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A NEW INTEGRATED GREY MCDM MODEL: CASE OF WAREHOUSE LOCATION SELECTION

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Abstract. *Warehouses link suppliers and customers throughout the entire supply chain. The location of the warehouse has a significant impact on the logistics process. Even though all other warehouse activities are successful, if the product dispatched from the warehouse fails to meet the customer needs in time, the company may face with the risk of losing customers. This affects the performance of the whole supply chain therefore the choice of warehouse location is an important decision problem. This problem is a multi-criteria decision-making (MCDM) problem since it involves many criteria and alternatives in the selection process. This study proposes an integrated grey MCDM model including grey preference selection index (GPSI) and grey proximity indexed value (GPIV) to determine the most appropriate warehouse location for a supermarket. This study aims to make three contributions to the literature. PSI and PIV methods combined with grey theory will be introduced for the first time in the literature. In addition, GPSI and GPIV methods will be combined and used to select the best warehouse location. In this study, the performances of five warehouse location alternatives were assessed with twelve criteria. Location 4 is found as the best alternative in GPIV. The GPIV results were compared with other grey MCDM methods, and it was found that GPIV method is reliable. It has been determined from the sensitivity analysis that the change in criteria weights causes a change in the ranking of the locations therefore GPIV method was found to be sensitive to the change in criteria weights.*

Key words: *Grey preference selection index, Grey proximity indexed value, Multi-criteria decision making, Warehouse location selection*

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1. INTRODUCTION

Warehouses are critical elements that affect the performance of an entire supply chain. In addition, warehouses are links between upstream suppliers and downstream customers throughout the entire supply chain. Warehouses can also be described as places where efficient using of space and equipment are made in. To react more quickly to client demands with reduced costs, efficient warehousing activities considerably decrease the order picking distance and processing time of item motion for order fulfillment within a warehouse [1]. No matter how successful the warehouse activities are, if the product dispatched from the warehouse fails to meet the customer needs in time, the company will risk losing customers.

One of the most important factors in the timely delivery of the product is the location of the warehouse therefore enterprises need to develop effective solutions for the warehouse location selection problem which has a significant impact on logistics processes [2]. The problem of warehouse location selection requires a crucial strategic decision plan for the businesses profitably. Deciding on distribution warehouse locations is one of the most important issues to be considered in logistics problems. Choosing the right warehouse location provides competition and benefits for companies. At the same time, the location of the distribution warehouse is important in issues such as proximity to distribution locations, cost, and labor. Since there are usually more than one alternative and more than one criteria to be considered in the problem of selecting a warehouse location, this problem can be solved by using multi-criteria decision-making (MCDM) methods. MCDM methods are frequently used in the solution of assessment and sequencing problems including many conflicting criteria [3]. They are useful in determining the best alternative in a system with multiple alternatives and multiple criteria to be taken into account.

Many real-world decision-making problems do not contain crisp data. Most of the data consist of uncertainty and vagueness. To deal with the uncertainty, different methodologies were developed such as fuzzy set theory, rough theory, D numbers, and grey theory. In the literature, these methodologies have mostly been used in combination with MCDM methods. For example, Ecer and Pamucar [4] have used fuzzy BWM (best worst method) to find the relative weights and fuzzy CoCoSo (combined compromise solution) with Bonferroni (CoCoSo'B) to rank alternatives in sustainable supplier selection problem. Ecer and Pamucar [5] assessed insurance companies according to their service quality in Covid-19 by using intuitionistic fuzzy MARCOS (measurement of alternatives and ranking according to compromise solution). Shojaei and Bolvardizadeh [6] has used rough AHP (analytic hierarchy process) and rough TOPSIS (technique for order performance by similarity to ideal solution) for assessing suppliers in terms of sustainability in construction industry. Stević et al. [7] has used rough PIPRECIA (pivot pairwise relative criteria importance assessment) to evaluate tools in sustainable production and fuzzy MARCOS to rank forest companies. Pamucar et al. [8] ranked zero-carbon strategies in London transportation system with fuzzy BWM-D and TODIM (an acronym in Portuguese for interactive and multi criteria decision making)-D. Tian et al. [9] have used AHP and grey correlation TOPSIS for material selection problem in construction industry. Tadić et al. [10] assessed location alternatives for dry ports by using Delphi, AHP, and CODAS (combinative distance-based assessment) with grey numbers.

Grey numbers' major benefit is its adaptability in dealing with complicated scenarios. In addition, grey theory can be used successfully compared to fuzzy sets in terms of a small amount of data and limited and incomplete data [11-13]. If the upper and lower values of criteria (including uncertain data) are known, these criteria can be expressed in grey numbers. As they are known in this decision problem, a grey MCDM method is used in this study. Decision-makers can also make use of rough set theory to deal with uncertainty. However, in the rough set theory, crisp numbers can be used to handle uncertainty. On the contrary, in grey theory, uncertainty is handled by using interval values, which helps to take the data in a larger framework rather than compressing the data into crisp numbers. Therefore, in this study, the grey extensions of MCDM (PSI and PIV) methods are proposed to solve the warehouse selection problem.

This study proposes an integrated grey MCDM model including GPSI (grey preference selection index) and GPIV (grey proximity indexed value) to determine the most appropriate warehouse location for a supermarket. While the GPSI method is used to determine the weights of the criteria, the GPIV method is used to evaluate the performance of the alternatives and to rank these alternatives. PSI's main benefit is that, unlike other MCDM approaches, it does not need assigning a relative priority between criteria [14]. Compared to other MCDM methods, PIV has comparatively straightforward and effective with simple computing steps, and minimizes rank reversal issues [15-16].

The flow of methodology is demonstrated in Fig. 1.

