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Performance Evaluation of Retail Warehouses: A Combined MCDM Approach Using G-BWM and RATMI

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Abstract: *Background*: The retail sector has experienced significant growth in recent years, necessitating efficient supply chain management and sustainable logistics practices. Evaluating the performance of retail warehouses is crucial for meeting customer expectations and enhancing operational efficiency. *Methods*: This study employed a combined multi-criteria decision-making (MCDM) approach, using the group best–worst method (G-BWM) for weighting criteria and ranking the alternatives based on the trace-to-median index (RATMI) for warehouse ranking. The performance criteria were cost, quality, time, productivity, and safety. Data were collected from four mega retail warehouses in the western region of Saudi Arabia for evaluation and analysis. *Results*: The evaluation of retail warehouse performance using the MCDM approach provided valuable insights for decision-makers and warehouse experts. The criteria weights were determined using the G-BWM, and the RATMI enabled the ranking of the warehouses based on their weighted performance scores. The results highlight the strengths and weaknesses of each warehouse, facilitating strategic planning, resource allocation, and operational improvements. *Conclusions*: This study presents a novel combined MCDM performance evaluation approach for retail warehouses. The study has implications for effective decision-making processes, resource allocation, and operational efficiency. Furthermore, it serves as a foundation for future research, exploring additional dimensions of warehouse performance and enabling sustainable logistics within the broader supply chain context.

Keywords: retail; warehouses; performance; evaluation; MCDM; G-BWM; RATMI

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1. Introduction

A warehouse is one of the most critical parts of many companies, essential to facilitating trade. With a robust warehouse management system, a business can satisfy customer demand. Additionally, it helps guarantee that the products are affordable, easily accessible, and delivered quickly to a network of customers. However, if not properly structured and managed, it may prevent a business from competing effectively, locally and worldwide. One of the most crucial ways to enhance warehouses and assist managers in continuously monitoring their operations is warehouse performance measurement. Management must establish a variety of criteria to gauge warehouse performance. Based on these criteria, they can determine whether the warehouse is performing well.

Each retail warehouse in Saudi Arabia's western region has a set of criteria for measuring its performance. Warehouses occupy a significant position in the economy of Saudi Arabia. They are among the most significant national focuses of development and improvement to increase the efficiency of the country's economy in logistics [1]. With Vision 2030, the government began to improve Saudi Arabia's logistics infrastructure, and as it grows, so does warehousing. The warehouse market expanded by 2.8% between 2015 and 2019, and it is expected to grow more in the future.

According to Statista, the operating revenue of warehousing was USD 8.84 billion between 2010 and 2017. The value of e-commerce warehousing in the Middle East could reach USD 500 million by 2024.

Because of the COVID-19 pandemic, the world has encountered numerous warehousing issues, as has Saudi Arabia. The pandemic has significantly impacted logistics, and Saudi Arabia must overcome some challenges to continue warehouse expansion.

According to Colliers International, the average price of warehouse space in Jeddah, Saudi Arabia, was SAR 131 (USD 35) per square meter in the first quarter of 2020. This high price means that retail warehouses must reduce operational expenses, optimize their management systems, and solve problems with cutting-edge scientific techniques.

Most real-world decision-making challenges require the simultaneous consideration of several competing criteria and objectives. Similar challenges occur in various professions, including engineering, medicine, and business. Multi-criteria decision-making (MCDM) is concerned with structuring and resolving problems involving multiple criteria and conflicting goals. With the increase in the number of warehouses in Saudi Arabia, the competition between them has increased, and every warehouse has evaluation criteria to prove its superiority over others. Therefore, this paper explains how combined approaches between the group best–worst method (G-BWM) and ranking the alternatives based on the trace-to-median index (RATMI) will help decision-makers evaluate and rank selected Saudi Arabian warehouse alternatives from best to worst. Both quantitative and qualitative factors can be considered in this MCDM problem.

The main objective of this study was to evaluate and compare the performance of retail warehouses in the western region of Saudi Arabia to identify the best-performing warehouse. An MCDM approach was used to systematically assess the warehouses against key performance criteria related to time, cost, quality, productivity, and safety. The G-BWM method was employed to determine the weights of the various criteria. The RATMI technique was used to rank the warehouses from best to worst based on their weighted performance scores. The results of this evaluation may provide decision-makers and warehouse managers with valuable insights into the strengths and weaknesses across the warehouses. This will allow for more effective strategic planning, resource allocation, and operational improvements to maximize the overall warehouse efficiency and competitiveness in the Saudi retail sector.

This study aimed to fill this research gap by presenting a novel approach to evaluating retail warehouse performance. Previous studies have used various methodologies, but a comprehensive and integrated method that considers multiple criteria and provides a robust assessment is needed. Furthermore, existing approaches often lack a systematic ranking mechanism to differentiate the performance of retail warehouses.

This research introduces a combined MCDM approach to address these limitations, specifically employing the G-BWM for criteria weighting and the RATMI for warehouse ranking. This innovative approach allows for a more holistic evaluation of retail warehouses by considering key performance criteria such as cost, quality, time, productivity, and safety. In addition to the novel methodology, this study distinguishes itself by using a unique dataset collected from four mega retail warehouses in the western region of Saudi Arabia. This dataset provides valuable insights into the performance of retail warehouses in a specific geographic context, enabling a more focused analysis and relevant findings. The implications of this research are significant. By employing the G-BWM and RATMI techniques, decision-makers and warehouse managers can gain valuable insights into the strengths and weaknesses of retail warehouses, facilitating strategic planning, resource allocation, and operational improvements. This approach contributes to more effective decision-making processes and enhances the overall operational efficiency of retail warehouses.

Moreover, this study opens avenues for future research endeavors. Exploring additional dimensions of warehouse performance and their influence on sustainable logistics represents a promising area for further investigation. Expanding the understanding of retail warehouse performance means that researchers and practitioners can work toward achieving more sustainable and efficient supply chains.

The rest of this paper is structured as follows. Section 2 provides a literature review on key topics related to warehouse performance measurement, applications of MCDM tools in warehousing, and commonly used MCDM techniques. Section 3 outlines the study methodology, including the identification of warehouses and criteria, determination of criteria weights, and evaluation of warehouse performance as alternatives. Section 4 presents the results, and Section 5 discusses the findings and results of the analysis. Finally, Section 6 summarizes the main conclusions and limitations of the study, as well as recommendations for future work.

2. Literature Review

This literature review provides an overview of previous research relevant to the topics studied in this paper. It is divided into three subsections to comprehensively cover the key areas. The first reviews studies on warehouse performance indicators and the key criteria considered essential for measuring warehouse operations. Several classification frameworks and findings from major literature reviews in this domain are summarized. The second subsection examines the available literature applying MCDM tools to assess warehouse performance evaluation problems. It outlines some notable applications and methodologies used in related contexts such as warehouse design, layout, and location selection. Finally, the third subsection explores common MCDM techniques discussed in the literature. An overview of various MCDM approaches is presented, highlighting relevant methods such as Elimination Et Choix Traduisant la Realité (ELECTRE), simple additive weighting (SAW), analytic hierarchy analysis (AHP), the best–worst method (BWM), and VlseKriterijuska Optimizacija I Komoromisno Resenje (VIKOR) [2]. This section thus provides the relevant background and establishes the need for the combined methodology evaluated in this study.

