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Full Length Article

Addressing last-mile delivery challenges by using euclidean distance-based aggregation within spherical Fuzzy group decision-making

Sarbast Moslem *, Francesco Pilla

School of Architecture Planning and Environmental Policy, University College Dublin, Belfield D04 V1W8, Dublin, Ireland

A R T I C L E I N F O

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A B S T R A C T

Optimal location selection plays a crucial role in enhancing logistic performance and addressing inefficiencies in last-mile delivery. Parcel lockers have emerged as an efficient solution in this regard. In the context of optimizing last-mile logistics in Dublin, Ireland, this research strives to identify the ideal locations for parcel lockers. It does so by pioneering the application of a unique decision-making model. To navigate the inherent uncertainties in decision-makers' preferences, the study harnesses the power of the Analytic Hierarchy Process (AHP) in Spherical Fuzzy environment with the Euclidean Distance-Based Aggregation Method (EDBAM) for the selection of parcel locker locations. The harmonious integration of these methodologies serves to mitigate the deterministic shortcomings typically associated with the AHP approach, presenting an innovative and robust solution for enhancing last-mile delivery efficiency. The outcomes of this research will provide valuable insights to policymakers in making informed strategic decisions regarding the selection of parcel locker locations in Dublin City.

1. Introduction

The last-mile delivery phase represents the final and often the most challenging segment of the supply chain. In this crucial step, goods move from a distribution center to the end consumer's doorstep. Several formidable challenges arise during this phase, including traffic congestion, strict delivery time windows, addressing accuracy issues, navigating rural or remote areas, combating parcel theft, reducing environmental impact, optimizing cost efficiency, managing returns effectively, ensuring the last leg of delivery is seamless, and accommodating diverse customer preferences. Innovative solutions are essential to overcome these obstacles and enhance last-mile delivery performance [1,2]. Logistics Service Providers (LSP) may suffer from costs and idle time due to a missed delivery. Home delivery has several inherent limitations. For example, since goods are delivered door to door rather than Business to Business (B2B), it cannot consolidate deliveries optimally. Home delivery rounds are also longer and have more loading and unloading stops. The other drawbacks of urban freight movement, including congestion, pollution, and an increase in the likelihood of accidents, are a result of these restrictions [3].

In light of the evolving work patterns where many individuals are engaged in their jobs throughout the day, traditional home delivery services may no longer be the most convenient or efficient option. These alternatives aim to strike a balance between accommodating customers' busy schedules and ensuring the cost-effectiveness and operational efficiency of delivery services. As such, the logistics and e-commerce industries are actively seeking innovative approaches to meet the changing demands of modern consumers while optimizing their delivery operations [4]. In order to highlight these issues, postal service providers have invested in value-added services such as delivery to monitored or automated collection points over the past decade. To meet end-users needs and expectations, these new delivery methods offer a viable alternative to home delivery. Given the rapid growth of the e-commerce sector and the expansion of logistics services, many experts have recognized the importance of parcel locker systems as a key component of last-mile delivery in the supply chain system. As a self-service solution, parcel locker systems offer an efficient approach to addressing the last-mile challenge, a critical bottleneck in the delivery process. By improving the quality of the delivery network and enhancing customer satisfaction, parcel lockers have the potential to significantly impact the delivery industry (Viu-Roig and Alvarez-Palau, 2020).

Several recent studies have addressed the complex challenges associated with parcel locker location problems and optimizing their service quality. Schaefer and Figliozzi [5] leveraged cluster analysis techniques

* Corresponding author.
E-mail address: sarbast.moslem@ucd.ie (S. Moslem).

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to enhance the quality of Amazon lockers, ensuring optimal placement. Ghaderi et al. [6] developed an integrated algorithm and linear program approach to streamline parcel locker location selection. Tang et al. [7] conducted statistical analysis and confirmatory factor analysis to assess parcel locker service quality, identifying key influencing factors and their impact on customer satisfaction. Keeling et al. [8] adopted a multiple-criteria method to address various parcel locker location challenges, contributing to the evolving field of last-mile logistics. Pan et al. [9] proposed an innovative approach that integrates Genetic Algorithms with the Lin-Kernighan Heuristic to optimize parcel locker service quality and efficiency. These studies collectively provide valuable perspectives and methodologies for improving parcel locker systems and their strategic placement.

Gokasar and Karaman [10] optimized the personnel service system in a systematic way and additionally, to integrate the system with public transportation to be able to obtain a novel method. Zheng [11] analyzed the factors which affect the ERP implementation in every stage and evaluated the result of implement ERP for Beijing Rail Transit. MCDM methods have been successfully applied to various problems [12–16].