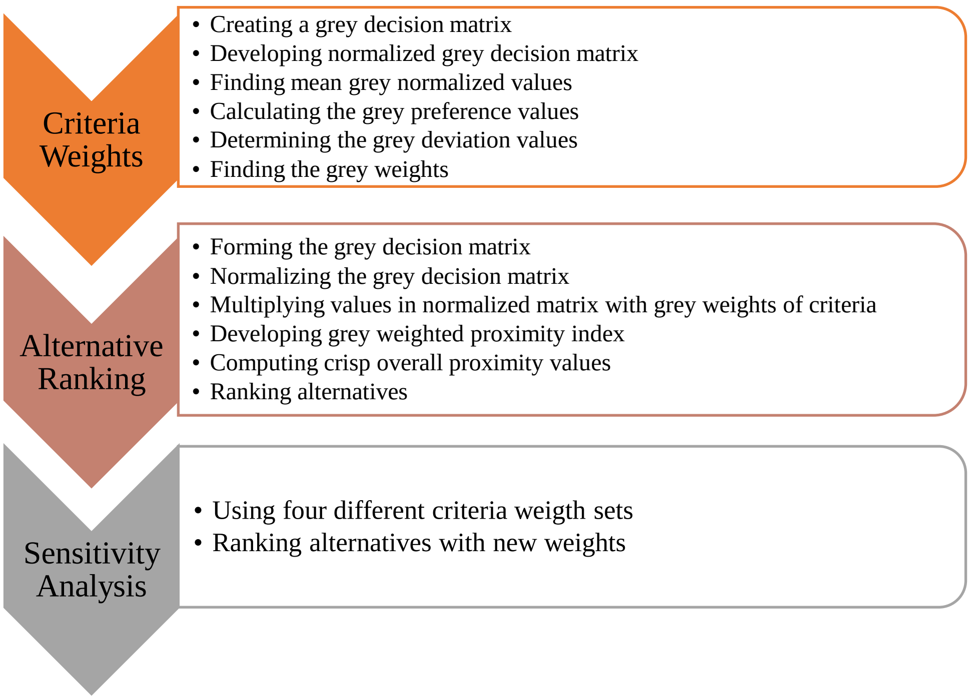

Fig. 1 The steps of grey MCDM methodology for location selection

This study aims to make three contributions to the literature. First, PSI and PIV methods combined with grey theory will be introduced for the first time in the literature. There is no study that combined grey theory with PSI and PIV methods to the best of our knowledge. Combining these two methods with grey theory will aid to effectively handle the uncertainties in the problem. Second, GPSI and GPIV methods will be combined and used to select the best warehouse location. It has not been seen in the literature that GPSI and GPIV methods are used together in solving any MCDM problems.

The study is organized as follows. In Section 2, the literature review is made concerning the warehouse location selection, PSI and PIV methods. In Section 3, the methodology of GPSI and GPIV methods is presented. In Section 4, the results of the proposed model are indicated. In Section 5, the results of GPSI are compared with the results of other grey MCDM, which are grey TOPSIS [17], grey WASPAS (weighted aggregated sum-product assessment) [18], and grey COPRAS (complex proportional assessment method) [19] and grey weights of criteria are changed using 4 different scenarios and sensitivity analysis is performed. In the last section, a brief conclusion is indicated.

2. LITERATURE REVIEW

In this section, first, the studies that solve the problem of selecting the warehouse location with MCDM methods will be presented, then, studies using PSI and PIV methods will be demonstrated.

2.1. Warehouse Location Selection Problem

The problem of warehouse location selection has been discussed many times in the literature. For example, Lee [20] discussed cost, Hakimi and Kuo [21] discussed maximizing profitability, Korpela and Lehmusvaara [22] developed a customer-oriented approach and used AHP and mixed integer programming model. In another study, Korpela et al. [23] used AHP and DEA (data envelopment analysis) with distribution time, quantity and quality of distributions, emergency distributions, frequency situations, special requests and capacity criteria. Ho and Emrouznejad [24] developed an application for users to select a warehouse location. Kuo et al. [25], Tabari et al. [26], Chen [27], Kahraman et al. [28], Karmaker and Saha [29] discussed warehouse location selection problem only with fuzzy methodologies. They examined scenario-based examples of wrong decisions that can be made in warehouse selection in terms of economic losses. Stevenson [30] and Frazelle [31] explained warehouse centers as a factor of commercial success and competition. Demirel et al. [32] discussed the critical success factors in warehouse selection in terms of logistics management and optimization. In this study, it was revealed that decision-making processes are extremely important in case of success and failure in the selection of warehouse location. At the same time, it was concluded that a balance should be struck between cost and effectiveness in potential locations in organizational terms. In this context, the warehouse selection model was first modeled by Kuehn and Hamburger [33]. In this study, cost minimization has been aimed with mathematical modeling techniques. Efroymson and Ray [34] and Khumawala [35] selected warehouse locations with the classical linear programming model in their studies. The location problem has been created by Weber and Friedrich [36] and Tellier [37] by minimizing the distances to the final distribution locations. Owen and Daskin [38] dealt with a comprehensive mathematical problem in their work. In this study, benefit and cost values have been considered as the main criteria. On the other hand, various criteria and methodologies have been used by introducing the MCDM methodology. Badri [39] used the AHP method together with linear programming. This study has been focused on 4 main criteria. These criteria are benefits, costs, risks and opportunities. Vlachopoulou et al. [40] suggested a geographic decision support system to choose warehouse location with geographic criteria. Kabak and Keskin [41] proposed geographical information systems (GIS) and AHP models for potential warehouse locations. Nine criteria have been proposed in this study. Yerlikaya et al. [42] suggested an AHP - CRITIC (the criteria importance through intercriteria correlation) –VIKOR (visekriterijumska optimizacija i kompromisno resenje) based approach. In the study, they used cost, speed, safety criteria. Mihajlovic et al. [43] studied fruit warehouse location selection based on AHP and WASPAS. Ma et al. [44] handled the choices of warehouse location utilizing an Integrated Multi-Attribute Decision Making Method based on the cumulative prospect theory. It has been determined a strategic ranking of decision-making schemes by presenting a cumulative foreground theory.