2.1. Warehouse Key Performance Indicators

Rouwenhorst et al. [3] classified warehouses from the perspectives of processes, resources, and organizational structures. They conducted a thorough literature review, concluding that most studies focused primarily on analysis and not warehouse design. Gu et al. [4] extensively reviewed warehouse operation planning problems. The problems were classified according to basic warehouse functions: receiving, storage, order picking, and shipping. The literature in each category was summarized, emphasizing the characteristics of various decision-support models and solution algorithms. Storage and order-picking functions impacted the warehouse operational performance the most. Staudt et al. [5] emphasized measuring operational warehouse performance. Performance indicators were extracted from relevant papers using the content analysis method and were categorized based on time, cost, quality, and productivity dimensions. Vatumalae et al. [6] discussed the Malaysian hypermarket retail sector in detail, followed by a thorough literature review on the warehouse management system. The literature review focused on the hypermarket retailers' warehouses, which are essential in the supply chain, facilitating the movement of materials between the supplier and the customer. A model presented by Ramirez-Malule et al. [7] identified variables that significantly impact warehouse performance with picker-to-parts storage systems, considering the dynamic nature of the model's processes and the possibility of non-linear relationships among its variables, as well as the simultaneous occurrence of seasonal demand and long and short product life-cycles. Phyllis [8] applied warehouse performance measurement in the case of a medium-sized warehouse in Nakuru Town. The warehouse performance indicators were classified into five categories: productivity, utilization, quality, time, and financial. The findings indicated that the most critical performance indicators were productivity for receiving, space utilization for storage, cycle time for order picking, and productivity for shipping. A study on measuring warehouse performance in third-party logistics (3PL) service providers was conducted by Ghaouta and Okar [9]. Their research had three main objectives: to review warehouse key performance indicators (KPIs) and categories using the systematic literature review method, to investigate categories and determine their relative importance using the Q-sort method, and to validate the order of performance measure categories using a single case study. The study grouped 30 KPIs into five categories and four subcategories using an integrated research methodology.

2.2. Warehouse Performance Evaluation Using MCDM Tools

Few studies have offered information about the MCDM tools employed in the warehouse performance evaluation context. A study by Kusrini et al. [10] assessed the performance of retail warehouses in supermarkets in Central Java and Yogyakarta, Indonesia. The criteria were weighted using the AHP approach. After assessing the warehouse's performance, the final score was calculated using the SNORM method. MCDM tools have a wide range of applications in warehouse location problems as well as issues with warehouse architecture and design. Al Amin et al. [11] employed AHP and the technique for order of preference by similarity to ideal solution (TOPSIS) to select the best warehouse among five based on five specified criteria (unit price, stock holding capacity, average distance to factory, flexibility, and layout). Demircioğlu and Ozceylan [12] conducted a thorough literature review using pertinent keywords in several worldwide databases to explore MCDM applications in warehouse layout and design. AHP, ELECTRE, and the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) were the most frequently used techniques, which are carried out by applying MCDM methods. To manage the benefits of employing many MCDM methods in a given field, MCDM approaches are employed in an integrated manner. Ulutaş et al. [13] suggested an integrated grey MCDM model including the grey preference selection index (GPSI) and grey proximity indexed value (GPIV) to determine the most appropriate warehouse location for a supermarket. Twelve criteria were employed to compare the effectiveness of five potential warehouse locations. The optimum warehouse location was chosen using a combination of GPSI and GPIV algorithms [13]. Fuzzy extensions of MCDM techniques have also been used in other contexts [14–16]. In the context of warehouses, Bairagi [17] employed fuzzy MCDM to assess the location. The warehouse selection indicator, known as the benefit–cost ratio (BCR) [18], is assessed using the aggregate modified weighted value of the warehouse locations' normalized scores.

2.3. MCDM Tools

MCDM tools are used to deal with challenging real-world problems since they can assess several options and choose the optimal one [19]. The literature includes many different MCDM approaches. The ELECTRE tool allows for identifying and eliminating options that are outranked by others, leaving a set of appropriate actions [20]. ELECTRE is a method that experts use to assess the effects of criteria and contrast them with one another based on the anticipated performance [21]. Another MCDM technique, SAW, aims to assess the effectiveness of various solutions [22,23]. The basic concept of SAW is to determine the weighted total of performance ratings for each alternative across all criteria. MCDM also includes stepwise weight assessment ratio analysis (SWARA). When using the SWARA technique, the criteria needs are ranked according to their importance by a group of experts [24]. Saaty [25] proposed the AHP method in the 1980s. AHP provides a logical framework for a decision that must be made by weighing the requirements and available alternatives and connecting those components to the primary objective. The BWM is an MCDM technique that Rezaei introduced in 2015 [26]. It can be used to evaluate alternative solutions in consideration of the criteria and assess the applicability of the criteria to discover a solution to accomplish the issue's main goal(s). Based on the BWM, a novel approach to group decision-making problems called the G-BWM was developed by Haseli et al. [27]. This approach assists in the analysis of decision-makers' preferences for employing the BWM structure for democratic decision-making. Another MCDM technique is VIKOR. This technique involves weighing and choosing options based on competing criteria by outlining in detail how close each alternative is to the best hypothetical answer [28–31]. TOPSIS is another MCDM tool that has been used successfully in many applications [32–36]. Its fundamental objective is to find an optimal solution with the largest and lowest distances to the positive and negative ideal solutions, respectively [37]. The Saudi National Commission for Academic Accreditation and Evaluation (NCAAA) created the Self-Evaluation Scale to evaluate higher education programs. The present study used the TOPSIS technique to compare NCAAA's original performance criteria and the proposed evaluation sub-criteria [38]. Abdulaal and Bafail [39] developed two new approaches: ranking alternatives based on median similarity (RAMS) and RATMI. RAMS is a developed method that utilizes the ranking alternatives perimeter similarity (RAPS) [40]. The RATMI technique combines the RAMS method with the multiple criteria ranking by alternative trace methodology, using a majority index and the concept of the VIKOR method [41]. RATMI is a new technique that has been applied in recent studies [39,40,42,43].

The rationale for using the G-BWM for criteria weighting and the RATMI for warehouse ranking in evaluating warehouse performance was based on their respective advantages and suitability for addressing the research objectives. The G-BWM technique was chosen for criteria weighting due to its ability to capture the collective preferences of a group of decision-makers. In evaluating warehouse performance, multiple criteria contributing to operational effectiveness and customer satisfaction must be considered. However, assigning appropriate weights to these criteria can be challenging since decision-makers may have different perspectives and priorities. The G-BWM addresses this challenge by involving experts or decision-makers who participate in pairwise criteria comparisons. By identifying the best and worst criteria in each pairwise comparison, the G-BWM aggregates the individual preferences to derive consensus-based weights for the criteria. This group-based approach ensures that the evaluation framework considers diverse perspectives and avoids undue influence from a single decision-maker. The RATMI technique is employed for warehouse ranking to evaluate warehouse performance systematically and comprehensively. Traditional ranking methods often suffer from limitations such as subjectivity, inconsistency, and a lack of consideration for the interrelationships between criteria. The RATMI overcomes these limitations by using the concept of the median performance profile. It traces the performance of individual warehouses relative to the median performance profile, capturing each warehouse's relative strengths and weaknesses across multiple criteria. This approach offers a more objective and comparative assessment, enabling decision-makers to identify the top-performing and underperforming warehouses in the context of the entire dataset.

The evaluation framework ensures a comprehensive and robust assessment of warehouse performance by combining the G-BWM for criteria weighting and the RATMI for warehouse ranking. The G-BWM incorporates group preferences and diverse perspectives, and the RATMI provides an objective and comparative ranking mechanism. Together, these techniques enhance the evaluation framework's accuracy, reliability, and applicability, enabling decision-makers to make informed decisions and drive operational improvements in retail warehouses.