Undoubtedly, placing parcel lockers in all cities to meet the demand of the hour is a complex and significant decision which needs to be supported by decision-making support models. However, multi-criteria decision-making (MCDM) approach has been widely adopted to identify and solve the challenging location selection problems [17–24]. Moslem and Pilla [25] identified the optimal parcel locker locations in Dublin, Ireland, by employing the innovative Spherical Fuzzy Analytic Hierarchy Process (SF-AHP), the results, while noteworthy, should be considered in light of its methodology; it didn't assess evaluator similarity and solely utilized the geometric mean for final weight generation, which may warrant further exploration in future research. Nonetheless, these findings hold promise for guiding policymakers' strategic decisions concerning parcel locker placements.

This work employed the most popular MCDM approach in solving location selection problems, the Analytic Hierarchy Process (AHP) with EDBAM under Spherical Fuzzy Sets (SFS). Fuzzy sets are employed in our study to handle and represent uncertainties, vagueness, and imprecision that often accompany real-world data and human judgments. Unlike traditional binary logic, which assigns elements to either a true or false category, fuzzy logic allows for partial memberships, meaning elements can belong to multiple categories to varying degrees. This versatility is particularly valuable when dealing with complex, ambiguous, or incomplete information, as it enables decision-makers to capture nuances in preferences, uncertainties in data, and imprecise measurements [26]. In the context of location selection, such as determining the best sites for parcel lockers, fuzzy sets are instrumental for accommodating the inherent uncertainty in decision criteria and preferences. This ensures that decision models can effectively capture and process the often-ambiguous nature of real-world location-based data, ultimately leading to more robust and reliable decision outcomes. By using fuzzy sets, decision-makers can make more informed choices in situations where traditional crisp logic falls short.

The model has been conducted for the evaluation process to select the proper location for parcel lockers in an academic-oriented manner. The AHP in a fuzzy environment generates significant and reliable results, and several works have approved this approach in the case of location selection (Rajak and Shaw, 2019; Guler and Yomralioglu, 2020; [27,28]). However, the main advantage of using AHP with SFS is avoiding the hesitancy issue of an evaluator estimation, where the hesitancy can be defined severally from membership and non-membership indexes [29].

The rationale behind integrating the Euclidean Distance-Based Aggregation Method (EDBAM) into this framework could benefit from a more comprehensive explanation to enhance the understanding of its role and significance [30]. While the research effectively incorporates EDBAM into the decision-making model for selecting parcel locker locations in Dublin, providing further detail would have clarified and justified this integration. Offering insights into why EDBAM was chosen over alternative aggregation methods and how it aligns with the objectives of parcel locker location selection would have strengthened the rationale. Additionally, a more elaborate description of the operational aspects of EDBAM, including its step-by-step process and underlying principles, would have demystified its application, particularly for readers unfamiliar with this method. Given that one of the main reasons for adopting the Spherical Fuzzy Analytic Hierarchy Process (SF-AHP) is to address uncertainty in decision maker preferences, it's essential to explain how EDBAM contributes to managing this uncertainty [29]. Articulating the synergies between SF-AHP and EDBAM and elucidating how they work together to handle uncertainty within the aggregation process would have provided a clearer understanding of their combined effectiveness.

The challenge of choosing suitable parcel locker locations has been addressed using an innovative academic-oriented hybrid approach, which combines Spherical Fuzzy Analytic Hierarchy Process (SFAHP) with the Euclidean Distance-Based Aggregation Method (EDBAM). This study marks the first instance in decision science and multi-criteria decision-making literature where EDBAM is integrated with group SF-AHP to solve a location-based problem. The application of this model has yielded valuable insights for policymakers and has been successfully utilized to determine optimal parcel locker locations in Dublin, Ireland. The demonstrated model exhibits the capability to identify optimal solutions for location selection challenges.

The study is structured into three key sections. Section 2 introduces the application of AHP in the distinctive domain of Spherical Fuzzy (SF) space, incorporating EDBAM. Section 3 presents a practical case study focusing on optimal parcel locker location selection in Dublin, featuring a thorough Sensitivity Analysis and similarity assessment. Finally, Section 4 discusses the study's findings, enriched by the analyses in Section 3, offering valuable insights for logistics stakeholders and policymakers in the realm of last-mile delivery.

2. Methodology

2.1. Spherical Fuzzy AHP (SFAHP)

The Analytic Hierarchy Process (AHP), initially conceptualized by Saaty in his seminal work [31], has since undergone improvements and has been applied to solve complex problems in various fields [32–34], particularly transport-related complex problems [35–39]. In our study, we selected AHP as the Multi-Criteria Decision Making (MCDM) approach for evaluating the optimal location of parcel lockers. To address the hesitancy issue of the decision maker, we proposed applying AHP in a Spherical Fuzzy environment using the Spherical Fuzzy AHP (SFAHP) model introduced by Kutlu Gundogdu and Kahraman [29]. In Fig. 1, we summarize the main steps of the SFAHP model with EDBAM for the location selection evaluation process. Indeed, there are similar MCDM method to AHP, such as, the Base-Criterion Method (BCM) [40–42] and Best-Worst Method (BWM) [43]. However, they differ in their specific approaches. While AHP uses pairwise comparisons and mathematical weighting, BCM focuses on base criteria and subsidiary criteria, while BWM emphasizes identifying the best and worst criteria within a set.

