mathematics

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Ranking of Autonomous Technologies for Sustainable Logistics Activities in the Confectionery Industry

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Abstract: The food supply chain (FSC) faces significant challenges, including the short shelf life of products, stringent food safety standards, and the growing demand for online ordering. These challenges underscore the need for a resilient and sustainable FSC, particularly in the confectionery industry, which is further burdened by the demand for innovative and healthier products. The aim of this paper is to optimize material handling activities in warehouse operations within the confectionery industry by ranking and selecting adequate material handling equipment (MHE). This paper proposes a novel hybrid multi-criteria decision-making model that integrates the Simple Aggregation of Preferences Expressed by Ordinal Vectors Group Decision Making (SAPEVO-M), Fuzzy Analytic Hierarchy Process (FAHP), and Fuzzy COmprehensive distance-Based Ranking (FCOBRA) methods. The model was applied to a real-world case study involving four alternative solutions and twelve defined evaluation criteria. The application of the model identified the implementation of an Automated Guided Vehicle system (AGVs) as the optimal alternative, offering substantial automation of logistics activities and addressing identified company challenges. The engagement of AGVs is estimated to reduce operational costs by 20%, improve warehouse operation efficiency by 30%, and decrease CO_2 emissions by 25%. The contribution of this paper lies in the development of a methodological framework for evaluating and selecting MHE, as well as in highlighting the importance of optimizing material handling processes in the confectionery industry.

Keywords: food supply chain; confectionery industry; automation; material handling; multi-criteria decision-making

MSC: 03B52

Academic Editor: Valério Salomon

Received: 25 December 2024
Revised: 22 January 2025
Accepted: 30 January 2025
Published: 2 February 2025

Citation: Božić, M.; Dabić-Miletić, S.; Andrejić, M.; Djurdjević, D. Ranking of Autonomous Technologies for Sustainable Logistics Activities in the Confectionery Industry. *Mathematics* **2025**, *13*, 498. https://doi.org/10.3390/math13030498

1. Introduction

The supply chain (SC) is a complex system requiring the coordination of numerous participants and resources. Its complexity has been further amplified by urbanization and the growth of e-commerce. As a specific category of SC, the food supply chain (FSC) faces unique challenges, such as the short shelf life of products, the rising volume of online orders, and changing consumer habits [1–3]. A growing number of consumers opting for home food delivery, placing additional strains the FSC. This trend can be attributed to the fast pace of modern life and the impact of global crises, such as the pandemic and the Ukraine crisis, which have significantly altered consumer behavior. According to data from the Statista platform, the international food delivery market is experiencing significant growth. By 2024, this market is expected to generate revenue of USD 1.20 trillion, with an annual growth rate of nearly 10% between 2024 and 2029 [4,5]. Furthermore, FSCs are challenged by the short shelf life of products, stringent food safety standards, and regulatory requirements related to quality. These strict standards are vital to ensure food safety for end consumers [1,2,6]. Current geopolitical circumstances further underscore the importance of FSC resilience, as these SCs now constitute a critical component of the global economic and social structure, ensuring food supply worldwide. Simultaneously, FSCs must address related political and economic factors, social sustainability, and environmental protection. These aspects are increasingly critical for maintaining competitiveness in demanding market conditions [1,2,7].

The confectionery industry plays a crucial role in the functioning of the FSC. Products such as chocolates, ice creams, biscuits, and other sweets are among the most popular consumer goods globally. This industry not only fulfills the demand for such products but also contributes significantly to economic growth. Shifting consumer habits and increasing awareness of healthy eating are shaping the development of the confectionery industry. For instance, the rising demand for organic, gluten-free, and vegan products presents challenges in production and distribution while simultaneously creating opportunities for innovation. Additionally, the industry faces increasing competition from "healthier" alternatives such as fruits and nuts due to heightened consumer awareness of healthy diets. Over the past decade, traditional confectionery products have experienced declining sales in markets like the United States, as consumers move away from items requiring longer consumption times or utensils. According to Nielsen's 2018 report, sales of healthy snacks in the United States increased by approximately 6% compared to the previous year, whereas traditional confectionery products showed a modest growth of just 1.2% [8]. This shift reflects changing consumer preferences toward healthier options. Furthermore, a 2019 study by Mintel revealed that 73% of American consumers considered nuts and dried fruits to be healthier alternatives to traditional sweets, driving their increasing consumption [9]. These findings indicate a grow consumers preference for perceived healthier products, presenting a challenge for traditional confectionery products [8,9]. To remain competitive, confectionery companies are begin pushed to develop new products with reduced sugar content and other healthier alternatives that align with modern consumer demands. Moreover, fluctuations in raw material prices, often driven by global disruptions such as armed conflicts, have a substantial impact on production costs. These price variations force manufacturers to raise prices, further threatening profitability, as even minor price increases can substantially affect profit margins [2,10,11]. To operate successfully in such conditions, confectionery manufacturers must demonstrate agility and flexibility by ensuring the timely procurement of raw materials and the adaptation of production processes to market demands. Although the challenges are substantial, innovation and responsiveness to market trends present opportunities for growth and long-term stability within the FSC. Understanding the confectionery industry's role in the global market is essential for analyzing and improving efficiency, sustainability, and safety in FSC. Identifying the specific challenges and obstacles faced by the confectionery industry facilitates the development of strategic management solutions, contributing to the optimization of the entire FSC [2,5,12].

The FSC encompasses all stages of a traditional SC, including raw material procurement, production, storage, and distribution of finished products. Within the FSC, the confectionery industry stands out due to its specific requirements to product quality, freshness, and safety. Previous research in this field has highlighted key challenges for FSC sustainability, including increasing production capacities. Confectionery products often contain ingredients such as chocolate, sugar, gluten, and other sensitive components that require specific storage and handling conditions to maintain their properties and prevent spoilage. Preserving product quality depends on maintaining appropriate temperature and humidity levels, which presents a significant challenge in the logistics processes of the confectionery industry [13–15].

The confectionery market reached a value of USD 1.1 trillion in 2023, with a projected annual growth rate of nearly 6% for 2023 to 2028. The Asia–Pacific region holds the largest market share, accounting for approximately 40%, with an expected annual growth rate exceeding 5% during the same period [4]. Achieving these growth targets depends heavily on the efficiency of logistics activities, which plays a critical role in cost reduction, delivery time optimization, and ensuring high levels of customer satisfaction. In a highly competitive environment, rapid and accurate order fulfillment is particularly important as consumers increasingly demand freshness, quality, and product personalization. Additionally, effective inventory and SC management allow companies to meet the growing demands for sustainable practices. This includes reducing environmental impacts through optimized routes and the adoption of energy-efficient vehicles and technologies. Consequently, logistics activities become a fundamental pillar for achieving competitive advantage and sustainable growth in the confectionery market [16,17].

Material handling plays a vital role in the logistics activities of the confectionery industry. These activities focus on the efficient movement, storage, and management of raw materials, semi-finished goods, and finished products within production and warehouse spaces. In an industry where product quality and freshness are paramount, effective material handling minimizes the risk of product damage and optimizes packaging, storage, and transportation processes. Material handling has a significant impact on overall logistics costs and delivery times. Within production systems, these activities involve a complex task that presents numerous challenges at both strategic and operational levels. The adoption of appropriate material handling equipment (MHE) enhances the optimization of product and material flow within production facilities, reduces downtime, and minimizes losses [18–20]. Table 1 presents the key challenges in the FSC within the confectionery industry, identified through an analysis of the relevant available literature, with a particular emphasis on material handling as a critical success factor. In Table 1, * indicates which author has considered the analyzed challenges.

Table 1. Critical challenges in FSC.

Authors	Challenges				
	Maintaining Freshness and Quality	**Food Safety**	**Regulations and Standards**	**Demand Variability and Seasonality**	**Materials Handling**
Rizou et al. [2]		*			
Yadav et al. [13]	*	*			*
Machálková et al. [15]				*	
Verghese et al. [21]	*	*			
Nakandala and Lau [22]	*	*			
Khan et al. [23]	*		*		*
Gurrala and Hariga [24]	*		*		*
Gokarn and Kuthambalayan [25]		*		*	
Bhat and Jõudu [26]		*		*	
Astill et al. [27]			*		
Kamilaris and Fonts [28]			*		
Dellino et al. [29]				*	
Abolghasemi et al. [30]				*	
Kumar et al. [31]					*
Malekjani and Jafari [32]					*

The challenges outlined in Table 1 underscore the complexity of managing the FSC within the confectionery industry, with particular emphasis on the critical role of the material handling process. Efficient material handling is essential not only for preserving product quality and freshness but also for reducing costs, minimizing delivery times, and enhancing customer satisfaction. While other challenges exist, such as maintaining food quality and safety, compliance with regulations, and inventory management, material handling remains a pivotal factor that can significantly contribute to FSC optimization. Optimizing material handling activities requires a strategic approach that incorporates the adoption of appropriate MHE and the integration of innovative technologies. These technologies enable us to adapt to evolving market and regulatory demands, ensuring the efficiency and sustainability of operations.

Material handling activities in the confectionery industry are carried out using MHE, which can be manual, mechanized, or automated. The selection and utilization of appropriate MHEs depend on the specific needs of the industry and the requirements of individual processes, with ensuring that the MHE is well-suited to the task being a critical factor. The engagement of unsuitable MHE is responsible for approximately 60% of total product damage occurring during handling, transportation, or storage in the confectionery industry [33]. In other words, more than half of all damages in the FSC can be attributed to the incorrect selection or utilization of MHE. This includes factors such as using the wrong type of MHE, inadequate maintenance, insufficient staff training, or improper application. Furthermore, engagement inadequate MHE can increase overall logistics costs in the FSC by more than 15%, placing additional strain on the efficiency and profitability of the industry [20,34].

The selection of MHE is identified as one of the critical challenges in the confectionery industry. The appropriate engagement of MHE can significantly optimize the entire FSC by reducing costs, improving material flow, and minimizing environmental impact. This paper aims to address this issue by examining how the selection and engagement of MHE influences the efficiency and sustainability of FSC operations in the confectionery industry. The paper's primary scientific contribution lies in the development and application of a hybrid multi-criteria decision-making model to evaluate and rank alternative MHE solutions. Furthermore, the paper contributes by emphasizing the significance of MHE selection and its role in the confectionery industry, alongside providing a comprehensive analysis of FSC dynamics within this sector.

The paper is structured into several sections. Following the introduction, which provides a detailed background of the problem under consideration, Section 2 presents a comprehensive literature review. This section first examines the problem of MHE selection in FSC, with a particular emphasis on manufacturing. It then analyzes the multi-criteria decision-making (MCDM) methods commonly applied in similar studies. Section 3 describes the methodology employed in the MHE selection model. Section 4 focuses on analyzing alternative MHE solutions to enhance logistics activities in the receiving warehouse of the observed company. Here, the results are evaluated and ranked based on the defined criteria, and a sensitivity analysis is conducted to assess the stability of the model and the accuracy of the proposed solution. Section 5 discusses the results and the overall problem-solving framework, highlighting the strengths and limitations of the applied model. Finally, Section 6 concludes the paper by addressing research limitations, theoretical and practical implications, and providing recommendations for future research.