In this paper, two combined MCDM techniques, comprising the G-BWM technique, were used to group the criteria and give weights to each one. The RATMI technique ranks the alternatives based on the weight given by the G-BWM. The G-BWM allows for group decision-making in determining the criteria weights. Since the evaluations involve subjectivity from multiple warehouse experts, using their collective judgments through G-BWM provides a more democratic weighting process. The RATMI enables a comprehensive ranking of the warehouse alternatives based on the weighted performance scores across all criteria. This helps to systematically produce an overall performance evaluation and ranking. Combining both techniques allows them to complement each other. The G-BWM provides the weights as input for the RATMI, which then uses those weights to generate the final ranking. This makes the evaluation more robust by leveraging the strengths of both methods. Both the G-BWM and the RATMI have been validated in previous studies for effectiveness in group MCDM problems. Applying them together extends their combined application to the warehouse performance evaluation context. The combination approach addresses the limitations of the individual techniques and provides the cross-validation of the results through the convergence of the two methods on a common solution or ranking. This enhances the reliability of findings. In summary, the researchers chose a combined G-BWM and RATMI approach to leverage their synergies, produce a rigorous yet democratic weighting process, and generate a validated overall performance ranking for strategic decision-making. This research aimed to contribute to the existing literature by filling the research gap and providing decision-makers and warehouse managers with a more robust and integrated method for evaluating retail warehouse performance. By addressing the need for a systematic ranking mechanism and considering multiple performance criteria, this study offers a novel perspective that enhances the understanding of warehouse effectiveness and supports data-driven decision-making in the retail sector.

3. Materials and Methods

The proposed framework of the methodology used for the performance evaluation and ranking of a group of chosen retail warehouses in Saudi Arabia's western region is shown in Figure 1. The methodology consists of three consecutive stages. The researchers conducted initial visits to various warehouses in the western region of Saudi Arabia in Stage 1. This allowed for the gaining of a first-hand understanding of warehouse operations, screening and selecting the four most suitable warehouses for the study based on predefined criteria, and building rapport with warehouse managers. Being on-site allowed for the introduction of the objectives of the performance evaluation study, distributing questionnaires to collect the required primary data, obtaining signed consent forms, and gathering any available secondary data on existing measurement processes. The visits proved crucial for gathering important operational context beyond documents, resolving ambiguities in the questionnaire, screening appropriate case warehouses, facilitating data collection processes, and strengthening the engagement of participants. Overall, conducting the preliminary warehouse visits was instrumental in setting the foundation for the subsequent stages of the MCDM evaluation approach. A questionnaire was designed and delivered to the warehouses and completed by warehouse experts to determine how they evaluated the performance of the warehouse's primary activities from their perspective. Each warehouse expert had different years of experience and education levels; Table A1 in Appendix A shows the warehouse experts' profiles. The G-BWM was employed in Stage 2 of the proposed methodology to calculate the criteria weights. In Stage 3, the chosen warehouses were ranked using RATMI. The details of each stage are provided in the following subsections.

3.1. Stage 1: Identifying the Warehouses and Their Performance Criteria

Step 1: This step deals with choosing the warehouses (alternatives). After visiting different warehouses in the western region of Saudi Arabia, four mega warehouses that have been operating for a long time in the retail sector were selected.

Step 2: In this step, a questionnaire is designed and distributed to the chosen warehouses to collect the required data for the second stage of the proposed methodology. The questionnaire contains 18 sections. Each section discusses different topics, starting from general information, respondents' profiles, the warehouses' primary activities, the KPIs of each primary activity, and the performance criteria of each KPI. The sections included 54 questions in total. For each question, the warehouse's experts were asked to rate on a scale from 1 to 9 to indicate their preference for the best activity over all the other activities and for all the other activities over the worst activity. Table 1 shows the scale meaning.

Step 3: This step shows the primary activities that all the chosen warehouses deal with.

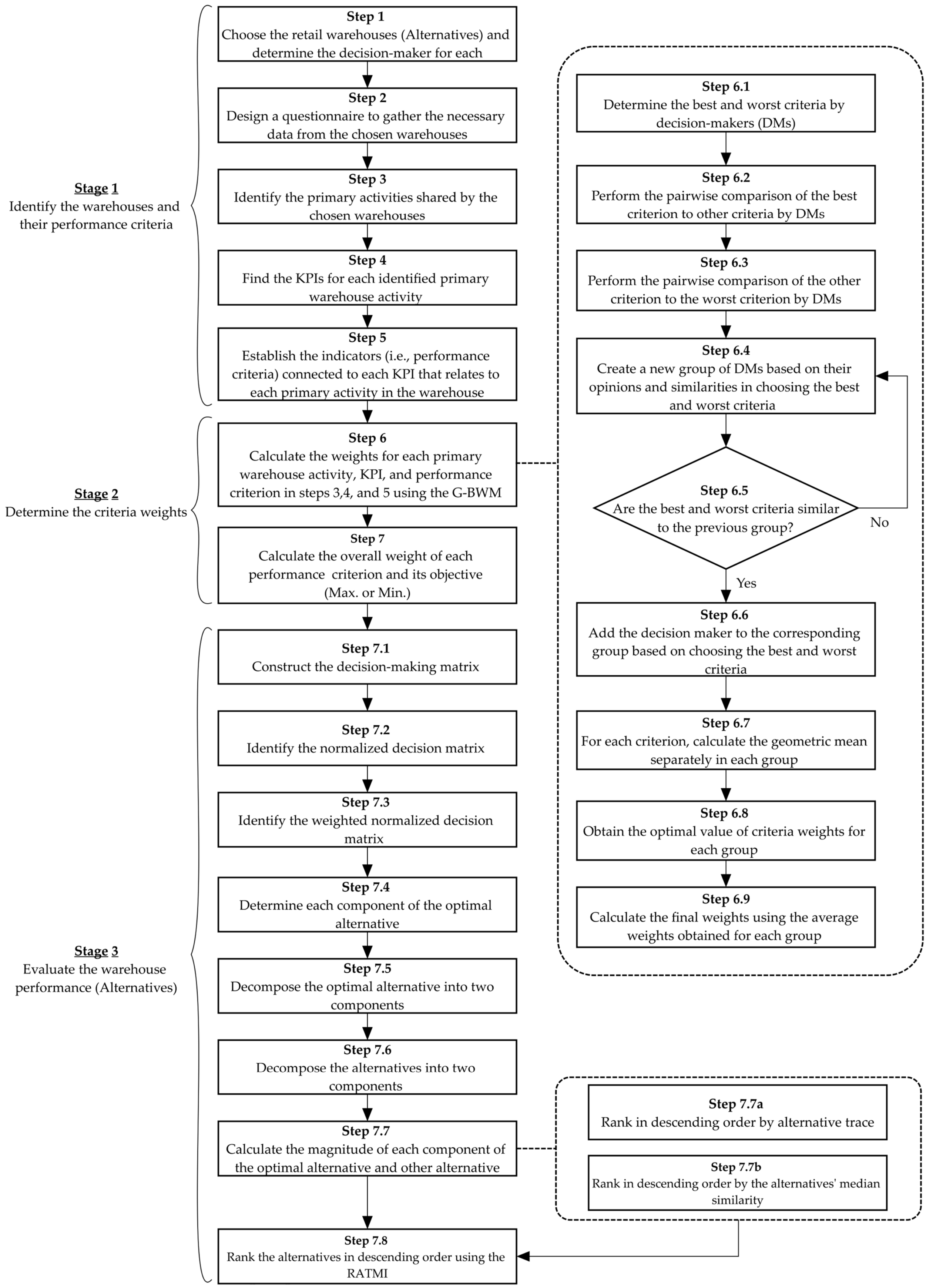

Figure 1. The proposed framework for retail warehouses' performance evaluation.

Table 1. Integer scale definition.

Integer Scale	Definition
1	Equally important
2, 3, 4	Moderately important
5, 6	Strongly important
7, 8	Very strongly important
9	Absolutely important

Step 4: This step is to find the KPIs for the primary activities. The KPIs of the chosen warehouses in this research study have been agreed to be the same, and are primarily used in different warehouses worldwide [3–9].

Step 5: Each KPI identified in Step 4 has indicators that give more accurate measurements of the performance of the warehouses.