Fuzzy sets are crucial for managing uncertainty in decision-making. They enable the representation of vague or imprecise information using linguistic variables. This flexibility is valuable when dealing with complex, real-world systems where precise data is scarce. Fuzzy sets also facilitate expert knowledge integration and multi-criteria decision-making by accommodating diverse criteria and uncertainties. Their applications span fields like control systems, AI, finance, and medicine, bridging the gap between mathematical rigor and human-like reasoning in uncertain scenarios [26]. However, Spherical Fuzzy Sets (SFS) have emerged as a powerful tool for addressing the complexity of decision-making hesitancy. They offer several advantages that significantly enhance our proposed model [29]. SFS introduces the concept of

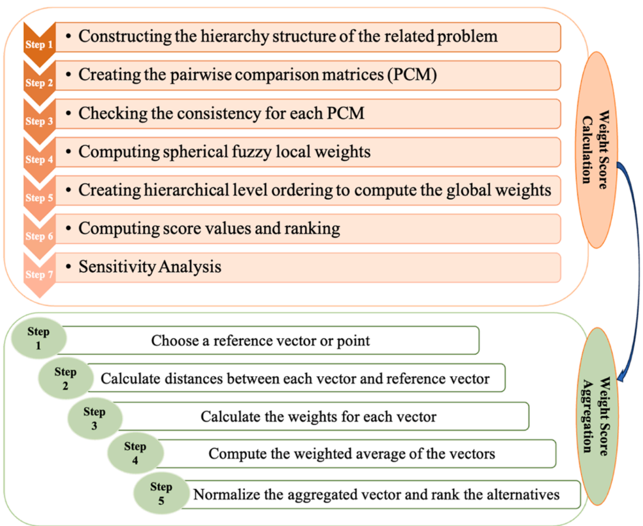

Fig. 1. The flowchart of the adopted model.

degrees of membership and non-membership as intervals, enabling a more nuanced representation of the hesitancy that decision-makers often face when assigning precise values to their preferences. This unique feature of SFS allows decision-makers to express their uncertainties and hesitations more accurately, leading to a more faithful representation of their cognitive processes. Consequently, the model effectively captures the intricate nuances of decision-makers' preferences, accounting for subtleties that may be overlooked in traditional crisp-valued approaches.

The studies by Kutlu Gundogdu and Kahraman [29] and Kutlu Gündoğdu and Kahraman [44] provide comprehensive insights into the application steps of the SF-AHP. These studies offer detailed explanations, methodologies, and practical examples, serving as valuable references for those seeking a deeper understanding of how SF-AHP can be effectively applied in decision-making contexts. A summary of the details of the evaluation process are depicted step by step in the following seven main steps:

Step 1: Structuring the hierarchy model of the location selection problem.

In the initial step, we establish a hierarchical framework founded on the views of experts and literature. This hierarchical structure typically encompasses three tiers. The first tier pertains to the target level or choosing the most suitable location. This tier may feature various levels in some scenarios, incorporating primary alternative level. Finally, the suggested possible m alternatives $X = \{x_1, x, \ldots x\}$ $(m >= 2)$ for location selection, provides the weights and score index (SI).

Step 2: Create pairwise comparisons (PCs) using SFSs, considering the linguistic terms Table 1). Eqs. (1) and ((2) are adopted to compute SI.

Table 1
The importance scale for PCs.

	$(\mu,\ \nu,\ \pi)$	SI
AMI	(0.9, 0.1, 0.0)	9
VHI	(0.8, 0,2, 0.1)	7
HI	(0.0, 0.0, 0.0)	5
SMI	(0.6, 0. 4, 0.3)	3
EI	(0.5, 0.4, 0.4)	1
SLI	(0.4, 0.6, 0.3)	1/3
LI	(0.3, 0.7, 0.2)	1/5
VLI	(0. 2, 0. 8, 0. 1)	1/7
ALI	(0.1, 0.9, 0.0)	1/9

$$SI = \sqrt{\left|100 * \left[\left(\mu_{\tilde{A}_s} - \pi_{\tilde{A}_s}\right)^2 - \left(\nu_{\tilde{A}_s} - \nu_{\tilde{A}_s}\right)^2\right]\right|} \tag{1}$$

$$\frac{1}{SI} = \frac{1}{\sqrt{\left|100 * \left[\left(\mu_{\tilde{A}_s} - \pi_{\tilde{A}_s}\right)^2 - \left(\nu_{\tilde{A}_s} - \nu_{\tilde{A}_s}\right)^2\right]\right|}} \tag{2}$$

for VLI; ALI; EI; SLI and LI

Step 3: Detect the consistency for each PC matrix (PCM) to omit inconsistent outcomes. To check the consistency, we replace the linguistic terms in the PCM with the corresponding SI. After that, we conduct the conventional process of computing the consistency ratio (CR). The CR threshold is 10 % for PCM with (5×5) size matrices and smaller ones. However, it is 20 % for PCM matrices bigger than (5×5).