2. Literature Review

The aim of this paper is to enhance the efficiency of the FSC by engagement of appropriate MHE in the production processes of the confectionery industry. Accordingly, the analysis of the relevant literature focuses on research addressing the problem of MHE selection in food production, as well as on the methods and tools utilized in decision-making processes related to this selection. To evaluate the advantages and disadvantages of potentially applicable MHE, this paper adopts an MCDM approach. Consequently, it is essential to examine which methods have been most frequently used in previous research dedicated to the problem of MHE selection.

2.1. Selecting MHE in Food Production

The analysis of research on MHE selection in food production provides an adequate foundation for identifying potential alternative solutions for the analyzed company. A critical review of the available relevant literature offers insights into various categories of MHE and their advantages and disadvantages in the context of the FSC. Based on the findings of the reviewed research, key conclusions and recommendations can be formulated for selecting the most suitable MHE to enhance process efficiency in the analyzed company. Furthermore, the literature review aids in identifying gaps in existing research within this field.

Bader and Rahimifard [16] developed a methodology for selecting robots in food production in a real case study, focusing on material handling and packaging activities. Their research considered three types of robots: articulated, parallel, and cartesian. Alghalayini [17] explored the improvement in material handling systems in a case study of a Swedish company in a dairy production company, aiming to enhance product delivery efficiency. The study focused on selecting suitable MHE by analyzing different types of forklifts. Satoglu and Türkekul [34] addressed the problem of MHE selection in the processing industry, using a case study from a Turkish company. They examined the engagement of various types of forklifts and pallet trucks. Goswami and Behera [20] analyzed the use of robots in the food industry, specifically focusing on three types of robots used for packaging tasks. Panda et al. [35] investigated the engagement of soft robots for automating material handling processes in the food industry. They emphasized that automation of these processes significantly contributes to increased profitability and reduced operational disruptions.

The analysis of the available literature indicates that the selection MHE in food production represents a field with significant research potential. Existing studies on MHE selection in food production have primarily concentrated on specific types of MHE, such as forklifts, AGVs, and robots, but often lack a comprehensive analysis of the full range of MHE applicable in this context. Moreover, current research neglects the specific requirements and challenges of the FSC, leading to incomplete evaluation of this sector. Additionally, a more thorough investigation of environmental factors and workplace safety in the context of MHE selection in food production is warranted. This paper seeks to address these gaps identified in the reviewed literature, contributing to a more holistic understanding of MHE selection in the FSC.

2.2. Analysis of Applied MCDM

In the context of decision-making for MHE selection, various tools and approaches can be utilized. These include analytical methods, algorithms, optimization models, simulations, mathematical programming, MCDM, multi-objective decision-making (MADM), and others. Through the application of MCDM methods, it is possible to objectively evaluate alternatives based on various criteria, facilitating the identification of optimal solutions under the given conditions. In the context of MHE selection in production, this systematic approach enables a better understanding of the different aspects of each alternative and their impact on the overall efficiency and performance of production processes. MCDM methods provide a structured framework for considering multiple criteria, which are often conflicting, in the decision-making process. An analysis of relevant research focuses on identifying various MCDM methods, their application in the selection context, and their relevance to decision-making. Through a literature review, potential gaps are also explored to identify directions for future research and to enhance the application of MCDM methods in decision-making processes.

In recent years, MCDM methods have gained increasing importance in addressing the problem of MHE selection. Various methods are used, such as the Analytic Hierarchy Process (AHP), the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), the VIseKriterijumska Optimizacija i Kompromisno Rešenje (VIKOR), Simple Additive Weighting (SAW), the Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHEE), the ELimination and Choice Expressing Reality (ELECTRE), the Evaluation Based on Distance from Average Solution (EDAS), the Combinative Distance-Based Assessment (CODAS), the Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA), and many others, including combinations of these methods or their development in fuzzy and gray environments. It is essential to review relevant studies in the field of MCDM to determine the significance, advantages, and disadvantages of individual methods, as well as to identify gaps in their application. The application of MCDM methods allows for a comprehensive assessment of the strengths, weaknesses, and limitations of potentially applicable MHE. This paper will combine the methods Simple Aggregation of Preferences Expressed by Ordinal Vectors (SAPEVO-M), Fuzzy AHP (FAHP), and Fuzzy Comprehensive Distance-Based Ranking (FCOBRA). The methods were developed in a fuzzy environment to adequately address the uncertainty and subjectivity often present in the evaluation of criteria and alternatives in real industrial and logistics facilities. The fuzzy approach, which models uncertainty through linguistic variables and fuzzy numbers, enhances the precision and reliability of results and is widely applied not only in logistics and industry but also in fields such as pharmacy, medicine, construction, and others.

The SAPEVO-M method represents an evolution of the original SAPEVO method, which was initially designed solely for scenarios involving a single decision-maker. The updated version accommodates multi-criteria analysis involving multiple decision-makers by incorporating matrix standardization processes. These processes include the adjustment of negative and zero criterion weights, enhancing the consistency of results [36]. The implementation of the SAPEVO-M method involves transforming ordinal preferences between criteria into vectors. Subsequently, criterion weights are calculated by determining the vector values of the matrices. SAPEVO-M offers significant advantages in multi-criteria decision-making, including the ability to incorporate multiple decision-makers and achieve greater result consistency through matrix standardization. Furthermore, the ordinal transformation of preferences enables the integration of subjective evaluations [36,37].

De Almeida et al. [37] tackled the problem of selecting a location for the headquarters of the Brazilian Navy fleet. In their study, the SAPEVO-M method was employed to determine the weights of the criteria, while the VIKOR method was used to select the most suitable location for the fleet. Maêda et al. [36] applied the SAPEVO-M method to evaluate various investment funds based on five criteria, aiming to optimize the distribution of a financial portfolio amidst economic uncertainties brought about by the pandemic. De Siqueira Silva et al. [38], in conjunction with other approaches such as AHP, TOPSIS-2N, and PROMETHEE, utilized the SAPEVO-M method to evaluate and rank different types of trucks. The evaluation was based on key criteria, including cost, reliability, delivery time, and driver comfort.

Parameswaran et al. [39] ranked robotic technologies using Fuzzy Delphi, FAHP, Fuzzy VIKOR, and Fuzzy TOPSIS methods. The Fuzzy Delphi method was applied to identify potentially applicable robots, while the FAHP method was used to determine the relative weights of the criteria. Subsequently, the Fuzzy VIKOR and Fuzzy TOPSIS methods were employed to rank the alternatives. Nguyen et al. [40] utilized FAHP and Fuzzy Additive Ratio Assessment (FARAS) for the ranking and selection of conveyors. FAHP was used to determine the relative weights of the criteria, and FARAS was applied for ranking the alternatives. Zubair et al. [41] employed the AHP method to identify the optimal alternative for selecting MHE in a warehouse. Similarly, Satoglu and Türkekul [34] combined AHP and MOORA methods for forklift selection. AHP was used to calculate the relative weights of the criteria, followed by ranking the alternatives using the MOORA method. Krstić et al. [42] examined which Industry 4.0 technology has the greatest impact on the food industry. Their analysis involved AHP and COBRA methods, with AHP determining the weights of the criteria and COBRA ranking the alternatives. Pavlov et al. [43] evaluated and ranked storage technologies by applying the FAHP method to determine criteria weights and the Weighted Aggregated Sum Product Assessment (WAPAS) method for ranking the alternatives.

Unlike other MCDM methods that rely solely on calculating the distance of alternatives from the optimal solution, the COBRA method employs two distinct metrics: Euclidean and Taxicab distances. These metrics are used to calculate the distance of each alternative from three types of solutions: ideal, anti-ideal, and average. Alternatives are then ranked based on their total distance from these observed solutions. The dual use of distance metrics allows for differentiation between distance values that might otherwise appear similar, thereby enhancing the reliability of decision-making process [44]. Although relatively new, the COBRA method has already been applied to address a variety of problems, demonstrating its versatility and potential for broader adoption.

Popović et al. [45] applied a combination of the Method based on the Effects of Criteria Removal (MEREC) and the COBRA method to select suitable strategies for the development of e-commerce. MEREC was used to define the weights of the criteria, while the COBRA method was employed to evaluate and rank the considered alternatives. Krstić et al. [44] utilized a combination of Fuzzy Delphi, Fuzzy Analytic Network Process (FANP), and FCOBRA methods for the evaluation and ranking of Industry 4.0 technologies in the context of sustainable circular economy systems and circular SC. Fuzzy Delphi and FANP were used to determine the weights of the criteria, while FCOBRA was employed for ranking the alternatives. Oğuz and Satır [46] analyzed the financial performance of retail companies using profitability indicators for the period 2021–2022. In their study, the MEREC method was used to determine the weights of the performance criteria, while the COBRA method was applied to rank the companies. Additionally, a two-stage sensitivity analysis was conducted to validate the stability of the results.

Existing research on decision-making using MCDM methods has primarily focused on individual techniques such as SAPEVO-M, FAHP, and FCOBRA to analyze specific problem aspect. While these methods have proven effective in certain contexts, there is a notable lack of studies integrating these techniques for a comprehensive analysis. Previous research has examined combinations such as SAPEVO-M and FAHP, as well as FAHP and FCOBRA. However, the integration of SAPEVO-M and FCOBRA, along the combination of all three approaches, remains unexplored. This gap in the literature represents a significant opportunity, which this paper seeks to address as its primary scientific contribution. Integration of these methods allows for a deeper understanding and more robust analysis of complex problems, particularly in the context of MHE selection in production under uncertain conditions. By proposing a novel hybrid methodological approach, this study advances the knowledge and methodologies related to MHE selection, addressing a critical gap in the existing literature.

3. Methodology

This research introduces a novel hybrid MCDM model designed to address the ranking and selection of MHE. The proposed model integrates the SAPEVO-M [36], FAHP [47], and FCOBRA methods [44]. The SAPEVO-M method is utilized to determine the weights of sub-criteria. Next, the FAHP method is applied to compare criteria and consolidate their weights. Finally, the FCOBRA method is used to rank the alternatives. The incorporation of methods developed within a fuzzy environment makes this model particularly suited for imprecise data, interval grades, and other uncertainties often encountered in decision-making processes. Figure 1 presents a flowchart of the methodology, providing a clear and concise overview of the steps involved in the application of the SAPEVO-M, FAHP, and FCOBRA methods. The diagram illustrates the key stages of the process, from problem definition to the evaluation and ranking of alternatives.

