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Evaluation of Potential Logistics Village Alternatives Using Bayesian Best-Worst Method

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Abstract

Logistics centres, essential for cost-effective logistics and integral to logistics strategies, serve as central hubs for activities involving public and private logistics organizations. Turkey's logistics sector has grown significantly due to rising national and international trade. Numerous logistics villages have been proactively established to meet this demand, with 11 currently operational. Among these, Sakarya province, recognized for its substantial trade volume, is a focal point. This study, employing the powerful Bayesian Best-Worst Method (B-BWM) for multicriteria decision-making, concentrates on selecting the optimal location for a logistics village in Sakarya. Criteria weights were determined, and alternatives were ranked through expert opinions, surveys, and interviews. The Sapanca and Arifiye regions emerged as prime choices. The study emphasizes the importance of logistics infrastructure, with distribution networks and logistics services as vital sub-criteria. The B-BWM method's efficacy in addressing logistics village planning challenges is evident, offering valuable guidance for decision-makers.

Keywords: Multicriteria decision-making methods, Logistic village, Site selection, Bayesian best-worst method.

1 | Introduction

Globalization has blurred borders, resulting in the more efficient and faster movement of goods, services, and information across countries and continents. As a result, the logistics sector has become increasingly important. The growth of international corporations and the rise of global businesses have boosted international trade volumes. Creating extensive regional territories through free trade agreements has also

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made it easier for people, goods, services, and capital to move, promoting trade and increasing trade volume. Consequently, logistics has rapidly evolved and now plays a crucial role in meeting operational needs, ensuring the smooth flow of logistics, and reducing operational costs [1].

Several terms are associated with establishing logistics centres, including logistics villages, logistics centres, logistics parks, land ports, distribution parks, and transportation centres. These facilities act as central hubs for a concentration of logistics activities, bringing together both public and private entities engaged in service provision. Often referred to as logistics villages, these centres are strategically located near transportation systems to ensure convenient access and extensive national and international connectivity [2].

Logistics villages offer a wide range of advantages, including cost reduction, optimization of delivery times, and enhancement of supply chains. Acting as centralized logistics hubs, they encourage collaboration between service providers and buyers from both the private and public sectors. The selection of the right location for logistics villages is paramount to their effectiveness and success. An ideal logistics village should be strategically positioned to ensure easy access to transportation networks and seamless integration with various supply chain stages. In this regard, using multicriteria decision-making techniques provides an objective and systematic approach to site selection [3–5].

Turkey's unique geopolitical location at the crossroads of continents grants it significant strategic importance in the logistics sector. This advantageous position allows Turkey to leverage benefits like transit routes and an extensive coastline. The country has experienced rapid development across various industries, establishing itself as a prominent global player in international trade. The substantial increase in both domestic and international trade volumes has underscored the need for the logistics sector to evolve and align with the competitive economic landscape. To address this growing demand, the Turkish State Railways (TCDD) has devised plans to establish 20 logistics villages across the country, with half already in operation.

This research tackles the challenge of selecting a suitable location for a proposed logistics village in Sakarya using multicriteria decision-making techniques. By addressing the current gap in research on logistics village selection and making contributions to decision-making processes within the logistics sector, this study aims to improve the management of logistics activities in Sakarya and establish a competitive advantage.

The following sections of this study will thoroughly explore the existing literature on logistics village selection, providing in-depth insights into prior research and its conclusions. Afterwards, the study will offer a comprehensive overview of the conceptual framework that underpins multicriteria decision-making techniques, clarifying their importance and practical applications. The subsequent section will focus on the practical implementation of these techniques to address the specific challenge of selecting a logistics village in Sakarya, presenting the results obtained and their implications. Lastly, the study will critically assess the significance of these findings, highlighting key outcomes and suggesting promising avenues for future research in this field.

2 | Related Works

2.1 | Logistic Village

The concept of logistics villages has been discussed in various forms in the literature, including logistics centres, logistics villages, freight villages, and logistics centres [2]. Logistics villages encompass a wide range of national and international logistics activities, including transportation, warehouses, distribution centres, offices, banking, postal services, insurance, and customs services [6]. Many studies have primarily focused on the challenge of selecting suitable locations for logistics villages.

While many studies have primarily focused on the challenge of selecting suitable locations for logistics villages, several notable transitions and connections between these studies provide valuable insights into this complex issue.

For instance, Ballis and Mavrotas [7] addressed the logistics village selection problem in the Thriasio region near Athens, treating it as a multicriteria decision-making problem. They employed the Preference Ranking Organization Method for Enrichment of Evaluations PROMETHEE method to determine the most appropriate location among three alternatives, using criteria such as maximum space utilization, warehouse sizes, cross-docking facilities, railway access, distance to external roads, traffic density, and the number of road crossings.

Building on this foundation, Turskis and Zavadskas [8] addressed the logistics centre location selection problem in a fuzzy environment. They proposed the ARAS-F methodology, utilizing fuzzy sets for optimal location selection. Their criteria included investment cost, operation time, expansion potential, and proximity to demand markets, which were evaluated using Analytical Hierarchy Process (AHP), and the alternative ranking was carried out using ARAS-F.

Erkayman et al. [9] further expand on the location selection problem, incorporating the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), method and considering geographical, physical, socioeconomic, and cost criteria. Their focus on the eastern provinces of Turkey-Erzurum, Diyarbakır, and Malatya establishes a connection between the theoretical framework and practical application.

Li et al. [10] introduce the axiomatic fuzzy set-TOPSIS methodology, which incorporates a broader set of logistics centre location selection criteria, fostering a more comprehensive decision-making process. Their approach is particularly relevant when evaluating numerous logistics centre alternatives based on 13 criteria.

Chen et al. [11] seamlessly integrate fuzzy TOPSIS and multichoice goal programming for logistics centre location selection. Their method, which uses five criteria to evaluate five different alternatives, highlights the importance of determining criteria weights with Fuzzy TOPSIS and achieving optimal location selection through multichoice goal programming.

As the studies progress, Żak and Węgliński [12] propose a two-stage multicriteria decision-making methodology for logistics centre location selection, emphasizing the significance of criteria weights with Multiple Criteria Decision Making (MCDM)/A in the first stage and alternative ranking with Elimination and Choice Expressing Reality (ELECTRE) III/IV in the second stage. This two-stage approach enhances the decision-making process's robustness.

Elevli [13] addresses the freight centre location selection problem using the fuzzy PROMETHEE method, thus continuing the exploration of fuzzy logic in logistics village selection, albeit in the context of evaluating alternative locations for Samsun City in Turkey.

Tomić et al. [14] introduce a combination of a greedy heuristic algorithm and AHP methods for logistics centre location selection in the Balkan Peninsula region. Their emphasis on selecting the most suitable alternative based on the environment-strategy-performance paradigm opens up new avenues for decision-making in complex logistics networks.

Yildirim and Önder [15] propose a two-stage AHP-PROMETHEE methodology for evaluating potential freight villages in Istanbul. This approach, which includes criteria related to transportation infrastructure, connections, proximity to the city centre, and total surface area, underscores the importance of a systematic decision-making process.

Özceylan et al. [16] introduce a GIS-MCDM methodology for solving the freight village location problem. Their approach, which combines GIS-based criteria determination, equal weighting of alternative locations, and criteria weighting with ANP, exemplifies the integration of Geographic Information Systems (GIS) into logistics village selection.

Pham et al. [17] bring a new perspective to logistics centre location selection with their fuzzy Delphi-TOPSIS methodology. This method, which incorporates criteria obtained from literature and expert opinions, bridges the gap between theoretical research and practical decision-making. Özmen and Aydoğan [4] developed a two-stage multicriteria decision-making methodology for selecting the location of a logistics centre in Kayseri,

Turkey, emphasizing the use of Best-Worst Method (BWM) for criteria weighting and EDAS methods for alternative ranking.

Uyanik et al. [18] address the logistics centre location selection problem in Istanbul, proposing a DEMATEL-IF-TOPSIS hybrid methodology that combines criteria weighting with DEMATEL and alternative evaluation with intuitionistic fuzzy TOPSIS.

Finally, Komchornrit [19] presents an AHP-TOPSIS hybrid methodology for logistics centre location selection in The Greater Mekong Subregion, further contributing to the evolving landscape of decision-making approaches in this field.

In summary, these studies build upon one another, showcasing the evolution of methodologies and approaches in selecting logistics village locations, ultimately contributing to developing a comprehensive decision-making framework for this complex issue. The literature summary is presented in *Table 1*.