Step 4: Computing the fuzzified local weights of each criterion and alternative.

The spherical fuzzy weights are calculated by using geometric mean (SWGM), which is assigned as follows:

$$\begin{aligned} SWAM_w(A_{S1}, A_{S2}, A_{S3}, \ldots A_{Sn}) &= w_1 A_{S1} + \ldots + w_n A_{Sn} \\ &= \left\langle \left[1 - \prod_{i=1}^{n}\left(1-\mu^2_{\tilde{A}_s}\right)^{w_i}\right]^{1/2}, \right. \\ &\left. \prod_{i=1}^{n} \nu^{wi}_{\tilde{A}_{si}}, \left[\prod_{i=1}^{n}\left(1-\mu^2_{\tilde{A}_s}\right)^{w_i} - \prod_{i=1}^{n}\left(1-\mu^2_{\tilde{A}_s} - \mu^2_{\tilde{A}_s}\right)^{w_i}\right]^{1/2} \right\rangle \end{aligned} \tag{3}$$

Concerning w:

$$w = (w_1, w_2 \ldots w_n);\ w_i \in [0, 1];\ \sum_{i=1}^{n} w_i = 1$$

Step 5:

We are creating the hierarchical level ordering to compute the global weights of each criterion and alternative.

The computation process is wisely applied from the lower to the top level.

The sore function is employed to adapt the crisp weights by using the following Eq. (4):

$$SI\left(\tilde{w}^s_j\right) = \sqrt{\left|100 * \left[\left(3\mu_{\tilde{A}_s} - \pi_{\tilde{A}_s}/2\right)^2 - \left(\nu_{\tilde{A}_s}/2 - \nu_{\tilde{A}_s}\right)^2\right]\right|} \tag{4}$$

The following Eq. (5) is applied to normalize the adopted weights:

$$\overline{w}^s_j = \frac{S\left(\tilde{w}^s_j\right)}{\Sigma^{nj=1} S\left(\tilde{w}^s_j\right)} \tag{5}$$

Step 6: The ultimate weight score for each alternative is determined using Eq. (4) with fuzzy logic.

Step 7: Concerning the defuzzified final weight scores, and rank the alternatives. The highest number refers to the best alternative.

2.2. *Aggregation by euclidean distance-based aggregation method (EDBAM)*

The EDBAM has been adopted in several studies [45,46]. However, here we depict a summary of the application process, the preference vector for each evaluator w^{ϵ} is the solution of the following formula normalized to one:

argument (x) where $x \in \mathrm{R}^n$ and $f(x)$ is defined as follows:

$$f(x) = \sum_{k=1}^{m}\left(a_k . d_E\left(w^k,\ x\right)\right) \tag{6}$$

where the Euclidean distance is:

$$d_E\left(w^k,\ x\right) = \sqrt{\sum_{i=1}^{n}\left(w_i^k - x_i\right)^2} \tag{7}$$

And $\sum_{k=1}^{m} a_k = 1$ as before. Thus, we depict the vector in R^n that is closest to individual priority vectors. After that, normalize it to 1.

3. Application to parcel lockers location selection in dublin

This integration promotes transparent and comprehensive decision-making. Decision-makers are no longer constrained to a strict numerical scale but can express their preferences over a range, reflecting the real-world complexities and uncertainties inherent in location selection problems. The use of SFS within the AHP framework serves to minimize the distortion of decision outcomes caused by hesitancy. This results in two key benefits: firstly, more reliable and insightful decisions that align with real-world uncertainties, and secondly, an improved decision-making process that empowers evaluators to engage more deeply with the selection problem, ultimately leading to strategic and well-informed choices. The SFAHP has been adopted to evaluate the parcel lockers' location problem in Dublin City; the applied model is based on 6 alternatives. In consonance with a comprehensive literature review and scientists' points of view in the related field, the specialists selecting the following six alternatives to be estimated as most preferred locations (*A1, A2, A3, A4, A5, A6*). The authors established the hierarchy structure of the parcel lockers location selection (Fig. 2. illustrates the alternatives) based on the for mentioned alternatives:

In the evaluation process, three specialists estimated the PCMs (one 6 × 6 matrix for the alternative level) employing the linguistic terms from Table 1. The consistency for each PCM was revealed by considering the corresponding values in the conventional AHP approach for the linguistic terms from Table 1. Due to the intricate nature of the problem at hand and its substantial scale, considerable attention and analysis are warranted within the scholarly discourse. of the PCM, the current evaluation considered 0.2 as the CR threshold; the reason comes from the limited ability of a human to estimate the large size PCMs [47]. The following Tables 2–4 present the evaluated PCs, the detected CR, the computed spherical fuzzy weights $\tilde{w}^s$ and the normalized crisp weights $\overline{w}^s$. Table 2 shows the estimated PCM of the alternatives based on the E1 point of view concerning the second criterion (C2). The CR was acceptable. A_3 and A_4 were the most significant alternatives from the E1 perspective.

