwise comparison matrix is constructed using pairwise comparisons scale (as shown in Table A10), based on expert opinions (as shown in Table 3).

Table 3. Pairwise comparison matrix.

	CRT1	CRT2	CRT3	CRT4	CRT5	CRT6
CRT1	1	4	7	3	9	5
CRT2	0.25	1	4	0.333333333	6	2
CRT3	0.142857143	0.25	1	0.166666667	1	0.5
CRT4	0.333333333	3	6	1	6	3
CRT5	0.111111111	0.166666667	1	0.166666667	1	1
CRT6	0.2	0.5	2	0.333333333	1	1
SUM.	2.037301587	8.916666667	21	5	24	12.5

Step-2: the normalized decision matrix is given in Table 4.

Table 4. Normalization matrix.

	CRT1	CRT2	CRT3	CRT4	CRT5	CRT6
CRT1	0.49085	0.44860	0.33333	0.60000	0.37500	0.40000
CRT2	0.12271	0.11215	0.19048	0.06667	0.25000	0.16000
CRT3	0.07012	0.02804	0.04762	0.03333	0.04167	0.04000
CRT4	0.16362	0.33645	0.28571	0.20000	0.25000	0.24000
CRT5	0.05454	0.01869	0.04762	0.03333	0.04167	0.08000
CRT6	0.09817	0.05607	0.09524	0.06667	0.04167	0.08000

Step-3: Table 5 shows the eigenvector. The eigenvector indicates the weights of the criteria. The most important criterion is identified as CRT1, which has the highest criterion weight.

Table 5. Eigenvector (weights of criteria).

Criteria	Eigenvector
CRT1	0.441296135
CRT2	0.150333954
CRT3	0.043462866
CRT4	0.245963
CRT5	0.045974835
CRT6	0.072969211

Step-4: Then, the λ values are calculated by dividing the column vector formed by the eigenvalues by the priority vector. The arithmetic mean of the λ values for each row gives the λ_{max} value. The calculation of λ_{max} is defined by Equation (A6).

CR, CI, and λ_{max} values (as shown in Table 6) are calculated using Equation (A4), Equation (A5), and Equation (A6), respectively. RI is provided using Table A11. A CR value less than 0.1 indicates consistency.

Table 6. Calculated values for consistency.

λ	λ_{max}	CI	RI	CR
6.488569355	6.268201565	0.053640313	1.24	0.043258317
6.24133484				
6.155644091				
6.503406651				
6.035678197				
6.184576255				

4.5. ARAS Method

Step-1: The decision matrix is created by experts' opinions and real-life values (as shown in Table 7). For CRT1, CRT3, CRT4, and CRT5, the criteria values range from 1 to 10, whereas for CRT2 and CRT6, they are the real-life numerical scores provided by experts. The individual expert evaluations (for CRT1, CRT3, CRT4 and CRT5) are provided in Appendix B (Table A2). The final decision matrix is constructed by calculating the arithmetic means of these individual assessments, which is a commonly adopted aggregation approach in expert-based MCDM studies.

Table 7. Decision matrix.

Weights (W)	0.441 CRT1	0.150 CRT2	0.043 CRT3	0.246 CRT4	0.046 CRT5	0.073 CRT6
FLT1	7	3000	6	3	5	31,000
FLT2	8	3000	9	5	9	32,000
FLT3	9	3500	7	10	10	37,000
FLT4	9	3500	9	9	9	36,000
FLT5	6	3500	6	3	4	22,250
FLT6	9	3000	9	8	9	30,500
FLT7	7	3500	6	8	7	26,500
FLT8	7	3500	8	7	7	33,000
FLT9	8	3500	8	7	7	29,750
FLT10	8	3500	8	9	9	31,250

Step-2: in determining the optimal values (Table 8), the maximum values are selected for benefit-oriented criteria, while the minimum values are used for non-benefit-oriented criteria.

Table 8. Decision matrix identifying the optimum values.

Weights	0.441 CRT1	0.150 CRT2	0.043 CRT3	0.246 CRT4	0.046 CRT5	0.073 CRT6
Optimum	9	3500	9	10	10	22,250
FLT1	7	3000	6	3	5	31,000
FLT2	8	3000	9	5	9	32,000
FLT3	9	3500	7	10	10	37,000
FLT4	9	3500	9	9	9	36,000
FLT5	6	3500	6	3	4	22,250
FLT6	9	3000	9	8	9	30,500
FLT7	7	3500	6	8	7	26,500
FLT8	7	3500	8	7	7	33,000
FLT9	8	3500	8	7	7	29,750
FLT10	8	3500	8	9	9	31,250

Step-3: At this stage, the non-benefit-oriented criterion, price (CRT6), is transformed into a benefit-oriented form by taking its reciprocal. Then, for the normalization matrix (as shown in Table 9), Equation (A9) is applied to the criteria for which lower values are preferred, whereas Equation (A10) is used for those for which higher values are desired.

Table 9. Normalized decision matrix.

Weights	0.441 CRT1	0.150 CRT2	0.043 CRT3	0.246 CRT4	0.046 CRT5	0.073 CRT6
Optimum	0.10345	0.09459	0.10588	0.12658	0.11628	0.11997
FLT1	0.08046	0.08108	0.07059	0.03797	0.05814	0.08610
FLT2	0.09195	0.08108	0.10588	0.06329	0.10465	0.08341
FLT3	0.10345	0.09459	0.08235	0.12658	0.11628	0.07214
FLT4	0.10345	0.09459	0.10588	0.11392	0.10465	0.07415
FLT5	0.06897	0.09459	0.07059	0.03797	0.04651	0.11997
FLT6	0.10345	0.08108	0.10588	0.10127	0.10465	0.08752
FLT7	0.08046	0.09459	0.07059	0.10127	0.08140	0.10073
FLT8	0.08046	0.09459	0.09412	0.08861	0.08140	0.08089
FLT9	0.09195	0.09459	0.09412	0.08861	0.08140	0.08972
FLT10	0.09195	0.09459	0.09412	0.11392	0.10465	0.08542

Step-4: The weighted normalized decision matrix obtained using Equation (A11) is presented in Table 10.

Table 10. Weighted normalized decision matrix.

Weights	**0.441 CRT1**	**0.150 CRT2**	**0.043 CRT3**	**0.246 CRT4**	**0.046 CRT5**	**0.073 CRT6**
Optimum	0.04565	0.01422	0.00460	0.03113	0.00535	0.00875
FLT1	0.03551	0.01219	0.00307	0.00934	0.00267	0.00628
FLT2	0.04058	0.01219	0.00460	0.01557	0.00481	0.00609
FLT3	0.04565	0.01422	0.00358	0.03113	0.00535	0.00526
FLT4	0.04565	0.01422	0.00460	0.02802	0.00481	0.00541
FLT5	0.03043	0.01422	0.00307	0.00934	0.00214	0.00875
FLT6	0.04565	0.01219	0.00460	0.02491	0.00481	0.00639
FLT7	0.03551	0.01422	0.00307	0.02491	0.00374	0.00735
FLT8	0.03551	0.01422	0.00409	0.02179	0.00374	0.00590
FLT9	0.04058	0.01422	0.00409	0.02179	0.00374	0.00655
FLT10	0.04058	0.01422	0.00409	0.02802	0.00481	0.00623

Step-5: The degree of optimality (S_i) for the decision alternatives and the optimal function value of the best decision alternative (S_0) are determined by Equation (A14), as shown in Table 11. Using Equation (A15), the benefit degrees (K_i) of each decision alternative are obtained. The ranking of these benefit degrees in descending order provides the ranking of the alternatives, as presented in the last column (R) in Table 11. According to the ARAS method, the best alternative is determined as FLT-3.

Table 11. Ranking of alternatives.

	CRT1	**CRT2**	**CRT3**	**CRT4**	**CRT5**	**CRT6**	**S_i**	**K_i (S_i/S_0)**	**R**
Opti	0.04565	0.01422	0.00460	0.03113	0.00535	0.00875	0.10971	1.00000	
FLT1	0.03551	0.01219	0.00307	0.00934	0.00267	0.00628	0.06906	0.62949	9
FLT2	0.04058	0.01219	0.00460	0.01557	0.00481	0.00609	0.08384	0.76417	8
FLT3	0.04565	0.01422	0.00358	0.03113	0.00535	0.00526	0.10520	0.95887	1
FLT4	0.04565	0.01422	0.00460	0.02802	0.00481	0.00541	0.10272	0.93627	2
FLT5	0.03043	0.01422	0.00307	0.00934	0.00214	0.00875	0.06796	0.61942	10
FLT6	0.04565	0.01219	0.00460	0.02491	0.00481	0.00639	0.09855	0.89827	3
FLT7	0.03551	0.01422	0.00307	0.02491	0.00374	0.00735	0.08879	0.80937	6
FLT8	0.03551	0.01422	0.00409	0.02179	0.00374	0.00590	0.08526	0.77712	7
FLT9	0.04058	0.01422	0.00409	0.02179	0.00374	0.00655	0.09097	0.82923	5
FLT10	0.04058	0.01422	0.00409	0.02802	0.00481	0.00623	0.09796	0.89287	4

4.6. MOORA Ratio Approach

Step-1: The decision matrix is shown in Table 12. For CRT1, CRT3, CRT4, and CRT5, the criteria values range from 1 to 10, whereas for CRT2 and CRT6, they are the real-life numerical scores provided by experts.

Table 12. Decision matrix.

Weights	**0.441 CRT1**	**0.150 CRT2**	**0.043 CRT3**	**0.246 CRT4**	**0.046 CRT5**	**0.073 CRT6**
FLT1	7	3000	6	3	5	31,000
FLT2	8	3000	9	5	9	32,000
FLT3	9	3500	7	10	10	37,000
FLT4	9	3500	9	9	9	36,000

Table 12. *Cont.*

Weights	0.441 CRT1	0.150 CRT2	0.043 CRT3	0.246 CRT4	0.046 CRT5	0.073 CRT6
FLT5	6	3500	6	3	4	22,250
FLT6	9	3000	9	8	9	30,500
FLT7	7	3500	6	8	7	26,500
FLT8	7	3500	8	7	7	33,000
FLT9	8	3500	8	7	7	29,750
FLT10	8	3500	8	9	9	31,250

Step-2: the normalized decision matrix is shown in Table 13.

Table 13. Normalized decision matrix.

Weights	0.441 CRT1	0.150 CRT2	0.043 CRT3	0.246 CRT4	0.046 CRT5	0.073 CRT6
FLT1	0.281581	0.282528966	0.246598	0.130189	0.20211302	0.314300974
FLT2	0.321807	0.282528966	0.369898	0.216982	0.36380344	0.324439716
FLT3	0.362033	0.329617127	0.287698	0.433963	0.40422604	0.375133421
FLT4	0.362033	0.329617127	0.369898	0.390567	0.36380344	0.36499468
FLT5	0.241355	0.329617127	0.246598	0.130189	0.16169042	0.22558699
FLT6	0.362033	0.282528966	0.369898	0.34717	0.36380344	0.309231604
FLT7	0.281581	0.329617127	0.246598	0.34717	0.28295823	0.268676639
FLT8	0.281581	0.329617127	0.328798	0.303774	0.28295823	0.334578457
FLT9	0.321807	0.329617127	0.328798	0.303774	0.28295823	0.301627548
FLT10	0.321807	0.329617127	0.328798	0.390567	0.36380344	0.31683566

Step-3: The weighted normalized matrix is shown in Table 14. Based on the weighted decision matrix data, the maximum and minimum values are determined for each row, and their differences are calculated. These differences (ΣMax − ΣMin) represent the ranking values. The ranking of the forklift alternatives is shown in the last column (R) of Table 14. The values of y_i^*, where i = 1, 2, …, n are sorted in descending order, and the optimal value is found as the one ranked first. According to the MOORA ratio approach, the best alternative is determined to be the "FLT3" alternative.

Table 14. Weighted normalized matrix.

W	0.441 CRT1	0.150 CRT2	0.043 CRT3	0.246 CRT4	0.046 CRT5	0.073 CRT6	ΣMax − ΣMin	R
FLT1	0.124261	0.042474	0.010718	0.032022	0.009292	0.022934	0.195832	**9**
FLT2	0.142012	0.042474	0.016077	0.053369	0.016726	0.023674	0.246984	**8**
FLT3	0.159764	0.049553	0.012504	0.106739	0.018584	0.027373	0.319771	**1**
FLT4	0.159764	0.049553	0.016077	0.096065	0.016726	0.026633	0.311551	**2**
FLT5	0.106509	0.049553	0.010718	0.032022	0.007434	0.016461	0.189774	**10**
FLT6	0.159764	0.042474	0.016077	0.085391	0.016726	0.022564	0.297867	**3**
FLT7	0.124261	0.049553	0.010718	0.085391	0.013009	0.019605	0.263326	**6**
FLT8	0.124261	0.049553	0.014291	0.074717	0.013009	0.024414	0.251416	**7**
FLT9	0.142012	0.049553	0.014291	0.074717	0.013009	0.022010	0.271572	**5**
FLT10	0.142012	0.049553	0.014291	0.096065	0.016726	0.023119	0.295527	**4**

4.7. ELECTRE Method

Step-1: As shown in Table 15, the decision matrix is constructed based on the criteria and alternatives. For CRT1, CRT3, CRT4, and CRT5 the criteria values range from 1 to 10, whereas for CRT2 and CRT6 they are the real-life numerical scores provided by experts.

Table 15. Decision matrix.