2.2 | Bayesian BWM

Bayesian Best-Worst Method (B-BWM) is a distinct variation of the BWM methodology, initially introduced by Mohammadi and Rezaei [20], wherein it considers multiple decision-makers instead of just one. Yanilmaz et al. [21] extended the Federal Emergency Management Agency (FEMA) and Seriousness Manageability Urgency Growth (SMUG) models with B-BWM to enhance disaster risk reduction. This study employed B-BWM to prioritize nine different disaster hazards in a specified region.

Ak et al. [22] proposed a hybrid methodology, B-BWM-VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), for assessing occupational risks in the textile industry. They employed B-BWM to assign weights to six different criteria for occupational risk assessment and used the VIKOR method to rank potential hazards arising from these risks.

Gul and Yucesan [23] introduced a B-BWM-TOPSIS methodology to evaluate the performance of Turkish universities, considering five Main Criteria (MC) and 34 sub-criteria. B-BWM was applied to determine the weightings for performance criteria, while the TOPSIS method was used to rank the universities.

Gul et al. [24] investigated the prioritization of control measures based on the Fine-Kinney risk assessment method for quantitative risk assessment. They presented a hybrid approach that combines B-BWM and Fuzzy VIKOR methods to prioritize these measures based on relevant criteria.

Munim et al. [25] explored the adoption of Blockchain technologies in the oil and gas industry. They ranked the criteria with the most impact on adoption by employing B-BWM for weighting.

B-BWM has also been found to apply to logistics studies. Tsang et al. [26] emphasized using the B-BWM methodology to prioritize areas for improvement in the Environmental, Social, and Governance (ESG) performance measurements of small and medium-sized logistics companies. Gupta et al. [27] investigated the challenges associated with smart and sustainable logistics, identifying and prioritizing strategies to address these challenges. They identified 19 barriers to smart, sustainable logistics through literature review and practitioner discussions and used B-BWM to prioritize these barriers against the proposed strategies.

Table 1. Summary of Literature on Logistics Village Location Selection.

Study	Approach/Methodology	Key Criteria Considered	Region/Area Studied	Key Findings/Contributions
[7]	PROMETHEE method	Space utilization, warehouse sizes, railway access, traffic density, and more	Thriasio region near Athens	Developed a MDM framework for logistics village location selection.
[8]	ARAS-F method	Investment cost, operation time, proximity to demand markets, expansion potential	Not specified	Introduced fuzzy logic into logistics centre location selection.
[9]	Fuzzy TOPSIS method	Geographical, physical, socioeconomic, and cost criteria	Eastern provinces of Turkey	Identified the most suitable location for a logistics centre in Eastern Turkey.
[10]	Axiomatic fuzzy set-TOPSIS method	Multiple criteria based on 13 aspects	Not specified	Provided a methodology for evaluating logistics centre alternatives with multiple criteria.
[11]	Fuzzy TOPSIS and multichoice goal programming	Five criteria for five alternatives	Not specified	Integrated fuzzy logic and multichoice goal programming into location selection.
[12]	Multicriteria decision-making	Criteria weights determined using MCDM/A	Not specified	Developed a two-stage decision-making process for the logistics centre location.
[13]	Fuzzy PROMETHEE method	Criteria for evaluating freight centre locations	Samsun city, Turkey	Applied fuzzy logic to the selection of freight centre locations.
[14]	Greedy heuristic algorithm and AHP	Environment-strategy-performance paradigm	Balkan Peninsula region	Introduced a novel approach based on the environment-strategy-performance paradigm.
[15]	AHP-PROMETHEE Method	Criteria related to transportation infrastructure, proximity, etc.	Istanbul	Proposed a systematic two-stage methodology for evaluating freight villages.
[16]	GIS-MCDM methodology	Criteria from GIS literature, ANP for weighting	Not specified	Incorporated GIS into location selection.
[17]	Fuzzy Delphi-TOPSIS method	Criteria from literature and expert opinions	Not specified	Integrated expert opinions and fuzzy logic into location selection.
[4]	BWM and EDAS methods	Criteria weighting with BWM EDAS for alternative ranking	Kayseri, Turkey	Developed a two-stage decision-making methodology for the logistics centre location.
[18]	DEMATEL-if-TOPSIS hybrid methodology	Criteria weighting with DEMATEL, intuitionistic fuzzy TOPSIS	Istanbul	Proposed a hybrid methodology combining DEMATEL and fuzzy logic for location selection.
[19]	AHP-TOPSIS hybrid methodology	Not specified	Greater Mekong Subregion	Presented an AHP-TOPSIS hybrid methodology for logistics centre location selection.

3 | Material and Methods

3.1 | Exploring Logistics Villages

The concept of logistics centres has been used for approximately three decades and has seen significant transformations in recent years. The ever-changing nature of production, storage, and distribution processes requires a continuous evolution and adjustment of the functional concept of logistics centres. Despite the presence of several definitions for logistics centres, a universally accepted definition has not been established yet [28]. The terminology related to logistics centres, including distribution centres, warehouse distribution centres, terminals, central warehouses, or logistics platforms, may sometimes differ in conceptual meanings from actual operational functions.

This section will delve into logistics villages, recognized as regions where comprehensive logistics activities occur. We will begin by providing an overview of selected logistics villages in Europe, followed by those in Asia and America. Although the history of establishing logistics villages is relatively recent, these practices have become indispensable in European countries, with more than 60 logistics villages already in operation. These European logistics villages are home to approximately 2,400 transport operators who benefit from the services offered within these villages.

Prominent countries hosting active logistics villages include France, Germany, Spain, Italy, Greece, Denmark, Netherlands, Belgium, Luxembourg, Poland, Ukraine, Hungary, and Portugal. Noteworthy logistics centres within these countries include HTC Hoeje and NTC Nordic in Denmark, Padova, Parma, Rogivo, and Verona in Italy, Dresden, Bremen, and Zal in Germany, and Barcelona in Spain [29]. Logistic villages, strategically located within a maximum distance of 40-50 km from industrial and urban centres, hold significant appeal for countries with advanced industries worldwide. Below, you will find detailed information about these logistics villages [30]:

- I. Rotterdam (Holland).
- II. Hamburg (Germany).
- III. Quadrante Europa (Interporto Verona) (Italy).
- IV. Singapur.
- V. Hong-Kong.
- VI. Alliance Global Logistics Hub/Texas/USA.
- VII. Atlantic Gateway-Halifax Logistics Park/ Canada.

3.2 | Key Factors and Evaluation Metrics for Successful Logistics Villages

The success of logistics villages relies on the presence of critical elements. These elements encompass extensive infrastructure, strategic positioning, efficient storage and inventory management, effective transportation and distribution systems, robust technological infrastructure, and the seamless integration of logistics services. By carefully considering these factors during the establishment of logistics villages, logistics activities can be significantly improved in terms of efficiency, speed, and cost-effectiveness.

The criteria for this study were derived from highly cited articles in the field of logistics site selection, providing a valuable source of inspiration and guidance. Notably, the study by Uyanık et al. [18] offered comprehensive insights into these criteria. The analysis revealed that the most frequently mentioned criterion was cost, mentioned 33 times [9], [11], [31]. Following closely, the criterion of environmental impact was mentioned 31 times [32], making it one of the most frequently cited criteria. Transportation accessibility also ranked high in terms of frequency, appearing 21 times [33–36]. Additionally, logistics infrastructure and the availability of a skilled labor force were mentioned several times.

These relevant criteria will serve as the evaluation metrics for the study, and their definitions are provided as follows.

Transportation accessibility: this criterion assesses the ease of access and connectivity of the logistics village to transportation networks, including roads, railways, seaports, and airports. It considers the quality of transportation infrastructure, the condition of roadways, and the availability of transportation links essential for the seamless flow of logistics activities.

Logistics infrastructure: this criterion involves assessing the infrastructure services and facilities available within the logistics village, including storage, distribution, customs clearance, and cargo handling. It is essential to evaluate whether the logistics village possesses the equipment, technology, and facilities to facilitate efficient and effective logistics operations.

Labour force: the potential labour force, along with the availability of skilled workers, their education levels, and employment opportunities in the vicinity of the logistics village, should be considered. Access to a pool of talented and experienced employees within the logistics sector is vital for successfully executing logistics activities.

Costs: cost considerations are integral when selecting a logistics village. Factors such as rental or purchase expenses, operating costs, labour expenditures, and transportation fees will directly impact the economic sustainability of your logistics operations.

