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AN INTEGRATED FUZZY MULTI-CRITERIA APPROACH FOR PARTNER SELECTION IN HORIZONTAL COOPERATION

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Abstract:

Horizontal cooperation has emerged as a key strategic tool in modern transport and logistics, enabling firms operating at the same supply chain level to enhance operational efficiency, reduce costs, and advance sustainability goals through shared resources and joint distribution. Despite its proven benefits, effective partner selection remains a complex challenge due to the multiple, often conflicting criteria involved and the lack of comprehensive frameworks that jointly address economic, social, and environmental dimensions. Existing approaches frequently overlook the inherent uncertainty and dynamic nature of transportation networks, creating a clear research gap in providing robust decision-support tools that integrate expert judgment under ambiguity. Addressing this gap, this paper proposes an integrated fuzzy multi-criteria decision-making (MCDM) framework for partner selection in horizontal cooperation. The framework combines the Fuzzy Extent Analysis with the Analytic Hierarchy Process (Fuzzy EW-AHP) to determine the relative importance of criteria and applies the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (Fuzzy TOPSIS) to rank potential partners. By leveraging fuzzy logic, the model effectively translates subjective expert assessments into quantitative evaluations, overcoming the limitations of traditional crisp approaches. The framework is validated through computational experiments simulating a fourth-party logistics scenario, supported by sensitivity analyses that confirm its stability under varying weight scenarios. The findings demonstrate the framework's ability to enhance informed, sustainable partner choices, ensuring alignment with strategic goals and sustainability commitments. This study contributes to theory by bridging the gap between fragmented criteria and the need for an integrated, uncertainty-resilient partner selection model. Practically, it offers managers a structured, adaptable decision-support tool suitable for diverse collaborative contexts. Future research should further refine and extend the proposed framework by integrating dynamic, real-time data streams, testing the methodology on larger and more diverse datasets, and developing accessible digital decision-support systems to facilitate its practical implementation. Such advancements would enhance managerial capacity to make robust, transparent, and sustainability-oriented partnership decisions within increasingly complex and dynamic transport and logistics networks.

Keywords: *horizontal cooperation, joint distribution, partner selection, transportation, logistics*

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1. Introduction

To improve operational efficiency and gain a competitive edge in the transportation sector, horizontal collaboration has increasingly emerged as a key strategic approach (Angelelli et al., 2022). This is particularly applicable to entities functioning at the same tier, such as wholesalers, retailers, or manufacturers. In this context, horizontal cooperation in transportation and logistics is gaining attention as an effective approach to reduce redundancies, enhance service quality, and improve the economic and environmental performance of distribution systems (Cruijssen, Dullaert, & Fleuren, 2007). Mason et al. (2007) assert that horizontal collaboration fosters cost reduction, logistical process optimisation, and overall enhancement of transportation efficiency by integrating diverse resources and capabilities. This is achieved by integrating various resources and expertise. Saenz et al. (2015) assert that this collaborative method not only improves responsiveness to changing market demands and external disruptions but also fosters more flexibility in manufacturing and distribution operations. Moreover, horizontal alliances facilitate collaboration in risk management, mitigating the adverse impacts of supply disruptions, price fluctuations, and other unforeseen challenges (Ding & Huang, 2024).

Given the potential benefits of such alliances, one of the most critical factors determining their success lies in the careful selection of partners. The selection of appropriate partners is a critical component in determining the effectiveness of horizontal collaboration (Asawasakulson, 2009). Mrabti et al. (2022) assert that good partner selection fosters synergy, alignment of strategic objectives, and mutual trust, which are crucial for generating lasting competitive advantages. Optimal business partners are those that contribute complementary resources and skills while demonstrating the ability to adjust to evolving market dynamics. Adverse partner selections, conversely, may hinder collaborative endeavours, potentially leading to inefficiencies and operational challenges (Ouhader & El Kyal, 2017). Due to the multidimensional nature of this decision, including technical, strategic, and relational aspects, selecting the right partners is often a complex and uncertain process. The multitude of factors to evaluate and the uncertainty inherent in decision-making both add to the complexity of this process. The methodology for selecting partner combinations in horizontal cooperation may be categorised into four primary types: multi-criteria decision-making approaches (MCDM), empirical research, optimisation methods, and hybrid approaches that integrate two or more of the aforementioned categories (He et al., 2016).