Weights	0.441 CRT1	0.150 CRT2	0.043 CRT3	0.246 CRT4	0.046 CRT5	0.073 CRT6
FLT1	7	3000	6	3	5	31,000
FLT2	8	3000	9	5	9	32,000
FLT3	9	3500	7	10	10	37,000
FLT4	9	3500	9	9	9	36,000
FLT5	6	3500	6	3	4	22,250
FLT6	9	3000	9	8	9	30,500
FLT7	7	3500	6	8	7	26,500
FLT8	7	3500	8	7	7	33,000
FLT9	8	3500	8	7	7	29,750
FLT10	8	3500	8	9	9	31,250

Step-2: The normalized decision matrix is obtained as shown in Table 16. Before obtaining the normalized decision matrix, the values for the cost-oriented criteria in the decision matrix are inverted to convert them into benefit-oriented criteria. Specifically, for this matrix, the reciprocal of the values in the column corresponding to the price criterion is first taken and then normalized.

Table 16. Normalized decision matrix.

Weights	0.441 CRT1	0.150 CRT2	0.043 CRT3	0.246 CRT4	0.046 CRT5	0.073 CRT6
FLT1	0.28158	0.28253	0.24660	0.13019	0.20211	0.30604
FLT2	0.32181	0.28253	0.36990	0.21698	0.36380	0.29647
FLT3	0.36203	0.32962	0.28770	0.43396	0.40423	0.25641
FLT4	0.36203	0.32962	0.36990	0.39057	0.36380	0.26353
FLT5	0.24136	0.32962	0.24660	0.13019	0.16169	0.42639
FLT6	0.36203	0.28253	0.36990	0.34717	0.36380	0.31106
FLT7	0.28158	0.32962	0.24660	0.34717	0.28296	0.35801
FLT8	0.28158	0.32962	0.32880	0.30377	0.28296	0.28749
FLT9	0.32181	0.32962	0.32880	0.30377	0.28296	0.31890
FLT10	0.32181	0.32962	0.32880	0.39057	0.36380	0.30359

Step-3: The weighted normalized decision matrix is obtained using Equation (A23), as presented in Table 17.

Table 17. Weighted normalized decision matrix.

Weights	0.441 CRT1	0.150 CRT2	0.043 CRT3	0.246 CRT4	0.046 CRT5	0.073 CRT6
FLT1	0.12426	0.04247	0.01072	0.03202	0.00929	0.02233
FLT2	0.14201	0.04247	0.01608	0.05337	0.01673	0.02163
FLT3	0.15976	0.04955	0.01250	0.10674	0.01858	0.01871
FLT4	0.15976	0.04955	0.01608	0.09606	0.01673	0.01923
FLT5	0.10651	0.04955	0.01072	0.03202	0.00743	0.03111
FLT6	0.15976	0.04247	0.01608	0.08539	0.01673	0.02270
FLT7	0.12426	0.04955	0.01072	0.08539	0.01301	0.02612
FLT8	0.12426	0.04955	0.01429	0.07472	0.01301	0.02098
FLT9	0.14201	0.04955	0.01429	0.07472	0.01301	0.02327
FLT10	0.14201	0.04955	0.01429	0.09606	0.01673	0.02215

Step-4 and Step-5: based on the compatibility sets determined according to Equation (A25), the compatibility matrix is constructed using the formula in Equation (A27), as shown in Table 18.

Table 18. Compatibility matrix.

	FLT1	FLT2	FLT3	FLT4	FLT5	FLT6	FLT7	FLT8	FLT9	FLT10
FLT1	-	0.223	0.073	0.073	0.777	0.150	0.485	0.514	0.000	0.073
FLT2	0.777	-	0.116	0.162	0.777	0.240	0.531	0.604	0.536	0.536
FLT3	0.9270	0.884	-	0.884	0.927	0.892	0.9357	0.892	0.892	0.892
FLT4	0.9270	0.838	0.116	-	0.9357	0.9357	0.9357	0.9357	0.9357	0.9357
FLT5	0.223	0.223	0.073	0.0643	-	0.223	0.267	0.2161	0.2161	0.2161
FLT6	0.850	0.760	0.108	0.0643	0.777	-	0.777	0.850	0.784	0.784
FLT7	0.515	0.469	0.064	0.0643	0.733	0.223	-	0.957	0.515	0.223
FLT8	0.486	0.396	0.108	0.0643	0.783	0.150	0.043	-	0.486	0.194
FLT9	1.000	0.464	0.108	0.0643	0.783	0.216	0.485	0.514	-	0.708
FLT10	0.9270	0.464	0.108	0.0643	0.783	0.216	0.777	0.806	0.292	-

Based on the incompatibility sets determined according to Equation (A26), the incompatibility matrix is constructed using the formula in Equation (A28), as shown in Table 19.

Table 19. Incompatibility matrix.

	FLT1	FLT2	FLT3	FLT4	FLT5	FLT6	FLT7	FLT8	FLT9	FLT10
FLT1	-	1	1	1	0.4947	1	1	1	1	1
FLT2	0.0328	-	1	1	0.267	1	1	1	1	1
FLT3	0.0484	0.067	-	0.335	0.166	0.1869	0.2087	0.0639	0.1424	0.1938
FLT4	0.0484	0.049	1	-	0.162	0.2835	0.1697	0.0430	0.1651	0.1439
FLT5	1	1	1	1	-	1	1	1	1	1
FLT6	0	0	1	1	0.138	-	0.1997	0.1997	0.3993	0.6022
FLT7	0	0.554	1	1	0.0816	1	-	0.3340	1	1
FLT8	0.0316	0.8314	1	1	0.2072	1	1	-	1	1
FLT9	0	0.1742	1	1	0.1603	1	0.6022	0	-	1
FLT10	0.0028	0.042	1	1	0.122	1	0.1955	0	0.0525	-

Step-6: The compatibility and incompatibility sets are determined based on the formulas in Equations (A25) and (A26), and the compatibility and incompatibility superiority matrices are presented in Table 20.

Table 20. Compatibility superiority and incompatibility superiority matrix.

X1,2	2,6	0.223	0	Y1,2	1,3,4,5	1	0
X1,3	6	0.073	0	Y1,3	1,2,3,4,5	1	0
X1,4	6	0.073	0	Y1,4	1,2,3,4,5	1	0
X1,5	1,3,4,5	0.777	1	Y1,5	2,6	0.495	1
X1,6	2	0.150	0	Y1,6	1,3,4,5,6	1	0
X1,7	1,3	0.485	0	Y1,7	2,4,5,6	1	0
X1,8	1,6	0.514	1	Y1,8	2,3,4,5	1	0
X1,9	-	0	0	Y1,9	1,2,3,4,5,6	1	0
X1,10	6	0.073	0	Y1,10	1,2,3,4,5	1	0
X2,1	1,3,4,5	0.777	1	Y2,1	2,6	0.0328	1

Table 20. *Cont.*

X2,3	3,6	0.116	0	Y2,3	1,2,4,5	1	0
X2,4	3,5,6	0.162	0	Y2,4	1,2,4	1	0
X2,5	1,3,4,5	0.777	1	Y2,5	2,6	0.267	1
X2,6	2,3,5	0.240	0	Y2,6	1,4,6	1	0
X2,7	1,3,5	0.531	1	Y2,7	2,4,6	1	0
X2,8	1,3,5,6	0.604	1	Y2,8	2,4	1	0
X2,9	1,3,5	0.536	1	Y2,9	2,4,6	1	0
X2,10	1,3,5	0.536	1	Y2,10	2,4,6	1	0
X3,1	1,2,3,4,5	0.927	1	Y3,1	6	0.0484	1
X3,2	1,2,4,5	0.884	1	Y3,2	3,6	0.067	1
X3,4	1,2,4,5	0.884	1	Y3,4	3,6	0.335	1
X3,5	1,2,3,4,5	0.927	1	Y3,5	6	0.166	1
X3,6	1,2,4,5	0.892	1	Y3,6	3,6	0.187	1
X3,7	1,2,3,4,5	0.936	1	Y3,7	6	0.209	1
X3,8	1,2,4,5	0.892	1	Y3,8	3,6	0.064	1
X3,9	1,2,4,5	0.892	1	Y3,9	3,6	0.142	1
X3,10	1,2,4,5	0.892	1	Y3,10	3,6	0.194	1
X4,1	1,2,3,4,5	0.927	1	Y4,1	6	0.0484	1
X4,2	1,2,4	0.838	1	Y4,2	3,5,6	0.0491	1
X4,3	3,6	0.116	0	Y4,3	1,2,4,5	0.162	1
X4,5	1,2,3,4,5	0.936	1	Y4,5	6	0.2835	1
X4,6	1,2,3,4,5	0.936	1	Y4,6	6	0.1697	1
X4,7	1,2,3,4,5	0.936	1	Y4,7	6	0.043	1
X4,8	1,2,3,4,5	0.936	1	Y4,8	6	0.165	1
X4,9	1,2,3,4,5	0.936	1	Y4,9	6	0.144	1
X4,10	1,2,3,4,5	0.936	1	Y4,10	6	1	0
X5,1	2,6	0.223	0	Y5,1	1,3,4,5	1	0
X5,2	2,6	0.223	0	Y5,2	1,3,4,5	1	0
X5,3	6	0.073	0	Y5,3	1,2,3,4,5	1	0
X5,4	6	0.064	0	Y5,4	1,2,3,4,5	1	0
X5,6	2,6	0.223	0	Y5,6	1,3,4,5	1	0
X5,7	2,3,6	0.267	0	Y5,7	1,4,5	1	0
X5,8	2,6	0.216	0	Y5,8	1,3,4,5	1	0
X5,9	2,6	0.216	0	Y5,9	1,3,4,5	1	0
X5,10	2,6	0.216	0	Y5,10	1,3,4,5	1	0
X6,1	1,3,4,5,6	0.850	1	Y6,1	2	0	1
X6,2	1,4,6	0.760	1	Y6,2	2,3,5	0	1
X6,3	3,6	0.108	0	Y6,3	1,2,4,5	1	0
X6,4	6	0.064	0	Y6,4	1,2,4,5	1	0
X6,5	1,3,4,5	0.777	1	Y6,5	2,6	0.138	1

Table 20. *Cont.*

X6,7	1,3,4,5	0.777	1	Y6,7	2,6	0.199	1
X6,8	1,3,4,5,6	0.850	1	Y6,8	2	0.199	1
X6,9	1,3,4,5	0.784	1	Y6,9	2,6	0.399	1
X6,10	1,3,5,6	0.784	1	Y6,10	2,4	0.602	0
X7,1	2,4,5,6	0.515	1	Y7,1	1,3	0	1
X7,2	2,4,6	0.469	0	Y7,2	1,3,5	0.554	1
X7,3	6	0.064	0	Y7,3	1,2,3,4,5	1	0
X7,4	6	0.064	0	Y7,4	1,2,3,4,5	1	0
X7,5	1,4,5	0.733	1	Y7,5	2,3,6	0.082	1
X7,6	2,6	0.223	0	Y7,6	1,3,4,5	1	0
X7,8	1,2,4,5,6	0.957	1	Y7,8	3	0.334	1
X7,9	2,4,5,6	0.515	1	Y7,9	1,3	1	0
X7,10	2,6	0.223	0	Y7,10	1,3,4,5	1	0
X8,1	2,3,4,5	0.486	0	Y8,1	1,6	0.028	1
X8,2	2,4	0.396	0	Y8,2	1,3,5,6	0.83	0
X8,3	3,6	0.108	0	Y8,3	1,2,4,5	1	0
X8,4	6	0.064	0	Y8,4	1,2,3,4,5	1	0
X8,5	1,3,4,5	0.783	1	Y8,5	2,6	0.207	1
X8,6	2	0.150	0	Y8,6	1,3,4,5,6	1	0
X8,7	3	0.043	0	Y8,7	1,2,4,5,6	1	0
X8,9	2,3,4,5	0.486	0	Y8,9	1,6	1	0
X8,10	2,3	0.194	0	Y8,10	1,4,5,6	1	0
X9,1	1,2,3,4,5,6	1	1	Y9,1	-	0	1
X9,2	2,4,6	0.464	0	Y9,2	1,3,5	0.174	1
X9,3	3,6	0.108	0	Y9,3	1,2,4,5	1	0
X9,4	6	0.0643	0	Y9,4	1,2,3,4,5	1	0
X9,5	1,3,4,5	0.784	1	Y9,5	2,6	0.16	1
X9,6	2,6	0.216	0	Y9,6	1,3,4,5	1	0
X9,7	1,3	0.485	0	Y9,7	2,4,5,6	0.602	0
X9,8	1,6	0.514	1	Y9,8	2,3,4,5	0	1
X9,10	1,2,3,6	0.708	1	Y9,10	4,5	1	0
X10,1	1,2,3,4,5	0.927	1	Y10,1	6	0.0028	1
X10,2	2,4,6	0.464	0	Y10,2	1,3,5	0.042	1
X10,3	3,6	0.108	0	Y10,3	1,2,4,5	1	0
X10,4	6	0.064	0	Y10,4	1,2,3,4,5	1	0
X10,5	1,3,4,5	0.784	1	Y10,5	2,6	0.122	1
X10,6	2,4	0.216	0	Y10,6	1,3,5,6	1	0
X10,7	1,3,5	0.777	1	Y10,7	2,6	0.196	1
X10,8	1,4,5,6	0.806	1	Y10,8	2,3	0	1
X10,9	4,5	0.292	0	Y10,9	1,2,3,6	0.053	1

According to Equation (A29), $X_{threshold}$ = 0.5, and according to Equation (A31), $Y_{threshold}$ = 0.591 are calculated. Subsequently, using Equations (A30) and (A32), the values of 1 and 0 in the compatibility superiority and incompatibility superiority matrices are generated and are presented in Table 20.

Step-7: Using Equations (A33) and (A34), compatibility and incompatibility values are generated, and the net ranking of the alternatives is obtained as shown in Table 21. According to the ELECTRE method, the best alternative is FLT-3.

Table 21. Ranking of alternatives according to X_p and Y_p.