Environmental impacts: sustainability and environmental considerations are of paramount importance. This criterion evaluates the logistics village's adherence to environmental regulations, energy efficiency measures, waste management practices, green spaces, and environmentally friendly initiatives. Ensuring that logistics activities are environmentally sustainable is a critical aspect of site selection.

The sub-criteria developed accordingly are illustrated in *Fig. 1*.

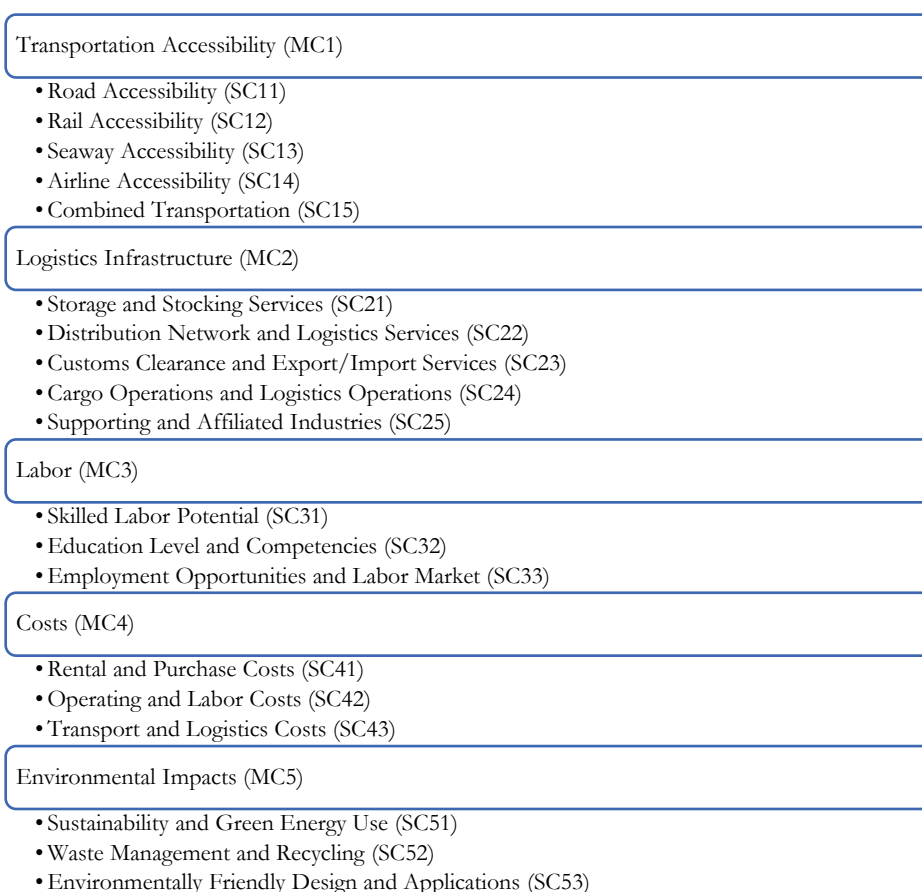


Fig. 1. MC and Sub Criteria (SC) for evaluating a logistic village.

3.3 | Evaluation of Sakarya Province in Terms of Logistics

In Turkey's strategically important Marmara Region, Sakarya stands out with significant logistics potential. According to data from 2021, Sakarya ranks among the top 10 provinces in exports and holds the 11th position for imports within the country. To assess Sakarya's logistics capacity, one must consider its geographical location, well-developed transportation infrastructure, organized industrial zones, and logistics infrastructure elements.

From a geographical perspective, Sakarya benefits from its proximity to major cities such as Istanbul and Ankara, facilitating efficient logistics operations in national and international trade. Additionally, its adjacency to the Black Sea Region contributes to regional trade growth.

Sakarya takes pride in its advanced transportation infrastructure, with the TEM Highway and E-5 Highway running through its provincial borders, facilitating efficient road transportation. Additionally, there are established rail links, providing opportunities for rail transport. Consequently, Sakarya offers a range of transportation options for logistics operations, ensuring versatility and accessibility. The presence of organized industrial zones significantly amplifies Sakarya's logistics potential. The province hosts numerous organized industrial zones spread across its territory, accommodating a multitude of factories and production facilities. This concentration of logistics activities in regions with high goods flow underscores the pivotal role played by organized industrial zones. These zones promote the seamless integration of supply chain processes and the effective management of logistics activities. Sakarya province is home to seven organized industrial zones, including the 1st, 2nd, and 3rd organized industrial zones, Ferizli organized industrial zone, Eastern Marmara machinery manufacturers specialized organized industrial zone, Kaynarca furniture specialized organized industrial zone, and Karasu organized industrial zone. These industrial zones, strategically located close to various transportation systems, bolster Sakarya's industrial and production capacity, create employment opportunities, and serve as focal points for concentrated logistics operations. Ongoing efforts are underway to expand the existing organized industrial zones in Sakarya and establish new ones. Particularly noteworthy is the work to create a logistics-oriented organized industrial zone in Sakarya¹.

Sakarya has undergone significant developments in its logistics infrastructure, encompassing storage facilities, distribution centres, and logistics service providers. This robust infrastructure is pivotal in supporting logistics businesses, enabling the smooth flow of goods and services, enhancing operational efficiency, and offering cost advantages. Furthermore, Sakarya has emerged as a logistics education and research hub, with its universities offering logistics programs and conducting research in this field. This contribution aids in the training of skilled logistics professionals and the overall advancement of the logistics sector.

Considering all these factors, it becomes evident that Sakarya possesses substantial potential in logistics. Its advantageous geographical location, well-established transportation infrastructure, presence of organized industrial zones, comprehensive logistics infrastructure and services, and commitment to logistics education and research position the province as a key player in the logistics sector. Sakarya's strategic location not only facilitates efficient logistics operations but also fosters trade facilitation and the growth of the logistics industry.

A recent study by Ateş and Esen [37] evaluated Sakarya's potential as a logistics base. They concluded that Sakarya's location, advantages related to efficient transportation, suitability for combined transportation, proximity to markets, well-established collection and distribution networks, and eligibility for investment incentives, among other criteria, make it a promising candidate to become a regional logistics hub. Additionally, Sakarya's abundance of potential, human resources, and financial infrastructure further reinforce its position.

3.4 | Multicriteria Decision-Making Methods and Techniques

MCDM methods encompass a variety of approaches and computational techniques, each with its unique methodology and calculation method. Notable examples of these methods include the AHP, TOPSIS, ELECTRE, Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), VIKOR, and BWM. These methods together form a comprehensive toolkit that assists decision-makers in navigating complex decision-making processes and analyzing preferences.

The choice of a specific method, characterized by its distinct properties and computational methodologies, depends on the preferences of the decision-maker, the structure of the problem at hand, and the availability of relevant data. These methods find effective applications across various domains, including business

¹ <https://www.satso.org.tr/>

operations, industrial projects, market research, and related areas, enhancing and streamlining the decision-making processes.

3.5 | Best-Worst Method

BWM is an effective approach in multicriteria decision-making. This method involves collecting input from decision-makers to identify the most favourable and unfavourable alternatives within a set of criteria. Decision-makers establish the criteria' relative importance or priority order while selecting the best and worst alternatives for each criterion. BWM provides a convenient and efficient way to uncover decision-makers' preferences. Through this method, decision-makers evaluate how criteria impact their differentiation between the best and worst alternatives. The best alternative demonstrates the highest values across specific criteria, while the worst alternative exhibits the lowest values. Consequently, decision-makers can rank the alternatives and determine their preferred choice.

BWM has proven its usefulness and effectiveness in decision-making processes across various fields. For instance, in healthcare, BWM has been applied to prioritize patient safety measures in hospitals [38], [39] and assess healthcare service quality [40], [41]. In environmental management, BWM has been used to evaluate the sustainability of renewable energy sources [42], [43] and rank environmental risks in urban planning [44]. Additionally, BWM is applicable in marketing research to assess consumer preferences for product attributes [45]. In supply chain management, BWM has been employed to optimize supplier selection criteria [45] and assess logistics performance indicators [46], [47]. These examples demonstrate the versatility of BWM and its effectiveness in aiding decision-making processes by providing valuable insights and prioritizing key factors.