To effectively navigate these complexities and uncertainties, decision-support tools based on fuzzy logic have gained popularity. Fuzzy set theory is employed to address the absence of quantitative evidence and the uncertainty regarding the decision maker's preferences. The language evaluations of decision-makers or experts are converted into triangular fuzzy numbers. This study introduces a comprehensive fuzzy MCDM framework for the selection of partners in horizontal collaborations. This implementation aims to address the stated concerns. The proposed framework is designed to address the above-mentioned challenges. The Fuzzy Extent Analysis on Analytic Hierarchy Process (Fuzzy EW-AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) serve as the core components of the developed methodology. By integrating subjective assessments and managing the inherent ambiguity in decision-making, fuzzy EW-AHP successfully determines the weights of selection criteria. Subsequently, Fuzzy TOPSIS was used because it allows for ranking potential partners based on their closeness to both the ideal and anti-ideal solutions, and its fuzzy extension effectively captures the vagueness and subjectivity of expert judgments, which is crucial for ensuring robust, realistic results in complex multi-criteria partner selection problems (He et al., 2016; Shukla et al., 2014; Venkatesh et al., 2019). A brief comparison of selected related studies applying fuzzy MCDM methods for partner selection is presented in Table 1 to contextualise this methodological choice.

Table 1. Comparison of studies on fuzzy MCDM methods for partner selection. Source: own work

Literature	Method used	Main focus	Context
He et al. (2016)	Fuzzy EW-AHP + TOPSIS	Optimal partner combination	Joint distribution alliance
Shukla et al. (2014)	Fuzzy AHP + Fuzzy TOPSIS	Supply chain coordination	Manufacturing supply chains
Venkatesh et al. (2019)	Fuzzy AHP-TOPSIS	Supplier selection	Humanitarian supply chains
Chen et al. (2020)	Fuzzy DEMATEL-TOPSIS	Sustainability factors	Green supplier selection

In order to assess the practical applicability and robustness of the proposed framework, a series of computational experiments were conducted under controlled simulation conditions. The framework is validated by computer experiments. These studies entail a fourth-party logistics (4PL) coalition responsible for selecting optimal partner combinations from a pool of manufacturers and suppliers. Sensitivity tests are conducted to assess the robustness of the results under various criterion weight scenarios. The results demonstrate that this integrated method effectively enhances informed decision-making, ensures strategic alignment among partners, and improves overall transportation operational efficiency. This study contributes to both academic research and practical applications by providing a comprehensive methodology for partner selection in horizontal partnerships. This underscores the need to integrate economic, social, and environmental considerations into decision-making within collaborative transportation management, while effectively addressing the uncertainties inherent in these systems. This paper's structural outline is as follows: Section 2 presents a review of the pertinent literature, followed by an elucidation of assessment criteria in Section 3, a discourse on the fuzzy approach in Section 4, an examination of computational experiments in Section 5, a presentation of the principal findings, and a conclusion offering insights and prospective research avenues in Section 6.

2. Literature review

This section provides a structured overview of the existing scientific literature on horizontal collaboration within transportation and logistics systems, with a focus on its strategic importance, operational benefits, and implementation barriers. Particular attention is devoted to the role of partner selection as a critical determinant of collaborative success. Moreover, the review highlights the growing application of fuzzy multi-MCDM techniques—most notably Fuzzy Extent Analysis on Analytic Hierarchy Process and the Technique for Order Preference by Similarity to Ideal Solution —as robust methodological tools for addressing the inherent complexity and uncertainty in the partner evaluation process. These approaches facilitate the integration of expert judgment with structured evaluation frameworks, thereby enhancing the analytical rigour and practical relevance of partner selection in horizontal cooperation models.

2.1. Horizontal collaboration in transport and logistics

Bahrami (2002) posits that horizontal cooperation has emerged as a transformative approach in modern supply chain management. This method allows organisations at the same level, such as wholesalers, merchants, or manufacturers, to consolidate resources, reduce expenses, and enhance operational efficiency. By pooling capabilities, firms gain flexibility in manufacturing and logistics processes while simultaneously increasing resilience to market fluctuations and external disruptions. This approach promotes adaptability in manufacturing and logistics processes while concurrently enhancing resistance to market fluctuations and external disruptions. Mason et al. (2007) and Muñoz-Villamizar et al. (2019b) assert that horizontal collaboration is gaining prominence due to its ability to enhance resource efficiency. This includes the use of transportation networks, storage facilities, and distribution channels. This approach facilitates the attainment of economies of scale and improves the overall efficacy of transportation activities.
In light of rapidly evolving consumer demands and increasing sustainability pressures, logistics cooperation is increasingly recognised as a strategic lever for improving efficiency and competitiveness in the global business environment. Horizontal collaboration is described as the cooperation of supply chain entities operating at the same level, with a major focus on sharing resources such as warehouses, distribution centres, and vehicles to create mutual benefits (Pomponi et al., 2013b). Bae et al. (2022) assert that this method is increasingly endorsed by digital platforms, facilitating seamless coordination and integration of stakeholder activities. The creation of these platforms establishes a foundation for sustainable economic models that facilitate resource sharing and advance economic, environmental, and social sustainability objectives.
From an operational perspective, horizontal collaboration is instrumental in reducing underutilized trips, optimising transportation assets, and improving delivery reliability (Cruijssen et al., 2007). The amalgamation of shipments from several enterprises facilitates a more equitable distribution of truck capacity, resulting in considerable decreases in

operating expenses and environmental impact (Bocewicz et al., 2021). This is particularly important in fragmented transport markets, where small and medium-sized enterprises often lack the scale necessary to achieve cost-effective transport performance (Cruijssen et al., 2007).