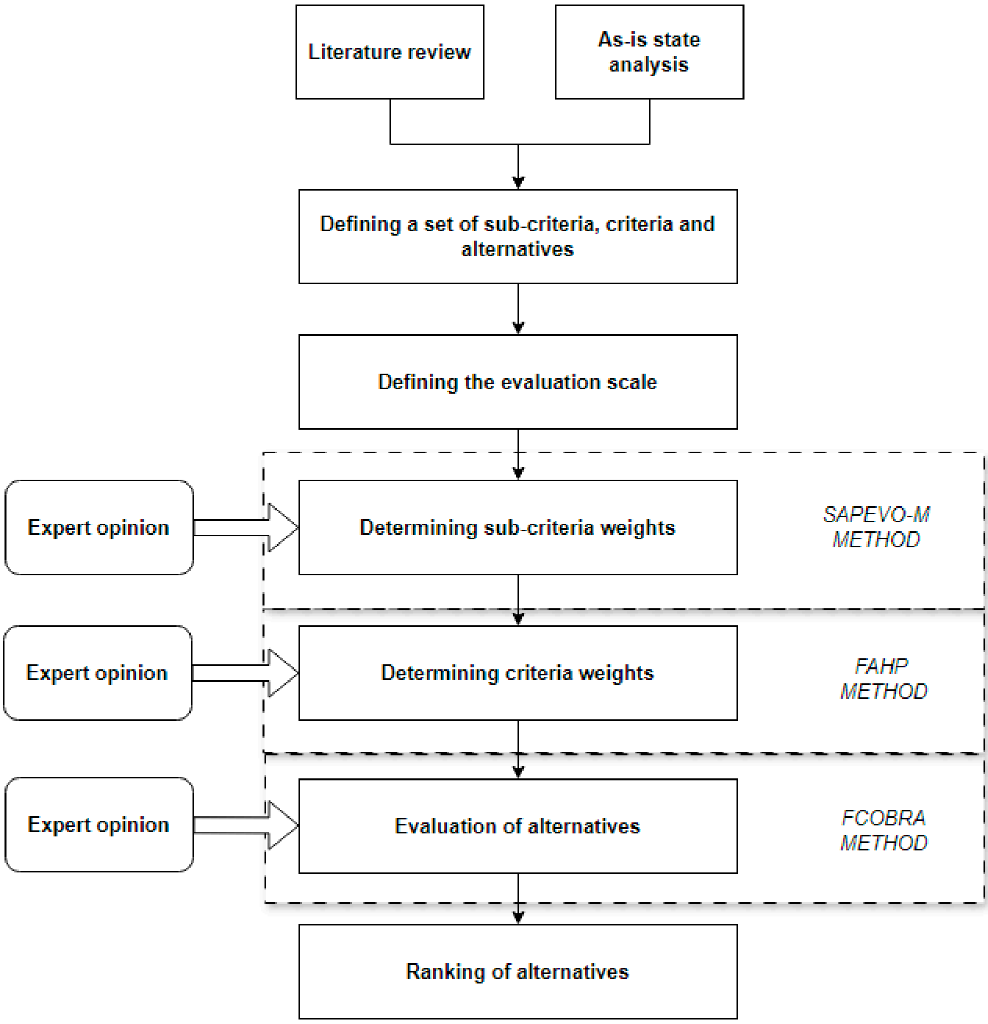

Figure 1. Flowchart of the proposed model.

The below text provides a detailed step-by-step description of the methodology that will complement the visual representation in Figure 1.

Step 1: Define the problem structure

The problem is structured hierarchically following the principles of the AHP method. The structure involves defining the goal, criteria, sub-criteria, and alternatives. The linguistic ratings and their corresponding triangular fuzzy numbers, used to evaluate the elements, are presented in Table 2.

Table 2. Fuzzy scale for the comparison of sub-criteria/criteria/alternatives.

Linguistic Term	Fuzzy Scales
Absolutely preferable/better (AP/B)	(8,9,10)
Very preferable/better (VP/B)	(7,8,9)
Strongly preferable/better (SP/B)	(6,7,8)
Pretty preferable/better (PP/B)	(5,6,7)
Quite preferable/better (QP/B)	(4,5,6)
Moderately preferable/better (MP/B)	(3,4,5)
Remotely preferable/better (RP/B)	(2,3,4)
Barely preferable/better (BP/B)	(1,2,3)
Equally important/good (EI/G)	(1,1,2)

Step 2: Defining criteria preferences

In this step, within the SAPEVO-M method, decision-makers compare the criteria with to determine the relative preferences. Based on the defined set of criteria i and j the decision-maker establishes the prefences of the criteria. The preferences are expressed through general elements (δ_{ij}), where

- $\delta_{ij} = 1$—criteria i and j are equally important $(i \sim= j)$;
- $\delta_{ij} > 1$—criterion i is slightly more important than criterion j $(i > j)$;
- $\delta_{ij} \geq 1$—criterion i is moderately more important than criterion j $(i \geq j)$;
- $\delta_{ij} \gg 1$—criterion i is significantly more important than criterion j $(i \gg j)$;
- $\delta_{ij} < 1$—criterion i is less important than criterion j $(i < j)$;
- $\delta_{ij} \leq 1$—criterion i is moderately less important than criterion j $(i \leq j)$;
- $\delta_{ij} \ll 1$—criterion i is significantly less important than criterion j $(i \ll j)$.

This step enables decision-making based on the comparison of criteria with each other, using ordinal scales to assess their relative importance.

Step 3: Transformation of ordinal preferences into cardinal values

In step 3, the SAPEVO-M method utilizes a scale to represent the preferences of criteria. These preferences are defined based on the relationships outlined in Table 3.

Table 3. SAPEVO-M criteria preference scale.

Relationship	Scale
$\ll 1$	−3
≤ 1	−2
<1	−1
$=1$	0
>1	1
≥ 1	2
$\gg 1$	3

Step 4: Aggregation of Decision Makers' preferences

In this step, the SAPEVO-M method aggregates the preferences of the decision-makers, enabling this the transformation of the matrix $DM^k = [\delta_{ij}]$ into the column vector $[V_i]$. This transformation is performed using the equation provided. V_i represents the aggregated preferences of the criteria, facilitating their analysis and use in the subsequent steps of the method.

$$VDM_i^k = \sum_{i=1}^{n} \sum_{j=1}^{m} \delta_{ij}, \tag{1}$$

- i, j—the number of criteria
- k—the number of decision-makers

Step 5: Normalization

After obtaining the vector with the ratings from the decision-makers, the normalization of each vector will be carried out in the following manner:

$$V = \frac{a_{ij} - \min_{a_{ij}}}{\max_{a_{ij}} - \min_{a_{ij}}}, \tag{2}$$

Step 6: Calculating the sub-criteria weights

According to convention, if the weight of a criterion is equal to zero, it is assigned a value equivalent to 1% of the next highest weight. The final weight of each criterion is then calculated by summing the partial weights provided by the decision-makers:

$$\omega_c = \sum_{i=1}^{n} \sum_{l=1}^{k} a_{il}, \tag{3}$$

Step 7: Pairwise comparison of criterion and formation of the fuzzy matrix $\tilde{\in}$

In this step, the fuzzy matrix used in the FAHP method for pair-wise comparison is defined. A matrix is formed for each set of criteria that are compared with each other.

$$\tilde{\in} = \begin{bmatrix} \tilde{a}_{11} & \cdots & \tilde{a}_{in} \\ \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \cdots & \tilde{a}_{nn} \end{bmatrix}, \tag{4}$$

Step 8: Determining the relative weight of the criteria

A priority vector is computed for each comparison W; $W = (w_1, \ldots, w_n) > 0$, $\sum_{j=1}^{n} w_j = 1$. The value of the vector W in the FAHP method can be calculated using various techniques and methods. For the purposes of this paper, the "Logarithmic Fuzzy Preference Programming" (LFPP) method developed by Wang and Chin [48] was chosen. Each triangular fuzzy number is defined as follows: $\tilde{\alpha}_{ij} = (l_{ij}, m_{ij}, u_{ij})$. The LFPP method is based on the calculation of the logarithmic function of the fuzzy number, as follows:

$$\ln \tilde{a}_{ij} \approx (\ln l_{ij}, \ln m_{ij}, \ln u_{ij}); i, j = 1, \ldots, n, \tag{5}$$

$$\mathrm{MinJ} = (1 - \lambda)^2 + M \times \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \left(\delta_{ij}^2 + \eta_{ij}^2\right), \tag{6}$$

$$\text{s.t.} \begin{cases} x_i - x_j - \lambda \ln (m_{ij}/l_{ij}) + \delta_{ij} \geq \ln l_{ij}, i = 1, \ldots, n-1; j = i+1, \ldots, n \\ -x_i + x_j - \lambda \ln (u_{ij}/m_{ij}) + \eta_{ij} \geq -\ln u_{ij}, i = 1, \ldots, n-1; j = i+1, \ldots, n \\ \lambda, y_i \geq 0, \ i = 1, \ldots, n \\ \delta_{ij}, \eta_{ij} \geq 0, \ i = 1, \ldots, n-1; j = i+1, \ldots, n \end{cases}, \tag{7}$$

where

- $y_i^*(i = 1, \ldots, n)$—optimal solution;
- $M = 10^3$—a specified sufficiently large.

Non-negative variables are defined to prevent the membership degree λ from taking a negative value δ_{ij} i η_{ij} to $i = 1, \ldots, n-1; j = i+1, \ldots, n$ in order to fulfill the following inequalities:

$$\ln w_i - \ln w_j - \lambda \ln \left(\frac{m_{ij}}{l_{ij}} \right) + \delta_{ij} \geq \ln l_{ij},\ i = 1, \ldots, n-1; j = i+1, \ldots, n, \quad (8)$$

$$-\ln w_i + \ln w_j - \lambda \ln \left(m_{ij}/l_{ij} \right) + \eta_{ij} \geq -\ln u_{ij},\ i = 1, \ldots, n-1; j = i+1, \ldots, n, \quad (9)$$

The crisp normalized priority vector of the matrix $\widetilde{A} = \left(\widetilde{a}_{ij} \right)_{n \times m}$ can be obtained as follows:

$$W_i^* = \frac{exp(x_i^*)}{\sum_{j=1}^{n} exp\left(x_j^*\right)},\ i = 1, \ldots n, \quad (10)$$

where

$$exp(x_i^*) = e^{x_i^*}, \quad (11)$$

The stability of results is controlled by calculating the Consistency Ratio (CR) for each matrix [49]:

$$CR = \frac{CI}{RI}, \quad (12)$$

where the Consistency Index (CI) is calculated as

$$CI = \frac{Z_{max} - 0}{0 - 1}, \quad (13)$$

and the Random Index (RI) depends on the matrix size and is given in Saaty [50]. Z_{max} in Equation (13) stands for the principal eigenvalue of the matrix $\widetilde{\in}$. CR values need to be less than 0.10 for all comparisons.

Step 9: Integration of sub-criteria and criteria weights W_{ij}

$$W_{ij} = W_i^* * w_j, \quad (14)$$

- W_i^*—criterion weight;
- w_j—sub-criterion weight.