	X_p	Y_p	Ranking (R)
FLT1	−4.314	7.2558	9
FLT2	−0.438	3.5424	7
FLT3	7.3187	−6.87383	1
FLT4	6.0078	−6.27577	2
FLT5	−5.631	8.2305	10
FLT6	2.524	−3.7997	3
FLT7	−1.5154	0.749	6
FLT8	−3.5407	3.3112	8
FLT9	−0.3217	−0.776	5
FLT10	−0.3847	−4.3636	4

5. Sensitivity Analysis

The purpose of the sensitivity analysis conducted in this study is to observe how the results change when the weights of the criteria are varied. It is performed to assess the consistency, reliability, and robustness of the methodological results and to validate the proposed model. Accordingly, confidence is placed in the stability of the methods' outcomes. In five different scenarios (Case1, Case2, Case3, Case4, and Case5), the criterion weights are altered by 10%, 20%, 30%, 60%, and 90%, respectively. In Table 22, the changes in the ranking of alternatives are observed by modifying the criterion weights used in the ARAS method.

Table 22. Sensitivity analysis of the ARAS method.

Case Number	Changes of Weights	Sequence of Alternatives
0	-	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT8>FLT2>FLT1>FLT5
1	%10	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT8>FLT2>FLT1>FLT5
2	%20	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT8>FLT2>FLT1>FLT5
3	%30	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT8>FLT2>FLT1>FLT5
4	%60	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT8>FLT2>FLT1>FLT5
5	%90	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT8>FLT2>FLT1>FLT5

In Table 23, the changes in the ranking of alternatives are observed by modifying the criterion weights used in the ELECTRE method.

In Table 24, the changes in the ranking of alternatives are observed by modifying the criterion weights used in the MOORA method.

Table 23. Sensitivity analysis of the ELECTRE method.

Case Number	Changes of Weights	Sequence of Alternatives
0	-	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT2>FLT8>FLT1>FLT5
1	%10	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT2>FLT8>FLT1>FLT5
2	%20	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT8>FLT2>FLT1>FLT5
3	%30	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT8>FLT2>FLT1>FLT5
4	%60	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT8>FLT2>FLT1>FLT5
5	%90	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT8>FLT2>FLT1>FLT5

Table 24. Sensitivity analysis of the MOORA (ratio approach) method.

Case Number	Changes of Weights	Sequence of Alternatives
0	-	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT8>FLT2>FLT1>FLT5
1	%10	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT8>FLT2>FLT1>FLT5
2	%20	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT8>FLT2>FLT1>FLT5
3	%30	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT8>FLT2>FLT1>FLT5
4	%60	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT8>FLT2>FLT1>FLT5
5	%90	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT8>FLT2>FLT1>FLT5

As shown in Tables 22 and 24, the rankings of the forklifts remained unchanged, despite variations in the weights of the criteria. Only a very minor change is observed in Table 23. This change is also consistent with the results obtained from other methods. The top-ranked alternatives maintained their positions. This indicates that the methods yield consistent, reliable, and effective results. Moreover, it validates the robustness of the model and accuracy of the forklift evaluations. As a result, the sensitivity analysis confirms the robustness, reliability, and consistency of the proposed model and its results. In this context, this study also serves as a guided reference for companies in the selection of sustainable forklifts.

5.1. Extreme Sensitivity Analysis

The initial sensitivity analysis indicates that the ranking of alternatives remained largely stable under moderate weight variations. While this stability suggests the structural robustness of the model, it also raises a legitimate concern regarding its responsiveness to substantial shifts in strategic priorities. In response to this concern, additional extreme sensitivity scenarios are constructed by assigning 80% weight to each criterion individually, while distributing the remaining 20% equally among the other criteria (see Table 25). The results reveal that ranking changes occur under specific dominance conditions.

When the Occupational Health and Safety (OHS) criterion is assigned an 80% weight, a top-rank reversal occurs. The baseline leading alternative (A3) is replaced by A4, indicating that A4 demonstrates superior safety-related performance. This finding confirms that the proposed decision model is sensitive to extreme safety prioritization and that the optimal solution is contingent upon strategic emphasis. Extreme sensitivity scenarios reveal that the ranking changes when specific criteria become strategically dominant. In particular, assigning 80% weight to "Occupational Health and Safety" or "Load Capacity" results in a top-rank reversal. This indicates that the baseline leading alternative does not uniformly dominate across all performance dimensions. Therefore, the optimal decision is contingent upon strategic priority: safety-oriented contexts favor one alternative, whereas productivity-oriented contexts promote another. Assigning 80% weight to the "Ergonomics"

criterion results in a top-rank reversal, indicating that the baseline leader does not dominate in human-centered performance dimensions. This finding demonstrates that the optimal alternative is contingent upon strategic emphasis on operator comfort and usability. Consequently, ergonomics-oriented decision contexts yield a different optimal solution compared to balanced weighting scenarios. Under durability and material sustainability dominance, the top-ranked alternative remains unchanged, indicating that the baseline leader also performs strongly in structural robustness. Nevertheless, internal rank shifts occur among mid-level alternatives, demonstrating selective sensitivity. This behavior suggests that the model balances robustness at the top level with discrimination within the ranking structure. When "Price" is assigned an 80% weight, a substantial top-rank reversal is observed. The leading alternative under the baseline condition dropped significantly in position, and a different alternative became optimal. This finding indicates that the initial leader does not possess cost superiority, and that price-driven decision contexts fundamentally alter the ranking structure. Among all scenarios, price dominance produced the most pronounced structural shift. The ranking changes under safety, capacity, and ergonomics dominance, whereas it remains stable under durability and material sustainability and agility dominance. This pattern demonstrates that the decision outcome is contingent upon strategic emphasis, thereby confirming the discriminative and context-sensitive nature of the proposed model.

Table 25. Extreme sensitivity analysis.

Case Number	Changes of Weights	Sequence of Alternatives (AHP-ARAS&AHP-MOORA)
0	-	FLT3>FLT4>FLT6>FLT10>FLT9>FLT7>FLT8>FLT2>FLT1>FLT5
1	%80 CRT1	FLT4>FLT3>FLT6>FLT10>FLT9>FLT2>FLT7>FLT8>FLT1>FLT5
2	%80 CRT2	FLT4>FLT3>FLT10>FLT9>FLT7>FLT8>FLT5>FLT6>FLT2>FLT1
3	%80 CRT3	FLT4>FLT6>FLT2>FLT10>FLT9>FLT8>FLT3>FLT7>FLT5>FLT1
4	%80 CRT4	FLT3>FLT4>FLT10>FLT6>FLT7>FLT9>FLT8>FLT2>FLT5>FLT1
5	%80 CRT5	FLT3>FLT4>FLT10>FLT6>FLT2>FLT9>FLT7>FLT8>FLT1>FLT5
6	%80 CRT6	FLT5>FLT7>FLT6>FLT9>FLT10>FLT2>FLT8>FLT1>FLT4>FLT3

Overall, the extreme sensitivity analysis demonstrates that ranking changes occur specifically under price, safety, capacity, and ergonomics dominance, whereas durability and material sustainability and agility dominance preserve the baseline leader. These findings confirm that the proposed decision framework is neither excessively rigid nor arbitrarily unstable. Instead, it exhibits context-dependent optimality: the optimal alternative depends on the strategic priority emphasized by the decision-maker. From a managerial perspective, the results imply that cost-driven firms, safety-oriented organizations, productivity-focused operations, and human-centered workplaces may each arrive at different optimal choices depending on their dominant strategic objective. Therefore, identifying the priority structure of the organization becomes a critical step in the decision-making process.

5.2. Scalability and Robustness Analysis

To evaluate the scalability and robustness of the proposed framework, additional analyses are conducted by modifying the structure of the decision matrix. First, a scalability analysis is performed by reducing the number of alternatives. While the original model included ten forklift alternatives, two additional scenarios are constructed with eight and six alternatives, respectively. The ranking results obtained using the AHP–ARAS model are presented in Appendix H (Table A8). The results indicate that the ranking positions

of the leading alternatives remain unchanged across all scenarios. In particular, FLT3, FLT4, and FLT6 consistently maintain the first three positions. Furthermore, Spearman rank correlation coefficients are calculated to quantitatively assess ranking stability. The correlation values between the base case (10 alternatives) and the reduced scenarios (with eight and six alternatives) are both ρ = 1.000, indicating perfect rank agreement. These findings demonstrate that the proposed decision framework maintains complete ranking stability even when the number of alternatives changes, confirming its scalability.

In addition to the alternative-reduction scenarios, a criterion-exclusion robustness analysis is conducted to examine the structural sensitivity of the model. Since the integrated framework relies on AHP-derived criterion weights, the AHP procedure is recalculated after removing selected criteria, and the ARAS method is reapplied using the updated weights. As seen in Appendix H (Table A9), two scenarios are considered: removal of the least influential criterion (CRT3) and removal of the most influential criterion (CRT1). The exclusion of CRT3 resulted in a moderate redistribution of weights, with CRT1 and CRT4 remaining the dominant criteria. In contrast, when CRT1 is excluded, CRT4 became the most influential criterion, followed by CRT2 and CRT6. These results indicate that the weighting structure adapts logically to structural changes in the criteria set and confirms the robustness and internal consistency of the proposed decision-making framework.

6. Spearman's Rank Correlation Analysis

Spearman's rank correlation analysis is employed to examine the degree of agreement among the ranking results obtained from different MCDM methods. This nonparametric measure evaluates the strength and direction of association between ranking results without requiring distributional assumptions. In this study, it is used to examine the degree of agreement among the alternative rankings obtained from the AHP–MOORA, AHP–ARAS, and AHP–ELECTRE methods. The analysis is conducted to assess the consistency and robustness of the proposed multi-method decision-making framework, and the high correlation values obtained indicate a strong concordance among the applied methods.

Spearman's rank correlation coefficient (ρ) is used to quantify the degree of agreement between the rankings obtained from different MCDM methods. The coefficient (ρ) is calculated as follows:

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)}$$

where d_i denotes the difference between the ranks of alternative i assigned by two methods, and n represents the total number of alternatives. The coefficient ranges from -1 to +1, with values close to +1 indicating strong agreement between rankings, values close to -1 indicating inverse rankings, and values around zero implying weak or no correlation. This analysis is applied to assess the consistency and robustness of the ranking results across the employed decision-making methods.

Spearman's rank correlation analysis reveals an almost perfect level of agreement among the applied methods. A perfect correlation (ρ = 1.00) is observed between the ARAS and MOORA rankings, indicating that these two methods produce identical ordering of the alternatives. Furthermore, very high correlation coefficients are obtained between ARAS and ELECTRE (ρ = 0.97) and between MOORA and ELECTRE (ρ = 0.97), demonstrating an exceptionally strong concordance. These results confirm that the different MCDM techniques yield highly consistent ranking outcomes, thereby supporting the robustness of the proposed multi-method decision-making framework.

7. Comparison of Weighting Methods (AHP, BWM, FUCOM, ENTROPY) and Ranking Results

To assess the robustness of the AHP-based results, alternative weighting methods BWM, FUCOM, and Entropy are used. The Best–Worst Method (BWM), proposed by Rezaei [31], is an optimization-based weighting approach in which decision-makers identify the most important (best) and least important (worst) criteria and perform pairwise comparisons only with respect to these two reference criteria. the Full Consistency Method, (FUCOM) proposed by Pamučar et al. [32], is employed to obtain consistent subjective weights. The Entropy weighting method, derived from Shannon's [33] information entropy theory is widely used to determine objective criterion weights based on the dispersion of decision data. Table 26 shows the obtained criteria weights by AHP, BWM, FUCOM and Entropy methods.

Table 26. Comparison of AHP, BWM, FUCOM, and Entropy Weights.

Criteria	BWM Weights	AHP Weights	FUCOM Weights	ENTROPY Weights
CRT1	0.333	0.441	0.667	0.050
CRT2	0.190	0.150	0.056	0.033
CRT3	0.048	0.043	0.014	0.100
CRT4	0.286	0.246	0.222	0.483
CRT5	0.048	0.046	0.014	0.250
CRT6	0.095	0.073	0.028	0.083

The weighting results obtained from AHP, BWM, FUCOM, and Entropy are presented in Table 26. These methods represent different weighting logics, where AHP, BWM, and FUCOM rely on expert judgment-based subjective evaluations, whereas Entropy derives weights objectively from the statistical dispersion of the data. As observed in Table 26, noticeable differences emerge in the distribution of criterion weights across the methods. For instance, the subjective methods assign relatively higher importance to CRT1, while the Entropy method identifies CRT4 as the most influential criterion due to its higher variability across alternatives.

Despite these differences in weight structures, the ranking results reported in Table 27 reveal a highly stable ordering of alternatives across all hybrid models combining different weighting techniques (AHP, BWM, FUCOM, and Entropy) with different decision-making methods (ARAS, MOORA, and ELECTRE). In particular, FLT3 consistently maintains the first rank across all weighting schemes and ranking methods, while FLT4 systematically appears in the second position. Moreover, the upper-ranking structure remains largely preserved, with only minor positional variations occurring among middle-ranked alternatives such as FLT6, FLT9, and FLT10. These variations are generally limited to shifts of one position and do not alter the dominance pattern among the leading alternatives. Table 27 shows the ranking results of the hybrid methods used.

Spearman rank correlation analysis is conducted to examine the consistency of ranking results obtained from different weighting and decision-making methods. The correlation coefficients range between 0.915 and 1.000 (see Appendix F (Table A6)), indicating very strong agreement among the rankings. In particular, rankings generated by the same decision-making method under different weighting schemes exhibit extremely high similarity ($\rho \approx 0.94$–0.98). These results demonstrate that the ranking structure of the alternatives remains largely stable despite variations in weighting logic and decision algorithms.

Therefore, the proposed decision framework can be considered methodologically robust and stable.