Pamučar and Božanić [45] selected location from the suggested choices using a Single-Valued Neutrosophic (SVNN) based MABAC (Multi Attributive Border Approximation Area Comparison) model. It was aimed to select the ideal logistics center location by applying an optimization routine reducing transport costs and improving the business performance, competitiveness and profitability. Tuzkaya et al. [46] used AHP to rank locations to reduce costs and maximize profit. Uysal and Tosun [47] developed a grey theory-based method to solve warehouse location problem and compared the results of ELECTRE (elimination et choix traduisant la realité) and TOPSIS decision-making models. Özcan et al. [48] set the criteria for the most optimal warehouse location in a retail sector and applied grey theory, ELECTRE, TOPSIS and AHP. In this study, the authors considered five criteria, which are stock holding capacity, unit price, mean distance to shops, mean distance to movement flexibility, and primary suppliers, when evaluating four warehouse location alternatives. In another study, Ashrafzadeh et al. [49] used fuzzy TOPSIS to choose the best warehouse location for an Iranian company. They considered fifteen criteria in the evaluation of five alternatives. Dey et al. [50] proposed an integrated fuzzy MCDM to solve warehouse location selection problem in a supply chain. García et al. [51] utilized AHP method to choose the ideal warehouse location for perishable agricultural products. They took into account six criteria, which are costs, distance, needs, security, acceptance and accessibility, in the evaluation of three alternatives. Aktepe and Ersöz [2] used AHP, MOORA (multi-objective optimization method by ratio analysis) and VIKOR methods to address warehouse location selection problem for a company. Six criteria were used in the evaluation of eleven alternatives. Dey et al. [52] proposed three fuzzy MCDM methods, namely fuzzy TOPSIS, fuzzy MOORA and fuzzy simple additive weighting to choose a warehouse location. Additionally, to evaluate the objective criteria, the classical normalization technique is used. Silva et al. [53] used SMARTER and lexicographic method to rank products and assign them to the locations of warehouse storage. Mangalan et al. [54] utilized weighted MOORA method to optimize warehouse site. The results of the proposed method and TOPSIS method were compared to prove the applicability of the proposed method. Temur [55] proposed cloud based design optimization technique tackling high uncertainty. This technique was used in a warehouse location problem in order to indicate the feasibility and performance of this technique. Dey et al. [56] developed a novel multi-criteria group decision-making to determine the best warehouse location for an

Indian company. Four criteria, which are space availability, transportation facility, cost and availability of markets, were considered in the evaluation process. Raut et al. [57] used AHP to determine the best sustainable warehouse location among four alternatives while considering eleven criteria. The most important criterion was determined as governmental policies, and regulations among eleven criteria. Emeç and Akkaya [3] integrated fuzzy VIKOR and stochastic AHP methods to address warehouse location problem for a supermarket. Seventeen criteria were considered when determining the best location among four alternatives. Micale et al. [58] proposed an interval extension of MCDM methods, which are ELECTRE TRI and TOPSIS, to solve storage location assignment problem for an Italian company. Canbolat et al. [59] used decision tree and MABAC methodologies for warehouse location selection. Ehsanifar et al. [60] prioritized and ranked ten criteria using UTASTAR methodology. The most commonly used criteria in the current studies are cost minimization, profitability and geographical factors.

2.2. Literature Related to PSI Method

Some recent studies, carried out on PSI method (developed by Maniya and Bhatt [61]), in the literature are summarized in Table 1.

Table 1 Literature related to PSI method

Authors	Methods	Application Area
Vahdani et al. [62]	Interval-Valued Fuzzy PSI	Application in Human Resource Management
Attri and Grover [63]	PSI	Illustrative Examples
Chamoli [64]	PSI	For an experiment, the determination of optimum roughness parameters
Akyüz and Aka [65]	PSI	Manufacturing performance measurement in the glass industry
Petković et al. [66]	PSI	Illustrative Examples
Madić et al. [67]	PSI	In determining of laser cutting process conditions
Tuş and Adalı [68]	CRITIC, PSI, and CODAS	In solving of a personnel selection problem for a textile firm
Jha et al. [69]	PSI	In determining of optimum composite combination
Pathak et al. [70]	PSI and Metaheuristic method	In determining of optimum value for parameters of scanning process
Ulutaş [71]	Fuzzy PSI and Fuzzy ROV	In solving of a green supplier selection problem for a textile company

2.3. Literature Related to PIV Method

Many MCDM methods [72-78] have been developed in recent years. PIV is one of the newly developed (by Mufazzal and Muzakkir [15]) MCDM methods and it minimizes the rank reversal problem. There are few studies about this method in the literature. Khan et al. [16] used PIV method to indicate the efficacy and applicability of this method. To do this, two illustrative examples related to the e-Learning websites selection were analyzed and the results of PIV method were compared with the results of other MCDM methods

(COPRAS, VIKOR, AHP, WEDBA and WDBA). In another study, Yahya et al. [79] integrated Entropy and PIV methods to use for multi-response optimization. Nine experiments were evaluated while considering two criteria, which are Zeta potential and viscosity.

As it can be observed from literature review, there are limited studies about PSI and PIV methods, and they are mostly used for different decision problems other than location selection. For location selection problem, most of the studies in the literature used crisp MCDM methods, such as AHP and TOPSIS. This clearly shows that there is a gap in the application of new MCDM methods on location selection problem.

Additionally, in this study, unlike most of the studies in the literature; costs will be handled in two types, which are holding costs (HC) and transportation costs (TC). In addition, geographical features of the supplied materials, which are distance to customers (DC), distance to suppliers (DS), distance to producers (DP), delivery time (DT), and distance to the opponents (DO), have been handled separately. The criteria list has been enriched by considering different criteria such as capacity of storage (CS), development rate (DR), and transportation diversity (TD). Besides, environmental conditions, specifically infrastructure (I) and climatic conditions (CC), have been used in the selection of the warehouse location. Unlike the most of the studies, 12 different criteria were considered in this study. In the most of the studies, linear programming and cost-benefit optimization, and crisp MCDM methodologies were used to select warehouse location. Also, fuzzy sets were also commonly used in the literature. Fuzzy sets have been used in problems with uncertainty, and they address the problem with linguistic expressions. However, in the case of the small amount of data and limited and incomplete data, the fuzzy set theory is not sufficient. In this context, it is thought that the study will fill the following gaps in the literature:

- Few studies in the literature have used grey MCDM methods for warehouse location selection.
- There are no grey extensions of the two MCDM methods (PSI and PIV) that have few computations steps and reach a solution quickly.