To implement BWM, the weights of the criterion $W=(w_1, w_2, \dots, w_n)$ must first be determined, where n is the number of criteria and m is the number of alternatives. After that, BWM involves several key steps to facilitate decision-making processes. Firstly, a set of criteria or attributes relevant to the decision problem is identified (C_1, C_2, \dots, C_m). These criteria should capture the essential aspects to consider when evaluating alternatives. Secondly, decision-makers are asked to compare and rank the criteria regarding their importance or weight. This step involves a pairwise comparison process, where decision-makers assess the relative significance of each criterion concerning others. Thirdly, decision-makers use a comparative rating scale to evaluate the alternatives against each criterion. The scale typically ranges from the "best" (C_{best}) to the "worst" (C_{worst}) performance. It allows decision-makers to assess the performance of each alternative to identified criteria. Fourthly, each criterion's best and worst performances are determined based on the decision-makers' ratings. Similarly, all criteria are compared with the worst criterion and the vector $A_W = (a_{w1}, a_{w2}, \dots, a_{wn})$ is generated. The scores obtained from the comparative ratings are used to calculate the relative weights of the criteria $W^* = (w_1^*, w_2^*, \dots, w_n^*)$. Finally, the overall score for each alternative is computed by aggregating the weighted scores of the criteria. W^* is the best weight vector, w_j^* specifies the optimum weight taken by the j . criterion. The calculation of optimum weights using mathematical modelling is done using the BWM method.

The aim is to ensure that the absolute differences are maximum. Thus, each $\frac{w_B}{w_j} = a_{Bj}$ and $\frac{w_j}{w_W} = a_{jW}$ the j value is calculated to minimize the absolute differences for $(|w_B - a_{Bj}w_j|, |w_j - a_{jW}w_W|)$. It means that the weights found only have one best weight. In this respect, this method has an important advantage in terms of the validity of the weights in the BWM method. In this study, the linear mathematical model in the BWM method is solved using an Excel solver. The mathematical model created in the BWM method is as follows:

$$\min \xi, \quad \left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \xi, \text{ for all } j \rightarrow \left| \frac{w_j}{w_W} - a_{jW} \right| \leq \xi, \text{ for all } j. \quad (1)$$

$$\sum w_j = 1 \text{ and } w_j \geq 0, \text{ for all } j. \quad (2)$$

The Consistency Ratio (CR) measures the consistency of expert pairwise comparisons. It is calculated by dividing the objective function value (ξ^*) obtained from the optimization process by the Consistency Index

(CI). The CI is calculated by subtracting the number of criteria from the sum of the criteria weights and dividing the result by the number of criteria minus one. If the CR value is less than or equal to 0.1, the consistency of the comparisons is considered acceptable. If greater than 0.1, comparisons need to be reevaluated.

$$CR = \frac{\xi^*}{CI}. \quad (3)$$

The CR takes values between 0 and 1, a lower CR ratio indicates better consistency. Threshold values for CR are from the Rezaei [48] study given in *Table 2*.

Table 2. CR threshold values.

Criteria		3	4	5	6	7	8	9
a _{BW}								
3		0.2087	0.2087	0.2087	0.2087	0.2087	0.2087	0.2087
4		0.1581	0.2352	0.2738	0.2928	0.3102	0.3154	0.3273
5		0.2111	0.2848	0.3019	0.3309	0.3479	0.3611	0.3741
6		0.2164	0.2922	0.3565	0.3924	0.4061	0.4168	0.4225
7		0.209	0.3313	0.3734	0.3931	0.4035	0.4108	0.4298
8		0.2267	0.3409	0.4029	0.423	0.4379	0.4543	0.4599
9		0.2122	0.3653	0.4055	0.4225	0.4445	0.4587	0.4747

Table 3 shows the CI for various dimensions of the decision matrix.

Table 3. CI values.

a _{BW}	1	2	3	4	5	6	7	8	9
CI	0	0.44	1	1.63	2.3	3	3.73	4.47	5.23

Separate weights are calculated for the criteria and sub-criteria considered in this study. Eq. 4 is used in the calculation of weight for all sub-criteria. Here, u_{ij} shows the normalized values of the alternative. Normalized values are obtained by dividing by the total value. This process is calculated as calculated in Eq. 5.

$$V_i = \sum_{j=1}^n w_j \times u_{ij} \text{ for all } i. \quad (4)$$

$$u_{ij} = \frac{x_{ij}}{\sum x_{ij}}. \quad (5)$$

3.5.1 | Bayesian BWM

The B-BWM is a multicriteria decision-making approach that combines the principles of BWM with Bayesian inference. This method specifically addresses decision problems characterized by uncertainty and subjective judgments. In the traditional BWM, decision-makers evaluate alternatives by identifying the best and worst criteria associated with each alternative. This process allows determining the relative importance or weights assigned to the criteria. However, the conventional BWM does not explicitly consider the uncertainties inherent in the decision-making process, nor does it effectively incorporate the preferences of multiple decision-makers in group decision-making scenarios. This is because it relies solely on the preferences of a single decision-maker to derive optimal weights. Mohammadi and Rezaei [39] introduced an enhanced version known as the B-BWM to address this limitation.

In contrast, the Bayesian extension of the B-BWM explicitly integrates Bayesian inference techniques to address uncertainties within the decision-making process. This approach introduces the concepts of prior and posterior probabilities, enabling decision-makers to update their beliefs and quantify uncertainties based on the most recent information. The B-BWM follows a structured framework in which decision-makers initially assign prior probabilities to the criteria weights, representing their initial subjective beliefs. Subsequently, they evaluate the alternatives by considering the best and worst criteria, which results in subjective scores. These

scores are then used to calculate the posterior probabilities of the criteria weights, considering both the initial beliefs and the observed data. By employing a probabilistic framework, the B-BWM allows decision-makers to express their uncertainty regarding the weights of the criteria explicitly. By incorporating observed data, decision-makers can refine their initial beliefs and make more informed and robust decisions. Using B-BWM offers several advantages, including its ability to effectively manage uncertainties, incorporate subjective judgments, and adapt to evolving information. It provides a rigorous and systematic decision-making approach that accommodates quantitative data and qualitative assessments.

For instance, considering the worst index, its probability distribution function can be represented by a polynomial equation.

$$P(A_w|w) = \frac{(\sum_{j=1}^n a_{jw})!}{\prod_{j=1}^n a_{jw}!} \prod_{j=1}^n w_j^{a_{jw}}, \tag{6}$$

where w represents a probability distribution.

In this context, the probability distribution function (denoted by w) is positively associated with the total number of occurrences of event j .

$$w_j \propto \frac{a_{jw}}{\sum_{j=1}^n a_{jw}} \text{ for all } j = 1, 2, \dots, n. \tag{7}$$

Hence, the probability of occurrence for the worst index denoted as w_w , can be mathematically expressed as follows:

$$w_w \propto \frac{a_{ww}}{\sum_{i=1}^n a_{iw}} = \frac{1}{\sum_{i=1}^n a_{iw}}. \tag{8}$$

$$\frac{w_j}{w_w} \propto a_{jw}. \tag{9}$$

In an equivalent manner, the best index A_B can be represented by a polynomial probability distribution; however, unlike the worst index A_W , its probability distribution is inverted.

$$A_B \sim \text{multinomial} \left(\frac{1}{w} \right). \tag{10}$$

$$\frac{1}{w_j} \propto \frac{a_{Bj}}{\sum_{i=1}^n a_{Bi}}, \frac{1}{w_B} \propto \frac{a_{BB}}{\sum_{i=1}^n a_{Bi}} = \frac{1}{\sum_{i=1}^n a_{Bi}} \rightarrow \frac{w_B}{w_j} \propto a_{Bj}, \text{ for all } j = 1, 2, \dots, n. \tag{11}$$

For the MCDM, the weight vector must fulfil non-negativity properties and sum up to one. Hence, the Dirichlet distribution is a suitable choice to represent the weights. The Dirichlet distribution of the weights w is defined by a parameter $a \in R^n$ [49]

$$\frac{1}{w_j} \propto \frac{a_{Bj}}{\sum_{i=1}^n a_{Bi}}, \frac{1}{w_B} \propto \frac{a_{BB}}{\sum_{i=1}^n a_{Bi}} = \frac{1}{\sum_{i=1}^n a_{Bi}} \rightarrow \frac{w_B}{w_j} \propto a_{Bj}, \text{ for all } j = 1, 2, \dots, n. \tag{11}$$

4 | Results and Discussion

In this research, the location selection for the proposed logistics village in Sakarya is conducted using a B-BWM, one of the multifaceted decision-making methodologies and techniques employed for this purpose.

Step 1. Identifying the criteria: in applying BWM, the initial step involves determining the criteria to evaluate the logistics village centre. To achieve this, interviews were conducted with relevant authorities, and extensive research was conducted to select the most suitable location for the logistics village centre in Sakarya. The criteria utilized in the logistics sector were thoroughly examined, serving as the basis for establishing the criteria employed in this study.