3.2. Stage 2: Determining the Criteria Weights

Step 6: This step will assign the weights to the warehouse performance criteria. The MCDM technique that will be used to give the weight for the criteria is G-BWM. The technique will be applied to calculate the weights three times: first on the primary warehouse activities, then on the KPIs of the primary activities, and last on the performance criterion (indicators). The G-BWM [27] technique has several steps to apply as follows:

Step 6.1: Considering a set of criteria $\{C_1, C_2, \ldots, C_m\}$ to achieve a decision through the decision makers $\{DM_1, DM_2, \ldots, DM_n\}$, where m is a set of criteria and n is the number of decision-makers. Each decision maker (i.e., warehouse expert) generally selects the best and worst criteria.

Step 6.2: A pairwise comparison using crisp integer score values between 1 and 9 is performed. The numerical scales of 1 to 9 are used to determine the relative importance of the pairwise comparisons. Here, a_{ij} = 1 represents the equal importance of the criterion i and over criterion j. Moreover, a_{ij} = 9 signifies the extreme importance preference of criterion i over criterion j, as shown in Table 1.

The vector of the best criterion over other criteria would be

$$A_{Bj} = (a_{B1},\ a_{B2},\ \cdots,a_{Bm}),\ \ j = 1,\ 2,\ 3,\ \cdots,\ m \tag{1}$$

A_{Bj} denotes the relative importance value of the best criterion over criterion j.

Step 6.3: The crisp numbers from 1 to 9 (Table 1) will also be used to perform the pairwise comparison in this step. As mentioned in the previous step, a_{ij} = 1 represents the equal importance of criterion i and over criterion j. Moreover, a_{ij} = 9 signifies the extreme importance preference of criterion i over criterion j. So, the vector of all criteria over the worst criterion would be

$$A_{jW} = (a_{1W},\ a_{2W},\ \cdots,\ a_{mW}\ ),\ \ j = 1,\ 2,\ 3,\ \cdots,\ m \tag{2}$$

A_{jW} stands for the relative importance value of criterion j over the worst criterion.

Step 6.4: The decision-makers who select the best and worst criteria belong to one group, G_i, where i = 1, 2, . . ., k, and k is the number of groups.

Step 6.5: After creating the group, the result of grouping decision makers would be

$$Group\ DM = (G_1,\ G_2, \ldots, G_k) \tag{3}$$

Step 6.6: In this step, the geometric mean in each group is used to evaluate the decision-makers for each Total A_{Bj} and Total A_{jW}. For each group (G_1, G_2, . . ., G_k):

$$\left(\prod_{i=1}^{n} \text{Total } a_{Bj(DM_i)}\right)^{\frac{1}{n}} = \sqrt[n]{a_{Bj(DM_1)} \times a_{Bj(DM_2)} \times \ldots a_{Bj(DM_n)}} \tag{4}$$

$$\left(\prod_{i=1}^{n} \text{Total } a_{jW(DM_i)}\right)^{\frac{1}{n}} = \sqrt[n]{a_{jW(DM_1)} \times a_{jw(DM_2)} \times \ldots a_{jW(DM_n)}} \tag{5}$$

Step 6.7: The optimal values of the weights for ω_B/ω_j and ω_j/ω_W are equal to A_{Bj} and A_{jW}, respectively. Since the criteria weights are aggregated and non-negative, the mathematical model can be written as follows:

For both minimize or maximize:

$$\left|\frac{\omega_B}{\omega_j} - a_{Bj}\right|, \left|\frac{\omega_j}{\omega_W} - a_{jW}\right| \tag{6}$$

Subject to

$$\begin{cases} \sum_{\mathrm{j}=1}^{n} (\omega_j) = 1 \\ \omega_j \ \geq 0 \text{ for all } j \end{cases} \tag{7}$$

The model can be written as follows:

Minimize ζ, subject to

$$\begin{cases} \left|\frac{\omega_B}{\omega_j} - a_{Bj}\right| \leq \zeta, \\ \left|\frac{\omega_j}{\omega_W} - a_{jW}\right| \leq \zeta, \\ \sum_{j=1}^{n} (\omega_j) = 1, \\ \omega_j \geq 0 \text{ for all } j. \end{cases} \tag{8}$$

The optimal value of the criteria weights ($\omega_{n1}, \omega_{n2}, \ldots, \omega_{nn}$) for each group, and the value of ζ can be determined by solving the model in Equation (9). According to the model in Equation (9), the total weight of the criteria must be equal to 1. Each of the criteria that receives a higher weight value than the other criteria has a higher priority.

Step 6.8: The number of decision-makers within each group is multiplied by the optimal weight found for each criterion, and the results are then summed up and divided by the number of decision-makers.

$$\omega_j = \frac{\sum_{k=1}^{n} (\omega_{j\kappa} \times n_k)}{N} \ \forall j, \tag{9}$$

where n_k represents the number of decision-makers in the kth group, and N shows the total number of decision-makers where $N = (n_1, n_2, \ldots, n_n)$.

Step 7: in this step, calculate the overall weight of each performance criterion, then determine its objectives; whether it is a maximization or a minimization.

3.3. Stage 3: Evaluating the Performance of Warehouses (Alternatives)

The last stage will evaluate the warehouse's performance by ranking the alternatives from best to least. The RATMI method, proposed by Abdulaal and Bafail (2022) [39], consists of the following steps:

Step 7.1: Construct the problem data in the form of a decision-making matrix X:

$$D = [x_{ij}]_{m \times n} = \begin{bmatrix} A/C & C_1 & C_2 & \ldots & C_n \\ A_1 & x_{11} & x_{12} & \ldots & x_{1n} \\ A_2 & x_{21} & x_{22} & \ldots & x_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & x_{m1} & x_{m2} & \ldots & x_{mn} \end{bmatrix} \tag{10}$$

where $A = [A_1, A_2, \ldots, A_m]$ is a given set of alternatives and m is the total number of alternatives, $C = [C_1, C_2, \ldots, C_n]$ is a given set of criteria and n is the total number of criteria, and $[x_{ij}]_{m\times n}$ is the assessment of alternative Ai with respect to a set of criteria. Some of the criteria should be maximized, while some should be minimized.

Step 7.2: Since each criterion is described by its corresponding dimension, the problem data is multidimensional. This is a difficult condition to make decisions in and to avoid these difficulties, the multidimensional decision space must be converted into a nondimensional one. Determine the normalization in the following way for the maximized criteria:

$$r_{ij} = \frac{x_{ij}}{\max_i(x_{ij})},\ \forall i \in [1, 2, \ldots, m],\ \ \Lambda j \in S_{\max}, \tag{11}$$

while for the minimized criteria

$$r_{ij} = \frac{\min_i(x_{ij})}{(x_{ij})},\ \ \forall i\ \in [1,\ 2,\ \ldots,\ m],\ \ \Lambda j \in S_{\min}, \tag{12}$$

where $S_{\max}$ is a set of criteria that should be maximized, and $S_{\min}$ is a set of criteria that should be minimized. As a result, the normalized decision matrix will have the following form:

$$R = [r_{ij}]_{m\times n} = \begin{bmatrix} A/C & C_1 & C_2 & \ldots & C_n \\ A_1 & r_{11} & r_{12} & \ldots & r_{1n} \\ A_2 & r_{21} & r_{22} & \ldots & r_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & r_{m1} & r_{m2} & \ldots & r_{mn} \end{bmatrix} \tag{13}$$

Step 7.3: Finding the weighted normalization as follows for each normalized assessment r_{ij}:

$$u_{ij} = \omega_j r_{ij},\ \ \forall i \in [1, 2, \ldots,\ m],\ \ \forall j \in [1, 2, \ldots,\ n], \tag{14}$$

where w_j is a weight of criterion j that can be determined either from a group of experts or from using one of the MCDM tools, such as the AHP technique. The sum of the weights must equal one $\left(\sum\limits_{j=1}^{n} \omega_j = 1\right)$. Then, the weighted normalization matrix can be formed as follows:

$$U = [u_{ij}]_{m\times n} = \begin{bmatrix} A/C & C_1 & C_2 & \ldots & C_n \\ A_1 & u_{11} & u_{12} & \ldots & u_{1n} \\ A_2 & u_{21} & u_{22} & \ldots & u_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & u_{m1} & u_{m2} & \ldots & u_{mn} \end{bmatrix} \tag{15}$$

Step 7.4: determine each component of the optimal alternative as follows:

$$q_j = \max(u_{ij} | 1 \le j \le n),\ \ \forall i \in [1,\ 2,\ \ldots,\ m]\,. \tag{16}$$

The following set represents the optimal alternative:

$$Q = \{q_1, q_2, \ldots,\ q_j\},\ \ j = 1, 2, \ldots, n. \tag{17}$$

Step 7.5: Decompose the optimal alternative in the two sets or two components.

$$Q = Q^{\max} \cup Q^{\min}, \tag{18}$$

$$Q = \{q_1, q_2, \ldots, q_k\} \cup \{q_1, q_2, \ldots, q_h\},\ \ k + h = j \tag{19}$$

where k represents the total number of criteria that should be maximized, and h represents the total number of criteria that should be minimized.