3. Methodology

In this study, a grey model consisting of GPSI and GPIV methods is proposed for the solution of the warehouse location problem. While the GPSI method is used to determine the weights of the criteria, the GPIV method is used to evaluate the performance of the alternatives and to rank these alternatives.

3.1. Grey Preference Selection Index

Step 1: The linguistic values shown in Table 2 will be assigned by the experts as the performance values of the alternatives in the criteria. These performance values are converted to grey values with the help of Table 2, thus forming a grey decision matrix ($\otimes F$).

$$\otimes F = \left[\otimes f_{ij}\right]_{m\times n} \tag{1}$$

In Eq. (1), $\otimes f_{ij}$ ($\otimes f_{ij} = \left[f_{ij}^{l}, f_{ij}^{u}\right]$) indicates grey performance value of ith alternative on jth criterion.

Table 2 Linguistic and grey performance values

Linguistic Performance Values	Grey Performance Values
Very High	[9, 10]
High	[7, 9]
Medium	[5, 7]
Low	[3, 5]
Very Low	[1, 3]

Step 2: By utilizing Eq. (2) (beneficial criteria) and Eq. (3) (cost criteria), $\otimes F$ can be normalized as below.

$$\otimes k_{ij} = \frac{\otimes f_{ij}}{max(\otimes f_{ij})} = \left[\frac{f_{ij}^l}{max(f_{ij}^u)}, \frac{f_{ij}^u}{max(f_{ij}^u)}\right] \tag{2}$$

$$\otimes k_{ij} = \frac{min(\otimes f_{ij})}{\otimes f_{ij}} = \left[\frac{min(f_{ij}^l)}{f_{ij}^u}, \frac{min(f_{ij}^l)}{f_{ij}^l}\right] \tag{3}$$

In Eqs. (2) and (3), $\otimes k_{ij}$ indicates the normalized version of $\otimes f_{ij}$.

Step 3: By using Eq. (4), the mean grey normalized value ($\otimes \bar{k}_{ij}$) of each criterion is calculated as,

$$\otimes \bar{k}_{ij} = \frac{\sum_{i=1}^{m} \otimes k_{ij}}{m} = \left[\frac{\sum_{i=1}^{m} k_{ij}^l}{m}, \frac{\sum_{i=1}^{m} k_{ij}^u}{m}\right] \tag{4}$$

Step 4: For each criterion, the grey preference value ($\otimes \delta_j = [\delta_j^l, \delta_j^u]$) is computed with Eq. (5).

$$\otimes \delta_j = \sum_{i=1}^{m} (\otimes k_{ij} - \otimes \bar{k}_{ij})^2 = \left[\sum_{i=1}^{m} (k_{ij}^l - \bar{k}_{ij}^l)^2, \sum_{i=1}^{m} (k_{ij}^u - \bar{k}_{ij}^u)^2\right] \tag{5}$$

Step 5: By Eq. (6), the grey deviation value ($\otimes \gamma_j$) for each criterion is obtained.

$$\otimes \gamma_j = [\gamma_j^l, \gamma_j^u] = |1 - \otimes \delta_j| = \left[|1 - \delta_j^u|, |1 - \delta_j^l|\right] \tag{6}$$

Step 6: The grey weight ($\otimes w_j = [w_j^l, w_j^u]$) of each criterion is computed with Eq. (7).

$$\otimes w_j = \frac{\otimes \gamma_j}{\sum_{j=1}^{n} \otimes \gamma_j} = \left[\frac{\gamma_j^l}{\sum_{j=1}^{n} \gamma_j^u}, \frac{\gamma_j^u}{\sum_{j=1}^{n} \gamma_j^l}\right] \tag{7}$$

After computing the grey weight of each criterion, these grey weights are dispatched into GPIV.

3.2. Grey Proximity Indexed Value

GPIV method consists of four steps shown as follows.

Step 1: In Eq. (1), the grey decision matrix is formed. The values in this matrix are normalized by using Eq. (8).

$$\otimes e_{ij} = [e_{ij}^l, e_{ij}^u] = \frac{\otimes f_{ij}}{\sqrt{\sum_{i=1}^{m} (\otimes f_{ij})^2}} = \left[\frac{f_{ij}^l}{\sqrt{\sum_{i=1}^{m} \left(f_{ij}^u\right)^2 + \sum_{i=1}^{m} \left(f_{ij}^l\right)^2}}, \frac{f_{ij}^u}{\sqrt{\sum_{i=1}^{m} \left(f_{ij}^u\right)^2 + \sum_{i=1}^{m} \left(f_{ij}^l\right)^2}}\right] \tag{8}$$

In Eq. (8), $\otimes e_{ij}$ is the normalized of $\otimes f_{ij}$.