Table 27. Results of the method rankings.

	AHP-ARAS	BWM-ARAS	AHP-MOORA	BWM-MOORA	AHP-ELECTRE	BWM-ELECTRE
FLT1	9	10	9	10	9	10
FLT2	8	8	8	8	7	7
FLT3	1	1	1	1	1	1
FLT4	2	2	2	2	2	2
FLT5	10	9	10	9	10	8
FLT6	3	4	3	4	3	3
FLT7	6	6	6	6	6	6
FLT8	7	7	7	7	8	9
FLT9	5	5	5	5	5	5
FLT10	4	3	4	3	4	4
	FUCOM-ARAS	**ENTROPY-ARAS**	**FUCOM-MOORA**	**ENTROPY-MOORA**	**FUCOM-ELECTRE**	**ENTROPY-ELECTRE**
FLT1	9	9	9	9	10	10
FLT2	6	8	6	8	7	7
FLT3	1	1	1	1	1	1
FLT4	2	2	2	2	2	2
FLT5	10	10	10	10	8	8
FLT6	3	4	3	4	3	4
FLT7	7	5	7	5	6	5
FLT8	8	7	8	7	9	9
FLT9	5	6	5	6	5	6
FLT10	4	3	4	3	4	3

Furthermore, although ARAS and MOORA are compensatory aggregation-based methods and ELECTRE relies on an outranking logic, similar ranking patterns emerge across these fundamentally different decision-making approaches. This convergence can be explained by the consistent and pronounced performance differentials among the leading alternatives across the dominant criteria. When a leading alternative demonstrates clear superiority in highly weighted criteria without triggering significant discordance conditions, both additive aggregation methods and outranking-based approaches tend to converge toward the same ordering. Consequently, the observed similarity in rankings is not coincidental, but reflects the structurally embedded performance dominance within the decision matrix.

From a theoretical perspective, the similarity of ranking outcomes can be attributed to the structural characteristics of the decision matrix. In the present case, the leading alternatives demonstrate consistently strong performance across the most influential criteria, creating a clear performance gap relative to other options. When such dominance exists, variations in weighting structures or decision logics tend to have limited influence on the final ordering. As a result, both compensatory aggregation-based methods (ARAS and MOORA) and the outranking-based ELECTRE method converge toward similar ranking

patterns. Therefore, the observed ranking similarity is not merely descriptive but can be explained by the structural dominance of the top-performing alternatives within the decision matrix.

Although the weighting results obtained from AHP, BWM, and FUCOM are highly similar due to their reliance on expert judgment, the Entropy method produces a different weight structure because it derives criterion importance from the statistical dispersion of the decision matrix. Despite these differences in weighting logic, the ranking results remain largely consistent across the hybrid models. Furthermore, similar ranking patterns are observed across decision-making methods that rely on different evaluation logics, including additive aggregation (ARAS), ratio-based evaluation (MOORA), and outranking relations (ELECTRE). This convergence across both subjective and objective weighting approaches, as well as across fundamentally different decision-making logics, indicates that the final ordering of alternatives is primarily driven by the structural performance characteristics of the decision matrix rather than by the assumptions of a particular method. In particular, the leading alternatives (FLT3 and FLT4) demonstrate consistently strong performance across several influential criteria, which preserves their relative superiority even when the weighting structure changes. Therefore, the observed stability of ranking results provides strong evidence for the robustness and reliability of the proposed decision-making framework.

8. Kendall's Concordance Results

To rigorously assess inter-expert reliability, Kendall's coefficient of concordance (W) is calculated for criteria CRT1, CRT3, CRT4, and CRT5 based on the ordinal evaluations of 20 experts across 10 alternatives. The coefficient is computed using the standard formulation $W = \frac{12S}{m^2(n^3-n)}$, and its statistical significance is tested through the chi-square approximation $X^2 = m(n-1)W$ with $n-1$ degrees of freedom.

To further demonstrate the robustness of expert-based evaluations, both inter-rater agreement and dispersion measures are jointly examined for criteria CRT1, CRT3, CRT4, and CRT5. Kendall's coefficient of concordance indicated statistically significant agreement among 20 experts across 10 alternatives for all criteria ($p < 0.001$), with concordance levels of W = 0.734 (CRT1), 0.838 (CRT3), 0.911 (CRT4), and 0.892 (CRT5). These values reflect strong to very strong consensus, particularly for CRT4 and CRT5, where the agreement approaches perfect levels.

In addition to concordance analysis, descriptive statistics (see Appendix E (Table A5)) are computed at the alternative level, including variance and range (max–min), in line with minimum robustness reporting standards. For CRT1, dispersion remained limited, with several alternatives exhibiting zero variance (e.g., FLT2 and FLT3), and a maximum range of 2. Similarly, CRT3 and CRT5 demonstrated controlled variability, with ranges consistently equal to 2 and only a few cases of zero variance, indicating homogeneous expert judgments (see Appendix E (Table A5)). Although CRT4 displayed slightly higher variance values for certain alternatives, the very high concordance coefficient (W = 0.911) confirms that this dispersion reflects consistent scale usage rather than disagreement in ordinal ranking patterns.

Overall, the combined evidence from Kendall's W and descriptive dispersion indicators confirms that expert evaluations are both statistically consistent and robust. The low-to-moderate variance levels, bounded score ranges, and high concordance coefficients collectively validate the stability of the aggregated decision matrix, supporting its suitability for subsequent multi-criteria decision-making analysis without concerns regarding excessive subjectivity or instability.

The presence of strong concordance among experts indicates that the evaluations are not driven by isolated individual judgments but reflect a consistent collective assessment. This level of agreement reduces the potential bias associated with subjective scoring and enhances the reliability of the aggregated evaluation matrix used in the subsequent multi-criteria decision-making analysis. Therefore, the expert-based assessments can be considered sufficiently robust for supporting the decision framework of this study.

9. Managerial Implications

The findings of this study offer several important managerial implications for decision-makers involved in forklift procurement within logistics and warehouse operations, particularly from a sustainability-oriented perspective.

First, the weighting analysis indicates that Occupational Health and Safety (CRT1) and durability and material sustainability (CRT4) emerge as the most influential criteria across all weighting methods. This finding suggests that forklift purchasing decisions should prioritize worker safety, operational reliability, material quality, and long-term equipment durability, rather than focusing primarily on short-term cost considerations. From a practical perspective, managers should evaluate forklift alternatives primarily in terms of advanced safety technologies and structural robustness, as these factors have the greatest impact on overall performance assessment. Furthermore, selecting forklifts with durable structural components and longer service life can significantly reduce long-term maintenance costs and enhance the sustainability of warehouse operations.

Second, the ranking results reveal that certain alternatives, particularly FLT3 and FLT4, consistently demonstrate superior performance compared to other options under different weighting schemes and decision-making methods. This outcome indicates that forklifts exhibiting balanced performance across multiple sustainability dimensions maintain their superiority even under varying evaluation assumptions. From a procurement perspective, this finding suggests that adopting a multi-criteria sustainability-oriented evaluation approach can reduce the risk of suboptimal investment decisions.

Third, several technical indicators presented in Appendix D (Table A4) more clearly illustrate how sustainability-based criteria translate into measurable operational characteristics. For instance, ergonomic sustainability (CRT3) is evaluated through parameters such as vibration levels and noise exposure, which directly affect operator comfort and long-term occupational health. Alternatives such as FLT3 and FLT4 exhibit relatively lower vibration levels and noise emissions, indicating more favorable ergonomic working conditions. Agility performance (CRT5), on the other hand, can be interpreted through operational indicators such as turning radius, lifting speed, and maneuverability in narrow warehouse environments. For example, a smaller turning radius, reduced aisle width requirements, and higher lifting speed contribute to improved operational efficiency in narrow aisles and high-density storage environments. The results indicate that alternatives such as FLT3, which combine high lifting speed with strong maneuverability and balanced agility characteristics, achieve higher ranking positions within the evaluation framework. In addition, FLT3 stands out due to its lower energy consumption, shorter acceleration time, and higher load-lifting capacity.

Finally, the proposed framework can be applied as a structured decision-support tool in real purchasing environments. Logistics managers can implement the model by first identifying relevant evaluation criteria, then obtaining expert judgments to determine their relative importance, and finally evaluating available forklift alternatives using the ranking methods proposed in this study. Through this systematic process, organizations can move beyond intuitive or purely price-based purchasing decisions and adopt a more transparent, evidence-based, and sustainability-oriented procurement strategy. Moreover, the proposed

decision framework is applied within the procurement evaluation process of companies operating in the manufacturing and logistics sectors. The forklift alternatives considered in the analysis represent potential procurement options identified by managers responsible for internal logistics operations. The evaluation process is conducted through structured meetings with experienced managers, and the decision matrix is constructed based on both available technical specifications and expert assessments.

10. Conclusions

The procurement of forklifts, essential material handling equipment widely used in the loading and transportation of goods, is of critical importance across various industries. Particularly, in sectors such as logistics and manufacturing, selecting the appropriate sustainable forklift has become a key concern for businesses, as it directly influences operational efficiency, cost reduction, and product quality improvement. Sustainable forklifts today are not merely "eco-friendly machines" but strategic assets that improve energy efficiency, reduce operating costs, enhance worker safety, and support corporate sustainability objectives. As such, they have become a foundational element in the green transformation of modern supply chains. Given the need to consider multiple factors, sustainable forklift selection constitutes a typical MCDM problem frequently encountered in practice.

In this study, forklift alternatives, forklift evaluation criteria, and their assessments are identified through meetings with several managers responsible for internal logistics and sustainability in firms across various sectors. The integrated methodologies are subsequently applied within a selected company. AHP is used to determine the weightings of the criteria. Subsequently, the ARAS, ELECTRE, and MOORA ratio methods are applied to rank and select the best alternatives. This study provides several significant contributions to the literature. Importantly, AHP-ARAS, AHP-ELECTRE, and AHP-MOORA (ratio approach) have not previously been applied to sustainable forklift selection and evaluation. Their performances are compared with the results obtained from all methods used. The top alternatives ranked identically across all methods, with only minor differences observed thereafter, demonstrating the methods' effective performance. The results of the sensitivity analyses validate the robustness of the model and demonstrate the consistency, reliability, and effectiveness of the method's results. Furthermore, Spearman's rank correlation analysis confirms that the rankings obtained from the different MCDM techniques exhibit strong and statistically significant agreement, indicating that the overall decision outcomes are not method-dependent. This high level of concordance strengthens the credibility of the proposed multi-method framework and supports its suitability for complex sustainability-oriented decision-making problems. Additionally, real-world criteria such as sustainability in occupational health and safety, agility, ergonomics, durability and material sustainability, load lifting capacity and price, which have not been considered in sustainable forklift selection studies, are incorporated into the evaluation. It has been determined that sustainability in occupational health and safety is a highly significant criterion in the selection of sustainable forklifts.

In this study, FLT3 has emerged as the best alternative due to its strong performance in criteria related to safety and agility, as well as its high load capacity (CRT2). Although it is not the lowest-priced option (CRT6), it provides an optimal balance between operational capability, safety features, and durability. The model demonstrates superior agility characteristics (CRT5) and high occupational health and safety performance (CRT1), making it particularly suitable for intensive warehouse operations where efficiency and risk reduction are of critical importance.

Despite the use of different weighting techniques (AHP, BWM, FUCOM, and Entropy), the obtained ranking results are largely consistent. While the subjective weighting methods based on expert judgment (AHP, BWM, and FUCOM) produced relatively similar weight distributions, the objective Entropy method generated a different weighting structure for certain criteria due to its data-driven nature. Nevertheless, the ranking results obtained from the hybrid decision models (ARAS, MOORA, and ELECTRE) reveal that the overall ranking structure of the alternatives remains largely preserved across different methodological combinations. In particular, FLT3 consistently maintained the first rank across all analyses, while FLT4 systematically appeared in the second position. Moreover, the upper-ranking structure remained largely stable across different weighting and decision-making configurations.

The results of the Spearman rank correlation analysis further confirm this finding. Very high correlation coefficients ($\rho > 0.90$) were obtained among the rankings generated by different weighting and decision-making methods, indicating a strong agreement in the ordering of alternatives. This stability can largely be explained by the dominant influence of the most heavily weighted criteria on the overall performance scores. Consequently, small differences in weight estimations do not significantly alter the final ranking results.

Furthermore, the fact that FLT3 consistently ranked first across all analyses indicates that the superiority of this alternative is not the result of a specific weighting technique, but rather stems from its structural performance dominance within the decision matrix. Therefore, the observed robustness of the ranking results arises not only from methodological consistency but also from the intrinsic performance advantage of the leading alternative in the decision matrix. These findings demonstrate that the proposed decision framework is methodologically robust and largely method-independent.

The results emphasize that managers should place greater importance on the criteria of sustainability in occupational health and safety—identified as the most critical factor—followed by durability and material sustainability, and sustainability in load lifting capacity when selecting forklifts. In addition, the findings indicate that focusing on these criteria enables more sustainable decision-making. This study provides a theoretical contribution to the sustainable forklift selection literature by proposing an integrated MCDM framework. This study is expected to serve as a guide and provide valuable contributions to companies, particularly those operating in the logistics sector, in the selection of sustainable forklifts. The findings are shared with participating firms, and relevant recommendations are provided.

10.1. Reasons for Method Selection

The methodological framework of this study is intentionally based on well-established classical MCDM techniques, as these methods are transparent, interpretable, and widely accepted in expert-driven decision-making contexts. In problems such as sustainable forklift selection, where the available data are limited and expert knowledge plays a central role, classical MCDM approaches provide a structured and logically interpretable decision environment.