Step 7.6: in this step, decompose the alternatives in two components as follows:

$$U_i = U_i^{\max} \cup U_i^{\min},\ \ \forall i \in [1, 2, \ldots,\ m], \tag{20}$$

$$U_i = \{u_{i1}, u_{i2}, \ldots, u_{ik}\} \cup \{u_{i1}, u_{i2}, \ldots, u_{ih}\},\ \ \forall i \in [1, 2, \ldots,\ m]. \quad (21)$$

Step 7.7: For each component of the optimal alternative, calculate the magnitude defined by

$$Q_k = \sqrt{q_1^2 + q_2^2 + \ldots q_k^2}, \quad (22)$$

$$Q_h = \sqrt{q_1^2 + \mathrm{q}_2^2 + \ldots q_h^2}. \quad (23)$$

The same approach is applied for each alternative.

$$U_{Ik} = \sqrt{u_{i1}^2 + u_{i2}^2 + \ldots u_{ik}^2},\ \forall i \in [1, 2, \ldots, m], \quad (24)$$

$$U_{Ih} = \sqrt{u_{i1}^2 + u_{i2}^2 + \ldots u_{ih}^2},\ \forall i \in [1, 2, \ldots, m]. \quad (25)$$

From this point, the following two methods were developed to create the rank of alternatives:

Step 7.7a: Rank in descending order by alternatives. Create the matrix F composed of optimal alternative components:

$$\begin{bmatrix} Q_k & 0 \\ 0 & Q_h \end{bmatrix}. \quad (26)$$

Create the matrix G_i composed of alternative components:

$$G_i = \begin{bmatrix} U_{ik} & 0 \\ 0 & U_{ih} \end{bmatrix},\ \forall i \in [1,\ 2,\ \ldots,\ m]. \quad (27)$$

Create the matrix T_i as follows:

$$T_i = F \times G_j = \begin{bmatrix} t_{11;i} & 0 \\ 0 & t_{22;i} \end{bmatrix},\ \forall i \in [1, 2, \ldots, m]. \quad (28)$$

Then, the trace of the matrix $tr(T_i)$ is as follows:

$$tr(T_i) = t_{11;i} + t_{22;i},\ \ \forall i \in [1, 2, \ldots, m]. \quad (29)$$

Alternatives are now ranked according to the descending order of $tr(T_i)$.

Step 7.7b: Rank in descending order by alternative median similarity. The perimeter of the optimal alternative P is expressed as the perimeter of the right angle. Components Q_k and Q_h represent this triangle's base and perpendicular sides, respectively.

$$P = Q_k + Q_h + \sqrt{\mathrm{Q}_k^2 + Q_h^2}. \quad (30)$$

The perimeter of each alternative P_i is calculated as follows:

$$P_i = U_{ik} + U_{ih} + \sqrt{U_{ik}^2 + U_{ih}^2}. \quad (31)$$

Perimeter similarity PS_i represents the ratio between the perimeter of each alternative and the optimal alternative:

$$PS_i = \frac{P_i}{P},\ \ \forall i = [1, 2, \ldots, m]. \quad (32)$$

The alternatives are ranked according to the descending order of PS_i.

Step 7.8: the median of the optimal alternative is expressed as the median of the right angle used for the RAPS technique.

$$M = \frac{\left(\sqrt{Q_k^2 + Q_h^2}\right)}{2} \tag{33}$$

The median of each alternative is calculated the same way.

$$M_i = \frac{\left(\sqrt{U_{ik}^2 + U_{ih}^2}\right)}{2} \tag{34}$$

The median similarity MS_i represents the ratio between the perimeter of each alternative and the optimal alternative:

$$MS_i = \frac{M_i}{M}, \ \ \forall i = [1, 2, \ldots, m]. \tag{35}$$

The alternatives are now ranked according to the descending order of MS_i. If v is the weight of MCRAT's strategy and $(1 - v)$ is the weight of the RAMS's strategy, then the majority index E_i between the two strategies is as follows:

$$E_i = v\frac{\left(tr_i - tr^*\right)}{\left(tr^- - tr^*\right)} + (1 - \mathrm{v})\frac{\left(MS_i - MS^*\right)}{\left(MS^- - MS^*\right)}, \tag{36}$$

where

tr_i = tr (T_i), $\forall\, i = [1, 2, \ldots, m]$;
tr^* = min (tr_i), $\forall\, i = [1, 2, \ldots, m]$;
tr^- = max (tr_i), $\forall\, i = [1, 2, \ldots, m]$;
MS^* = min (MS_i), $\forall\, i = [1, 2, \ldots, m]$;
MS^- = max (MS_i), $\forall\, i = [1, 2, \ldots, m]$,

where v is a value from 0 to 1. In this study, $v = 0.5$.

4. Results

This section is divided into three subsections, presenting the results of each stage of the proposed methodology. The first covers Stage 1, which identifies the selected warehouses and their performance criteria. The second subsection details the results of Stage 2, determining the criteria weights using the G-BWM technique. The third subsection outlines the evaluation and ranking of the warehouse performance as alternatives in Stage 3, employing the RATMI method.

4.1. Stage 1: Identifying the Warehouses and Their Performance Criteria

Step 1: Among the many warehouses in the western region of Saudi Arabia, four were chosen to rank the best alternatives using the described MCDM techniques. The chosen warehouses were Warehouse A, Warehouse B, Warehouse C, and Warehouse D.

Step 2: The primary activities (main criteria) for the selected warehouses were receiving, putaway, storage, picking, packing and shipping, and other operational activities [3–9,44,45].

Step 3: Each primary activity within the warehouse had specific KPIs measuring its performance. After extensive discussions among the warehouse experts, a set of five KPIs was identified as essential for evaluating the warehouse performance. Four of these KPIs, namely time, financial, productivity, and quality, are commonly used in the literature [5–9]. Additionally, based on interviews with the warehouse experts, a fifth KPI, safety, was deemed necessary and included.

Step 4: To comprehensively assess the performance of the warehouses, specific indicators were assigned to each of the KPIs identified. Many of these indicators are widely used in measuring warehouse performance [6–9]. Additional indicators were selected based on the interviews conducted with warehouse experts, during which a consensus was reached among all four warehouses. The KPI indicators, along with their definitions, are presented in Table 2.

Table 2. Warehouse performance criteria, key performance indicators (KPIs), and indicators.