Step 2: These normalized values are multiplied by grey weights of criteria (obtained in GPSI) with Eq. (9).

$$\otimes t_{ij} = \left[t_{ij}^l, t_{ij}^u\right] = \otimes w_j \times \otimes e_{ij} = \left[w_j^l \times e_{ij}^l, w_j^u \times e_{ij}^u\right] \tag{9}$$

Step 3: Grey weighted proximity index ($\otimes g_{ij} = \left[g_{ij}^l, g_{ij}^u\right]$) is computed for beneficial (Eq. (10)) and cost criteria (Eq. (11)) as follows.

$$\otimes g_{ij} = max\left(\otimes t_{ij}\right) - \otimes t_{ij} = \left[max\left(t_{ij}^l\right) - t_{ij}^u, max\left(t_{ij}^u\right) - t_{ij}^l\right] \tag{10}$$

$$\otimes g_{ij} = \otimes t_{ij} - min\left(\otimes t_{ij}\right) = \left[t_{ij}^l - min\left(t_{ij}^u\right), t_{ij}^u - min\left(t_{ij}^l\right)\right] \tag{11}$$

Step 4: Grey ($\otimes d_i = \left[d_i^l, d_i^u\right]$) and crisp ($d_i$) overall proximity values are computed respectively with Eqs. (12) and (13).

$$\otimes d_i = \sum_{j=1}^{n} \otimes g_{ij} = \left[\sum_{j=1}^{n} g_{ij}^l, \sum_{j=1}^{n} g_{ij}^u,\right] \tag{12}$$

$$d_i = \frac{d_i^l + d_i^u}{2} \tag{13}$$

Finally, alternative with the least crisp overall proximity value is designated as the best alternative.

4. APPLICATION

The application of the integrated grey MCDM model is performed in a supermarket, which has over ten years of experience in the sector. During the Covid-19 pandemic, there were delays due to restrictions on transportation of the business. In addition, there has been an increase in costs in terms of warehouse and workforce during the pandemic. In order to overcome these problems, the supermarket chain decided to develop a project. At this point, consultancy service was received for logistics and crisis management. This study was carried out for 6 weeks with five experts who are the general manager of the supermarket chain, the director of logistics and transportation department, and 3 people from the consultancy company. The owner of the supermarket chain has 25 years of experience in the field of business graduate. The logistics director of the supermarket chain has a PhD in the logistics field and has 20 years of experience. In addition, 3 people in the consultancy company are industrial engineers with over 15 years of experience in the fields of engineering and logistics. Criteria were determined by literature review. In the 6-week meetings, the criteria in the literature were discussed with 5 experts, new criteria were added and removed. While determining the criteria, the cost criteria have been expanded to holding cost and transportation cost due to increasing in the costs during pandemic. Unlike the literature review, criteria such as infrastructure and climate conditions have been added. In addition, the criteria were developed by examining the distance functions in detail.

Totally, twelve criteria were identified for utilizing in warehouse location selection. These criteria are Holding Cost (HC), Transportation Costs (TC), Distance to Customers (DC), Distance to Suppliers (DS), Distance to Producers (DP), Delivery Time (DT), Distance to Opponents (DO), Capacity of Storage (CS), Development Rate (DR), Transportation Diversity (TD), Infrastructure (I) and Climatic Conditions (CC). The first six criteria are assigned as cost criteria and the others are assigned as beneficial criteria. The expert team identified five suitable alternatives for the warehouse location. The grey data of the first criterion were collected from expert team as actual data. The unit of this grey data is US Dollars and represents the holding cost per month. The expert team did not give the TC criterion as actual grey data for commercial reasons. For, TC and the other criteria, the grey data were determined together by the expert team and using the linguistic values shown in Table 2. The grey decision matrix was formed with all collected data. This matrix is presented in Table 3.

Table 3 The Grey decision matrix

Criteria / Locations	HC	TC	DC
Location 1	[340, 380]	[3, 5]	[7, 9]
Location 2	[420, 440]	[5, 7]	[5, 7]
Location 3	[320, 360]	[5, 7]	[3, 5]
Location 4	[430, 460]	[5, 7]	[3, 5]
Location 5	[330, 350]	[7, 9]	[3, 5]
Criteria / Locations	DS	DP	DT
Location 1	[5, 7]	[3, 5]	[3, 5]
Location 2	[3, 5]	[1, 3]	[5, 7]
Location 3	[5, 7]	[1, 3]	[5, 7]
Location 4	[3, 5]	[1, 3]	[7, 9]
Location 5	[7, 9]	[3, 5]	[5, 7]
Criteria / Locations	DO	CS	DR
Location 1	[5, 7]	[7, 9]	[3, 5]
Location 2	[3, 5]	[5, 7]	[7, 9]
Location 3	[5, 7]	[5, 7]	[3, 5]
Location 4	[3, 5]	[7, 9]	[7, 9]
Location 5	[5, 7]	[7, 9]	[1, 3]
Criteria / Locations	TD	I	CC
Location 1	[5, 7]	[3, 5]	[1, 3]
Location 2	[7, 9]	[5, 7]	[5, 7]
Location 3	[5, 7]	[5, 7]	[5, 7]
Location 4	[7, 9]	[5, 7]	[5, 7]
Location 5	[5, 7]	[3, 5]	[3, 5]

By means of Eqs. (2) and (3), the grey decision matrix is normalized. The normalized grey decision matrix is presented in Table 4.

Table 4 The normalized grey decision matrix (for GPSI)

Criteria / Locations	HC	TC	DC
Location 1	[0.842, 0.941]	[0.6, 1]	[0.333, 0.429]
Location 2	[0.727, 0.762]	[0.429, 0.6]	[0.429, 0.6]
Location 3	[0.889, 1]	[0.429, 0.6]	[0.6, 1]
Location 4	[0.696, 0.744]	[0.429, 0.6]	[0.6, 1]
Location 5	[0.914, 0.970]	[0.333, 0.429]	[0.6, 1]
Criteria / Locations	DS	DP	DT
Location 1	[0.429, 0.6]	[0.2, 0.333]	[0.6, 1]
Location 2	[0.6, 1]	[0.333, 1]	[0.429, 0.6]
Location 3	[0.429, 0.6]	[0.333, 1]	[0.429, 0.6]
Location 4	[0.6, 1]	[0.333, 1]	[0.333, 0.429]
Location 5	[0.333, 0.429]	[0.2, 0.333]	[0.429, 0.6]
Criteria / Locations	DO	CS	DR
Location 1	[0.714, 1]	[0.778, 1]	[0.333, 0.556]
Location 2	[0.429, 0.714]	[0.556, 0.778]	[0.778, 1]
Location 3	[0.714, 1]	[0.556, 0.778]	[0.333, 0.556]
Location 4	[0.429, 0.714]	[0.778, 1]	[0.778, 1]
Location 5	[0.714, 1]	[0.778, 1]	[0.111, 0.333]
Criteria / Locations	TD	I	CC
Location 1	[0.556, 0.778]	[0.429, 0.714]	[0.143, 0.429]
Location 2	[0.778, 1]	[0.714, 1]	[0.714, 1]
Location 3	[0.556, 0.778]	[0.714, 1]	[0.714, 1]
Location 4	[0.778, 1]	[0.714, 1]	[0.714, 1]
Location 5	[0.556, 0.778]	[0.429, 0.714]	[0.429, 0.714]