For criteria weighting, both subjective and objective approaches are incorporated. AHP, BWM, and FUCOM are employed as representative subjective weighting methods since they rely on expert judgments to capture decision-maker preferences and domain knowledge. AHP provides a hierarchical structure that enables systematic pairwise comparisons while ensuring logical consistency through the consistency ratio (CR). In contrast, BWM and FUCOM are designed to reduce the number of pairwise comparisons and improve consistency in expert evaluations, thereby increasing the reliability of subjective weighting results. In addition to these expert-based approaches, the Entropy method is

included as an objective weighting technique that determines criterion importance based on the statistical dispersion of the decision matrix. Integrating both subjective and objective weighting schemes allows the analysis to examine how expert-based and data-driven weight structures influence the final ranking outcomes.

For the ranking stage, three widely used MCDM methods with different decision logics are adopted. ARAS represents an additive aggregation-based method that evaluates alternatives through normalized weighted utility values. MOORA relies on ratio-based evaluation and provides a computationally simple and stable ranking mechanism for benefit–cost type decision problems. ELECTRE, on the other hand, belongs to the outranking family of methods and evaluates alternatives based on pairwise dominance relations, allowing the identification of non-compensatory preferences among criteria. By combining additive aggregation (ARAS), ratio-based evaluation (MOORA), and outranking logic (ELECTRE), this study enables alternatives to be assessed from fundamentally different decision perspectives rather than being restricted to a single aggregation mechanism.

Compared with many advanced or data-intensive MCDM models, the selected methods offer several advantages, including transparency, interpretability, relatively low computational complexity, and strong compatibility with expert-based evaluations. These characteristics make them particularly suitable for sustainability-oriented decision problems where criteria involve qualitative judgments and conceptual interdependencies.

Finally, the simultaneous application of multiple weighting schemes and ranking methods provides complementary insights into the decision-making process. While different weighting methods capture variations in the perceived importance of criteria, the use of multiple ranking algorithms allows the analysis to examine whether the ordering of alternatives is sensitive to different decision logics. Therefore, the integration of multiple weighting schemes and ranking algorithms enables the evaluation of the decision problem from complementary methodological perspectives and provides additional validation for the robustness and credibility of the obtained results.

The use of multiple MCDM methods in this study does not represent methodological redundancy but rather reflects the integration of conceptually distinct evaluation perspectives. The weighting methods employed differ fundamentally in their underlying logic. AHP, BWM, and FUCOM are subjective methods based on expert judgments, yet they differ in terms of pairwise comparison structure, consistency control, and optimization mechanisms. In contrast, the Entropy method is an objective approach that determines criterion weights based on the dispersion of data within the decision matrix. Similarly, the ranking methods used in this study are conceptually different. ARAS is based on an additive utility function, MOORA relies on a ratio-based normalization approach, and ELECTRE adopts an outranking logic that evaluates dominance relationships between alternatives. Accordingly, the conceptual differences among the employed weighting and ranking methods are summarized in Table A7. These methodological differences imply that each method evaluates the same decision problem through a different mathematical perspective. Therefore, the convergence of results across these diverse methods should not be interpreted as redundancy or a predetermined outcome. On the contrary, it indicates the presence of structural performance dominance within the decision matrix, where certain alternatives consistently outperform others across multiple criteria. This consistency strengthens the robustness and reliability of the findings, demonstrating that the results are not method-dependent but driven by the intrinsic characteristics of the evaluated alternatives.

Although various modern, data-driven, and advanced hybrid MCDM approaches have been proposed in recent literature, their applicability largely depends on the availability of large-scale and homogeneous datasets. In the present decision problem, several critical evaluation criteria involve qualitative assessments and expert-based judgments, for

which consistent secondary data are not fully available. Under such conditions, data-driven or machine-learning-based MCDM models may yield unstable or misleading results due to insufficient training data and reduced interpretability. While modern data-driven and hybrid approaches present valuable opportunities for future research, their implementation typically requires extensive datasets and additional modeling assumptions, which fall outside the scope of the current study.

Therefore, classical MCDM methods are deemed the most appropriate choice for achieving the research objectives. The decision matrix incorporates both technical data obtained from manufacturers and expert-based scores due to constraints related to data availability. In this respect, classical hybrid MCDM methods are preferred because of their ability to transparently and interpretably handle mixed data structures comprising both qualitative and quantitative information. The robustness of the results is assessed through sensitivity analysis, which verified the stability of alternative rankings under different weighting scenarios. In addition, the Spearman rank correlation analysis is applied to examine the consistency among rankings obtained from different hybrid methods; the high level of agreement further supports the reliability of the results.

10.2. Limitations of This Study

Expert judgment limitation: Since both quantitative and qualitative data are taken into consideration in the evaluation of criteria, such as sustainability in ergonomics and sustainability in agility, a 1–10 scoring scale was employed. The primary limitation in this context arises from the fact that qualitatively assessed specifications are not provided by manufacturers in a standardized format. In many cases, such specifications are disclosed only in terms of whether a particular feature is present in a given alternative, and the corresponding values are either inherently qualitative in nature or shared as qualitative information. However, the explicit definition of the measurement components and their systematic structuring by experts, together with the adoption of the 1–10 scale—which is frequently used in the literature under similar data constraints—ensure the transparency and replicability of this study. Accordingly, the evaluation of certain criteria, including ergonomic sustainability and agility sustainability, by experts using a 1–10 scoring scale is considered reasonable and methodologically appropriate. The use of a 1–10 scale is also widely adopted in the literature in situations where data limitations exist.

Limited number of criteria: The criteria were determined based on expert opinions and the experts' knowledge of the relevant literature, and the forklift models considered in the evaluation are those deemed appropriate by the experts based on sectoral relevance. Although this study may appear to be limited to a relatively small dataset, the fact that both the criteria and alternatives are identified by domain-expert managers in accordance with the real needs of firms operating in practice significantly enhances the reliability and robustness of this study in terms of real-life applicability. In this context, the selection of alternatives from different types of forklift models (brands), reflecting real-world decision challenges faced by firms, and the identification and structuring of criteria by field experts based on actual decision-making practices, render this study realistic, original, and methodologically strong.

Furthermore, the explicit description of the experts (see Appendix A (Table A1)) and the fact that they are experienced industry professionals contribute to the robustness of this study; the reporting of the individual scores assigned by each expert (see Appendix B (Table A2)) ensures transparency; and the determination and evaluation of criteria and alternatives by 20 domain-expert industry professionals demonstrate that this study was conducted at an acceptable and credible scale.

In the literature, different criteria and alternatives are considered depending on the objectives and scope of this study. Therefore, the number of criteria and alternatives considered may be regarded as a limitation of this study. As also stated in Section 2 (Literature Review) of this study, international research on forklift selection and evaluation generally considers the assessment and selection of approximately 10 or fewer forklift alternatives, depending on the study scope. Similarly, international studies have been conducted using around five evaluation criteria in accordance with the specific objectives and requirements of each study. Moreover, a review of the literature indicates that an expert size in the range of 15–20 decision-makers is generally regarded as acceptable and methodologically valid, and numerous international studies have been published in line with this practice.

Real-time operational performance data: Despite the structured evaluation framework, the use of expert-based scoring introduces a certain degree of subjectivity into the decision-making process. Although the involvement of experienced professionals and the use of clearly defined evaluation criteria help mitigate this limitation, individual perceptions and judgments may still influence the assigned scores.

In addition, the absence of standardized quantitative indicators for certain criteria necessitates the use of subjective assessment methods. Moreover, several criteria considered in this study (e.g., ergonomics, agility, and occupational health and safety) cannot be directly quantified using standardized numerical indicators, as they do not possess standardized measurable metrics due to their multidimensional, user experience-based and context-dependent nature (e.g., operator comfort, maneuverability in confined spaces, field of vision, usability of control layout, perceived safety, and application-specific experiential factors such as the presence or absence of certain equipment features such as sensors). Therefore, the use of a structured expert-based scoring approach is not only appropriate but also necessary to ensure a meaningful and comparable evaluation across alternatives.

It should be noted that this study incorporates objective technical performance data obtained from manufacturers' specifications (e.g., turning radius, lift speed, vibration level, noise level, and energy consumption). However, these data represent standardized performance values measured under controlled conditions rather than real-time operational data collected from actual field usage. Therefore, while this study benefits from objective technical inputs, it does not capture dynamic, real-time operational performance variations that may arise from operator behavior, workload conditions, and environmental factors.

Aggregated price criterion: The price criterion was intentionally modeled as an aggregated life-cycle cost (LCC) indicator, which integrates multiple cost components, including initial purchase, energy consumption, maintenance, repair, spare parts, battery replacement, and end-of-life disposal and recycling costs. This approach was adopted to ensure model tractability, consistency, and comparability across alternatives, particularly given that detailed cost components are not uniformly available or reported in a standardized manner across forklift manufacturers.

In real-world procurement environments, especially in industrial equipment selection, cost information is often provided as bundled or partially disclosed values. Therefore, using a fully disaggregated cost structure could introduce inconsistencies and reduce the reliability of cross-alternative comparisons. By employing an aggregated LCC representation, this study preserves the long-term economic perspective of sustainability, rather than focusing solely on short-term acquisition costs.

Generalizability: The findings are based on evaluations conducted by 20 experts from international companies operating in Turkey and on a specific set of forklift alternatives. Therefore, the results may not be directly generalizable to different geographical contexts, industries, or decision environments. In addition, the inclusion of expert-based qualitative

assessments may introduce context-dependent judgments, which can vary across different expert groups.

10.3. Future Research Suggestions

- Future studies may be conducted using larger and/or more diverse datasets. In addition, the problem may be solved using alternative methods such as modern, data-driven (if access to large data sets is available).
- If uncertainty is incorporated into the decision-making process, fuzzy MCDM methods may be employed in future studies.
- The problem may be solved with other hybrid MCDM methods to compare the results. Different methods may also be employed for determining criterion weights and ranking alternatives. While the rationale for the selected methods has been discussed within the scope of this study, future research may apply this methodological framework, particularly in contexts where uncertainty is present.
- Future studies may be incorporated with sensor-based measurements, real-time operational data, or longitudinal performance records.
- Future research may extend the proposed framework by decomposing the price criterion into its individual cost components.
- Future studies may enhance external validity by applying the proposed framework to larger datasets, different regions, and alternative industrial settings.
- Recent MCDM literature has moved beyond classical approaches, highlighting the emergence of data-driven and artificial intelligence–integrated hybrid methodologies. In particular, the integration of data envelopment analysis (DEA) with machine learning and explainable artificial intelligence techniques has gained increasing attention. For instance, the XDEA approach combines the traditional DEA model with methods such as XGBoost and SHAP, enabling not only performance evaluation but also improved interpretability of input–output relationships [34]. Similarly, the multi-stage DEA–Random Forest–SHAP framework developed for financial sustainability analysis provides accurate performance prediction while explaining the effects of decision variables, thereby mitigating the "black-box" problem [35]. In addition, advanced machine learning algorithms such as NGBoost, CatBoost, SVR, and GPR, which are used in reverse osmosis system performance prediction, offer high predictive accuracy, while SHAP analysis enhances the interpretability of model outputs [36]. These next-generation approaches enable MCDM studies not only to rank alternatives but also to analyze the dynamics of the decision-making process and the marginal effects of variables. Therefore, future research can support classical methods with such explainable, data-driven hybrid models.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The author confirms that the data supporting the findings of this study are available within the article.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A

Table A1. Descriptions of experts.

Expert No	Experience	Roles	Age	Sector	Professional Roles
1	15	Logistics Manager	37	Automotive manufacturing	Internal logistics operations optimization, sustainable and operational logistics decision-making
2	18	Supply Chain and Logistics Manager	38	Logistics	Implementing sustainable practices in logistics, developing sustainable supply chains, coordinating supply chain and logistics activities, and conducting sustainable multi-criteria analysis in logistics and supply chains
3	16	Sustainability Manager	35	Logistics	Green logistics decisions, energy-efficient and eco-friendly logistics practices, multi-criteria decision making in sustainable logistics operations and equipment
4	20	Warehouse Manager	45	Logistics	Multi-criteria analysis for logistics decisions, warehouse and distribution center operations management; responsible for warehouse operations and forklift utilization efficiency
5	18	Sustainability Manager	40	Automotive manufacturing	Sustainable logistics, sustainable multi-criteria analysis in logistics
6	19	Logistics Manager	38	Electronics manufacturing	Decision-making in logistics operations, procurement and evaluation of material handling technologies, and improvement of transportation efficiency
7	19	Sustainability Manager	39	Textile manufacturing	Planning efficient transportation; sustainable multi-criteria analysis in logistics routes, mode, MHE selection; and evaluation of logistics equipment alternatives and transportation efficiency
8	15	Logistics Manager	36	Automotive manufacturing	Transportation efficiency, MHE selection and performance evaluation, sustainable multi-criteria analysis in logistics
9	16	Logistics Manager	38	Food manufacturing	Conducting research on logistics decision-making, and sustainable MHE optimization
10	18	Logistics Manager	40	Polyester manufacturing	Ensuring safety compliance in logistics operations and logistics decision-making using analytical and optimization techniques
11	15	Sustainability Manager	36	Logistics	Assessment of environmental impact of logistics operations, sustainable logistics systems decisions
12	18	Sustainability Manager	37	Food manufacturing	Conducts green logistics and supply chain management systems and decision making

Table A1. *Cont.*

Expert No	Experience	Roles	Age	Sector	Professional Roles
13	15	Warehouse Manager	38	Logistics	Oversees MHE selection and procurement decisions, operational planning for transportation and distribution systems, warehouse material handling system management, assessment and selection of industrial vehicles for warehouse operations, and supervision of warehouse material handling equipment and forklift operations
14	22	Sustainability Manager	46	Polyester manufacturing	Eco-friendly forklift selection, environmental impact assessment in logistics operations, sustainable logistics decisions
15	24	Logistics Manager	49	Textile manufacturing	Plans for efficient forklift selection and routes, operational safety and compliance in logistics activities, sustainable forklift selection
16	15	Logistics Manager	37	Food and beverage manufacturing	Logistics system efficiency and operational performance analysis; oversees forklift selection
17	16	Sustainability Manager	38	Automotive manufacturing	Sustainable logistics and green supply chain implementation, evaluation of logistics equipment alternatives and transportation efficiency
18	24	Logistics Manager	46	Food and beverage manufacturing	Forklift fleet management and equipment procurement decisions
19	16	Logistics Manager	38	Automotive manufacturing	Analysis of MHE (forklift) performance and MHE purchasing decisions, and route optimization
20	15	Logistics Manager	37	Automotive manufacturing	Coordination of logistics operations and equipment performance evaluation, and development of sustainable logistics strategies

Appendix B

Table A2. Individual expert evaluations.