Table 3 shows the estimated PCM of the alternatives based on the E2 point of view concerning the second criterion (C2). The CR was acceptable. A_3 and A_4 were the most significant alternatives from the E2 perspective.

Table 4 shows the estimated PCM of the alternatives based on the E3 point of view concerning the fourth criterion (C4). The CR was acceptable. A_4, followed by A_3 and A_2, were the most significant alternatives from the E3 perspective.

Fig. 3. demonstrates the alternatives rank taking into consideration the experts' point of view.

To perform distance-based aggregation for these three vectors, we need to follow these steps:

Step 1: Choose a reference vector or point, where we choose the mean vector as the reference vector. The mean vector for the three vectors representing the decision maker's point of view is (0.140, 0.146, 0.214, 0.202, 0.187, 0.110).

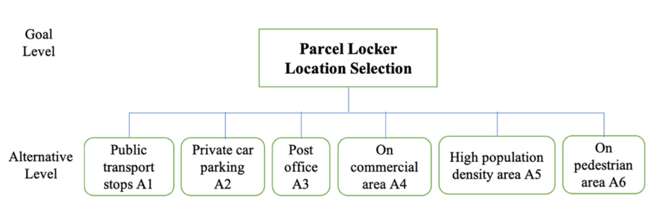

Fig. 2. The hierarchy framework for choosing parcel locker location.

Table 2
Pairwise comparison of locations caused by reliability based on E1 evaluation.

	A_1	A_2	A_3	A_4	A_5	A_6
A_1	EI	SMI	LI	SLI	SLI	HI
A_2	SLI	EI	VLI	VLI	LI	HI
A_3	HI	VHI	EI	EI	SLI	VHI
A_4	SMI	VHI	EI	EI	SMI	HI
A_5	SMI	HI	HI	SLI	EI	HI
A_6	LI	LI	LI	VLI	LI	EI

Table 3
Pairwise comparison of locations caused by reliability based on E2 evaluation.

	A_1	A_2	A_3	A_4	A_5	A_6
A_1	EI	SMI	LI	LI	SLI	SMI
A_2	SLI	EI	VLI	LI	SLI	HI
A_3	HI	VHI	EI	SMI	SMI	VHI
A_4	HI	HI	SLI	EI	SMI	VHI
A_5	SMI	SMI	SLI	SLI	EI	VHI
A_6	SLI	LI	VLI	VLI	VLI	EI

Table 4
Pairwise comparison of locations caused by reliability based on E3 evaluation.

	A_1	A_2	A_3	A_4	A_5	A_6
A_1	EI	SLI	LI	LI	LI	SLI
A_2	SMI	EI	SLI	SLI	SLI	SMI
A_3	HI	SMI	EI	SMI	SMI	HI
A_4	HI	SMI	SLI	EI	SMI	HI
A_5	HI	SMI	SLI	SLI	EI	HI
A_6	SMI	SLI	LI	LI	LI	EI

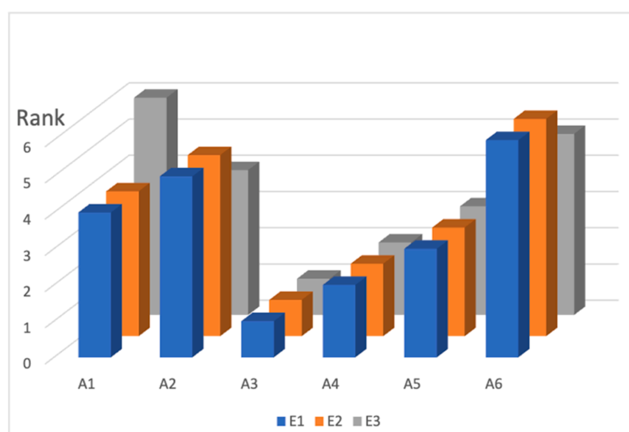

Fig. 3. The normalized weight scores taking into consideration the experts' point of view.