To give an example of the calculation of the values shown in Table 4, the HC (Eq. 3) grey normalized values of Location 1 are found as follows.

$$\otimes k_{11} = \frac{\otimes f_{11}}{max(\otimes f_{ij})} = \left[\frac{min(f_{ij}^{l})}{f_{11}^{u}}, \frac{min(f_{ij}^{l})}{f_{11}^{l}}\right] = \left[\frac{320}{380}, \frac{320)}{340}\right] = [0.842\ , 0.941]$$

The grey preference values ($\otimes\delta_j$), grey deviation values ($\otimes\gamma_j$) and grey weights ($\otimes w_j$) are calculated by using Eqs. (5-7), respectively. Table 5 presents the results.

Table 5 The GPSI method's results

Criteria / Results	HC	TC	DC
$\otimes\delta_j$	[0.039, 0.059]	[0.037, 0.178]	[0.063, 0.298]
$\otimes\gamma_j$	[0.941, 0.961]	[0.822, 0.963]	[0.702, 0.937]
$\otimes w_j$	[0.087, 0.101]	[0.076, 0.101]	[0.065, 0.098]
Criteria / Results	**DS**	**DP**	**DT**
$\otimes\delta_j$	[0.055, 0.270]	[0.021, 0.533]	[0.037, 0.178]
$\otimes\gamma_j$	[0.730, 0.945]	[0.467, 0.979]	[0.822, 0.963]
$\otimes w_j$	[0.067, 0.099]	[0.043, 0.103]	[0.076, 0.101]
Criteria / Results	**DO**	**CS**	**DR**
$\otimes\delta_j$	[0.097, 0.099]	[0.060, 0.060]	[0.357, 0.357]
$\otimes\gamma_j$	[0.901, 0.903]	[0.940, 0.940]	[0.643, 0.643]
$\otimes w_j$	[0.083, 0.095]	[0.087, 0.098]	[0.059, 0.067]
Criteria / Results	**TD**	**I**	**CC**
$\otimes\delta_j$	[0.060, 0.060]	[0.097, 0.099]	[0.260, 0.260]
$\otimes\gamma_j$	[0.940, 0.940]	[0.901, 0.903]	[0.740, 0.740]
$\otimes w_j$	[0.087, 0.098]	[0.083, 0.095]	[0.068, 0.077]

To give an example of the calculation of the values shown in Table 5, the grey deviation values ($\otimes\gamma_1$) and the grey weights ($\otimes w_1$) of HC are computed by Eqs. (6) and (7) respectively as follows.

$$\otimes\gamma_1 = [\gamma_1^l, \gamma_1^u] = \left[|1-\delta_1^u|, \left|1-\delta_1^l\right|\right] = [|1-0.059|, |1-0.039|] = [0.941, 0.961]$$

$$\otimes w_1 = \frac{\otimes\gamma_1}{\sum_{j=1}^{n} \otimes\gamma_j} = \left[\frac{0.941}{0.961+0.963+0.937\ldots.+0.740}, \frac{0.961}{0.941+0.822+0.702\ldots.+0.740}\right] = [0.087, 0.101]$$

The grey weights of criteria ($\otimes w_j$) found in the GPSI method are transferred to the GPIV method. Eq. (8) is applied to the grey decision matrix, which is shown in Table 3, in order to develop the normalized grey decision matrix for GPIV. This matrix is presented in Table 6.

Table 6 The normalized grey decision matrix for GPIV

Criteria / Locations	HC	TC	DC
Location 1	[0.279, 0.311]	[0.153, 0.254]	[0.400, 0.514]
Location 2	[0.344, 0.360]	[0.254, 0.356]	[0.286, 0.400]
Location 3	[0.262, 0.295]	[0.254, 0.356]	[0.171, 0.286]
Location 4	[0.352, 0.377]	[0.254, 0.356]	[0.171, 0.286]
Location 5	[0.270, 0.287]	[0.356, 0.458]	[0.171, 0.286]
Criteria / Locations	**DS**	**DP**	**DT**
Location 1	[0.269, 0.376]	[0.303, 0.505]	[0.153, 0.254]
Location 2	[0.161, 0.269]	[0.101, 0.303]	[0.254, 0.356]
Location 3	[0.269, 0.376]	[0.101, 0.303]	[0.254, 0.356]
Location 4	[0.161, 0.269]	[0.101, 0.303]	[0.356, 0.458]
Location 5	[0.376, 0.484]	[0.303, 0.505]	[0.254, 0.356]
Criteria / Locations	**DO**	**CS**	**DR**
Location 1	[0.294, 0.411]	[0.302, 0.388]	[0.163, 0.272]
Location 2	[0.176, 0.294]	[0.216, 0.302]	[0.381, 0.490]
Location 3	[0.294, 0.411]	[0.216, 0.302]	[0.163, 0.272]
Location 4	[0.176, 0.294]	[0.302, 0.388]	[0.381, 0.490]
Location 5	[0.294, 0.411]	[0.302, 0.388]	[0.054, 0.163]
Criteria / Locations	**TD**	**I**	**CC**
Location 1	[0.228, 0.319]	[0.176, 0.294]	[0.061, 0.184]
Location 2	[0.319, 0.410]	[0.294, 0.411]	[0.307, 0.429]
Location 3	[0.228, 0.319]	[0.294, 0.411]	[0.307, 0.429]
Location 4	[0.319, 0.410]	[0.294, 0.411]	[0.307, 0.429]
Location 5	[0.228, 0.319]	[0.176, 0.294]	[0.184, 0.307]