Expert1	CRT1	CRT3	CRT4	CRT5	Expert2	CRT1	CRT3	CRT4	CRT5
FLT1	7	6	3	5	FLT1	6	6	3	5
FLT2	8	10	5	9	FLT2	8	9	5	8
FLT3	9	7	10	10	FLT3	9	8	10	10
FLT4	9	9	10	9	FLT4	10	9	8	9
FLT5	6	6	3	4	FLT5	6	6	2	4
FLT6	9	9	8	9	FLT6	9	9	8	8
FLT7	7	6	8	7	FLT7	7	5	8	7
FLT8	6	8	7	7	FLT8	7	9	7	7

Table A2. *Cont.*

Expert1	**CRT1**	**CRT3**	**CRT4**	**CRT5**	**Expert2**	**CRT1**	**CRT3**	**CRT4**	**CRT5**
FLT9	8	8	7	7	FLT9	8	7	8	7
FLT10	7	8	9	9	FLT10	9	8	8	9
Expert3	**CRT1**	**CRT3**	**CRT4**	**CRT5**	**Expert4**	**CRT1**	**CRT3**	**CRT4**	**CRT5**
FLT1	8	5	2	5	FLT1	7	5	3	5
FLT2	8	8	5	9	FLT2	8	9	5	8
FLT3	9	6	10	10	FLT3	9	7	10	10
FLT4	8	10	9	8	FLT4	9	9	8	9
FLT5	6	6	4	4	FLT5	6	6	3	4
FLT6	9	9	9	9	FLT6	9	9	8	10
FLT7	8	6	7	7	FLT7	6	6	7	7
FLT8	8	9	8	7	FLT8	6	7	7	7
FLT9	8	9	6	7	FLT9	8	8	7	7
FLT10	9	8	10	9	FLT10	7	8	9	9
Expert5	**CRT1**	**CRT3**	**CRT4**	**CRT5**	**Expert6**	**CRT1**	**CRT3**	**CRT4**	**CRT5**
FLT1	8	6	4	5	FLT1	6	7	3	5
FLT2	8	9	5	8	FLT2	8	8	5	9
FLT3	9	7	10	10	FLT3	9	7	10	10
FLT4	8	9	10	8	FLT4	9	8	9	9
FLT5	6	7	4	3	FLT5	6	7	3	5
FLT6	9	9	9	10	FLT6	9	9	7	9
FLT7	7	6	9	7	FLT7	6	6	9	7
FLT8	6	8	6	7	FLT8	7	8	7	7
FLT9	8	6	7	7	FLT9	9	10	7	7
FLT10	8	8	9	9	FLT10	8	8	9	9
Expert7	**CRT1**	**CRT3**	**CRT4**	**CRT5**	**Expert8**	**CRT1**	**CRT3**	**CRT4**	**CRT5**
FLT1	7	5	3	4	FLT1	7	5	3	4
FLT2	8	9	6	9	FLT2	8	8	5	10
FLT3	9	7	10	10	FLT3	9	7	10	10
FLT4	10	8	9	8	FLT4	9	8	9	10
FLT5	6	5	2	4	FLT5	6	5	4	5
FLT6	9	9	8	9	FLT6	9	9	8	8
FLT7	8	6	7	7	FLT7	7	6	9	7
FLT8	7	7	7	7	FLT8	7	8	7	7
FLT9	7	8	7	7	FLT9	8	8	7	7
FLT10	8	8	8	9	FLT10	8	8	8	9
Expert9	**CRT1**	**CRT3**	**CRT4**	**CRT5**	**Expert10**	**CRT1**	**CRT3**	**CRT4**	**CRT5**
FLT1	6	6	3	6	FLT1	8	7	3	6
FLT2	8	9	5	10	FLT2	8	9	4	9
FLT3	9	7	10	10	FLT3	9	7	10	10

Table A2. *Cont.*

Expert9	**CRT1**	**CRT3**	**CRT4**	**CRT5**	**Expert10**	**CRT1**	**CRT3**	**CRT4**	**CRT5**
FLT4	9	9	8	10	FLT4	9	9	8	10
FLT5	5	6	2	3	FLT5	6	5	3	4
FLT6	10	9	7	9	FLT6	9	9	9	9
FLT7	7	5	8	7	FLT7	7	6	7	7
FLT8	8	8	7	6	FLT8	7	8	6	8
FLT9	8	8	7	7	FLT9	8	8	7	7
FLT10	8	8	10	9	FLT10	7	8	10	9
Expert11	**CRT1**	**CRT3**	**CRT4**	**CRT5**	**Expert12**	**CRT1**	**CRT3**	**CRT4**	**CRT5**
FLT1	6	6	3	5	FLT1	8	6	3	5
FLT2	8	9	5	9	FLT2	8	9	5	9
FLT3	9	7	10	10	FLT3	9	7	10	10
FLT4	8	10	10	9	FLT4	10	10	10	9
FLT5	7	5	4	4	FLT5	6	7	4	4
FLT6	8	9	8	9	FLT6	9	9	8	9
FLT7	7	6	7	7	FLT7	7	6	9	7
FLT8	6	8	8	7	FLT8	8	8	7	7
FLT9	8	8	7	7	FLT9	8	8	8	7
FLT10	9	8	9	9	FLT10	8	8	9	9
Expert13	**CRT1**	**CRT3**	**CRT4**	**CRT5**	**Expert14**	**CRT1**	**CRT3**	**CRT4**	**CRT5**
FLT1	7	6	3	5	FLT1	7	6	3	5
FLT2	8	9	5	10	FLT2	8	10	4	9
FLT3	9	7	10	10	FLT3	9	7	10	10
FLT4	9	9	9	10	FLT4	10	9	9	8
FLT5	6	7	3	4	FLT5	6	5	3	4
FLT6	9	9	8	9	FLT6	8	8	8	9
FLT7	7	7	8	7	FLT7	7	7	8	7
FLT8	6	8	7	7	FLT8	8	8	7	7
FLT9	8	9	6	7	FLT9	8	7	6	7
FLT10	7	8	9	9	FLT10	9	8	9	9
Expert15	**CRT1**	**CRT3**	**CRT4**	**CRT5**	**Expert16**	**CRT1**	**CRT3**	**CRT4**	**CRT5**
FLT1	8	6	2	5	FLT1	6	6	4	5
FLT2	8	10	6	9	FLT2	8	9	5	9
FLT3	9	7	10	10	FLT3	9	7	10	10
FLT4	8	9	9	9	FLT4	9	9	9	9
FLT5	6	5	3	4	FLT5	6	7	3	4
FLT6	9	9	9	9	FLT6	10	10	7	9
FLT7	8	6	9	7	FLT7	6	7	7	7
FLT8	7	9	7	7	FLT8	7	7	7	7
FLT9	8	7	8	7	FLT9	8	9	7	7
FLT10	7	8	9	9	FLT10	9	8	9	9

Table A2. *Cont.*

Expert17	CRT1	CRT3	CRT4	CRT5	Expert18	CRT1	CRT3	CRT4	CRT5
FLT1	7	7	3	6	FLT1	7	7	3	5
FLT2	8	9	5	9	FLT2	8	9	5	9
FLT3	9	7	10	10	FLT3	9	7	10	10
FLT4	9	10	9	10	FLT4	10	9	9	8
FLT5	6	6	3	3	FLT5	6	6	3	5
FLT6	9	9	8	10	FLT6	9	9	8	8
FLT7	6	6	8	7	FLT7	8	6	8	7
FLT8	7	8	7	7	FLT8	7	8	7	7
FLT9	8	8	7	8	FLT9	8	8	7	6
FLT10	8	8	9	9	FLT10	8	8	9	9
Expert19	**CRT1**	**CRT3**	**CRT4**	**CRT5**	**Expert20**	**CRT1**	**CRT3**	**CRT4**	**CRT5**
FLT1	7	6	3	5	FLT1	7	6	3	4
FLT2	8	9	5	9	FLT2	8	9	5	9
FLT3	9	7	10	10	FLT3	9	7	10	10
FLT4	9	8	10	9	FLT4	8	9	8	9
FLT5	6	6	3	4	FLT5	6	6	3	4
FLT6	9	8	8	9	FLT6	9	10	8	9
FLT7	6	5	8	7	FLT7	8	6	8	7
FLT8	7	7	7	7	FLT8	7	9	7	7
FLT9	8	8	7	8	FLT9	8	8	7	6
FLT10	8	7	9	8	FLT10	8	9	9	10

Appendix C

Table A3. Technical specifications of alternatives.

Criteria	Main Technical References Used by Experts
CRT1—Occupational Health & Safety	Safety sensors, presence of automatic braking (safety systems), automatic collision-avoidance sensors and emission-free or low-noise electric drive systems, advanced safety systems, oriented protective mechanisms and sensor-based designs, environmentally friendly and human-centered characteristics
CRT3—Ergonomics	Noise level, vibration level, cabin comfort, human–machine interface, intelligent seat-occupancy sensors, adaptive steering systems, noise-insulated cabins, digital displays, ergonomic cabin layouts, vibration- and noise-reduction technologies, and posture-supporting suspension seats; physical comfort, cognitive ease, and environmental responsibility converge situation
CRT4—Durability & Material Sustainability	Material quality, service life, structural robustness, durability, recyclability, and environmental friendliness of the materials used in forklift manufacturing
CRT5—Agility	Turning radius, lift speed, aisle width, acceleration performance, and vehicle responsiveness to the operating surface; intelligent motion control, smart driving systems, adaptive steering, and regenerative braking technologies, forklifts lifting mechanism (mast) design and fork actuation systems, electric power steering, proportional hydraulic control, traction-control systems, and AI-assisted stability sensors

Appendix D

Table A4. Technical measurable specifications of alternatives.

Model	Forklift Type	Battery Type	Capacity (kg)	Turning Radius (mm)	Aisle Width (AST) (mm)	Lift Speed (m/s)	Vibration Level (m/s^2)	Noise in dB	Acceleration Time (s) (Loaded–Unloaded)	Energy Consumption Data (kWh/h) (Unloaded–Loaded)
FLT1	Electric counter-balance (EC)	Li-ion	3000	2610	3646	0.43	1.32	64.9	6.0–5.4	5.40–5.80
FLT2	EC	Li-ion	3000	2672	3972	0.53	0.94	79	5.2–4.5	5.01–5.42
FLT3	EC	Li-ion	3500	2140	3595	0.62	0.78	63.2	3.8–3.4	2.65–3.11
FLT4	EC	Li-ion	3500	2540	3679	0.47	0.89	63.8	3.9–3.5	2.88–3.23
FLT5	EC	Li-ion	3500	2190	3850	0.54	1.89	79	6.1–5.5	5.30–5.72
FLT6	EC	Li-ion	3000	2270	3897	0.38	0.92	70	4.7–4.0	2.90–3.40
FLT7	EC	Li-ion	3500	2155	3775	0.41	1.22	83.5	5.0–4.6	3.32–3.99
FLT8	EC	Li-ion	3500	2235	3885	0.54	1.31	71	5.1–4.4	4.45–4.90
FLT9	EC	Li-ion	3500	2149	3820	0.66	1.10	72	5.0–4.3	3.19–3.87
FLT10	EC	Li-ion	3500	2755	3640	0.41	0.99	70	5.1–4.2	2.98–3.66

Appendix E

Table A5. Descriptive statistics.

Criteria–Alternative	Variance	Range (Max–Min)
CRT1-FLT1	0.5263	2
CRT1-FLT2	0.0000	0
CRT1-FLT3	0.0000	0
CRT1-FLT4	0.5263	2
CRT1-FLT5	0.1053	2
CRT1-FLT6	0.2105	2
CRT1-FLT7	0.5263	2
CRT1-FLT8	0.4711	2
CRT1-FLT9	0.1053	2
CRT1-FLT10	0.5263	2
CRT4-FLT1	0.2105	2
CRT4-FLT2	0.2105	2
CRT4-FLT3	0.0000	0
CRT4-FLT4	0.5263	2
CRT4-FLT5	0.4105	2
CRT4-FLT6	0.3658	2
CRT4-FLT7	0.5763	2
CRT4-FLT8	0.2105	2
CRT4-FLT9	0.3158	2
CRT4-FLT10	0.3158	2

Table A5. *Cont.*

Criteria–Alternative	Variance	Range (Max–Min)
CRT3-FLT1	0.4211	2
CRT3-FLT2	0.3158	2
CRT3-FLT3	0.1053	2
CRT3-FLT4	0.4211	2
CRT3-FLT5	0.5763	2
CRT3-FLT6	0.2105	2
CRT3-FLT7	0.3158	2
CRT3-FLT8	0.4211	2
CRT3-FLT9	0.1053	2
CRT3-FLT10	0.1053	2
CRT5-FLT1	0.3158	2
CRT5-FLT2	0.3158	2
CRT5-FLT3	0.0000	0
CRT5-FLT4	0.5263	2
CRT5-FLT5	0.3158	2
CRT5-FLT6	0.3158	2
CRT5-FLT7	0.0000	0
CRT5-FLT8	0.1053	2
CRT5-FLT9	0.2105	2
CRT5-FLT10	0.1053	2

Appendix F

Table A6. Spearman rank correlation matrix of ranking results.