Step 2: Calculate the distances between each vector and the reference vector

The Euclidean distances between each vector and the reference vector are:

The Euclidean distance d_1 between v_1 and the reference vector is computed as follows:

$$\begin{aligned} d_{E1} &= sqrt\left((0.160-0.140)^2+(0.138-0.146)^2\right.\\ &\quad \left.+(0.213-0.214)^2+(0.2-0.202)^2+(0.190-0.187)^2+(0.1-0.110)^2\right)\\ &=0.095 \end{aligned}$$

The Euclidean distance between v_2 and the reference vector is

$$d_{E2} = sqrt\left((0.140-0.140)^2+(0.141-0.146)^2+(0.223-0.214)^2+(0.208-0.202)^2+(0.185-0.187)^2+(0.097-0.110)^2\right) = 0.075$$

The Euclidean distance between v_3 and the reference vector is computed as follows:

$$d_{E3} = sqrt\left((0.117-0.140)^2+(0.158-0.146)^2+(0.205-0.214)^2+(0.197-0.202)^2+(0.188-0.187)^2+(0.134-0.110)^2\right) = 0.070$$

Step 3: Calculate the weights for each vector

We will use a linear function to calculate the weights. The weights for each vector are:

We adopted the linear function for computing the weights (W_1, W_2, W_3) for each vector (w_1, w_2, w),

The weight for v_1 is computed as follows:

$$W_1 = 1-(d_{E1}/(d_{E1}+d_{E2}+d_{E3})) = 1-(0.095/(0.095+0.075+0.070)) = 0.358$$

The weight for v_2 is computed as follows:

$$W_2 = 1-(d_{E2}/(d_{E1}+d_{E2}+d_{E3})) = 1-(0.075/(0.095+0.075+0.070)) = 0.291$$

The weight for v_3 is computed as follows:

$$W_3 = 1-(d_{E3}/(d_{E1}+d_{E2}+d_{E3})) = 1-(0.070/(0.095+0.075+0.070)) = 0.351$$

Step 4: Compute the weighted average of the vectors:

We compute the weighted average of the vectors using the weights as coefficients. The aggregated vector can be adopted by calculating the weighted average of the vectors (w_1, w_2, w_3),

$(W_1 w_1 + W_2 w_2 + W_3 w_3) / (W_1+W_2+W_3)=$

$$((0.358)\times(0.160, 0.138, 0.213, 0.20, 0.190, 0.100)+(0.291)\times(0.140,0.141,0.223,0.208,0.185,0.097)+(0.351)\times(0.117,0.158,0.205,0.197,0.188,0.134))/(0.358+0.291+0.351) = (0.1429, 0.147, 0.213, 0.201, 0.187, 0.111)$$

Step 5: Normalize the aggregated vector and rank the alternatives (Fig. 4.)

The obtained final normalized aggregated vector is (0.1428, 0.146, 0.211, 0.199, 0.186, 0.110). The priority of the alternatives is $A_3 > A_4 > A_5 > A_1 > A_2 > A_6$. The best location for locating the parcel lockers is A_3 *"Post office"* with a weighted score (of 0.211), followed by A_4 *"On commercial area"* with a weighted score (of 0.199) and A_5 with a weighted score (of 0.186).

The findings, including the identification of the top three optimal locations, namely "Post office," "On commercial area," and "High population density area," along with their respective weight scores, provide valuable insights for policymakers making strategic decisions regarding parcel locker placements in Dublin city. These findings hold significant implications for policymakers and stakeholders involved in last-mile delivery logistics and urban planning in Dublin. The identification of the top three optimal locations for parcel lockers offers a clear roadmap for strategic decision-making. "Post Office" reflects the convenience of leveraging existing postal infrastructure, potentially streamlining the last-mile delivery process. Placing parcel lockers in "Commercial Areas" can enhance accessibility for both businesses and residents, reducing the distance and time needed for parcel pickup. "High Population Density Areas" often experience greater delivery challenges. Parcel lockers in these locations can alleviate congestion and enhance delivery efficiency. By providing these insights, our study aids in optimizing resource allocation, reducing delivery times, and improving customer satisfaction. Policymakers can use this information to strategically position parcel lockers, enhancing the efficiency and sustainability of last-mile delivery in Dublin.

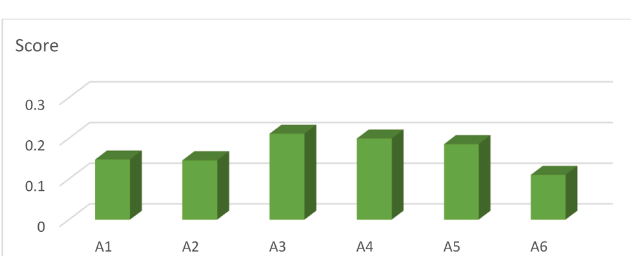

Fig. 4. The final normalized aggregated weight scores for the parcel locker's location alternatives.

3.1. Similarity test

To check the similarities in rankings among the three evaluators (E1, E2, E3), we use the Spearman Rank Correlation Coefficient [48]. The Spearman Rank Correlation is a non-parametric measure of statistical dependence between two variables, in this case, the rankings provided by the evaluators. It assesses how well the rankings from different evaluators agree or disagree.