Given that transportation infrastructure holds utmost significance within the logistics domain, the planning process should consider a logistics village's location, potential, and diversity in terms of transportation systems, encompassing road, rail, sea, and air. Sakarya, in general, possesses most of these transportation systems; however, efficient planning that includes the cost considerations and logistics operations associated

with employing multiple modes of transportation (intermodal) seamlessly and without disruptions is a crucial factor affecting speed and costs.

Another critical factor to consider is the logistics load potential. In this regard, industrial development is important, and proximity to organized industrial zones where logistics activities are carried out intensively is also a key factor. Additionally, the infrastructure required for logistics villages and the associated costs should be carefully considered. Logistics villages represent a substantial investment, and the costs must be considered, from land acquisition to construction.

A crucial aspect of a new logistics village facility is its capacity for expansion and growth, given the world's rapid developments and trade. Therefore, the location and ground structure of the land must be considered.

Based on the information provided, the upper criteria and sub-criteria determined for evaluation are presented in *Fig. 1*. These criteria listed in the figure represent factors that can be utilized to assess the performance of a freight village. Businesses or countries can use these criteria to analyze or enhance logistics performance.

These upper and lower criteria offer a more detailed and customizable evaluation process in selecting logistics villages. While the upper criteria provide general categories, the sub-criteria offer more specific evaluation points within these categories, allowing for a more thorough assessment.

Step 2. Establishing the criteria's relative importance: to determine the order of importance among the identified criteria, it is essential to assign weights. This weighting process can be accomplished through expert opinions, a literature review, or analytical methods. In this study, expert opinions were solicited for the evaluation. During the evaluation process, the best and worst criteria were initially identified. Subsequently, comparisons were made to establish the superiority of the best criterion over the others. This involved assigning a numerical score, ranging from 1 to 9, to express the decision maker's preference for the best criterion over all other criteria and all other criteria over the worst criterion. The magnitude and explanation of the ratings provided when making these superiority comparisons are as follows:

- I. Equal importance.
- II. Between equality and intermediate.
- III. Slightly more important than moderate.
- IV. Between medium and strong.
- V. Strongly more important.
- VI. Between strong and very strong.
- VII. Very strongly more important.
- VIII. Between the powerful and the absolute.
- IX. More important than absolute.

For this evaluation, a panel of 7 experts Decision Makers (DMs) was assembled, comprising individuals with either academic backgrounds or private sector experience in logistics. *Table 4* details these diverse DMs' areas of expertise, departments, roles, ages, years of experience, and education levels. It is evident that the decision-makers have varied professional backgrounds and educational levels. This diversity offers insights into the competencies and experiences of the decision-makers.

Table 4. Information of DMs.

Decision Maker	Field	Department or Task	Age	Experience	Education
DM1	Faculty member	Research Assistant	27	5	PhD
DM2	Faculty member	Department of logistics	43	22	PhD
DM3	Faculty member	Industrial engineering	34	10	PhD
DM4	Faculty member	Industrial engineering	47	25	PhD
DM5	Logistic	Trade and documents manager	39	17	Master
DM6	Logistic	Akemsan authority	40	20	High school
DM7	Logistic	PRN construction company representative	39	20	Bachelor

Based on the decision-makers' inputs, weighting values will be determined for the identified criteria. However, it's important to account for differences in knowledge and experience among the decision-makers. To address this, the study employs the AHP to establish a ranking among the decision-makers.

The criteria considered for the AHP study include the decision-makers' age, experience, and education levels. *Table 5* outlines the evaluation scores to be utilized for the characteristics of the decision-makers. This table includes a correlation matrix that illustrates the relationships between these variables. Age and experience are represented numerically, while education levels are recorded as follows: 1 for high school, 2 for undergraduate, 3 for master's, and 4 for doctorate.

Table 5. Decision-maker evaluation criteria.

	Age	Experience	Education
Age	1	0,2	0,5
Experience	5	1	2
Education	2	0,50	1

The priority index of the obtained matrix is given in *Table 6*. The CI obtained according to the priority index was 0.03, and the CR was 0.05. These ratios indicate that the weighting performed is acceptable.

Table 6. Priority index values of decision-maker characteristics.

	Age	Experience	Education
Priority Index	0,128	0,594	0,276

Table 8 provides pairwise comparison matrices constructed for the seven decision-makers as part of the AHP application. These matrices quantify the relative superiority coefficients of each decision maker when compared to the others in terms of age, experience, and education levels. These coefficients reflect the DMs' assessments of each other's attributes.

The ultimate calculation for the characteristics of the decision-makers is presented in *Table 7*. Based on the weights provided in *Table 7*, it is evident that DM4 holds the highest weight value, signifying their significant influence on decision-making. Conversely, DM1 has the lowest weight value due to its relatively lower age and experience characteristics. These weights reflect the perceived importance of each DMs attributes in the study context.

Table 7. Final weighting values of decision-makers.

	Age	Experience	Education	Sum
DM1	0.013	0.025	0.048	0.086
DM2	0.021	0.110	0.048	0.179
DM3	0.016	0.050	0.048	0.114
DM4	0.022	0.125	0.048	0.196
DM5	0.019	0.085	0.036	0.140
DM6	0.019	0.100	0.012	0.131
DM7	0.019	0.100	0.036	0.155

Table 8. Superiority comparison matrix for the characteristics of decision-makers.

Criteria	Decision Maker	DM1	DM2	DM3	DM4	DM5	DM6	DM7
Age	DM1	1.0	0.6	0.8	0.6	0.7	0.7	0.7
	DM2	1.6	1.0	1.3	0.9	1.1	1.1	1.1
	DM3	1.3	0.8	1.0	0.7	0.9	0.9	0.9
	DM4	1.7	1.1	1.4	1.0	1.2	1.2	1.2
	DM5	1.4	0.9	1.1	0.8	1.0	1.0	1.0
	DM6	1.5	0.9	1.2	0.9	1.0	1.0	1.0
	DM7	1.4	0.9	1.1	0.8	1.0	1.0	1.0
Experience	DM1	1.0	0.2	0.5	0.2	0.3	0.3	0.3
	DM2	4.4	1.0	2.2	0.9	1.3	1.1	1.1
	DM3	2.0	0.5	1.0	0.4	0.6	0.5	0.5
	DM4	5.0	1.1	2.5	1.0	1.5	1.3	1.3
	DM5	3.4	0.8	1.7	0.7	1.0	0.9	0.9
	DM6	4.0	0.9	2.0	0.8	1.2	1.0	1.0
	DM7	4.0	0.9	2.0	0.8	1.2	1.0	1.0
Education	DM1	1.0	1.0	1.0	1.0	1.3	4.0	1.3
	DM2	1.0	1.0	1.0	1.0	1.3	4.0	1.3
	DM3	1.0	1.0	1.0	1.0	1.3	4.0	1.3
	DM4	1.0	1.0	1.0	1.0	1.3	4.0	1.3
	DM5	0.8	0.8	0.8	0.8	1.0	3.0	1.0
	DM6	0.3	0.3	0.3	0.3	0.3	1.0	0.3
	DM7	0.8	0.8	0.8	0.8	1.0	3.0	1.0

Step 3. Criteria evaluation using BWM: the decision-makers assessed the five primary criteria and their respective sub-criteria. DMs were tasked with identifying the best criterion among the overarching criteria for the BWM application. The best criteria, as determined by the decision-makers, are outlined in *Table 9*. This table displays the scores various DMs assign to the MC, with each DM's best criterion indicated in the table.

Table 9. According to the decision-makers, the preference levels between the upper criteria and the most important criteria determined.

	Best Criteria	MC1	MC2	MC3	MC4	MC5
DM1	K1	1	2	6	4	8
DM2	K2	2	1	5	4	7
DM3	K2	2	1	4	5	7
DM4	K2	5	1	9	5	3
DM5	K2	5	1	8	5	3
DM6	K2	2	1	5	3	7
DM7	K2	7	1	9	4	3

Likewise, the worst criterion preferences were taken from the decision-makers and shared in *Table 10*.

Table 10. The preference levels between the upper criteria and the worst criterion determined according to the decision-makers.

	Worst Criteria	MC1	MC2	MC3	MC4	MC5
DM1	K5	8	7	3	5	1
DM2	K5	7	6	3	4	1
DM3	K5	5	7	3	2	1
DM4	K3	6	9	1	4	3
DM5	K3	4	8	1	4	3
DM6	K5	6	5	3	4	1
DM7	K3	4	9	1	5	3

The weights of the primary criteria, as determined by the BWM method, are presented in *Table 11*. Additionally, the table includes the CR value. It's important to note that the decision maker's weights were considered when calculating the weighted averages.