Method	AHP-ARAS	BWM-ARAS	FUCOM-ARAS	ENTROPY-ARAS	AHP-MOORA	BWM-MOORA	FUCOM-MOORA	ENTROPY-MOORA	AHP-ELECTRE	BWM-ELECTRE	FUCOM-ELECTRE	ENTROPY-ELECTRE
AHP-ARAS	1.000	0.976	0.964	0.976	1.000	0.976	0.964	0.976	0.988	0.939	0.939	0.915
BWM-ARAS	0.976	1.000	0.939	0.976	0.976	1.000	0.939	0.976	0.964	0.952	0.952	0.952
FUCOM-ARAS	0.964	0.939	1.000	0.915	0.964	0.939	1.000	0.915	0.939	0.951	0.951	0.915
ENTROPY-ARAS	0.976	0.976	0.915	1.000	0.976	0.976	0.915	1.000	0.976	0.915	0.915	0.939
AHP-MOORA	1.000	0.976	0.964	0.976	1.000	0.976	0.964	0.976	0.988	0.939	0.939	0.915
BWM-MOORA	0.976	1.000	0.939	0.976	0.976	1.000	0.939	0.976	0.964	0.952	0.952	0.952
FUCOM-MOORA	0.964	0.939	1.000	0.915	0.964	0.939	1.000	0.915	0.939	0.951	0.951	0.915
ENTROPY-MOORA	0.976	0.976	0.915	1.000	0.976	0.976	0.915	1.000	0.976	0.915	0.915	0.939
AHP-ELECTRE	0.988	0.964	0.939	0.976	0.988	0.964	0.939	0.976	1.000	0.964	0.964	0.939
BWM-ELECTRE	0.939	0.952	0.951	0.915	0.939	0.952	0.951	0.915	0.964	1.000	1.000	0.976
FUCOM-ELECTRE	0.939	0.952	0.951	0.915	0.939	0.952	0.951	0.915	0.964	1.000	1.000	0.976
ENTROPY-ELECTRE	0.915	0.952	0.915	0.939	0.915	0.952	0.915	0.939	0.939	0.976	0.976	1.000

Appendix G

Table A7. Conceptual differences among the methods.

Method	Type	Logic	Key Difference
AHP	Subjective weighting	Pairwise comparison based on expert judgments with consistency ratio	Provides structured hierarchical evaluation with consistency control
BWM	Subjective weighting	Best–worst comparisons to derive optimal weights	Requires fewer comparisons and improves consistency compared to AHP
FUCOM	Subjective weighting	Full consistency optimization based on rank ordering of criteria	Minimizes deviation from full consistency with reduced computational complexity
Entropy	Objective weighting	Weight determination based on data dispersion within the decision matrix	Eliminates subjectivity by relying entirely on quantitative data variability
ARAS	Ranking method	Additive utility function based on normalized performance values	Evaluates alternatives through overall utility scores relative to an optimal solution
MOORA	Ranking method	Ratio-based normalization and aggregation of beneficial and non-beneficial criteria	Separates beneficial and cost criteria using a simple ratio system
ELECTRE	Ranking method	Outranking approach using concordance and discordance relations	Compares alternatives pairwise based on dominance rather than aggregate scores

Appendix H

Table A8. Alternative reduction scenarios.

Alternative	Base Case (10 Alt.)	Scenario 1 (8 Alt.)	Scenario 2 (6 Alt.)
FLT1	9	7	5
FLT2	8	6	4
FLT3	1	1	1
FLT4	2	2	2
FLT5	10	8	6
FLT6	3	3	3
FLT7	6	4	-
FLT8	7	5	-
FLT9	5	-	-
FLT10	4	-	-

Table A9. Revised AHP weights under criterion exclusion.

Criterion	Base Case	Excluding CRT3	Excluding CRT1
CRT1	0.441	0.4836	–
CRT2	0.150	0.1488	0.2645
CRT3	0.043	–	0.0678
CRT4	0.246	0.2480	0.4677
CRT5	0.046	0.0478	0.0777
CRT6	0.073	0.0718	0.1222

Appendix I

Appendix I.1. AHP Method

In the first step of the AHP method, the priorities among the criteria are determined through a pairwise comparison matrix. This matrix is constructed based on expert opinions using Table 1 [15]. Based on this scale, each criterion is compared with the others in the matrix and scored accordingly. This matrix (Z) is shown in Equation (A1).

Table A10. Saaty's pairwise comparisons scale.

Importance Level	Definition
1	Equal Importance
3	Less Importance
5	Strong Importance
7	Very strong Importance
9	Extreme Importance
2,4,6,8	Intermediate Values

$$Z_{ij} = \begin{bmatrix} z_{11} & \cdots & z_{1n} \\ \vdots & \ddots & \vdots \\ z_{n1} & \cdots & z_{nn} \end{bmatrix} \quad \text{(A1)}$$

In the second step, a normalization process is performed. The pairwise comparison matrix constructed in the first step is normalized using Equation (A2). In this process, each element in the matrix is divided by the sum of the values in its respective column.

$$b_{ij} = \frac{a_{ij}}{\sum_{i=1}^{a} a_{ij}} \quad \text{(A2)}$$

In the third step, the eigenvector is determined using Equation (A3). At this stage, following the normalization of the pairwise comparison matrix, the eigenvector—which represents the relative importance of each criterion with respect to the others—is calculated. Accordingly, weights of the criteria are determined in this step as well.

$$W_i = \frac{\sum_{j=1}^{a} b_{ij}}{n} \quad \text{(A3)}$$

In the fourth step, the consistency of the values obtained through pairwise comparisons is evaluated. In an AHP procedure, the consistency ratio (CR) is calculated using Equation (A4). A CR value less than 0.1 indicates consistency in the decision-making process.

$$CR = \frac{CI}{RI} \tag{A4}$$

The column vector obtained from the Z·w operation is divided elementwise by the priority vector w. To calculate the maximum of eigenvalue (λ_{max}), firstly, the pairwise comparison matrix (Z) must be multiplied by the priority vector (w). Then, the λ values are calculated by dividing the column vector formed by the eigenvalues by the priority vector. The arithmetic means of the λ values obtained for each row will yield the λ_{max} value. The RI value is the standard correction value provided in Table 2 based on the number of criteria (n). And the consistency index (CI) is calculated using Equation (A5). For calculating CI, the maximum eigenvalue should be calculated using Equation (A6).

$$CI = \frac{(\lambda_{max} - n)}{n - 1} \tag{A5}$$

$$\lambda_{max} = \frac{\sum_{j=1}^{n} a_{ij}.w_j}{w_i} \tag{A6}$$

Table A11. Random index values.

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

A CR value less than 0.10 is expected. A result greater than this indicates a calculation error in the AHP process or inconsistency in the decision-maker's pairwise comparisons. In such cases, it is necessary to return to the first step.

Appendix I.2. ARAS Method

This method is a MCDM method that ranks decision alternatives based on their utility function subject to criteria [37].

Step 1: The decision matrix is constructed by assigning the alternatives to rows and the criteria to columns, as shown in Equation (A7). Unlike other methods, the decision matrix formed in this approach includes an additional row consisting of the optimal values corresponding to each criterion.

$$X_{ij} = \begin{bmatrix} x_{11} & \dots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \dots & x_{mn} \end{bmatrix} \qquad i = 0, 1, 2, \dots m \;\; ; \;\; j = 0, 1, 2, \dots n \tag{A7}$$

In the decision matrix X, x_{ij}: denotes the performance value of *i*th the alternative with respect to the *j*th criterion. Here, m represents the number of alternatives to be evaluated, and n indicates the number of criteria. x_{1j} refers to the optimal value of the *j*th criterion.

Step 2: If the optimal value of the *j*th criterion is unknown, Equation (A8) is employed.

$$\begin{cases} Eğer & mak_i x_{ij} \quad ise \quad x_{0j} = mak_i x_{ij} \\ Eğer & min_i x^*_{ij} \quad ise \quad x_{0j} = min_i x^*_{ij} \end{cases} \tag{A8}$$

Step 3: In most evaluations, the criteria used may vary in terms of dimensions and scales. At this stage, criteria with different dimensions are normalized to achieve a stan-

dardized form. As a result, all criteria are transformed to values within the [0, 1] interval. For normalization, Equation (A9) is applied to criteria where higher values are preferred, while Equation (A10) is used for criteria where lower values are desired.

$$\overline{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \tag{A9}$$

$$\overline{x}_{ij} = \frac{\frac{1}{x_{ij}}}{\sum_{i=0}^{m} \frac{1}{x_{ij}}} \tag{A10}$$

The normalized decision matrix is constructed as shown in Equation (A11):

$$A_{ij} = \begin{bmatrix} \overline{x}_{01} & \cdots & \overline{x}_{0n} \\ \vdots & \ddots & \vdots \\ \overline{x}_{m1} & \cdots & \overline{x}_{mn} \end{bmatrix} \tag{A11}$$

Step 4: The criterion weights w_{ij} range between 0 and 1, with the sum of all weights equating to 1. The normalized weights are calculated using Equation (A12). In Equation (A12), w_j represents the weight (importance level) of the jth criterion, and $\overline{x}_{ij}$ represents the normalized value of the jth criterion for the ith alternative. Based on the weighted decision matrix Equation (A13), the optimality function value of each alternative is computed using Equation (A14). In this context, S_i denotes the optimality function value corresponding to the ith decision alternative. The alternative with the highest S_i value is considered the most favorable, whereas the one with the lowest S_i value is deemed the least favorable. Accordingly, a higher S_i value indicates a more effective decision alternative.

$$\overline{\overline{x}}_{ij} = \overline{x}_{ij} w_j \quad \mathrm{i} = 0, 1, \ldots, \mathrm{m} \tag{A12}$$

$$A_{ij} = \begin{bmatrix} \overline{\overline{x}}_{01} & \cdots & \overline{\overline{x}}_{0n} \\ \vdots & \ddots & \vdots \\ \overline{\overline{x}}_{m1} & \cdots & \overline{\overline{x}}_{mn} \end{bmatrix} \tag{A13}$$

$$S = \sum_{j=1}^{n} x_{ij} \quad i = 0, 1, \ldots, m \tag{A14}$$

Step 5: The benefit degree, denoted as *Ki*, is determined by Equation (A15). By ranking the *Ki* values in descending order, the decision alternatives can be systematically prioritized from the most to the least favorable.

$$K = \frac{S_i}{S_0} \qquad \mathrm{i} = 0, \ldots, \mathrm{m} \tag{A15}$$

Appendix I.3. MOORA Ratio Approach

The MOORA ratio system approach is employed, in which the response of each alternative to a specific objective is normalized by a denominator that represents the collective performance of all alternatives with respect to that objective [38].

Step 1: The decision matrix is constructed to include the criteria, the corresponding criterion weights, and the alternatives, as presented in Equation (A16):

$$X_{ij} = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \tag{A16}$$

Criteria for which higher values have a negative impact are subjected to minimization, whereas criteria for which higher values have a positive impact are subjected to maximization.

Step 2: Let i = 1, 2, . . ., m denote the number of alternatives and j = 1, 2, . . ., n represent the number of criteria. Given i = 1, 2, . . ., m as the number of alternatives and j = 1, 2, . . ., n as the number of criteria, the normalization process is carried out according to the formula in Equation (A17):

$$x_{ij}* = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} {x_{ij}}^2}} \tag{A17}$$

x_{ij}^*; denotes the normalized value of the ith alternative with respect to the jth criterion. While $x_{ij}^* \in [0, 1]$, in general, in some cases it may fall within the range $x_{ij}^* \in [-1, 1]$.

Step 3: After this normalization process, the sum of the normalized minimum performance values is subtracted from the sum of the normalized maximum performance values. Let j = 1, 2, . . ., h represent the objectives to be maximized, and j = h + 1, h + 2, . . ., n represent the objectives to be minimized; then the expression can be written by Equation (A18) as follows:

$$y_i^* = \sum_{j=1}^{h} x_{ij}^* - \sum_{j=g+1}^{n} x_{ij}^* \tag{A18}$$

y_i^* represents the normalized value of alternative i with respect to all objectives. The method is completed by ranking the y_i^* values. According to this ranking, the alternative ranked first is identified as the most suitable option.

Appendix I.4. ELECTRE Method

The ELECTRE method is characterized as an approach based on the concept of outranking relationships [39]. The ELECTRE method is explained as follows.