The calculation of Spearman Rank Correlation Coefficient for each pair of evaluators (E1 vs. E2, E1 vs. E3, and E2 vs. E3) has been done as follow:

1. Assign ranks to the alternatives based on each evaluator's rankings.
2. Calculate the difference in ranks for each alternative between the two evaluators you want to compare (e.g., E1 and E2):
3. Square the rank differences and sum them up.
4. Use the following formula to calculate the Spearman Rank Correlation Coefficient (ρ) for each pair of evaluators:

$$\rho = 1 - \frac{6.\ \sum (Rank\ Difference)^2}{n*(n^2-1)} \tag{8}$$

where:

- Σ(Rank Difference)^2 is the sum of the squared rank differences.
- n is the number of alternatives (in your case, 6).

1. Calculate ρ for E1 vs. E2, E1 vs. E3, and E2 vs. E3.

A higher ρ value indicates greater similarity in rankings between the two evaluators. If ρ is close to 1, it indicates strong agreement, while ρ close to −1 indicates strong disagreement.

The process has been applied for each pair of evaluators to assess the similarities in their rankings (Table 5).

ρ calculation for each pair:

E1 vs. E2:

Table 5
The alternatives rank based on experts' evaluation.

Alternative	E1	E2	E3
A1	4	4	6
A2	5	5	4
A3	1	1	1
A4	2	2	2
A5	3	3	3
A6	6	6	5

1. Calculate the rank differences.
2. Square the rank differences and sum them up:

$$\sum (Rank\ Difference)^2 = 0$$

3. Calculate ρ using the formula:

$$\rho = 1 - \frac{6.\ \sum (Rank\ Difference)^2}{n*(n^2-1)} = 1-6*06*(62-1) = 1-6*(62-1)6*0$$

$= 1-0 =1$

E1 vs. E3:

1. Calculate the rank differences.
2. Square the rank differences and sum them up:

$$\sum (Rank\ Difference)^2 = 6$$

3. Calculate ρ:

$$\rho = 1 - \frac{6.\ \sum (Rank\ Difference)^2}{n*(n^2-1)} = 0.8$$

E2 vs. E3:

1. Calculate the rank differences.
2. Square the rank differences and sum them up:

$$\sum (Rank\ Difference)^2 = 6$$

3. Calculate ρ:

$$\rho = 1 - \frac{6.\ \sum (Rank\ Difference)^2}{n*(n^2-1)} = 0.8$$

Results:

- E1 vs. E2: ρ = 1 (Strong agreement)
- E1 vs. E3: ρ = 0.8 (Strong agreement)
- E2 vs. E3: ρ = 0.8 (Strong agreement)

All three pairs of evaluators show strong agreement in their rankings.

3.2. Sensitivity analysis

Sensitivity analysis is a technique used to assess how the variability or uncertainty in the input parameters of a model or system affects the output or outcomes [49]. It involves systematically changing one or more input variables while keeping other factors constant to observe how these changes impact the results. In our research on parcel locker locations, sensitivity analysis can be applied to evaluate the robustness and reliability of the model's outcomes.

We perform a sensitivity analysis by varying the weights of these alternatives within a certain range. We consider that we are going to vary the weights of A1 by 5 % while keeping the weights of A2, A3, A4, A5, and A6 constant. Fig. 5. presents the results of the sensitivity analysis scenarios for the alternatives with A1 wt adjustments:

The sensitivity analysis of the alternative weights reveals the dynamic nature of the decision-making process. While the original weights offer a stable foundation for evaluation, slight adjustments can significantly alter the final outcome. Decreasing the weight of A1 shifts the focus towards other alternatives, highlighting their relative importance. Conversely, increasing A1′s weight amplifies its influence, potentially overshadowing other alternatives. This analysis underscores the need for a balanced approach that considers both the stability of original weights and the potential impact of extreme scenarios. In most scenarios, the proposed model demonstrates its capability, correctness, and robustness in handling varying weight distributions.

3.3. Comparison analysis

In this step, the Geometric Mean, and Arithmetic Mean approaches have been conducted to measure the reliability of the proposed model, this comparison is done to observe the ranking consistency across the different methods. Fig. 6. Depicts no any changes in alternatives ranking and this justify the reliability of the adopted outcomes. This stability in ranking ensures that the model's outcomes are reliable and not significantly influenced by the choice of the ranking method. Such consistency is vital in decision-making processes, as it indicates that the model's recommendations for selection or ranking of alternatives are not arbitrary but based on a stable and well-founded methodology.