The normalized values are multiplied by the grey weights of criteria with the aid of Eq. (9). The grey weighted proximity values are calculated with Eqs. (10) and (11). For example, the grey weighted proximity values of Location 1's HC criterion are computed by Eq. (11) as follows.

$$\otimes g_{11} = \otimes t_{11} - min(\otimes t_{ij}) = \left[t_{11}^{l} - min(t_{ij}^{u}), t_{11}^{u} - min(t_{ij}^{l})\right] = [0.024 - 0.029, 0.031 - 0.023] = [-0.005, 0.008]$$

Calculated all grey weighted proximity values are shown in Table 7.

Table 7 The grey weighted proximity values

Locations \ Criteria	HC	TC	DC
Location 1	[-0.005, 0.008]	[-0.014, 0.014]	[-0.002, 0.039]
Location 2	[0.001, 0.013]	[-0.007, 0.024]	[-0.009, 0.028]
Location 3	[-0.006, 0.007]	[-0.007, 0.024]	[-0.017, 0.017]
Location 4	[0.002, 0.015]	[-0.007, 0.024]	[-0.017, 0.017]
Location 5	[-0.006, 0.006]	[0.001, 0.034]	[-0.017, 0.017]
Locations \ Criteria	**DS**	**DP**	**DT**
Location 1	[-0.009, 0.026]	[-0.018, 0.048]	[-0.014, 0.014]
Location 2	[-0.016, 0.016]	[-0.027, 0.027]	[-0.007, 0.024]
Location 3	[-0.009, 0.026]	[-0.027, 0.027]	[-0.007, 0.024]
Location 4	[-0.016, 0.016]	[-0.027, 0.027]	[0.001, 0.034]
Location 5	[-0.002, 0.037]	[-0.018, 0.048]	[-0.007, 0.024]
Locations \ Criteria	**DO**	**CS**	**DR**
Location 1	[-0.015, 0.015]	[-0.012, 0.012]	[0.004, 0.023]
Location 2	[-0.004, 0.024]	[-0.004, 0.019]	[-0.011, 0.011]
Location 3	[-0.015, 0.015]	[-0.004, 0.019]	[0.004, 0.023]
Location 4	[-0.004, 0.024]	[-0.012, 0.012]	[-0.011, 0.011]
Location 5	[-0.015, 0.015]	[-0.012, 0.012]	[0.011, 0.030]
Locations \ Criteria	**TD**	**I**	**CC**
Location 1	[-0.003, 0.020]	[-0.004, 0.024]	[0.007, 0.029]
Location 2	[-0.012, 0.012]	[-0.015, 0.015]	[-0.012, 0.012]
Location 3	[-0.003, 0.020]	[-0.015, 0.015]	[-0.012, 0.012]
Location 4	[-0.012, 0.012]	[-0.015, 0.015]	[-0.012, 0.012]
Location 5	[-0.003, 0.020]	[-0.004, 0.024]	[-0.003, 0.020]

By using Eq. (12), grey overall proximity value ($\otimes d_i$) for each location alternative is computed. The crisp overall proximity value (d_i) for each location alternative is computed by Eq. (13). For example, the grey overall proximity values and crisp overall proximity value for Location 1 are computed by Eqs. (12) and (13) respectively as follows.

$$\otimes d_1 = \sum_{j=1}^{n} \otimes g_{ij} = [-0.005 + -0.014 + -0.002 \dots. +0.007\ , 0.008 + 0.014 + 0.039 \dots. +0.029] = [-0.085, 0.272]$$

$$d_1 = \frac{d_1^l + d_1^u}{2} = \frac{-0.085 + 0.272}{2} = 0.094$$

The same operations are repeated for other location alternatives. The results and the rankings of location alternatives are indicated in Table 8.

Table 8 The results of GPIV

Results / Locations	$\otimes d_i$	d_i	Rankings
Location 1	[-0.085, 0.272]	0.094	4
Location 2	[-0.123, 0.225]	0.051	2
Location 3	[-0.118, 0.229]	0.056	3
Location 4	[-0.130, 0.219]	0.045	1
Location 5	[-0.075, 0.287]	0.106	5

According to Table 8, the warehouse locations are listed as follows; Location 4, Location 2, Location 3, Location 1 and Location 5. Thus, Location 4 is designated as the best warehouse location.

5. Discussion

The GPIV results are compared with the results of other grey MCDM methods, which are grey TOPSIS, grey WASPAS, and grey COPRAS, to test whether the GPIV results are accurate. The coefficients of Spearman's correlation for all these grey MCDM are indicated in Table 9.

Table 9 Spearman correlation coefficients

Grey MCDM	GPIV	Grey TOPSIS	Grey WASPAS	Grey COPRAS
GPIV	1.000	0.700	1.000	1.000
Grey TOPSIS	-	1.000	0.700	0.700
Grey WASPAS	-	-	1.000	1.000
Grey COPRAS	-	-	-	1.000

According to Table 9, GPIV method has reached the same results as grey WASPAS and grey COPRAS methods. Although the correlation coefficient between the grey TOPSIS and GPIV methods is lower than the other correlation coefficients, the first two locations (Location 4 and Location 2) are obtained as the same ranked according to the results of both methods. As a result, it has been proved that GPIV method has reached correct results when compared with other grey MCDM methods. Compared with other grey MCDM methods, it was observed that the GPIV method is easier and have fewer steps.

In order to track the change in the rankings of the locations with regard to the change in criteria weights, the sensitivity analysis is performed. Four sets of criteria weights are designated for this analysis. Table 10 indicates these sets.