Step 10: Formation of the fuzzy matrix $\widetilde{\mathbf{F}}$

In the second part of the model, FCOBRA is applied to rank the alternatives. After calculating the relative weights using the FAHP method, the input parameters for the FCOBRA method must be defined. This involves forming a matrix that compares the alternatives against all criteria.

$$\widetilde{F} = \left[\begin{pmatrix} \widetilde{f}_{11} & \cdots & \widetilde{f}_{1o} \\ \vdots & \ddots & \vdots \\ \widetilde{f}_{p1} & \cdots & \widetilde{f}_{po} \end{pmatrix} \right], \quad (15)$$

where $\widetilde{f}_{kj} = \left(l_{kj}, m_{kj}, u_{kj} \right)$ are the evaluations of the alternatives $k(i = 1, \ldots, p)$ in relation to the criteria $j(j = 1, \ldots, o)$ that are obtained using the scale given in Table 2; p is the total number of the alternatives taken into consideration; o is the total number of criteria; and l_{kj}, m_{kj}, u_{kj} are the lower, middle and upper values of the triangular fuzzy number $\widetilde{f}_{kj}$, respectively.

Step 11: Normalization of the fuzzy matrix

The normalized fuzzy matrix is obtained as follows:

$$\widetilde{\Phi} = \left[\widetilde{\varphi}_{kj}\right]_{p\times o}, \tag{16}$$

where is $\widetilde{\varphi}_{kj} = \left(\alpha_{kj}, \theta_{kj}, \rho_{kj}\right)$ is the normalization triangular fuzzy number, whose values are obtained as follows:

$$\alpha_{kj} = \frac{l_{kj}}{\left(\max\limits_{k} u_{kj}\right)}, \forall k = 1, \ldots, p; \forall j = 1, \ldots, o\text{—lowervaluesfuzzynumber}, \tag{17}$$

$$\theta_{kj} = \frac{m_{kj}}{\left(\max\limits_{k} u_{kj}\right)}, \forall k = 1, \ldots, p; \forall j = 1, \ldots, o\text{—middlevaluesfuzzynumber}, \tag{18}$$

$$\rho_{kj} = \frac{u_{kj}}{\left(\max\limits_{k} u_{kj}\right)}, \ \forall k = 1, \ldots, p; \ \forall j = 1, \ldots, o\text{—uppervaluesfuzzynumber}, \tag{19}$$

Step 12: Weighted normalized fuzzy decision matrix $\widetilde{\Phi}_w$

After normalization, by multiplying the matrix with the relative weight of the criteria (w_j) that are obtained via the FAHP method, a weighted fuzzy matrix is obtained, and its mathematical notation is as follows:

$$\widetilde{\Phi} = \left[\widetilde{\varphi}_{kj}\right]_{p\times o}, \tag{20}$$

Step 13: Determination of fuzzy ideal, fuzzy anti-ideal and fuzzy average solutions

For each criterion function, the fuzzy ideal ($\widetilde{PIS}_j$), fuzzy anti-ideal ($\widetilde{NIS}_j$) and fuzzy average solution ($\widetilde{AS}_j$) are determined as follows:

$$\widetilde{PIS}_j = \left(\alpha_{kj}^{PIS}, \theta_{kj}^{PIS}, \rho_{kj}^{PIS}\right) = \left(\max_k\left(w_j \times \alpha_{kj}\right), \max_k\left(w_j \times \theta_{kj}\right), \max_k\left(w_j \times \rho_{kj}\right)\right), \ \forall j = 1, \ldots, o \ for \ j \in J^B, \tag{21}$$

$$\widetilde{PIS}_j = \left(\alpha_{kj}^{PIS}, \theta_{kj}^{PIS}, \rho_{kj}^{PIS}\right) = \left(min_k\left(w_j \times \alpha_{kj}\right), min_k\left(w_j \times \theta_{kj}\right), min_k\left(w_j \times \rho_{kj}\right)\right), \ \forall j = 1, \ldots, o \ for \ j \in J^C, \tag{22}$$

$$\widetilde{NIS}_j = \left(\alpha_{kj}^{PIS}, \theta_{kj}^{PIS}, \rho_{kj}^{PIS}\right) = \left(\min_k\left(w_j \times \alpha_{kj}\right), \min_k\left(w_j \times \theta_{kj}\right), \min_k\left(w_j \times \rho_{kj}\right)\right), \ \forall j = 1, \ldots, o \ for \ j \in J^B, \tag{23}$$

$$\widetilde{NIS}_j = \left(\alpha_{kj}^{PIS}, \theta_{kj}^{PIS}, \rho_{kj}^{PIS}\right) = \left(\max_k\left(w_j \times \alpha_{kj}\right), \max_k\left(w_j \times \theta_{kj}\right), \max_k\left(w_j \times \rho_{kj}\right)\right), \ \forall j = 1, \ldots, o \ for \ j \in J^C, \tag{24}$$

$$\widetilde{AS}_j = \left(\alpha_{kj}^{AS}, \theta_{kj}^{AS}, \rho_{kj}^{AS}\right) = \left(\operatorname*{mean}_k\left(w_j \times \alpha_{kj}\right), \operatorname*{mean}_k\left(w_j \times \theta_{kj}\right), \operatorname*{mean}_k\left(w_j \times \rho_{kj}\right)\right), \ \forall j = 1, \ldots, o \ for \ j \in J^B, J^B, \tag{25}$$

Step 14: Determining the distance of the alternative from the fuzzy ideal, fuzzy anti-ideal and fuzzy average solutions

For each alternative, it is necessary to determine the distance of the alternative from the fuzzy ideal $\left(d\left(\widetilde{PIS}_j\right)\right)$, fuzzy anti-ideal $\left(d\left(\widetilde{NIS}_j\right)\right)$, fuzzy positive average $\left(d\left(\widetilde{AS}_j\right)^+\right)$ and fuzzy negative average $\left(d\left(\widetilde{AS}_j\right)^-\right)$ solutions, as follows:

$$d\left(\widetilde{S}_j\right) = dE\left(\widetilde{S}_j\right) + \xi \times dE\left(\widetilde{S}_j\right) \times dT\left(\widetilde{S}_j\right) \forall_j = 1, \ldots, o, \tag{26}$$

where

$\widetilde{S}_j$ is any solution $\left(\widetilde{PIS}_j, \widetilde{NIS}_j, or\ \widetilde{AS}_j\right)$, and ξ is the correction coefficient obtained as follows:

$$\xi = \max_k dE\left(\widetilde{S}_j\right)_k - \min_k dE\left(\widetilde{S}_j\right)_k, \tag{27}$$

$dE\left(\widetilde{S}_j\right)$i and $dT\left(\widetilde{S}_j\right)$ denote the Euclidian and taxicab distances, respectively, which are for the positive ideal solution, obtained as follows:

$$dE\left(\widetilde{PIS}_j\right)_k = \sum_{j=1}^{o} \sqrt{\left(\left(\alpha_{kj}^{PIS} - w_j \times \alpha_{kj}\right)^2 + 4 \times \left(\theta_{kj}^{PIS} - w_j \times \theta_{kj}\right)^2 + \left(\rho_{kj}^{PIS} - w_j \times \rho_{kj}\right)^2\right)/6}, \ \forall k = 1, \ldots, p;\ \forall j = 1, \ldots, o, \tag{28}$$

$$dT\left(\widetilde{PIS}_j\right)_k = \sum_{j=1}^{o} \sqrt{\left(\left|\alpha_{kj}^{PIS} - w_j \times \rho_{kj}\right|^2 + 4 \times \left|\theta_{kj}^{PIS} - w_j \times \theta_{kj}\right|^2 + \left|\rho_{kj}^{PIS} - w_j \times \alpha_{kj}\right|^2\right)/6}, \ \forall k = 1, \ldots, p;\ \forall j = 1, \ldots, o, \tag{29}$$

The anti-ideal solution is obtained as follows:

$$dE\left(\widetilde{NIS}_j\right)_k = \sum_{j=1}^{o} \sqrt{\left(\left(\alpha_{kj}^{NIS} - w_j \times \alpha_{kj}\right)^2 + 4 \times \left(\theta_{kj}^{NIS} - w_j \times \theta_{kj}\right)^2 + \left(\rho_{kj}^{NIS} - w_j \times \rho_{kj}\right)^2\right)/6}, \ \forall k = 1, \ldots, p;\ \forall j = 1, \ldots, o, \tag{30}$$

$$dT\left(\widetilde{NIS}_j\right)_k = \sum_{j=1}^{o} \sqrt{\left(\left|\alpha_{kj}^{NIS} - w_j \times \rho_{kj}\right|^2 + 4 \times \left|\theta_{kj}^{NIS} - w_j \times \theta_{kj}\right|^2 + \left|\rho_{kj}^{NIS} - w_j \times \alpha_{kj}\right|^2\right)/6}, \ \forall k = 1, \ldots, p;\ \forall j = 1, \ldots, o, \tag{31}$$

The positive distance from the average solution is obtained as follows:

$$dE\ \left(\widetilde{AS}_j\right)_k^+ = \sum_{j=1}^{o} \sqrt{\left(\tau^+\left(\alpha_{kj}^{AS} - w_j \times \alpha_{kj}\right)^2 + 4 \times \tau^+\left(\theta_{kj}^{AS} - w_j \times \theta_{kj}\right)^2 + \tau^+\left(\rho_{kj}^{AS} - w_j \times \rho_{kj}\right)^2\right)/6}, \ \forall k = 1, \ldots, p;\ \forall j = 1, \ldots, o, \tag{32}$$

$$T\left(\widetilde{AS}_j\right)_k^+ = \sum_{j=1}^{o}\sqrt{\left(\tau^+\left|\alpha_{kj}^{AS} - w_j\times\rho_{kj}\right|^2 + 4\times\tau^+\left|\theta_{kj}^{AS} - w_j\times\theta_{kj}\right|^2 + \tau^+\left|\rho_{kj}^{AS} - w_j\times\alpha_{kj}\right|^2\right)/6},\ \forall k = 1,\ldots,p;\ \forall j = 1,\ldots o, \quad (33)$$

where

$$\tau^+ = \begin{cases} 1\ if\ \widetilde{AS} < w_j\times\varphi_{kj} \\ 0\ if\ \widetilde{AS} > w_j\times\varphi_{kj} \end{cases}, \quad (34)$$

The negative distance from the average solution is obtained as follows:

$$dE\left(\widetilde{AS}_j\right)_k^- = \sum_{j=1}^{o}\sqrt{\left(\tau^-\left(\alpha_{kj}^{AS} - w_j\times\alpha_{kj}\right)^2 + 4\times\tau^-\left(\theta_{kj}^{AS} - w_j\times\theta_{kj}\right)^2 + \tau^-\left(\rho_{kj}^{AS} - w_j\times\rho_{kj}\right)^2\right)/6},\ \forall k = 1,\ldots,p;\ \forall j = 1,\ldots,o, \quad (35)$$

$$dT\left(\widetilde{AS}_j\right)_k^- = \sum_{j=1}^{0}\sqrt{\left(\tau^-\left|\alpha_{kj}^{AS} - w_j\times\rho_{kj}\right|^2 + 4\times\tau^-\left|\theta_{kj}^{AS} - w_j\times\theta_{kj}\right|^2 + \tau^-\left|\rho_{kj}^{AS} - w_j\times\alpha_{kj}\right|^2\right)/6},\forall k = 1,\ldots,p;\forall j = 1,\ldots,o, \quad (36)$$

where

$$\tau^- = \begin{cases} 1\ if\ \widetilde{AS} < w_j\times\varphi_{kj} \\ 0\ if\ \widetilde{AS} > w_j\times\varphi_{kj} \end{cases}, \quad (37)$$