Table 11. Calculated weights for decision-makers.

	DM Weight	MC1	MC2	MC3	MC4	MC5	Threshold	CR
DM1	0.086	0.455	0.273	0.091	0.136	0.045	0.296	0.214
DM2	0.179	0.270	0.432	0.108	0.135	0.054	0.282	0.214
DM3	0.114	0.254	0.459	0.127	0.102	0.059	0.282	0.119
DM4	0.196	0.115	0.590	0.047	0.134	0.115	0.306	0.292
DM5	0.140	0.120	0.509	0.052	0.120	0.200	0.296	0.214
DM6	0.131	0.257	0.408	0.103	0.171	0.060	0.282	0.190
DM7	0.155	0.087	0.512	0.046	0.152	0.203	0.306	0.264
BWM weighted Avg.		0.203	0.472	0.079	0.136	0.110		
B-BWM Avg.		0.240	0.374	0.103	0.172	0.111		

The results for the sub-criteria can be found in the Appendix. The calculated input-based CR values are anticipated to be below the threshold values, which is considered acceptable. Thus, the evaluation conducted in this context is deemed acceptable. Ideally, a lower CI is preferred. However, in this study, while there is some inconsistency among the criteria, it remains within acceptable limits. The threshold values employed for the CI can be found in *Table 12*.

Table 12. Inconsistency limits.

Criteria	5
Scale	
3	0.1667
4	0.1898
5	0.2306
6	0.2643
7	0.2819
8	0.2958
9	0.3062

Table 13 presents the weights of the primary criteria, the local weights of the sub-criteria, global weights, and rankings of specific criteria. The "local weight" column indicates the importance of the sub-criteria within their respective parent criteria. These weights signify the level of significance of the sub-criteria within the overarching upper criterion. The "global weight" column displays the cumulative weights of the sub-criteria when considering all criteria. These weights represent the importance of the sub-criteria in the overall ranking. The "rank" column denotes the sub-criteria's position in the overall ranking, with higher-ranked sub-criteria deemed more important. In the table, MC2 carries the highest top criterion weight with a value of 0.472, signifying its utmost importance among all criteria. On the other hand, SC15 ranks highest in importance, boasting a global weight of 0.425. Lastly, MC3 possesses the lowest main criterion weight at 0.079, making it the least significant main criterion among all the criteria.

Table 13. Global and local weight values of main and sub-criteria.

	MC Weights	SC Weights	Local Weight	Global Weight	Rank
MC1	0.240	SC11	0.160	0.038	12
	0.240	SC12	0.161	0.039	11
	0.240	SC13	0.187	0.045	10
	0.240	SC14	0.133	0.032	13
	0.240	SC15	0.358	0.086	3
MC2	0.374	SC21	0.207	0.078	4
	0.374	SC22	0.295	0.110	2
	0.374	SC23	0.165	0.062	7
	0.374	SC24	0.135	0.050	8
	0.374	SC25	0.198	0.074	5
MC3	0.103	SC31	0.464	0.048	9
	0.103	SC32	0.255	0.026	17
	0.103	SC33	0.281	0.029	15
MC4	0.172	SC41	0.166	0.029	16
	0.172	SC42	0.175	0.030	14
	0.172	SC43	0.659	0.113	1
MC5	0.111	SC51	0.568	0.063	6
	0.111	SC52	0.221	0.024	18
	0.111	SC53	0.212	0.023	19

Fig. 2 presents the credal rankings for this study's MC and sub-criteria. The credal ranking is a methodology designed to accommodate uncertainty in decision-making by representing the possible range of rankings for each criterion. The credal ranking graphs visually represent the priority and uncertainty associated with each criterion and sub-criterion in the logistics site selection decision-making process.

These rankings can aid decision-makers in assessing and comparing various options while accounting for potential variations and uncertainties inherent in the decision context. In the MC graph, MC2 is depicted as having the highest ranking, underscoring its significance in logistics site selection. Following MC2, MC1 and MC4 hold slightly lower rankings but remain essential in decision-making.

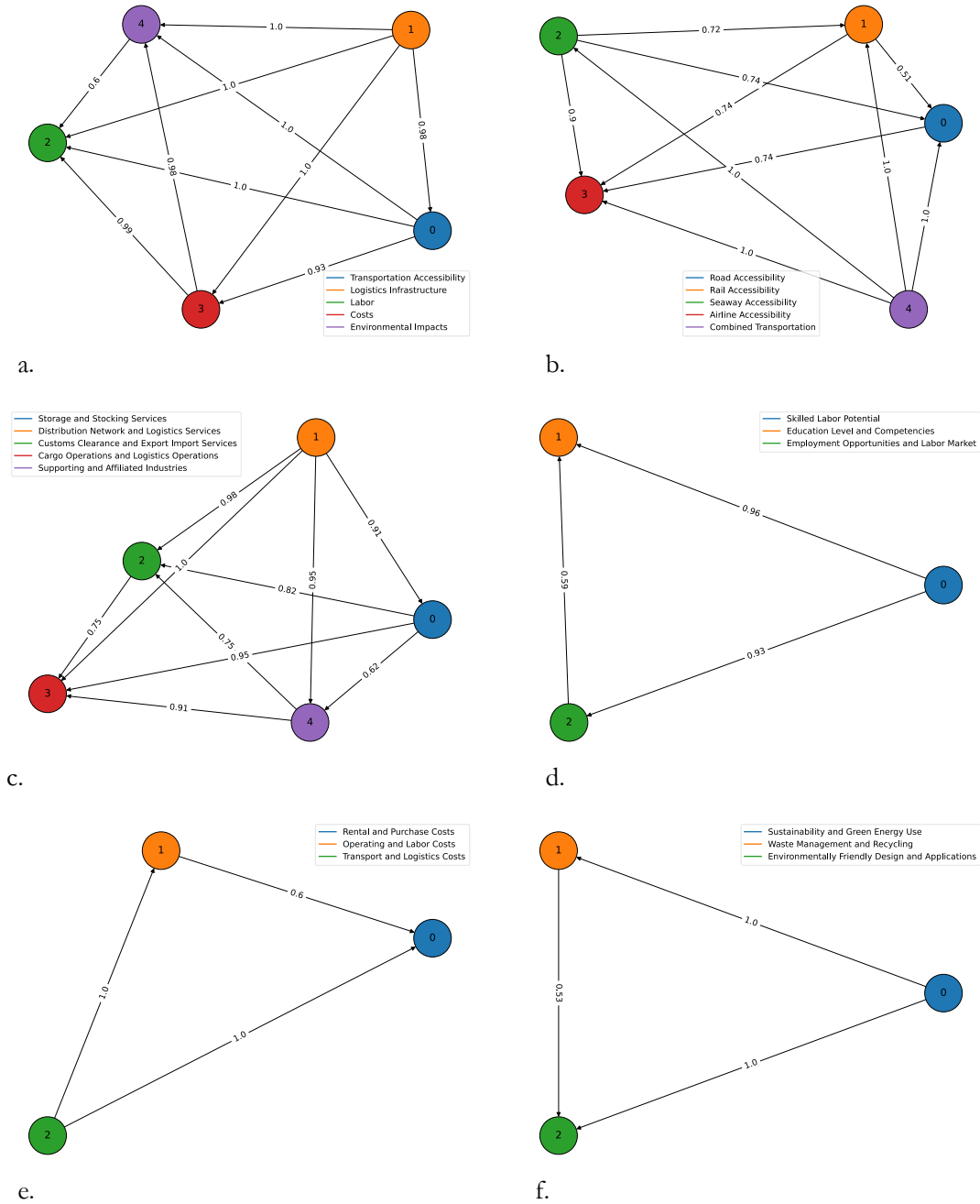


Fig. 2. The visualization of the credal ranking of; a. MC, and b,c,d,e,f. SCs respectively.

Step 4. Step 4 involves identifying the potential regions that could serve as logistics village centres, which may encompass various districts or regions within Sakarya. The following are the places to be considered as logistics village centres at this stage:

- I. Adapazari, Ferizli, Kaynarca, Söğütlü Region.
- II. Karapürçek, Akyazı, Trench Area.
- III. Karasu, Kocaali Region.
- IV. Pamukova, Geyve, Taraklı Region.
- V. Sapanca, Arifiye, Erenler, Serdivan Region.