4. Discussion and conclusion

The initial step in location selection usually identifies the demand for usage and additional capacity. The analysis for optimal location is then conducted based on this. The increasing customer demand for shipping and parcel volumes has created the need for low shipping costs. However, many retailers hide the true shipping costs in order to promote sales. This study introduces a novel decision support approach using a

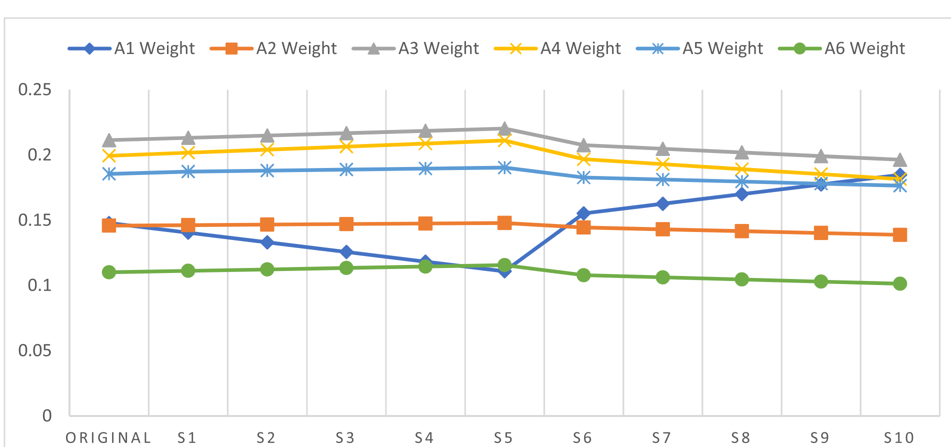

Fig. 5. The Results of the Sensitivity Analysis.

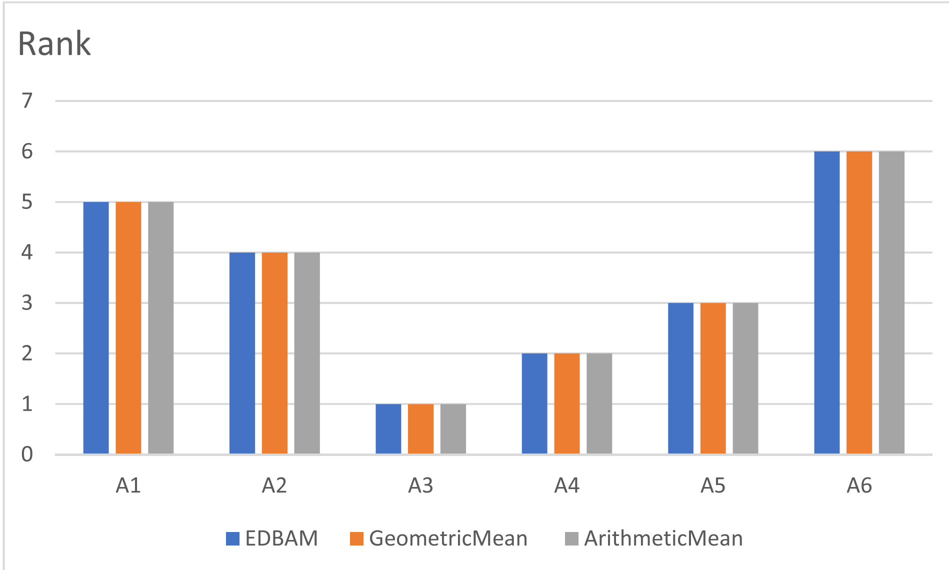

Fig. 6. Comparisons with Geometric Mean and Arithmetic Mean Results.

new estimation system for the selection of parcel lockers. In order to systematically estimate the location selection problem for parcel lockers, a dynamic approach is needed, such as the MCDM approach. To estimate the alternatives from specialists' points of view towards the problem, the AHP approach is usually applied. However, decision-makers can be hesitant during the evaluation process. This is why the AHP has been utilized with spherical fuzzy sets to accurately estimate the impact of the factors.

In this study, six locations (A_1; A_2; A_3; A_4; A_5 *and* A_6) are used to select the optimal location of parcel lockers. The data are collected from three specialists in the transport and logistics field, Each of these individuals possesses a minimum of five years of practical expertise, thereby demonstrating a substantial level of professional experience. The convenient SFAHP model successfully highlighted the post offices as the most suitable locations for placing parcel lockers; the spherical fuzzy extent determines alternatives priorities efficiently. The comparison analysis justified the reliability of the proposed model in our study.

In future, we will focus on involving different stakeholder groups in order to deliver more sustainable solutions for the parcel lockers locations selection problem. Moreover, extend the work by applying it to each district in Dublin to get a real demand-based district. As methodology, the Parsimonious extension can be adopted in future studies. In addition, some recent decision-making models [50,51] and aggregation operators [52–54] can be applied to save the survey time and evaluators efforts.

Ethical approval

This article does not contain any studies with human participants or animals performed by the author.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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