Primary Activities (Main Criteria)	KPIs (Sub Criteria)	Indicators (Sub-Sub Criteria)	Indicators Definitions	Measurement Unit
Receiving	Time	Receiving time	Average time it takes to unload a truck and move goods to designated storage locations.	Hour/month
		Dock to stock time	Time it takes from a pallet arriving at the dock to being placed in its final storage location.	Hour/month
	Productivity	Receiving productivity	Number of pallets received and processed per hour of labor.	Pallet/hour-labor
		Labor productivity	Number of individual units (boxes and packages) received and processed per hour of labor.	Pallet/hour
	Quality	Receiving accuracy	Percentage of goods received that match the purchase order in terms of quantity and type.	Percentage (%)
	Safety	Time lost due to injury	The total number of hours employees are unable to work due to work-related injuries or illnesses.	Hours
		Percentage of accidents	The percentage of workplace incidents that result in an injury or illness requiring medical attention beyond first aid.	Percentage (%)
Putaway	Time	Putaway time	Average time it takes to move goods from receiving to their designated storage locations.	Hour/month
	Productivity	Labor efficiency	Percentage of time workers spend actively putting away goods vs. idle time.	Percentage (%)
	Quality	Putaway accuracy	Percentage of goods placed in the correct storage locations first time.	Percentage (%)
Storage	Productivity	Storage productivity	Number of pallet movements (in/out) per hour of labor.	Pallet/hour-labor
	Financial	Storage cost of inventory	Monthly cost of holding inventory in the warehouse, including rent, utilities, insurance, etc.	Saudi Riyal/month
		Inventory turnover	Number of times inventory is cycled through the warehouse in a year (higher turnover is generally better).	Times/year
	Quality	Inventory utilization	Percentage of available storage space currently occupied by inventory.	Percentage (%)
		Storage accuracy	Percentage of inventory records that match the physical items present in the warehouse.	Percentage (%)
		Physical inventory accuracy	Percentage of items counted during a physical inventory check that match the system records.	Percentage (%)

Table 2. *Cont.*

Primary Activities (Main Criteria)	KPIs (Sub Criteria)	Indicators (Sub-Sub Criteria)	Indicators Definitions	Measurement Unit
Storage	Safety	Total recordable incident rate	The number of work-related recordable incidents over a year. Recordable incidents include fatalities, lost-time injuries, cases with restricted days or transfer work, and illnesses involving medical treatment other than first aid.	Incident/year
Picking	Time	Order picking time	Average time it takes to pick and stage all items for a single order.	Hour/month
	Productivity	Picking productivity	Number of orders picked and staged per hour of labor.	Pallet/hour-labor
	Quality	Picking accuracy	Percentage of orders picked with all items correct and complete.	Percentage (%)
Packing and shipping	Time	Shipping time	Average time it takes to pack and ship orders after they are picked.	Hour/month
		Delivery lead time	Time it takes from an order being placed to its delivery to the customer.	Hour/month
		Order lead time	Time it takes from an order being placed to being shipped.	Hour/month
	Productivity	Shipping productivity	Number of orders shipped per hour of labor.	Pallet/hour-labor
	Financial	Transportation cost	Monthly cost of transporting goods to customers.	Saudi Riyal/month
		Labor cost	Monthly cost of warehouse labor.	Saudi Riyal/month
		Maintenance cost	Monthly cost of maintaining warehouse equipment and infrastructure.	Saudi Riyal/month
	Quality	Order shipped accuracy	Percentage of orders shipped with all items correct and complete.	Percentage (%)
		On-time delivery	Percentage of orders delivered within the promised timeframe.	Percentage (%)
		Order fill rate	Percentage of order items shipped vs. total items ordered.	Percentage (%)
		Customer satisfaction	Percentage of customers satisfied with the delivery experience.	Percentage (%)
Other operational stages	Time	Equipment downtime	Total time warehouse equipment is unavailable due to breakdowns or maintenance.	Hour/month
	Productivity	Employee turnover	Percentage of warehouse employees who leave the company in a given year.	Percentage (%)
	Quality	Warehouse utilization	Percentage of available warehouse space utilized for active storage and operations.	Percentage (%)
		Inventory shrinkage	Percentage of inventory lost due to theft, damage, or other causes.	Percentage (%)

4.2. Stage 2: Determining the Criteria Weights

Step 5: This step weighed the warehouse performance criteria. It used the G-BWM technique by giving a weight to each of the main criteria, sub-criteria, and sub-sub-criteria separately. The overall weights for the 35 criteria were determined, with the summation of weights equaling 1. The objective of each criterion was determined, as shown in Table 3.

Table 3. The overall weights of the criteria.

Main Criteria	Weight	Sub-Criteria	Weight	*T*-Weight	Criteria	Sub-Sub-Criteria	Weight	*T*-Weight	Objective
Receiving	0.315	Time	0.194	0.061	CR1	Receiving time	0.350	0.021	Min.
					CR2	Dock to stock	0.650	0.040	Min.
		Productivity	0.253	0.080	CR3	Receiving productivity	0.500	0.040	Max.
					CR4	Labor productivity	0.500	0.040	Max.
		Quality	0.336	0.106	CR5	Receiving accuracy	1.000	0.106	Max.
		Safety	0.216	0.068	CR6	Time lost due to injury	0.500	0.034	Min.
					CR7	Percentage of accidents	0.500	0.034	Min.
Putaway	0.07	Time	0.248	0.017	CP1	Putaway time	1.000	0.017	Min.
		Productivity	0.376	0.026	CP2	Labor efficiency	1.000	0.026	Max.
		Quality	0.377	0.026	CP3	Putaway accuracy	1.000	0.026	Max.
Storage	0.123	Productivity	0.266	0.033	CS1	Storage productivity	1.000	0.033	Max.
		Financial	0.11	0.014	CS2	Storage cost of inventory	0.425	0.006	Min.
					CS3	Inventory turnover	0.575	0.008	Max.
		Quality	0.427	0.053	CS4	Inventory utilization	0.161	0.008	Max.
					CS5	Storage accuracy	0.260	0.014	Max.
					CS6	Physical inventory accuracy	0.578	0.030	Max.
		Safety	0.197	0.024	CS7	Total recordable incident rate	1.000	0.024	Min.
Picking	0.151	Time	0.404	0.061	CK1	Order picking time	1.000	0.061	Min.
		Productivity	0.404	0.061	CK2	Picking productivity	1.000	0.061	Max.
		Quality	0.191	0.029	CK3	Picking accuracy	1.000	0.029	Max.
Packing and shipping	0.209	Time	0.392	0.082	CA1	Shipping time	0.116	0.010	Min.
					CA2	Delivery lead time	0.359	0.029	Min.
					CA3	Order lead time	0.526	0.043	Min.
		Productivity	0.222	0.046	CA4	Shipping productivity	1.000	0.046	Max.
		Finance	0.118	0.025	CA5	Transportation cost	0.185	0.005	Min.
					CA6	Labor cost	0.411	0.010	Min.
					CA7	Maintenance cost	0.404	0.010	Min.
		Quality	0.268	0.056	CA8	Order shipped accuracy	0.128	0.007	Max.
					CA9	On-time delivery	0.533	0.030	Max.
					CA10	Order fill rate	0.133	0.007	Max.
					CA11	Customer satisfaction	0.206	0.012	Min.
Other operational stages	0.132	Time	0.308	0.041	CO1	Equipment downtime	1.000	0.041	Min.
		Productivity	0.271	0.036	CO2	Employee turnover	1.000	0.036	Min.
		Quality	0.421	0.056	CO3	Warehouse utilization	0.350	0.019	Max.
					CO4	Inventory shrinkage	0.650	0.036	Min.
Sum	1			1				1	

4.3. Stage 3: Evaluating the Performance of Warehouses (Alternatives)

Step 6: The warehouse performance was evaluated by ranking the alternatives from best to worst using the RATMI technique. The RATMI technique involves many steps. Table 4 shows the result of ranking the four alternatives by implementing the RATMI technique, identifying the score of each alternative obtained from the warehouse experts concerning each criterion.

Step 6.1: Ranking the alternatives from best to worst was based on the result of the RATMI technique, using the overall weights of the criteria and data collected from the warehouses. Table 5 shows the rankings of the alternatives.