Step 15: Ranking of alternatives

The alternatives are ranked based on the increasing values of the comprehensive distances dC_k, which are calculated using the following formula:

$$dC_k = \frac{d\left(\widetilde{PIS}_j\right)_k - d\left(\widetilde{NIS}_j\right)_k - d\left(\widetilde{AS}_j\right)_k^+ - d\left(\widetilde{AS}_j\right)_k^-}{4},\forall k = 1,\ldots,p, \quad (38)$$

4. Problem Description

The increasing market demands for adapting to customer needs and shortening delivery times pose significant challenges in the FSC [51]. Insufficient production capacities often hinder companies' competitive advantage, increase logistics and manufacturing costs, extend delivery times, and negatively impact product quality [52,53]. Consequently, the receiving warehouse plays a pivotal role within the FSC, as it directly impacts on the efficiency and sustainability of production processes. Optimizing receiving processes ensures the timely supply of raw materials, reduces the risk of delays and losses, and material handling costs. This, in turn, significantly contributes to the continuity and quality of the production process [51,54].

A confectionery production company located in northwestern Serbia is facing the challenge of expanding its production capacity due to an increased product range. Additionally, it faces challenges in meeting growing demand, recruiting a qualified workforce, implementing technological innovations, and integrating sustainable practices into its operations. Established with the goal of providing consumers with high-quality products, the company is renowned for its innovative approach to product development. By employing contemporary technologies in production and adhering to strict quality standards, the company maintains and enhances its competitive position in the market. Furthermore, it is committed to sustainable development and responsible business practices, as demonstrated by its efforts to minimize environmental impact through efficient resource management and the implementation of eco-friendly practices. The company's vision is to become a leader in the confectionery industry in the region, while its mission is to deliver products that meet consumer needs and desires, all while respecting sustainability principles. As a key success factor, the company actively invests in the training and development of its employees.

The analyzed company operates with two key logistics subsystems: a receiving warehouse for packaging and raw materials and a distribution warehouse for finished products. The receiving warehouse has a capacity of 4780 pallet positions, with 65% of the space adapted to controlled temperature regimes. In activities include receiving, quality and quantity control, storage, and preparation of raw materials for production, with a focus on optimizing space utilization and minimizing transport time to production lines. The distribution warehouse has a capacity of 9684 pallet positions, organized into three zones: export, storage in ambient conditions, and storage at 18 °C for temperature-controlled products. The primary function of the distribution warehouse is to dispatch both locally produced and imported finished products to supermarkets and distribution centers, serving domestic and international markets. Imported products are integrated with local products in the distribution center before being delivered to customers.

The distribution warehouse operates as a closed (deterministic and stationary) system, characterized by a known number of suppliers and customers, as well as a clearly defined assortment, unit types, and quantities. Over time, this system has been optimized to achieve a minimal error rate less than 3%. Consequently, an analysis of the current state highlights the needs of the receiving warehouse, which faces unique challenges compared to the distribution warehouse. The receiving warehouse is a critical point in the FSC, where raw materials and packaging enter the production process. Key challenges in the receiving warehouse include space and resources, ensuring fast and efficient material handling, and minimizing the risk of damage or loss. The diverse types of raw materials and their specific characteristics, such as packaging and temperature requirements, further complicate the organization of warehouse space and equipment. In the context of growing demand, flexibility in adapting to variations in the volume and type of materials is essential to meet market needs. Analyzing the receiving warehouse can provide valuable insights into receiving and storage processes, supporting the development of strategies to improve operational efficiency and enhance the company's competitiveness.

The receiving warehouse of the analyzed company faces challenges related to the wide assortment of raw materials and packaging, which complicates material handling activities. The arrival of goods on various types of pallets, combined with unpredictable quantities, further complicates the planning and optimization of receiving processes. Variations in the quantities and types of units, along with specific storage requirements, increase the risk of errors and negatively impact the efficiency of managing inbound flows. To address these issues, the company aims to improve its receiving warehouse by implementing modern and sustainable MHE. The engagement of appropriate MHE can enhance operational efficiency, reduce costs, and improve productivity, thereby strengthening the company's market position. An analysis of the receiving warehouse activities identified challenges in the goods-receiving process.

- Challenges arising from the use of inadequate technology:
- Unloading dock;
- Engagement MHE;
- Employing storage technology;
- Inefficient warehouse layout;

- Workforce.
- Issues resulting from these challenges:
- Reduced productivity of the receiving warehouse;
- Damage to goods during handling;
- Different operating conditions;
- Operational inefficiency.

The first issue in the receiving warehouse is the presence of only one unloading dock, which reduces productivity and creates a bottleneck during periods of increased demand. Additionally, the dock is not level with the warehouse floor, further complicating unloading operations, as vehicles are positioned at a higher level than the storage area. This misalignment necessitates a two-step unloading process involving manual pallet jacks and forklifts, increasing time, resource requirements, and the risk of materials damage. Moreover, the need for a transitional zone with specific conditions adds complexity to operations and jeopardizes worker safety. Another significant challenge in the receiving warehouse is the engagement of inadequate MHE. Currently, front forklifts adapted for selective racks are employed, which complicates handling near-entry racks. This mismatch between MHE and storage equipment elevates the risk of material damage, negatively impacts product quality, and system efficiency. Furthermore, the engagement of unsuitable MHE endangers worker safety, increasing the likelihood of injuries during material handling operations.

Zones in the warehouse with different temperature regimes present additional areas for optimization. Approximately 65% of the warehouse space is divided into three zones with varying storage conditions, which complicates the maintenance of standardized procedures and creates confusion among employees. The current MHE is not suited to these conditions, as the same forklifts that are used for the ambient section are employed across all zones, reducing handling efficiency. Variable storage conditions can negatively affect material quality, increase the risk of damage, and contribute to an unsafe working environment. The company is also facing a workforce shortage, which hampers the logistics activities of the receiving warehouse. Employee overload reduces operational efficiency and increases the likelihood of errors during receiving operations. Beyond operational challenges, the company is striving to integrate sustainable practices and energy efficiency. In line with international environmental standards, the company aims to reduce CO_2 emissions by 20% over the next three years through eco-friendly solutions in both the warehouse and production processes. Given these challenges and issues, the company plans to invest in advanced solutions to optimize MHE activities and support its sustainability goals.

4.1. Alternative Solutions for Material Handling

One of the potential solutions for addressing the significant challenges in the receiving warehouse of the observed company is the implementation of modern and sustainable MHE. The adoption of advanced MHE would optimize unloading, handling, and storage processes, enable more efficient management of variable working conditions, reduce the risk of product damage, and improve workplace safety. Furthermore, modern MHE can support the integration of sustainable practices and the enhancement of energy efficiency. Implementing advanced MHE provides a strong foundation for increasing sustainability and significantly contributes to reducing negative environmental impacts. In this context, the selection and engagement of appropriate MHE become critical factors for ensuring an efficient flow of materials within the receiving warehouse and throughout the entire production process. The selected MHE will primarily be implemented in the receiving warehouse, playing a vital role in connecting the raw materials and packaging storage areas with the production facility.

The selection of an appropriate MHE is crucial for the success of a company from multiple perspectives. Suitable MHE facilitates efficient management of logistics processes, enhancing the flow of materials through all stages, from receiving to shipment, reducing downtime, and simultaneously increasing productivity. Furthermore, as the company expands its production capacity, the engagement MHE can support a higher volume of diverse operations, enabling better resource utilization. The use of energy-efficient MHE reduces operational costs, particularly in terms of energy and maintenance, while also contributing to business sustainability by lowering CO_2 emissions and waste. The flexibility offered by modern MHE allows the company to quickly adapt to new market demands, such as changes in the assortment of products. Therefore, the selection and application of MHE is a central issue that must be addressed to ensure successful and sustainable operations.

In practice, various types of MHE can be engaged to perform logistics activities in the receiving warehouse of the observed company, ranging from manual and mechanized to fully automated and robotic MHE. The deployment of suitable MHE can enhance the warehouse system by optimization workforce utilization, thereby increasing its flexibility and productivity. Selecting MHE involves a series of steps and decisions undertaken by decision-makers to identify the MHE that will most effectively meet the set task requirements [52,55]. At certain decision-making levels, it is insufficient to simply assume that a conveyor is needed for the task. Instead, it is necessary to specify the type of conveyor and define its technical and operational characteristics. Accordingly, the selection of MHE can be classified into multiple levels [56]:

- Level I: Focused on identifying the appropriate category of MHE. This includes analyzing conveyors, cranes, forklifts, industrial vehicles, positioning equipment, and similar options.
- Level II: Focused on identifying the appropriate type of MHE within the selected category. The selection is directed towards choosing the best variant within the category, such as belt conveyors, roller conveyors, or similar options.
- Level III: Focused on identifying the appropriate model of MHE within the selected type. For example, selecting the best alternative among types of hand pallet trucks in terms of dimensions and technical–operational characteristics.

The task of selecting MHE in this study encompasses Level I, which involves choosing the optimal category of MHE. For the purposes of this study, alternative solutions were generated based on prior research focusing on the selection of MHE in food production, while also taking into account the specific the needs and capabilities of the analyzed company. Various approaches and strategies proposed or implemented by researchers to enhance production processes, including those in the confectionery industry, were analyzed. By adhering to the criteria defined in the reviewed literature and the company's specific needs and capabilities, alternatives that have been proposed or tested in practice were identified. The subsequent stages of the research will focus on a detailed analysis of the proposed alternatives, assessing their feasibility and efficiency in the context of the confectionery industry.

Automated Guided Vehicle System (A1)

A1 represents a material handling system commonly used in current industrial and warehouse operations. Developed for the autonomous handling of loads within facilities with minimal human intervention, it significantly enhances operational efficiency. A1 is capable of managing various types of units, including pallets, boxes, and individual units, making them adaptable to diverse production requirements [57,58]. Depending on the specific type of A1, the load capacity can reach up to 4 t, with a maximum lifting height of up to 7 m, which can also be a limitation. A1 can move at a speed of up to 2 m/s, meeting the specific requirements of the confectionery industry [56,58]. One of the key advantages of A1 is its ability to operate 24/7 without breaks, enabling uninterrupted production and enhancing overall productivity. These systems are easy to program and can be quickly adapted to changes in production processes or warehouse configurations, making them a highly flexible solution. Compared to the existing system, A1 requires minimal modifications and investments relative to other alternatives. Additionally, A1 reduces human errors and improves workplace safety by minimizing the need for workers' physical presence in warehouse zones with temperature controls or special working conditions. These systems also produce lower greenhouse gas emissions and consume fewer resources than traditional forklifts, thereby reducing their negative environmental impact. While the initial costs of purchasing and implementing A1 may be high, the long-term savings in operational costs and increase efficiency often justify the investment [55,57,58].