Step 5. Evaluation of each alternative: this involves the evaluation of each alternative (logistics village center) using the predetermined criteria. For each criterion, both the best (highest score) and worst (lowest score) alternatives were identified. Subsequently, the final criterion weights and decision-maker weighted scores were computed for each alternative. These scores were derived by multiplying the local weights assigned to each criterion. The total scores were then determined by summing up the weighted scores for each alternative based on the criteria. These calculated values offer an overall assessment of the alternatives. The best and worst alternatives were determined according to the total score, as presented in *Table 14*. This table displays the comprehensive scores and rankings of the alternative logistics villages. Notably, the A5 alternative freight village achieved the highest score, with an overall score of 4.126, securing the top position. Based on the evaluation criteria, this result designates it as the preferred option and recommends it as the logistics village of choice.

Table 14. Grand total points and rankings of each alternative.

Alternative	BWM Score	B-BWM Score	BWM Rank	B-BWM Rank
A1	3.486	3.383	2	2
A2	2.626	2.586	4	4
A3	3.434	3.382	3	3
A4	2.517	2.525	5	5
A5	4.267	4.126	1	1

4 | Conclusion

The increasing globalization of trade and the accelerated pace of global flows have made it imperative to establish logistics centres, often referred to as logistics villages. These centres are crucial in optimizing supply chains, cutting costs, and expediting delivery times. Recognizing the vital role of the logistics sector in a competitive economic landscape, Turkey has strategically developed several logistics villages, capitalizing on its advantageous location and extensive transportation networks. Consequently, selecting the right locations for logistics villages has become a paramount and systematic endeavour. This study aims to bridge this gap by concentrating on the location selection problem for a logistics village in Sakarya, Turkey, intending to contribute to the logistics sector's decision-making processes. The study's findings are anticipated to enhance the management of logistics operations in Sakarya and promote a competitive edge.

To address the logistics village location issue in Sakarya, the study proposes a solution utilizing the BWM as a MCDM technique. The criteria for selecting the location were determined through a thorough review of the literature and expert opinions. The study emphasizes the pivotal role of logistics villages in streamlining logistics activities and reducing costs. Logistics villages act as central hubs, bringing together businesses and offering them comprehensive services. Given Turkey's strategic location and burgeoning trade volume, logistics villages have been recognized as having significant potential within the country.

The BWM method was employed to resolve the logistics village location problem in Sakarya. BWM is a highly effective MCDM technique used in decision-making processes that involve multiple criteria. It facilitated the selection of the most suitable location for the logistics village in Sakarya province, resulting in definitive outcomes.

The study delved into the importance of logistics villages and the methodologies employed in their selection through a comprehensive literature review. Evaluation criteria for logistics village selection were established using both the BWM and the AHP. Weightings for these criteria were calculated based on expert opinions and collected data. The results revealed that the logistics infrastructure criterion held the highest significance among the upper-level criteria, with the distribution network and logistics services sub-criterion emerging as the most influential factors. The assessment of alternative logistics village options demonstrated that the Sapanca, Arifiye, Erenler, and Serdivan regions achieved the highest scores, making them the most suitable and preferred choices for logistics village selection.

In conclusion, this study represents a significant advancement in selecting logistics villages by identifying the most suitable alternatives based on the evaluation criteria. These methodologies contribute to critical aspects such as cost reduction, increased efficiency, and a competitive edge in logistics. However, it is essential to acknowledge certain limitations, including potential errors in determining evaluation criteria and calculating weights based on expert opinions. Additionally, future research should contemplate enlarging sample sizes, employing different MCDM techniques, and examining the influence of other factors, such as environmental and social considerations, on logistics village selection.

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Author Contribution

Conceptualization, Emre Ceviz and Caner Erden; Methodology, Caner Erden; Software, Caner Erden; Validation, Serkan Koç, Caner Erden, and Çağdaş Ateş; Formal Analysis, Emre Ceviz; Investigation, Emre Ceviz; Resources, Emre Ceviz; Data Maintenance, Emre Ceviz; Writing - Creating the Initial Design, Serkan Koç; Writing - Reviewing and Editing, Serkan Koç; Visualization, Çağdaş Ateş; Monitoring, Serkan Koç; Project Management, Serkan Koç; Funding Procurement, Caner Erden. All authors have read and agreed to the published version of the manuscript.

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Data Availability

The data supporting the reported findings in this study will be made available upon request. Please contact the corresponding author for inquiries regarding access to the data.

Conflicts of Interest

No conflicts.

References

- [1] Millar, M. (2015). *Global supply chain ecosystems: strategies for competitive advantage in a complex, connected world*. Kogan Page Publishers.
- [2] Kaynak, R., Koçoğlu, İ., & Akgün, A. E. (2014). The role of reverse logistics in the concept of logistics centers. *Procedia - social and behavioral sciences*, 109, 438–442. DOI: 10.1016/j.sbspro.2013.12.487
- [3] Alkhatib, S. F., Darlington, R., Yang, Z., & Nguyen, T. T. (2015). A novel technique for evaluating and selecting logistics service providers based on the logistics resource view. *Expert systems with applications*, 42(20), 6976–6989. DOI: 10.1016/j.eswa.2015.05.010

- [4] Özmen, M., & Aydoğan, E. K. (2020). Robust multi-criteria decision making methodology for real life logistics center location problem. *Artificial intelligence review*, 53(1), 725–751. DOI: 10.1007/s10462-019-09763-y
- [5] Hashemkhani Zolfani, S., Görçün, Ö. F., & Küçükönder, H. (2021). Evaluating logistics villages in turkey using hybrid improved fuzzy swara (Imf swara) and fuzzy mabac techniques. *Technological and economic development of economy*, 27(6), 1582–1612. DOI: 10.3846/tede.2021.16004
- [6] Higgins, C. D., Ferguson, M., & Kanaroglou, P. S. (2012). Varieties of logistics centers developing standardized typology and hierarchy. *Transportation research board of the national academies*, 2288, 1–20. <http://docs.trb.org/prp/12-3874.pdf>
- [7] Ballis, A., & Mavrotas, G. (2007). Freight village design using the multicriteria method PROMETHEE. *Operational research*, 7(2), 213–231. DOI: 10.1007/bf02942388
- [8] Turskis, Z., & Zavadskas, E. K. (2010). A new fuzzy additive ratio assessment method (ARAS-F). Case study: The analysis of fuzzy Multiple criteria in order to select the logistic centers location. *Transport*, 25(4), 423–432. DOI: 10.3846/transport.2010.52
- [9] ErKayman, B., Gundogar, E., Akkaya, G., & Ipek, M. (2011). A fuzzy topsis approach for logistics center location selection. *Journal of business case studies (JBCS)*, 7(3), 49–54. DOI: 10.19030/jbcs.v7i3.4263
- [10] Li, Y., Liu, X., & Chen, Y. (2011). Selection of logistics center location using axiomatic fuzzy set and TOPSIS methodology in logistics management. *Expert systems with applications*, 38(6), 7901–7908. DOI: 10.1016/j.eswa.2010.12.161
- [11] Chen, K. H., Liao, C. N., & Wu, L. C. (2014). A selection model to logistic centers based on TOPSIS and MCGP methods: The case of airline industry. *Journal of applied mathematics*, 2014(1), 470128. DOI: 10.1155/2014/470128
- [12] Zak, J., & Węgliński, S. (2014). The selection of the logistics center location based on MCDM/A methodology. *Transportation research procedia*, 3, 555–564. DOI: 10.1016/j.trpro.2014.10.034
- [13] Elevli, B. (2014). Logistics freight center locations decision by using Fuzzy-PROMETHEE. *Transport*, 29(4), 412–418. DOI: 10.3846/16484142.2014.983966
- [14] Tomić, V., Marinković, D., & Marković, D. (2014). The selection of logistic centers location using multi-criteria comparison: case study of the Balkan Peninsula. *Acta polytechnica hungarica*, 11(10), 97–113. DOI: 10.12700/aph.11.10.2014.10.6
- [15] Yildirim, B. F., & Önder, E. (2014). Evaluating potential freight villages in istanbul using multi criteria decision making techniques. *Journal of logistics management*, 2014(1), 1–10. DOI: 10.5923/j.logistics.20140301.01
- [16] Özceylan, E., Erbaş, M., Tolon, M., Kabak, M., & Durut, T. (2016). Evaluation of freight villages: A GIS-based multi-criteria decision analysis. *Computers in industry*, 76, 38–52. DOI: 10.1016/j.compind.2015.12.003
- [17] Pham, T. Y., Ma, H. M., & Yeo, G. T. (2017). Application of fuzzy Delphi TOPSIS to locate logistics centers in vietnam: The logisticians' perspective. *Asian journal of shipping and logistics*, 33(4), 211–219. DOI: 10.1016/j.ajsl.2017.12.004
- [18] Uyanik, C., Tuzkaya, G., Kalender, Z. T., & Oguztimur, S. (2020). An integrated dematel–if–topsis methodology for logistics centers' location selection problem: An application for istanbul metropolitan area. *Transport*, 35(6), 548–556. DOI: 10.3846/transport.2020.12210
- [19] Komchornrit, K. (2021). Location selection of logistics center: a case study of greater mekong subregion economic corridors in northeastern thailand. *ABAC journal*, 41(2), 137–155.
- [20] Mohammadi, M., & Rezaei, J. (2020). Bayesian best-worst method: A probabilistic group decision making model. *Omega (united kingdom)*, 96, 102075. DOI: 10.1016/j.omega.2019.06.001
- [21] Yanilmaz, S., Baskak, D., Yucesan, M., & Gul, M. (2021). Extension of FEMA and SMUG models with Bayesian best-worst method for disaster risk reduction. *International journal of disaster risk reduction*, 66, 102631. DOI: 10.1016/j.ijdrr.2021.102631
- [22] Ak, M. F., Yucesan, M., & Gul, M. (2022). Occupational health, safety and environmental risk assessment in textile production industry through a Bayesian BWM-VIKOR approach. *Stochastic environmental research and risk assessment*, 36(2), 629–642. DOI: 10.1007/s00477-021-02069-y