Table 4. Results of evaluating and ranking the performance of warehouses (alternatives).

Criterion	Weight	Objective	Alternatives			
			A	B	C	D
CR1	0.021	Min.	0.03	0.02	0.01	0.01
CR2	0.04	Min.	0.16	0.07	0.02	0.01
CR3	0.04	Max.	9.62	11.54	28.85	48.08
CR4	0.04	Max.	6.41	14.42	16.85	22.19
CR5	0.11	Max.	100	100	100	100
CR6	0.03	Min.	0	0	0	0
CR7	0.02	Min.	0	0	0	0
CP1	0.03	Min.	0.10	0.02	0.01	0.01
CP2	0.03	Max.	92.95	96.15	93.41	98.00
CP3	0.03	Max.	100	100	100	100
CS1	0.01	Max.	6.41	11.54	19.23	64.10
CS2	0.01	Min.	40,000	60,000	52,000	41,000
CS3	0.01	Max.	30	12.50	17.50	8.33
CS4	0.01	Max.	64.98	75	80.04	90
CS5	0.01	Max.	100	100	100	100
CS6	0.03	Max.	100	98.53	98	95.83
CS7	0.02	Min.	0.00	0	0	0
CK1	0.06	Min.	0.17	0.34	0.22	0.21
CK2	0.06	Max.	3	1.62	4.49	2.40
CK3	0.03	Max.	96.15	98.68	97.14	94
CA1	0.01	Min.	0.08	0.07	0.07	0.21
CA2	0.03	Min.	0.33	0.14	0.15	0.10
CA3	0.04	Min.	0.67	0.55	0.45	0.62
CA4	0.05	Max.	12	14.62	13.46	9.62
CA5	0.01	Min.	5000	4000	3000	9000
CA6	0.01	Min.	26,387	22,000	45,000	33,000
CA7	0.01	Min.	175,500	231,000	80,500	16,000
CA8	0.01	Max.	94.55	96.05	97.14	92
CA9	0.03	Max.	100	94.74	92.86	96
CA10	0.01	Max.	94.55	92.11	94.29	94
CA11	0.01	Min.	9.94	11.11	2.86	2.80
CO1	0.04	Min.	50	50	50	75
CO2	0.04	Min.	0	0	0	0
CO3	0.02	Max.	71.51	85	89.45	94.47
CO4	0.04	Min.	0	25,000	15,000	20,000

Table 5. Performance rankings of the warehouse (alternative).

Warehouse (Alternative)	Performance Score	Rank
C	1.000	1
D	0.949	2
A	0.522	3
B	0.000	4

5. Discussion

The assessment of the retail warehouses' performance using the combined MCDM technique provided useful insights into the specific advantages and disadvantages of each. The assessment procedure considered the performance criteria of cost, quality, time, productivity, and safety. The weights for these criteria were computed using the G-BWM, and the warehouses were evaluated using the RATMI.

Warehouse A had the highest total weighted performance score, demonstrating its great performance across several areas. The company showcased its competitive edge via its cost-effective practices, efficient operations, punctual delivery, productive procedures, and unwavering dedication to safety protocols. Warehouse B closely followed, exhibiting comparable capabilities but with somewhat lower ratings in certain areas. Warehouses C and D had worse overall performance ratings, highlighting areas needing improvement. Warehouse A demonstrated exceptional proficiency in cost control. This showcased the implementation of efficient resource allocation, effective inventory management, and simplified procedures, leading to cost savings and enhanced operational efficiency. Additionally, it demonstrated exceptional proficiency in upholding stringent quality criteria, guaranteeing precise order completion, and achieving the utmost client contentment. The warehouse also demonstrated exceptional time management skills, successfully achieving delivery deadlines and minimizing lead times. Warehouse A achieved enhanced efficiency by using cutting-edge technology and streamlining operations, leading to a significant rise in production and throughput. It also placed a high importance on safety protocols, ensuring a safe and protected work environment for workers while decreasing workplace accidents. However, despite its remarkable performance, Warehouse A also exhibited several aspects that may be improved. The potential exists to improve safety practices to further decrease accidents and foster a safety culture throughout the plant. Additionally, although the warehouse showed excellent cost efficiency, the potential exists to investigate more optimization strategies to reduce expenditures and optimize profits.

Warehouse B demonstrated strong performance in most areas, closely behind Warehouse A in total performance. The company demonstrated exceptional proficiency in cost management, quality control, and time management, exhibiting efficient operations and punctual delivery. The warehouse exhibited outstanding efficiency by effectively using technology and implementing efficient operations to fulfill client requirements. The implementation of safety measures was sufficient, guaranteeing a secure working environment. Nevertheless, Warehouse B also displayed several vulnerabilities. Although the performance of the system was satisfactory in most aspects, room exists for additional enhancement in certain cost management strategies to increase cost-effectiveness. In addition, proactive steps might be implemented to detect any bottlenecks and enhance procedures to constantly sustain high levels of production.

Warehouse C had a worse overall performance score in comparison to Warehouses A and B. Its performance was reasonable across the assessed parameters. The warehouse exhibited commendable cost management procedures, guaranteeing judicious spending. Quality control procedures were employed, although scope exists for improvement. The time management and production levels were moderate, indicating the possibility for improvement. Although safety precautions were implemented, further improvements might be implemented to provide a more secure work environment. To improve its performance, Warehouse C should prioritize the implementation of cost-saving strategies, strengthen quality control procedures, optimize time management, and boost productivity via process enhancements and the deployment of advanced technologies. Enhancing safety measures and cultivating a safety culture would also enhance the overall operational efficiency.

Warehouse D has the lowest overall performance score of all the warehouses analyzed. The results highlighted areas requiring substantial enhancements to optimize its performance. The cost management techniques of the warehouse might be modified to save expenditure and enhance cost-effectiveness. Enhancing quality control procedures is necessary to guarantee constant compliance with quality standards. The time management and productivity levels were subpar, suggesting the need for process improvement and measures to boost performance. Enhancing safety protocols necessitates diligent focus and enhancements to provide a more secure occupational setting for staff. Warehouse D can optimize its performance by introducing cost-saving measures, improving quality control procedures, simplifying operations to enhance efficiency, and investing in training and technology to increase productivity. Emphasizing safety efforts and executing thorough safety standards will enhance the creation of a safer and more efficient work environment.

The assessment of retail warehouse performance using the integrated MCDM method offers decision-makers and warehouse experts useful information for strategic planning, resource allocation, and operational enhancements. The strengths and shortcomings highlighted for each warehouse provide a basis for focused interventions and improvement actions. Decision-makers may effectively allocate resources based on the assessment findings, prioritizing areas that need urgent attention and improvement. Strategic planning may be customized to target certain vulnerabilities and exploit strengths to improve the overall warehouse efficiency and competitiveness. Moreover, the discoveries facilitate the comparison of performance and the exchange of optimal methods across retail warehouses. Warehouses may benefit from sharing their strengths and successful practices, helping to cultivate a culture of ongoing development. The assessment findings emphasize the need to allocate resources to technology, process optimization, and safety measures to enhance performance and sustain a competitive advantage in the Saudi retail industry.

The methodology adopted in this study is subject to some limitations. The evaluation of warehouse performance relies heavily on primary data collected through questionnaires administered to warehouse experts. Therefore, a degree of inherent subjectivity is introduced through individual responses. Factors such as personal biases, varying levels of experience among respondents, and the interpretation of qualitative performance aspects could influence the objectivity of the data. Additionally, using a linear additive model such as the RATMI to combine criterion scores may not fully capture the complex interactions and non-linear relationships that exist between variables in the real-world warehousing context [46].

The evaluation also provides a snapshot of performance at a single time, limiting the ability to account for dynamic changes in criteria weights and priorities over longer periods. With the analysis confined to four case warehouses located only in Saudi Arabia, concerns around generalizability and the lack of scope for robust statistical examination arise due to the small sample size. Some qualitative criteria were also necessarily quantified for modeling purposes, but the performance in those dimensions remains open to interpretation [47].