Robotic Material Handling System (A2)

A2 represents a fully automated solution for industrial and warehouse systems, enabling complete automation in handling various types of units and effectively eliminating the need for human labor. A2 is capable of adapting to different unit types, including pallets and boxes. Its high speed in task execution and ability to operate 24/7 without breaks makes them an exceptionally efficient solution [59,60]. A notable advantage of A2 is its ease of programming or reprogramming, which allows for rapid adaptation to changes in production processes or the type of products being handled. The lifting height of A2 is approximately 20% lower than that of A1, while its load capacity remains up to four tons. A2, however, has a higher speed, reaching up to 3.1 m/s. Unlike A1, A2 provides a higher degree of automation. However, it is important to note that the costs associated with purchasing and operating A2 are significantly higher, and they require more substantial modifications to the existing system [61]. From an environmental perspective, A2 typically produces lower greenhouse gas emissions and consumes fewer resources compared to traditional forklifts. The high level of automation in the A2 system requires regular and specialized maintenance, including both software and hardware aspects. In addition to high initial procurement costs, operational costs, including energy consumption and part replacements, can also be significant. Regulatory and safety standards are crucial for the use of robots in industrial settings, as ensuring worker safety and preventing accidents is essential [16,59].

Automated Storage and Retrieval System (A3)

A3 is a technologically advanced solution increasingly adopted for managing the storage of raw materials for production and finished confectionery products. These systems integrate robots, software, and various mechanisms to optimize storage, retrieval, and material handling processes. In production environments where efficiency and speed are crucial, A3 can significantly enhance operations, particularly in terms of speed, precision, and safety [62,63]. Automation with A3 enables faster task execution, such as receiving raw materials and reducing unloading times. Another key advantage is space optimization, as these systems utilize vertical storage space, allowing companies to increase storage capacity without requiring additional physical space. Similarly, if a conventional forklift requires a 2.74 m aisle, an A3 utilizing a 2.13 m aisle can increase storage space by approximately 20%. The benefits of A3 include increased efficiency, reduced errors, optimization space utilization, lower labor costs, and seamless integration with other technologies. However, there are drawbacks to consider. High initial installation costs, maintenance complexity, and potential limitations in flexibility may present challenges for companies. The need for installing multiple separate A3 systems can increase costs and management complexity, especially in warehouses that require different regimes, such as controlled temperature or hygienic conditions. Although A3 offers long-term savings through space optimization and reduced labor costs, the high initial installation and implementation costs can be a barrier for smaller companies or those with limited budgets. Moreover, reliance on technology means that the failure of a component in the A3 could lead to slowdowns or even a halt in the production process [3,64].

Forklift (A4)

A4 represents a widely utilized technology in many industrial and warehouse systems. It involves the acquisition and deployment of various types of forklifts, selected based on the specific processes in the receiving warehouse. This requires ensuring the appropriate types for each zone, particularly those with specific storage conditions and regimes, as well as for handling goods stored in incoming racks and performing unloading activities. Compared to more modern technologies, the use of A4 is often considered a less efficient and sustainable solution [65,66]. Furthermore, A4 presents certain challenges. Different types of forklifts require various types of batteries, infrastructure, and maintenance, which can complicate operations and increase costs. A4 typically features a load capacity ranging from one to five tons, a lifting height of up to 10 m, a maximum speed of up to 5.5 m/s, and is powered by either internal combustion engines or electric batteries, depending on the model. Acquiring a larger number of forklift types results in higher overall costs, both in terms of procurement and maintenance, and also necessitates employing more workers. Additionally, A4 generates noise and dust and poses risks of damage to goods and worker injuries, which can negatively impact the working environment. The use of batteries also creates additional waste, further increasing its negative environmental impact [54,66].

4.2. Criteria for Evaluating Alternatives

Criteria are essential elements used to evaluate and rank alternative solutions in the MHE selection process. Factors such as cost, efficiency, environmental impact, and other serve as the foundation for decision-making, facilitating the selection of the most effective solution that aligns with the specific requirements and objectives of the analyzed company. This study incorporates twelve criteria, chosen based on a comprehensive analysis of relevant research on MHE selection in production, as well as insights gathered through discussions with company employees.

Numerous studies have investigated the different criteria used in the MHE selection process, emphasizing the importance of technical, economic, and social aspects. Tadić et al. [67] highlighted criteria such as efficiency, energy consumption, procurement costs, maintenance costs, and employee perception, offering a comprehensive approach to decision-making. In a subsequent study, Tadić et al. [68] expanded the analysis to include productivity, investment costs, operating costs, employee safety, and eco-indicators, placing a strong emphasis on sustainability and safety. Similarly, Pamučar and Ćirović [69] focused on economic and technical criteria, including purchase price, service network availability, and average maintenance costs, contributing to a deeper understanding of cost-related decision-making factors. On the other hand, Satoglu and Türkekul [34] emphasized operational and functional criteria, such as ease of operation, application, flexibility in material handling, and risk. Additionally, Asadi et al. examined criteria across technical, environmental, and economic dimensions, underscoring the need for an integrated approach that balances efficiency and sustainability. These studies provide a robust foundation for the selection and grouping of criteria in this research, ensuring alignment with both academic findings and practical considerations.

The criteria are grouped into three categories: technical–technological, economic, and social–ecological. Considering these criteria not only aids in selecting the optimal solution but also contributes to the long-term sustainability and competitiveness of the company. A more detailed description of the proposed criteria follows.

Technical–technological [66–71]

- **Compatibility with current MHE (C1)**—The level of compliance of the alternative MHE with the currently utilized technology.
- **Operation frequency and duration (C2)**—Frequency of material handling activities.
- **Layout and characteristics of the building (C3)**—Convenience of current layout for implementation of suggested MHE alternative.
- **Maintenance convenience (C4)**—Availability of spare parts, service centers, and manufacturer support to ensure that maintenance is efficient and reliable.

Economic [66,71,72]

- **Purchasing cost (C5)**—The price of the MHE, which encompasses the basic equipment and potential accessories, along with any applicable discounts.
- **Operating expenditures (C6)**—Expenses associated with the daily operation of MHE. This includes energy consumption, fuel usage, labor costs, and other resources necessary for the efficient functioning of the system.
- **Maintenance fees (C7)**—Expenses related to routine and extraordinary servicing.
- **Setup investments (C8)**—Outlays for equipment installation, infrastructure connection, system configuration, and testing.

Social–ecological [73,74]

- **Eco indicator (C9)**—Indicators of environmental impacts of MHE, such as greenhouse gas emissions, resource consumption or noise generation.
- **Waste generation (C10)**—The percentage reduction in waste generated during the handling of confectionery products due to the utilization of alternative MHE.
- **Regulatory and safety standards (C11)**—The extent to which environmental and safety standards are met through the implementation of the selected MHE alternative.
- **User friendliness (C12)**—The degree of acceptance of the proposed MHE alternative by employees, including any additional training requirements.

4.3. Model Solution

In line with the hierarchical structure of the FAHP method outlined in Section 3, the problem has been formulated accordingly. The goal of the analysis, which addresses the selection of MHE in the production of confectionery products, is defined in Section 4. The alternative solutions for evaluation are presented in Section 4.1, while the (sub)criteria used for evaluating these alternatives are thoroughly discussed in Section 4.2. The following section presents the solution to the problem, focusing on the evaluating and ranking MHE using the model defined in Section 3.

The evaluation of criteria and alternatives in this study was conducted with the participation of a panel of ten experts, covering both theoretical research and practical work in the fields of logistics, material handling, and warehouse processes. The panel included researchers in logistics, warehouse process management, and material handling; warehouse managers, responsible for operational management of warehouse processes; and production planners, responsible for optimizing processes within supply chains. The experts were selected based on their significant experience, with each panel member having more than three years of work in positions directly related to this issue. Their expertise encompasses both theoretical aspects of multi-criteria decision-making and practical implementation of MHE in logistics and warehouse processes. Based on interviews and a panel discussion with experts, criteria for evaluating alternatives were defined, with the experts emphasizing that in the confectionery industry, criteria related to all aspects of sustainability are particularly important. The experts then evaluated both these criteria and the alternative solutions using a hybrid model. This methodological approach ensured the collection of relevant and reliable data, thereby further enhancing the validity of the research results.

As previously outlined in the methodology, the criteria are divided into three groups. Within each group, sub-criteria were evaluated by experts and assessed using the SAPEVO-M method. The Tables 4–9 below present the scores assigned by the experts for each sub-criterion.

Table 4. Assigned scores for technical–technological sub-criteria by experts.

	C1	**C2**	**C3**	**C4**
C1	0	−1	−2	2
C2	1	0	1	2
C3	2	−1	0	1
C4	−2	−2	−1	0

Table 5. Weights of technical–technological sub-criteria.

	C1	**C2**	**C3**	**C4**
w_j	0.1996	0.4491	0.3493	0.0020

Table 6. Assigned grades to economic sub-criteria by experts.

	C5	**C6**	**C7**	**C8**
C5	0	−1	2	1
C6	1	0	3	2
C7	−2	−3	0	−1
C8	−1	−2	1	0

Table 7. Weights of economic sub-criteria.

	C5	**C6**	**C7**	**C8**
w_j	0.3328	0.4992	0.0017	0.001664

Table 8. Assigned grades to social–ecological sub-criteria by experts.

	C9	**C10**	**C11**	**C12**
C9	0	1	1	2
C10	−1	0	−2	1
C11	−1	2	0	3
C12	−2	−1	−3	0

Table 9. Weights of social–ecological sub-criteria.

	C9	**C10**	**C11**	**C12**
w_j	0.4106	0.1664	0.4160	0.0017

After applying the SAPEVO-M method, groups of criteria were compared using the FAHP method. Subsequently, after the experts provided pairwise evaluations for the criteria and subcriteria, consistency ratios (within the FAHP method) were calculated to determine whether their assessments were consistent and logical. The resulting values fell within acceptable ranges, indicating that the experts' opinions can be considered reliable. The ratings assigned by the experts are shown in Table 10.

Table 10. Fuzzy ratings of criteria assigned by experts.

	K1	K2	K3
K1	/	3	5
K2	1/3	/	2
K3	1/5	1/2	/

After applying the FAHP method, the weights of the criteria were obtained, which are shown in Table 11. Then, the weights of the criteria and sub-criteria were weighted. The final sub-criteria weights, which represent the input data for the FCOBRA method used to rank the alternatives, are shown in Table 12.

Table 11. Criteria weights.