Table 10 Criteria weights sets

Criteria \ Sets	Set 1	Set 2	Set 3	Set 4
HC	[0.210, 0.250]	[0.350, 0.380]	[0.150, 0.180]	[0.120, 0.150]
TC	[0.030, 0.060]	[0.030, 0.060]	[0.050, 0.060]	[0.060, 0.080]
DC	[0.070, 0.080]	[0.070, 0.080]	[0.090, 0.100]	[0.050, 0.080]
DS	[0.070, 0.090]	[0.070, 0.090]	[0.080, 0.090]	[0.060, 0.100]
DP	[0.050, 0.060]	[0.050, 0.060]	[0.060, 0.080]	[0.050, 0.105]
DT	[0.060, 0.070]	[0.060, 0.070]	[0.080, 0.100]	[0.170, 0.180]
DO	[0.090, 0.095]	[0.070, 0.080]	[0.085, 0.090]	[0.080, 0.090]
CS	[0.060, 0.080]	[0.010, 0.020]	[0.080, 0.090]	[0.080, 0.095]
DR	[0.050, 0.080]	[0.040, 0.050]	[0.060, 0.070]	[0.070, 0.090]
TD	[0.060, 0.080]	[0.040, 0.050]	[0.080, 0.090]	[0.080, 0.090]
I	[0.090, 0.105]	[0.020, 0.030]	[0.060, 0.065]	[0.030, 0.040]
CC	[0.040, 0.070]	[0.100, 0.120]	[0.050, 0.060]	[0.020, 0.030]

These weights of criteria are utilized to perform the sensitivity analysis. The results are indicated in Fig. 2.

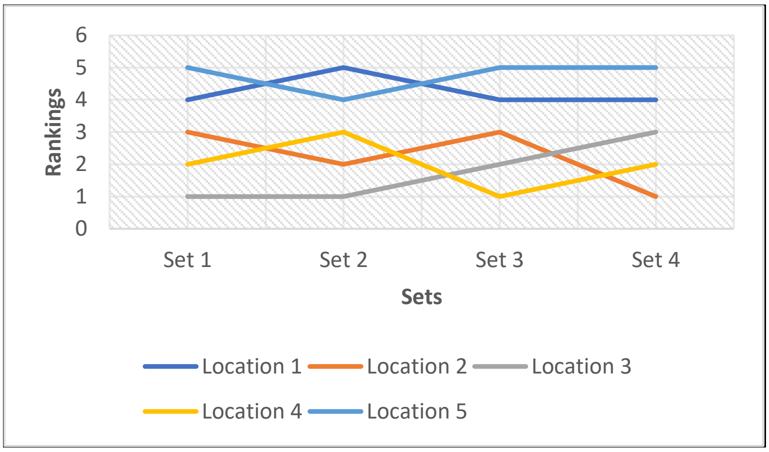

Fig. 2 The sensitivity analysis's results

As it can be observed from sensitivity analysis, there is a change in the ranking of all locations. Location 3 is designated as the best location in Set 1 and Set 2, however, Location 4 and Location 2 are designated as the best locations in Set 3 and Set 4 respectively. As a result, the change in criteria weights causes a change in the ranking of the locations. Thus, GPIV method was found to be sensitive to the change in criteria weights. Although the proposed methods have achieved accurate results with easy calculations, the methods have individual limits. The solution efficiency of the PSI method decreases as the number of alternatives increases [67]. Also, since the PSI method does not take into account the correlation between the criteria, it stands weak compared to the CRITIC method in finding the objective weights of the criteria. The limits mentioned for the PSI method are also valid for the GPSI method. Both GPSI and GPIV methods work with grey data. In a situation where there is no grey data and the uncertainty is higher, it may be difficult to reach the correct results and both methods may not work. In addition, both methods do not have a membership function as in fuzzy numbers. This will cause the proposed model to deal with uncertainty in less detail compared to comprehensive fuzzy (interval type 2, intuitionistic, spherical, and fermatean) methods. In addition, in the proposed method, only the objective weights of the criteria are considered. Subjective weights of criteria can also be obtained using grey MCDM methods (such as Grey AHP, Grey SWARA, and Grey FUCOM), and stronger and more consistent results can be obtained by combining objective and subjective weights of criteria.

6. Conclusion

This study proposes an integrated grey MCDM model including GPSI and GPIV to determine the most appropriate warehouse location for a supermarket. While the GPSI method is used to determine the weights of the criteria, the GPIV method is used to evaluate the performance of the alternatives and to rank these alternatives. This study aims to make three contributions to the literature. PSI and PIV methods combined with grey theory will be introduced for the first time in the literature. In addition, GPSI and GPIV methods will be combined and used to select the best warehouse location.

In this study, the performances of five location alternatives were measured by considering twelve criteria. According to the results of GPIV, Location 4 is designated as the best warehouse location. In this study, the results of the GPIV method and other grey MCDM methods were compared. Accordingly, it was found that GPIV method reached the correct results. In addition, a sensitivity analysis was performed by changing the weights of the criteria. It has been observed that the change in criteria weights causes a change in the ranking of the locations. Thus, GPIV method was found to be sensitive to the change in criteria weights.

This study has been carried out for the selection of warehouse location during the Covid-19 pandemic. In this context, the criteria considered has been expanded. These criteria can be used in conjunction with other methodologies to compare results. It is expected that the GPSI based GPIV methodology proposed for the first time in this study will be used in future studies therefore will become widespread and cited in the literature. In the proposed method, only the objective weights of the criteria are considered. Future studies use grey MCDM methods (such as Grey AHP, Grey SWARA, and Grey FUCOM) to obtain subjective weights of criteria after that they can combine objective and subjective weights of criteria to obtain stronger and more consistent results. Future studies may utilize the proposed model to address other MCDM problems, such as energy sources selection, supplier selection and third-party logistics provider selection etc. Particularly, the number of studies on the logistics center location selection problem is few in the literature [80-83]. Therefore, the proposed model can be utilized to solve this problem.

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