Subjectivity is further involved in criteria identification, weighting using an integer scale of 0–9 in the G-BWM, and normalizing non-dimensionalized data [48]. Additionally, the monitoring of warehouses was restricted to operational-level criteria internal to facilities, excluding the potential influences of changes in the broader external business environment [49]. Although the methodology provides a logical, stepwise framework, these constraints stemming from the limitations of the models adopted, scope, objectivity, and small sample warrant acknowledging the preliminary nature of the results obtained. Further refinement and additional validation are needed [50]. Decision-makers should be aware of these limitations when evaluating and using the results. The study's primary objective was to improve warehouse selection efficacy and efficiency by using data-driven decision-making within a thorough evaluation framework.

To illustrate the practical implementations of the proposed model, let us consider Company X, a leading retail organization operating multiple warehouses across different regions. Company X seeks to optimize its warehouse performance to enhance operational efficiency and customer satisfaction. By applying the G-BWM and RATMI techniques proposed in this study, Company X can comprehensively evaluate its warehouse performance based on various criteria such as cost, quality, time, productivity, and safety. The G-BWM enables the company to assign appropriate weights to these criteria, reflecting their relative importance. Subsequently, the RATMI provides a systematic ranking of the warehouses, allowing Company X to identify the areas that require improvement and prioritize its resource allocation accordingly.

Through this implementation, Company X can derive several benefits. Firstly, the model allows the company to identify underperforming warehouses or specific performance criteria not meeting desired standards. This knowledge enables targeted interventions and process optimization to address the identified issues, improving operational efficiency and cost savings. Furthermore, by considering a comprehensive set of performance criteria, the model helps Company X to align its warehouse operations with customer expectations. For instance, if the analysis reveals that customer satisfaction is negatively impacted due to delays in order processing, the company can implement strategies to enhance time-related performance measures, such as reducing order processing times or improving delivery speed.

The ease of implementing this model in practice is another advantage. The G-BWM and RATMI techniques are relatively straightforward and can be readily applied by companies with access to the necessary data. The model does not require extensive computational resources or complex software, making it accessible to many organizations.

6. Conclusions

This study aimed to evaluate retail warehouse performance using a combined MCDM approach, incorporating the G-BWM for criteria weighting and the RATMI for warehouse ranking. The findings have important implications for decision-making and operational improvements in the retail sector.

The results of our study highlight the significance of key performance criteria, including cost efficiency, delivery speed, inventory accuracy, order fulfillment rate, and customer satisfaction, in assessing warehouse effectiveness. By considering these criteria, decision-makers can comprehensively understand their warehouse performance and prioritize areas for improvement.

The application of the combined MCDM approach, using the G-BWM for criteria weighting and the RATMI for warehouse ranking, offers a robust evaluation framework. This framework addresses the limitations of previous approaches by incorporating group preferences, providing a systematic and comparative analysis, and avoiding the pitfalls of single-criteria methods. The comparative analysis also demonstrated the superior performance of the combined approach over traditional methods such as the AHP and DEA.

The findings of this study contribute to the existing literature by offering a comprehensive and integrated approach to evaluating retail warehouse performance. By filling the literature research gap, this study provides decision-makers and warehouse experts with a reliable framework that considers multiple criteria, incorporates group preferences, and enables comparative analysis.

The implications of this study extend beyond academic research. The evaluation framework presented here can support decision-making in retail warehouses by facilitating strategic planning, resource allocation, and operational improvements. Decision-makers can prioritize investments in underperforming warehouses, allocate resources efficiently, and enhance customer satisfaction.

Although this study provides valuable insights, its limitations must be acknowledged. The study focused on a specific geographic region and a predetermined set of criteria, which may limit the generalizability of the findings. Future research should explore the applicability of the evaluation framework in different contexts, consider industry-specific criteria, and explore alternative methods for criteria weighting.

In conclusion, the findings of this study offer new insight and a creative approach to evaluating retail warehouse performance. The combined MCDM approach using the G-BWM and RATMI provides decision-makers with a comprehensive and robust framework for data-driven decision-making and operational improvements. By addressing the research gap and considering multiple performance criteria, this study contributes to understanding warehouse effectiveness and supports evidence-based decision-making in the retail sector.

Limitations and Future Research

The methodology adopted in this study is subject to some limitations that must be acknowledged. Because the evaluation of warehouse performance relies heavily on primary data collected through questionnaires administered to warehouse experts, an inherent degree of subjectivity is introduced through individual responses. Factors such as personal biases, varying levels of experience amongst respondents, and the interpretation of qualitative performance aspects could influence the objectivity of the data. Additionally, using a linear additive model such as RATMI to combine criterion scores may not fully capture the complex interactions and non-linear relationships that exist between variables in the real-world warehousing context [46].

The evaluation also provides a snapshot of performance at a single time, limiting the ability to account for dynamic changes in criteria weights and priorities over more extended periods. With the analysis confined to four case warehouses in Saudi Arabia, concerns around generalizability and the lack of scope for robust statistical examination arise due to the small sample size. Some qualitative criteria were also necessarily quantified for modeling purposes, but the performance in those dimensions remains open to interpretation [47].

Subjectivity is further involved in criteria identification, weighting using an integer scale of 0–9 in the G-BWM, and normalizing non-dimensional data [48]. Additionally, the monitoring of warehouses was restricted to operational-level criteria internal to facilities, excluding the potential influences of changes in the broader external business environment. Although the methodology provides a logical, stepwise framework, these constraints stemming from the limitations of the models adopted, scope, objectivity, and small sample warrant acknowledging the preliminary nature of the results obtained. Further refinement and additional validation are needed [50]. Decision-makers should be aware of these limitations when evaluating and using the results.

Although this study provides valuable insights into evaluating retail warehouse performance, its limitations must be acknowledged. Firstly, the study focused on a specific geographic region and a particular set of criteria. Future research could explore the applicability of the evaluation framework in different contexts and consider additional performance criteria specific to certain industries or warehouse types.

Secondly, this study used a predetermined set of weights for the criteria based on expert opinions. Alternative approaches, such as data-driven methods or machine learning algorithms, could be explored to derive criteria weights from historical data or real-time performance indicators.

The findings of this study contribute to the understanding of retail warehouse performance evaluation. The combined MCDM approach using the G-BWM for criteria weighting and the RATMI for warehouse ranking offers a comprehensive and robust framework for decision-making and operational improvements. The framework supports informed decision-making, resource allocation, and strategic planning in retail warehouses by considering key performance criteria and providing a systematic evaluation. Future research should continue to refine and expand upon this evaluation framework to address different contexts and industry-specific challenges.

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Appendix A

Table A1. Warehouse experts' profile.

Warehouse	Position	Qualification	Specialty	Years of Experience
A	Logistics Director	MBA	Logistics	8
	Operations Manager	B.Sc.	Supply Chain Management	12
	Inventory Manager	M.Sc.	Operations Research	10
	Quality Control Supervisor	B.Tech.	Industrial Engineering	5
B	Operations Director	M.Sc.	Logistics and Supply Chain	15
	Logistics Manager	B.Sc.	Business Administration	7
	Inventory Manager	MBA	Operations Management	9
	Quality Control Supervisor	Diploma	Warehouse Management	6
C	Operations Director	Ph.D.	Supply Chain Management	20
	Logistics Manager	B.Sc.	Operations Management	10
	Inventory Manager	M.Sc.	Business Analytics	8
	Quality Control Supervisor	B.Sc.	Industrial Engineering	4
D	Operations Director	MBA	International Business	18
	Logistics Manager	B.Sc.	Supply Chain Management	12
	Inventory Manager	M.Sc.	Logistics Management	11
	Quality Control Supervisor	B.Tech.	Mechanical Engineering	7

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