	K1	K2	K3
w_j	0.667	0.222	0.111

Table 12. Weighted weights of criteria and sub-criteria.

Ci	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
w_{ij}	0.1331	0.2996	0.2330	0.0013	0.0739	0.1108	0.0004	0.0369	0.0462	0.0185	0.0462	0.002

The alternatives were evaluated by experts, and the results are shown in Table 13. After that, the FCOBRA method was applied.

Table 13. Fuzzy ratings of alternatives by criteria assigned by experts.

Ci	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	8	8	9	6	7	8	7	8	9	8	9	9
A2	7	6	4	2	3	8	7	3	9	7	5	6
A3	3	8	2	4	4	5	5	3	7	4	8	7
A4	6	4	5	4	4	2	4	4	2	2	3	7

By considering the evaluations of alternatives against the criteria assigned by experts (Table 13) and the weights of the criteria (Table 12), the ranking of alternatives was determined using the COBRA method. The results of this ranking are presented in Table 14.

Table 14. Ranking of alternatives.

		Norm	Rank
dC (A1)	−0.254	0.00	1
dC (A2)	0.017	0.69	2
dC (A3)	0.063	0.81	3
dC (A4)	0.137	1.00	4

Following the application of the COBRA method, the ranking results (Table 14) indicate that the A1 alternative holds the first position, followed by A2 in second place. A3 ranks third, while the alternative based on the use of A4 occupies the fourth and last position.

4.4. Sensitivity Analysis

After resolving the problem, it is crucial to conduct a sensitivity analysis to evaluate the efficiency and accuracy of the obtained solution and to determine whether, and to what extent, changes in input data could impact the results. For this analysis, five different scenarios (Sc.) were defined, each involving specific adjustments to the criteria weights or the exclusion of certain criteria. In Sc. 1, the weights of all criteria were equalized. In Sc. 2, Sc. 3, and Sc. 4, criteria C3, C6, and C11 were excluded from the model, respectively. The excluded criteria represent those with the highest weights within their respective groups. In the Sc. 5, all three (C1. C6 and C11) of the aforementioned criteria were excluded. Afterward, the sensitivity analysis was expanded by assigning equal weights (0.333) to criteria K1, K2, and K3, representing scenario Sc. 6. Subsequently, in individual scenarios, the sub-criteria with the highest weights within the groups of criteria were excluded. In scenario Sc. 7, sub-criterion C3 was excluded; in Sc. 8, sub-criterion C6; and in Sc. 9, sub-criterion C11.

Table 15 presents the results for each Sc. Across all scenarios, the top-ranked alternative is A1, while the lowest-ranked alternative is A4. In Sc. 1, Sc. 2, Sc. 3, Sc. 4, Sc. 6, and Sc. 9 alternative A2 secured the second position. However, in Sc. 5, Sc. 7, and Sc. 8 alternative A3 ranked second.

Table 15. Sensitivity analysis.

	Sc. 0	Sc. 1	Sc. 2	Sc. 3	Sc. 4	Sc. 5	Sc. 6	Sc. 7	Sc. 8	Sc. 9
dC (A1)	−0.254	−0.274	−0.225	−0.223	−0.244	−0.171	−0.230	−0.182	−0.174	−0.182
dC (A2)	0.017	−0.016	0.014	0.026	0.010	0.054	0.009	−0.005	0.050	−0.004
dC (A3)	0.063	0.038	0.025	0.056	0.065	0.026	0.013	−0.023	0.009	0.038
dC (A4)	0.137	0.192	0.150	0.109	0.129	0.093	0.170	0.162	0.112	0.124

The results of the sensitivity analysis (as shown in Figure 2) demonstrate that the defined methodology is sufficiently stable, ensuring that the obtained solution is both reliable and valid. This conclusion is reinforced by the consistent ranking of alternative A1 as the best option across all defined scenarios.

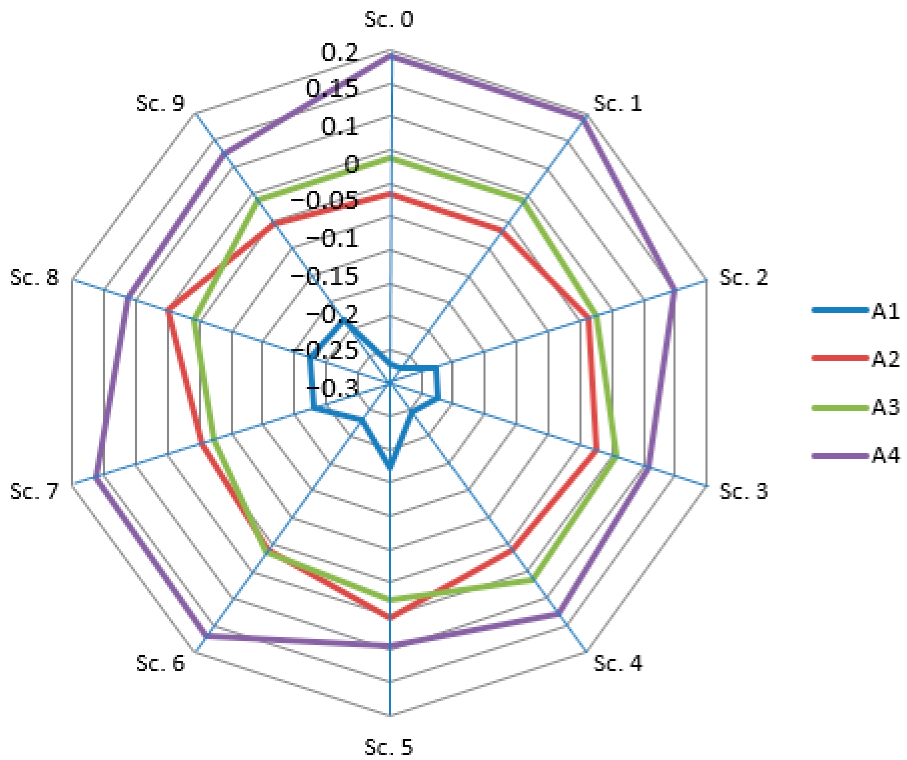

Figure 2. Sensitivity analysis.

5. Discussion

The ranking results unequivocally confirm that alternative A1 is the most efficient solution for enhancing the receiving warehouse of the observed company, in contrast to the findings of Soufi et al. [74]. In their study, the results of the applied model indicated that AGVs ranked second. Their research focused on a company considering an investment in MHE for handling heavy metal boxes filled with screws, comparing AGVs, pallet trucks, and conveyors. This choice is based on an evaluation of key criteria and the substantial benefits A1 offers in terms of efficiency and sustainability of logistics activities. A1 stands out as the optimal solution by substantially improving critical warehouse operations. Its implementation can reduce material handling time by up to 40%, eliminate human errors, enhance operational flexibility, and improve hygiene standards. Additionally, A1 enables the simultaneous handling of multiple pallets and optimizes unloading processes, even with minimal infrastructure, such as a single ramp. Compared to traditional alternatives like A4, A1 significantly expedites the transport of goods from the dock to storage areas, reducing external vehicle dwell time by 35%. Its adaptability to varying working conditions (e.g., lighting, temperature, humidity) ensures uninterrupted operation, while automation alleviates workforce strain. Furthermore, A1 enhances productivity and supports the company's sustainable development goals. A1 significantly contributes to addressing challenges in the confectionery industry by providing safe and precise handling of delicate products, minimizing damage, and ensuring consistent quality in material handling activities. Integration with temperature control systems enables the preservation of confectionery product quality, while the flexibility and scalability of AGVs allow adaptation to seasonal demand fluctuations. Consequently, the company can anticipate a 30% increase in warehouse efficiency, a 20% reduction in operational costs, and a 25% decrease in CO_2 emissions over the next three years, which directly promotes environmental sustainability. Social sustainability is reflected in the fact that the implementation of the A1 system removes employees from unfavorable working conditions, thereby improving their safety and working environment. The economic sustainability of A1 implementation is examined through the analysis of initial costs, operational expenses, and savings achieved through increased efficiency and reduced labor costs.

A2 ranked second in the evaluation of alternatives, whereas in the study by Goswami and Behera [20], it was identified as the best option. Their research considered AGVs, robots, and conveyors in the context of selecting MHE for handling and transporting materials in industrial facilities. Unlike A1, the implementation of A2 requires significant investments, including cost for development, installation, and adaptation of the working environment. This involves the integration of complex motion control systems and specialized stations for receiving and storing goods. A2 is particularly well-suited for handling a wide range of products under varying storage conditions, offering extremely flexible in dynamic environments. While A2 provides greater flexibility compared to A3 systems, its implementation demands extensive technical and infrastructural support, significantly increases the overall costs. Nevertheless, its ability to adapt to changes in production activities and optimize complex logistics operations makes it indispensable for warehouses with demanding productivity requirements. Despite these challenges, A2 is highly efficient in managing warehouse activities and can significantly enhance the speed and productivity of receiving operations. Environmentally, A2 reduces greenhouse gas emissions, optimizes energy and resource consumption, and reduces waste. Socially, it improves safety and working conditions by removing employees from dangerous and unfavorable environments, while enabling professional development through training. Economically, despite the high initial costs, it brings long-term savings by increasing efficiency, reducing errors, and reducing operating costs. A3 ranked third in the evaluation due to their specific requirements and limited adaptability. In the study by Tadić et al. [67], the AS/RS system ranked last. They research analyzed the use of AGVs, robots, and drones in activities related to order preparation for delivery in an urban area. The efficiency of A3 is most evident in specialized storage operations where precision and automation are essential for managing large volumes of storage units. However, its fixed infrastructure and high operating costs make them less appealing for dynamic environments that require frequent changes in storage processes. A3 is well-suited for optimization space utilization and reducing the time required to access inventory. However, it demands significant technological investments and lacks adaptability to changes in production processes. Despite these limitations, A3 can enhance accuracy and shorten storage activities durations, particularly in operations requiring a high degree of automation and minimal human labor involvement. A3 is especially advantageous for companies with stable operational processes and high demands for efficient inventory management. Environmentally, A3 reduces greenhouse gas emissions, optimizes energy consumption by minimizing unnecessary movements, and maximizes space utilization, reducing the need for additional storage facilities. Socially, it enhances safety by minimizing manual handling and employee exposure to hazardous conditions, while offering opportunities for upskilling through system operation and maintenance training. Economically, despite high initial investment costs, A3 provides long-term savings through improved storage efficiency, reduced labor costs, and fewer errors in material handling.