- [23] Gul, M., & Yucesan, M. (2022). Performance evaluation of Turkish universities by an integrated Bayesian BWM-TOPSIS model. *Socio-economic planning sciences*, 80, 101173. DOI: 10.1016/j.seps.2021.101173
- [24] Gul, M., Yucesan, M., & Ak, M. F. (2022). Control measure prioritization in Fine – Kinney-based risk assessment: a Bayesian BWM-fuzzy VIKOR combined approach in an oil station. *Environmental science and pollution research*, 29(39), 59385–59402. DOI: 10.1007/s11356-022-19454-x
- [25] Munim, Z. H., Balasubramaniyan, S., Kouhizadeh, M., & Ullah Ibne Hossain, N. (2022). Assessing blockchain technology adoption in the Norwegian oil and gas industry using Bayesian best worst method. *Journal of industrial information integration*, 28, 100346. DOI: 10.1016/j.jii.2022.100346
- [26] Tsang, Y. P., Fan, Y., & Feng, Z. P. (2023). Bridging the gap: Building environmental, social and governance capabilities in small and medium logistics companies. *Journal of environmental management*, 338, 117758. DOI: 10.1016/j.jenvman.2023.117758
- [27] Gupta, H., Shreshth, K., Kharub, M., & Kumar, A. (2024). Strategies to overcome challenges to smart sustainable logistics: a Bayesian-based group decision-making approach. *Environment, development and sustainability*, 26(5), 11743–11770. DOI: 10.1007/s10668-023-03477-6
- [28] Rimienė, K., & Grundey, D. (2007). Logistics centre concept through evolution and definition. *Engineering economics*, 4(4), 87–95. <https://www.ceeol.com/search/article-detail?id=120728>
- [29] Karadeniz, V., & Akpınar, E. (2011). Logistics village applications in Turkey and a new logistics village proposal. *Marmara geography magazine*, 23(1303–2429), 49–71. <https://dergipark.org.tr/en/download/article-file/3253>
- [30] Sheffi, Y. (2013). Logistics-intensive clusters: Global competitiveness and regional growth. In *International series in operations research and management science* (pp. 463–500). Springer. DOI: 10.1007/978-1-4419-6132-7_19
- [31] Regmi, M. B., & Hanaoka, S. (2013). Location analysis of logistics centres in Laos. *International journal of logistics research and applications*, 16(3), 227–242. DOI: 10.1080/13675567.2013.812194
- [32] Kayikci, Y. (2010). A conceptual model for intermodal freight logistics centre location decisions. *Procedia - social and behavioral sciences*, 2(3), 6297–6311. DOI: 10.1016/j.sbspro.2010.04.039
- [33] Arıkan, F. (2012). *Freight villages and an application* [Thesis]. .
- [34] Can, A. M. (2012). Selection the location of freight village in samsun with multi-criteria decision making. *Yüksek lisans tezi. kayseri: erciyes university*.
- [35] ELGÜN, M. N., & Cemal, E. (2011). A model proposal for the selection of logistics village centers in terms of local, national and international transportation and trade. *Manisa celal bayar university journal of social sciences*, 9(2), 630–645.
- [36] Eryürük, S. H., Kalaoglu, F., & Baskak, M. (2012). A site selection model for establishing a clothing logistics center. *Tekstil ve konfeksiyon*, 22(1), 40–47.
- [37] ATEŞ, Ç., & ESEN, S. (2022). Evaluation of Sakarya province in terms of its potential as a logistics base. *Sakarya university business institute journal*, 4(2), 35–41. DOI: 10.47542/sauied.1175207
- [38] Rowshan, M., Shojaei, P., Askarifar, K., & Rahimi, H. (2020). Identifying and prioritizing effective factors on outsourcing in public hospitals using fuzzy BWM. *Hospital topics*, 98(1), 16–25. DOI: 10.1080/00185868.2019.1711482
- [39] Amiri, M., Hashemi-Tabatabaei, M., Ghahremanloo, M., Keshavarz-Ghorabae, M., Zavadskas, E. K., & Antucheviciene, J. (2020). A new fuzzy approach based on BWM and fuzzy preference programming for hospital performance evaluation: A case study. *Applied soft computing journal*, 92, 106279. DOI: 10.1016/j.asoc.2020.106279
- [40] Nabeeh, N. A., Abdel-Monem, A., & Abdelmouty, A. (2019). A novel methodology for assessment of hospital service according to BWM, MABAC, PROMETHEE II. *Neutrosophic sets and systems*, 31(1), 63–79.
- [41] Torkayesh, A. E., Pamucar, D., Ecer, F., & Chatterjee, P. (2021). An integrated BWM-LBWA-CoCoSo framework for evaluation of healthcare sectors in Eastern Europe. *Socio-economic planning sciences*, 78, 101052. DOI: 10.1016/j.seps.2021.101052
- [42] Aghaloo, K., Ali, T., Chiu, Y. R., & Sharifi, A. (2023). Optimal site selection for the solar-wind hybrid renewable energy systems in Bangladesh using an integrated GIS-based BWM-fuzzy logic method. *Energy conversion and management*, 283, 116899. DOI: 10.1016/j.enconman.2023.116899

- [43] Alshamrani, A., Majumder, P., Das, A., Hezam, I. M., & Božanić, D. (2023). An integrated BWM-TOPSIS-I Approach to Determine the Ranking of Alternatives and Application of Sustainability Analysis of renewable energy. *Axioms*, 12(2), 1–19. DOI: 10.3390/axioms12020159
- [44] Foroozesh, F., Monavari, S. M., Salmanmahiny, A., Robati, M., & Rahimi, R. (2022). Assessment of sustainable urban development based on a hybrid decision-making approach: Group fuzzy BWM, AHP, and TOPSIS–GIS. *Sustainable cities and society*, 76, 103402. DOI: 10.1016/j.scs.2021.103402
- [45] Li, Q., Rezaei, J., Tavasszy, L., Wiegmans, B., Guo, J., Tang, Y., & Peng, Q. (2020). Customers' preferences for freight service attributes of China railway express. *Transportation research part a: policy and practice*, 142, 225–236. DOI: 10.1016/j.tra.2020.10.019
- [46] Beysenbaev, R., & Dus, Y. (2020). Proposals for improving the logistics performance index. *Asian journal of shipping and logistics*, 36(1), 34–42. DOI: 10.1016/j.ajsl.2019.10.001
- [47] Rezaei, J., van Roekel, W. S., & Tavasszy, L. (2018). Measuring the relative importance of the logistics performance index indicators using best worst method. *Transport policy*, 68, 158–169. DOI: 10.1016/j.tranpol.2018.05.007
- [48] Rezaei, J. (2015). Best-worst multi-criteria decision-making method. *Omega*, 53, 49–57.
- [49] Forbes, C., Evans, M., Hastings, N., & Peacock, B. (2011). *Statistical distributions*. John Wiley & Sons.