Step 1: The decision matrix B is constructed, where the rows correspond to the alternatives to be evaluated, and the columns correspond to the evaluation criteria to be used in decision-making. This matrix is denoted as shown in Equation (A19):

$$B_{ij} = \begin{bmatrix} b_{11} & \dots & b_{1n} \\ \vdots & \ddots & \vdots \\ b_{m1} & \dots & b_{mn} \end{bmatrix} \tag{A19}$$

Step 2: During the normalization of matrix B, different normalization formulas are applied for cost and benefit criteria. For cost criteria, Equation (A20) is used:

$$c_{ij} = \frac{\frac{1}{r_{ij}}}{\sqrt{\sum_{i=1}^{m} (\frac{1}{r_{ij}})^2}} \qquad i = 1, 2, \dots, m \quad j = 1, 2, \dots, n \tag{A20}$$

For benefit criteria, Equation (A21) is used:

$$c_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{n} {r_{ij}}^2}} \qquad i = 1, 2, \dots, m \quad j = 1, 2, \dots, n \tag{A21}$$

Equation (A22) represents the normalized decision matrix:

$$C_{ij} = \begin{bmatrix} c_{11} & \dots & c_{1n} \\ \vdots & \ddots & \vdots \\ c_{m1} & \dots & c_{mn} \end{bmatrix} \tag{A22}$$

Step 3: The weights (w_i) associated with each evaluation criterion are determined. The normalized matrix is then multiplied by these weights to obtain the weighted normalized matrix, as presented with Equation (A23). Equation (A24) represents the weighted normalized decision matrix:

$$d_{ij} = w_j * c_{ij} \tag{A23}$$

$$D_{ij} = \begin{bmatrix} d_{11} & \cdots & d_{1n} \\ \vdots & \ddots & \vdots \\ d_{m1} & \cdots & d_{mn} \end{bmatrix} \tag{A24}$$

Step 4: For each pairwise comparison of alternatives, the criteria are classified into two distinct sets. If alternative B_p is preferred over B_q with respect to a given criterion j, it is included in the concordance set, defined in Equation (A25):

$$X(p,q) = \left\{ j, \qquad d_{ej} \geq d_{fj} \right\} \tag{A25}$$

If B_p is a worse alternative than B_q the discordance set is constructed, defined in Equation (A26):

$$Y(p,q) = \left\{ j, \qquad d_{ej} < d_{fj} \right\} \tag{A26}$$

The concordance set j$*$ is defined as the set of criteria j for which alternative B_p is at least as good as B_q, i.e., the elements contained in X(p,q). The concordance set j$*$ consists of the elements included in X(p,q). The discordance set j_0 is defined as the set of criteria j for which alternative B_p performs worse than B_q, i.e., the elements contained in Y(p,q). The discordance set j_0 consists of the elements included in Y(p,q).

Step 5: The concordance matrix (X) is constructed based on the concordance sets using the formulation in Equation (A27):

$$X_{pq} = \sum_{j^*} w_{j^*} \tag{A27}$$

Similarly, the discordance matrix (Y) is derived from the discordance sets, and its elements are calculated using Equation (A28):

$$Y_{pq} = \frac{\left(\sum_{j^0} \left| v_{pj^0} - v_{qj^0} \right| \right)}{\sum_j |v_{pj} - v_{qj}|} \tag{A28}$$

Step 6: The concordance dominance matrix is established by first computing a threshold value, defined as the average of all concordance indices (Equation (A29)). The elements of the concordance matrix are then compared against this threshold using Equation (A30). A parallel procedure is employed to construct the discordance dominance matrix using Equations (A31) and (A32). The final dominance scores are obtained by multiplying the corresponding elements of the concordance and discordance dominance matrices.

$$X_{threshold} = \frac{1}{m(m-1)} \sum_{a=1}^{m} \sum_{b=1}^{m} x_{ab} \tag{A29}$$

$$t_{ab} = \begin{cases} t_{ab} = 1 & x_{ab} \geq X_{threshold} \\ t_{ab} = 0 & x_{ab} < X_{threshold} \end{cases} \tag{A30}$$

$$Y_{threshold} = \frac{1}{m(m-1)} \sum_{a=1}^{m} \sum_{b=1}^{m} y_{ab} \tag{A31}$$

$$z_{ab} = \begin{cases} z_{ab} = 1 & y_{ab} \geq Y_{threshold} \\ z_{ab} = 0 & y_{ab} < Y_{threshold} \end{cases} \quad \text{(A32)}$$

Step 7: In scenarios where multiple alternatives surpass a given alternative, net concordance and net discordance scores are computed for the purpose of ranking. These scores are calculated as described in Equations (A33) and (A34), with alternatives ordered in descending order of X_p values and ascending order of Y_p values, respectively.

$$X_p = \sum_{\substack{k=1 \\ k=p}}^{m} X_{pk} - \sum_{\substack{k=1 \\ k=p}}^{m} X_{kp} \quad \text{(A33)}$$

$$Y_p = \sum_{\substack{k=1 \\ k=p}}^{m} Y_{pk} - \sum_{\substack{k=1 \\ k=p}}^{m} Y_{kp} \quad \text{(A34)}$$

References

1. Goswami, S.S.; Behera, D.K. Solving material handling equipment selection problems in an industry with the help of entropy integrated COPRAS and ARAS MCDM techniques. *Process Integr. Optim. Sustain.* **2021**, *5*, 947–973. [CrossRef]
2. Chakraborty, S.; Saha, A.P. Selection of forklift unit for transport handling using integrated MCDM under Neutrosophic environment. *Facta Univ. Ser. Mech. Eng.* **2024**, *22*, 235–236. [CrossRef]
3. Dua, T.V. Forklift selection by multi-criteria decision-making methods. *East. Eur. J. Enterp. Technol.* **2023**, *5*, 95–101. [CrossRef]
4. Chakraborty, S.; Banik, D. Design of a material handling equipment selection model using analytic hierarchy process. *Int. J. Adv. Manuf. Technol.* **2006**, *28*, 1237–1245. [CrossRef]
5. Tuzkaya, G.; Gülsün, Ö.; Kahraman, C.; Özgen, D. An integrated fuzzy multi-criteria decision-making methodology for material handling equipment selection problem and an application. *Expert Syst. Appl.* **2010**, *37*, 2853–2863. [CrossRef]
6. Mousavi, S.M.; Vahdani, B.; Tavakkoli-Moghaddam, R.; Tajik, N. Soft computing based on a fuzzy grey group compromise solution approach with an application to the selection problem of material handling equipment. *Int. J. Comput. Integr. Manuf.* **2014**, *27*, 547–569. [CrossRef]
7. Khandekar, A.V.; Chakraborty, S. Selection of Material Handling Equipment Using Fuzzy Axiomatic Design Principles. *Informatica* **2015**, *26*, 259–282. [CrossRef]
8. Chakraborty, S.; Prasad, K. A QFD-based expert system for industrial truck selection in manufacturing organizations. *J. Manuf. Technol. Manag.* **2016**, *27*, 800–817. [CrossRef]
9. Nguyen, H.-T.; Dawal, S.Z.M.; Nukman, Y.; Rifai, A.P.; Aoyama, H. An Integrated MCDM Model for Conveyor Equipment Evaluation and Selection in an FMC Based on a Fuzzy AHP and Fuzzy ARAS in the Presence of Vagueness. *PLoS ONE* **2016**, *11*, e0153222. [CrossRef] [PubMed]
10. Saputro, T.E.; Rouyendegh, B.D. A hybrid approach for selecting material handling equipment in a warehouse. *Int. J. Manag. Sci. Eng. Manag.* **2016**, *11*, 34–48. [CrossRef]
11. Varun, S.; Harshita, R.; Pramod, S.; Nagaraju, D. Evaluation and selection of material handling equipment in iron and steel industry using analytic hierarchy process. In *Frontiers in Automobile and Mechanical Engineering*; IOP Conference Series: Materials Science and Engineering; IOP Publishing: Bristol, UK, 2017; Volume 197, p. 012060.
12. Nayal, D.; Paul, V.K.; Kumar, K. Selection of Tower Crane using Multi-Criteria Decision-Making Techniques. *Int. J. Eng. Res. Technol.* **2020**, *9*, 31–35.
13. Ulutaş, A.; Karabasevic, D.; Popovic, G.; Stanujkic, D.; Nguyen, P.T.; Karaköy, Ç. Development of a Novel Integrated CCSD-ITARA-MARCOS Decision-Making Approach for Stackers Selection in a Logistics System. *Mathematics* **2020**, *8*, 1672. [CrossRef]
14. Mohamadghasemi, A.; Hadi-Vencheh, A.; Lotfi, F.H.; Khalilzadeh, M. An integrated group FWA-ELECTRE III approach based on interval type-2 fuzzy sets for solving the MCDM problems using limit distance mean. *Complex Intell. Syst.* **2020**, *6*, 355–389. [CrossRef]
15. Hornakova, N.; Jurik, L.; Chovanova, H.H.; Caganova, D.; Babcanova, D. AHP method application in selection of appropriate material handling equipment in selected industrial enterprise. *Wirel. Netw.* **2021**, *27*, 1683–1691. [CrossRef]
16. Ulutaş, A.; Stanujkić, D.; Karabašević, D.; Popović, G.; Novaković, S. Pallet truck selection with MEREC and WISP-S methods. *Strateg. Manag.* **2022**, *27*, 023–029. [CrossRef]
17. Veskovic, S.; Stevic, Z.; Nunic, Z.; Milinkovic, S.; Mladenovic, D. A novel integrated large-scale group MCDM model under fuzzy environment for selection of reach stacker in a container terminal. *Appl. Intell.* **2022**, *52*, 13543–13567. [CrossRef]

18. Fulzele, S.B.; Khatke, S.B.; Kadam, S.J.; Kamble, A.G. Application of multi-attribute decision-making methods for the selection of conveyor. *Soft Comput.* **2022**, *26*, 9873–9881. [CrossRef]
19. Zolfani, S.H.; Görçün, Ö.F.; Küçükönder, H. Evaluation of the Special Warehouse Handling Equipment (Turret Trucks) Using Integrated FUCOM and WASPAS Techniques Based on Intuitionistic Fuzzy Dombi Aggregation Operators. *Arab. J. Sci. Eng.* **2023**, *48*, 15561–15595. [CrossRef]
20. Goswami, S.S.; Behera, D.K. Developing Fuzzy-AHP-Integrated Hybrid MCDM System of COPRAS-ARAS for Solving an Industrial Robot Selection Problem. *Int. J. Decis. Support Syst. Technol.* **2023**, *15*, 1–38. [CrossRef]
21. Yu, J.; Xiao, H.; Sun, F.; Yan, L.; Liu, M. Research on the Safety Evaluation Method for Quayside Container Cranes Based on the Best–Worst Method–Pythagorean Fuzzy VIKOR Approach. *Appl. Sci.* **2024**, *14*, 1312. [CrossRef]
22. Görçün, Ö.F.; Saha, A.; Ecer, F. Evaluation of crawler crane for large-scale construction and infrastructure projects: An intuitionistic fuzzy consensus-based approach. *J. Ind. Inf. Integr.* **2025**, *44*, 100784. [CrossRef]
23. Atanaskovic, P.; Gajic, V.; Dadic, I.; Nikolicic, S. Selection of forklift unit for warehouse operation by applying multi-criteria analysis. *Promet Traffic Transp.* **2013**, *25*, 379–386. [CrossRef]
24. Průsa, P.; Jovcic, S.; Nemec, V.; Mrazec, P. Forklift truck selection using TOPSIS method. *Int. J. Traffic Transp. Eng.* **2018**, *8*, 390–398.
25. Pamučar, D.; Ćirovic, G. The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation area Comparison (MABAC). *Expert Syst. Appl.* **2015**, *42*, 3016–3028. [CrossRef]
26. Fazlollahtabar, H.; Smailbasic, A.; Stevic, Z. Fucom Method in Group Decision-Making: Selection of Forklift in a Warehouse. *Decis. Mak. Appl. Manag. Eng.* **2019**, *2*, 49–65. [CrossRef]
27. Mahmutagić, E.; Stević, Ž.; Nunić, Z.; Chatterjee, P.; Tanackov, I. An integrated decision-making model for efficiency analysis of the forklifts in warehousing systems. *Facta Univ. Ser. Mech. Eng.* **2021**, *19*, 537–553. [CrossRef]
28. Ulutaş, A.; Topal, A.; Karabasevic, D.; Balo, F. Selection of a forklift for a cargo company with fuzzy BWM and fuzzy MCRAT methods. *Axioms* **2023**, *12*, 467. [CrossRef]
29. Huskanović, E.; Stević, Ž.; Simić, S. Objective-Subjective CRITIC-MARCOS Model for Selection Forklift in Internal Transport Technology Processes. *Mechatron. Intell. Transp. Syst.* **2023**, *2*, 20–31. [CrossRef]
30. Fargnoli, M.; Minicis, M.D.; Tronci, M. Design Management for Sustainability: An integrated approach for the development of sustainable products. *J. Eng. Technol. Manag.* **2014**, *34*, 29–45. [CrossRef]
31. Rezaei, J. Best–Worst Multi-Criteria Decision-Making Method. *Omega* **2015**, *53*, 49–57. [CrossRef]
32. Pamučar, D.; Stević, Ž.; Sremac, S. A new model for determining weight coefficients of criteria in MCDM models: Full Consistency Method (FUCOM). *Symmetry* **2018**, *10*, 393. [CrossRef]
33. Shannon, C.E. A mathematical theory of communication. *Bell Syst. Tech. J.* **1948**, *27*, 379–423. [CrossRef]
34. Lee, E.H. eXplainable DEA approach for evaluating performance of public transport origin-destination pairs. *Res. Transp. Econ.* **2024**, *108*, 101491. [CrossRef]
35. Shi, Y.; Charles, V.; Zhu, J. Bank financial sustainability evaluation: Data envelopment analysis with random forest and Shapley additive explanations. *Eur. J. Oper. Res.* **2025**, *321*, 614–630. [CrossRef]
36. Alizamir, M.; Wang, M.; Ikram, R.M.A.; Kim, S.; Ahmed, K.O.; Heddam, S. Developing an efficient explainable artificial intelligence approach for accurate reverse osmosis desalination plant performance prediction: Application of SHAP analysis. *Eng. Appl. Comput. Fluid Mech.* **2024**, *18*, 2422060. [CrossRef]
37. Zavadskas, E.K.; Turskis, Z. A new additive ratio assessment (ARAS) method in multicriteria decision-making. *Technol. Econ. Dev. Econ.* **2010**, *16*, 159–172. [CrossRef]
38. Brauers, W.K.; Zavadskas, E.K. The MOORA method and its application to privatization in a transition economy. *Control Cybern* **2006**, *35*, 445–469.
39. Roy, B. Classement et choix en presence de points de vue multiples (La Methode ELECTRE). *Rev. Inform. Rech. Oper.* **1968**, *2*, 57–75.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.