Although a traditional alternative, A4 ranked last due to numerous limitations in productivity, employee safety, protection of goods and facilities, and overall sustainability. In a study by Zubair et al. [41], forklifts ranked last when compared to conveyors and AGVs. The research focused on a pharmaceutical company that initially relied on trolleys to handle various materials required for pharmaceutical products but encountered numerous challenges in material handling. The reliance of A4 on human resources increases the risk of errors and accidents, thereby negatively impacting social sustainability. Operational costs, including driver training and maintenance, are significantly higher compared to modern alternatives. Additionally, A4 is environmentally unfriendly, as it often depends on fossil fuels and produces high emissions of harmful gases. Its limited automation and low flexibility further diminish its efficiency in dynamic warehouse environments where rapid changes and adjustments are critical. Environmentally, A4 are less sustainable due to their reliance on fossil fuels or significant energy consumption in the case of electric models, leading to higher greenhouse gas emissions compared to automated systems. Socially, they present safety risks to workers due to the possibility of accidents in manual operations and require employees to work in potentially hazardous environments. Economically, while forklifts have lower initial costs, their long-term expenses, including fuel, maintenance, and frequent replacements, often outweigh their initial affordability, making them less cost-effective and sustainable in the long run. As a result, traditional material handling solutions remain in use, but there is an increasing shift toward the adoption of autonomous and sustainable alternatives.

Based on the previous discussion, Table 16 presents the key characteristics, advantages, and challenges of each alternative for improving warehouse operations in the observed company. The table summarizes the evaluation results across aspects of efficiency, sustainability, and cost-effectiveness, providing an overview of the key impacts on logistics activities. This summary enables a quick and clear identification of optimal solutions and their advantages compared to traditional material handling methods.

Table 16. Summary of key characteristics of evaluated alternatives.

Alternative	Ranking	Key Benefits	Key Challenges	Environmental Impact	Social Impact	Economic Impact
A1	1	reduces handling time by 40%	high initial investment costs	reduces CO_2 emissions by 25%	improves safety	20% reduction in operational costs
A2	2	high flexibility, suitable for dynamic environments	high initial investment costs	minimizes waste	removes workers from hazardous environments	long-term savings costs
A3	3	effective in specialized storage operations	limited adaptability, fixed infrastructure	minimizes greenhouse gas emissions	reduces manual labor	high initial investment
A4	4	lower initial cost compared to modern alternatives	high long-term operational costs (fuel, maintenance)	relies on fossil fuels, generates high emissions	unfavorable working conditions	high operating costs

6. Conclusions

An analysis of the relevant literature reveals that, in addition to these challenges, material handling issues are particularly significant due to their substantial contribution to overall costs and process durations, which are closely linked to the specific characteristics of the products themselves (Table 2). These challenges are further amplified by the increasing demand for confectionery products, the expanding product variety driven by evolving consumer preferences, and the growing need for faster and more efficient delivery systems. The rising demand for healthier products necessitates handling and storage of raw materials under specific conditions to maintain their freshness and quality. Additionally, the use of eco-friendly packaging requires customized handling solutions that address specific storage and transport requirements. The diversification of product assortments further complicates handling processes due to varying product forms [20]. As production volumes and assortments of plant-based confectionery products, which require careful handling and controlled storage conditions, continue to expand [4,5], the selection and implementation of appropriate MHE has become a critical challenge in the confectionery industry.

The selection and engagement of appropriate MHEs is a complex task due to numerous constraints. On one hand, the characteristics of confectionery products, such as their sensitivity to temperature, humidity, and other factors, must be considered. On the other hand, MHE must possess technical and operational features that align with the specific requirements of the tasks. This study examines the importance of selecting and engaging suitable MHE as a key factor directly influencing the efficiency, costs, and sustainability of FSC. Optimal MHE selection and engagement contribute significantly to reducing material damage, optimizing logistics activities, and enhancing end-customer satisfaction. Beyond operational efficiency, the use of adequate MHE supports the long-term sustainability goals of companies. Efficient material handling reduces waste, optimizes material flows, and minimizes the environmental impact. By focusing on the selection of MHE, companies can achieve substantial improvements in both the sustainability and efficiency of FSCs [18].

The study examines the selection of sustainable MHE in a confectionery production company in Serbia. In addition to its production sector, the company operates all supporting logistics subsystems necessary for the production and distribution of goods. An analysis of the current state revealed significant challenges in the processes of receiving raw materials and packaging. In the receiving warehouse, several issues were identified, including the presence of only one unloading ramp, the use of inadequate MHE relative to the storage technology, and the misalignment of warehouse zones with varying temperature regimes and storage conditions. Additional challenges include a workforce shortage and the need to integrate sustainable practices into warehouse operations. To address these challenges, the study proposes the implementation of modern MHE. Selecting the most suitable MHE for the defined tasks is critical for implementing this solution. Four alternative solutions were considered, and to compare the proposed alternatives, twelve criteria were defined and grouped into three categories: technical–technological, economic, and social–ecological. To rank the alternatives, a novel hybrid MCDM model was developed and implemented, combining SAPEVO-M, FAHP, and FCOBRA, which represents a key contribution to this study. SAPEVO-M was used to determine the weights of criteria within each group. Subsequently, FAHP was applied to calculate the weights of the grouped criteria, while FCOBRA was used to rank the alternatives. The model's solution indicated that deploying A1 would most significantly enhance the performance of raw material and packaging receipt processes in the receiving warehouse. Based on the analysis, the implementation of A1 represents an efficient and sustainable solution for improving logistics activities in the observed company. A1 not only optimizes operations and reduces operational costs but also enhances flexibility, safety, and sustainability in the receiving warehouse.

A2 and A3 offer notable significant advantages, particularly in specialized or high-intensity flow warehouses, their high implementation costs and limited flexibility are significant drawbacks. In contrast, A4, despite its widespread use, demonstrates substantial weaknesses in productivity, safety, and sustainability. These findings further underscore the superiority of modern technologies like A1, which are increasingly becoming indispensable in contemporary and competitive logistics systems.

In the current business environment, theoretical research and its practical application play a crucial role in improving operations. This study not only advances knowledge of the role and importance of MHE selection in the confectionery sector but also provides specific recommendations for practitioners. The theoretical implications of this study are reflected in several key aspects. A novel approach for evaluating and selecting MHE is proposed, integrating the SAPEVO-M, FAHP, and FCOBRA methods. The development of this new MCDM model is motivated by the need to address problems that involve multiple groups of diverse and conflicting criteria. This approach facilitates comprehensive analysis in the MHE selection process and serves as a solid foundation for future research in the field of FSCs. The study addresses specific problems and challenges in the confectionery industry, which are rarely explored in the existing literature. It underscores the importance of the confectionery industry and FSCs in modern business and the global economy, highlighting the need for efficient solutions in this sector. Recognizing the inseparable connection between theory and practice, this study also offers practical implications. The proposed model for evaluating and selecting MHE can serve as a decision-support system in real-world applications. It is applicable extends beyond the confectionery industry to related systems and industries. Furthermore, the study provides an overview of the advantages and disadvantages of specific MHE, enabling practitioners to develop a more realistic understanding of their potential applications. The practical implications of implementing alternative A1 are significant and multifaceted. Its adoption can enhance warehouse efficiency by 30%, reduce operational costs by 20%, and lower CO_2 emissions by 25%, directly supporting environmental sustainability goals. Additionally, A1 improves employee safety and working conditions by automating tasks and removing workers from unfavorable environments, contributing to social sustainability. From an economic perspective, the implementation of A1 balances initial costs with long-term savings through increased efficiency, reduced labor expenses, and optimized logistics operations. Implementation of A1 may face challenges such as high initial costs, the need for infrastructure changes, integration with existing solutions, and employee resistance, along with specific issues like handling temperature-sensitive products or packaging materials. In addition to technical barriers, potential financial and operational risks should also be considered when introducing A1. These risks include high initial procurement and maintenance costs, possible downtime or slowdowns during the adaptation of existing infrastructure, as well as the need for staff training to effectively leverage new technologies. These barriers can be mitigated through strategies like government subsidies, phased implementation, employee training programs, and customizing A1 to meet industry-specific needs, ensuring smoother adoption and effective operation.

Although the results of this study indicate significant improvements in the sustainability of the observed company's operations, it is important to highlight several key limitations that may affect their generalizability. First, the number of considered criteria should be taken into account. This study analyzed 12 criteria, which, based on a review of the literature, are relevant for selecting the optimal alternative. However, the selection of these specific criteria significantly influences the research results, suggesting that considering different or additional criteria might lead to alternative solutions. Second, the analyzed alternatives were selected based on the available literature and the specific needs of the observed company. While these alternatives were carefully chosen to reflect practical needs within the industry, their limited diversity may have an impact on the applicability of the results to a broader range of industries or companies with differing needs and technological capabilities. Third, the specific context of the observed company (input data) represents an additional limitation. Factors such as company size, resource availability, and existing logistical infrastructure play a crucial role in shaping the results. Therefore, the findings of this study may not be entirely applicable to companies operating under different conditions or with varying strategic objectives. Despite these limitations, the study provides valuable insights that can serve as a foundation for future research. It is recommended to expand future studies to include a larger set of criteria, more diverse alternatives, and varied contextual factors. This approach would enhance the generalizability of the results and enable the methodology's application across different industrial facilities.

Some potential directions for future research that could enhance understanding and application of MHE in the confectionery industry include the following:

- Innovations in MHE: Analyzing the engagement of a broader range of modern MHEs in the confectionery industry, considering other logistics processes beyond goods reception.
- Combination of MHE: Exploring the possibilities of integrating different types of MHE, such as AGVs and drones, to optimize goods reception processes and increase efficiency.
- Cost–benefit analysis: Expanding the cost–benefit analysis for each alternative, considering the long-term effects on operations, productivity, and customer satisfaction. This could also include the selection of MHE at Level III, which was not covered in this study.
- Development of simulation models: Developing simulation models to test various scenarios in MHE selection and application, providing valuable insights for decision-making.
- Extending the framework to other industries: Investigating the adaptability of the proposed framework in industries beyond the confectionery sector, addressing different operational and logistical challenges.

- Integration of advanced technologies: Incorporating advanced technologies like Artificial Intelligence (AI) and the Internet of Things (IoT) to enhance decision-making processes, predictive maintenance, and real-time operational efficiency in MHE systems.
- Application of alternative methods: In future research, the application of the Delphi method could be considered if a larger number of experts were involved, and greater emphasis was placed on quantitative criteria. Additionally, DEA (Data Envelopment Analysis) could be a useful approach, but it would require a different problem structure—namely, a larger number of alternatives and fewer criteria—which opens up opportunities for new research in scenarios where such a balance can be achieved.

These recommendations have the potential to substantially enhance the understanding of MHE engagement and selection, offering practitioners and researchers deeper insights into the complexities and challenges inherent to the confectionery industry. The integration of advanced technologies as essential components of FSC sustainability supports the development of viable solutions aimed at optimizing operational efficiency, reducing costs, and improving the quality of manufacturing processes within confectionery production.

Author Contributions: Conceptualization, M.B., S.D.-M., M.A. and D.D.; formal analysis, M.B., S.D.-M., M.A. and D.D. Methodology, M.B., M.A. and S.D.-M.; writing—original draft, M.B., S.D.-M., M.A. and D.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data used are owned by the company. They may be made available with the company's permission.

Conflicts of Interest: The authors declare no conflicts of interest.

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