Cruijssen et al. (2007) further clarify that horizontal collaboration encompasses all stages of transportation network development. At the strategic level, it enables the collaborative design of distribution frameworks, facilitating the consolidation of product flows and the optimisation of transportation routes. At the tactical level, it facilitates collaborative scheduling, routing, and fleet capacity optimisation. At the operational level, horizontal collaboration enables logistics partners to handle daily transportation execution cohesively, minimising redundancy and enhancing resource usage. This multilayered collaboration structure significantly contributes to enhanced economic efficiency and ecological sustainability, reinforcing the value of horizontal collaboration in modern transportation systems.

While much of the literature emphasises the economic advantages of horizontal cooperation, recent research stresses the importance of evaluating such collaborations through the broader lens of sustainability, encompassing economic, environmental, and social dimensions (Aloui et al., 2021b). This contrasts with the predominant study that emphasises on the economic savings potentially realised by horizontal cooperation.

Moreover, horizontal cooperation facilitates collaborative risk management by mitigating the adverse impacts of supply disruptions, price fluctuations, and unforeseen issues (Ding & Huang, 2024). In addition to risk reduction, collaborative logistics can offer substantial environmental benefits by optimising routing and supporting resource-sharing strategies. Soysal et al. (2018) demonstrate that such practices reduce greenhouse gas emissions, contributing to climate goals. According to the findings of Lehoux et al. (2014), horizontal cooperation enhances service quality, elevates consumer happiness, and fortifies market positions by unifying operations across participants.

2.2. Partner selection in horizontal collaboration

The selection of appropriate partners represents a critical strategic decision in the formation of horizontal collaborations, particularly within the transportation and logistics sectors. The long-term success and sustainability of such partnerships largely depend on the alignment of operational capabilities and strategic goals among the involved entities (Pomponi et al., 2015). In response to increasing competitive pressures, evolving customer expectations, and the growing importance of sustainable operations, firms have intensified efforts to establish collaborative frameworks aimed at enhancing network performance and reducing operational expenditures (Cao & Zhang, 2010).

Effective collaboration in transport networks contributes to improved service levels, optimised routing, reduced empty mileage, and enhanced system responsiveness (Maheshwari et al., 2006). Horizontal cooperation specifically entails collaborations among firms situated at the same tier of the supply chain — including logistics service providers, distribution centres, manufacturers, or retailers — that collectively consolidate transport capacities, coordinate shipment flows, and optimise resource allocation to attain mutual operational and strategic advantages (McLaren et al., 2002). Given the complexity and strategic significance of these alliances, partner selection necessitates a rigorous evaluation process based on multidimensional criteria (Soosay et al., 2008; Stank et al., 2001). Key assessment elements include strategic compatibility, complementary capabilities, mutual trust, commitment to collaboration, and a shared orientation toward long-term cooperation (Blomqvist, 2002). These dimensions are essential for establishing synergetic partnerships that can adapt to changing market conditions while maintaining collaborative integrity.

Organisations adopt various approaches to partner selection. While some firms rely on structured, formalised assessments grounded in strategic criteria, others depend on managerial intuition, prior experiences, or specific customer demands when identifying suitable collaborators (Parvatiyar & Sheth, 2002). The research about partner selection in horizontal collaboration underscores the necessity of delineating explicit objectives and defining the partnership's scope (Marty & Rueal, 2024). This includes specifying the expected outcomes—such as cost reduction, service level improvements, or increased innovation capabilities—as well as establishing operational boundaries and governance mechanisms. Such clarity enables better alignment between partners and facilitates the measurement of collaborative performance over time.

2.3. Fuzzy Multi-Criteria Decision-Making Techniques for partner selection

In the context of horizontal partnerships, the complexity of partner selection—driven by the presence of multiple and often conflicting criteria—has led to the growing application of fuzzy multi-criteria decision-making (MCDM) approaches (Ben at al., 2018; Tatarczak 2020). These approaches utilise subjective assessments and systematic evaluation procedures to adeptly handle ambiguity, rendering them especially appropriate for decision-making situations with several competing criteria. Among the most widely adopted fuzzy MCDM techniques are Fuzzy Extent Analysis on Analytic Hierarchy Process (Fuzzy EW-AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). These methods are often integrated into comprehensive frameworks that support structured evaluation and prioritisation of potential partners. Fuzzy EW-AHP is employed to determine the relative importance of selection criteria by translating qualitative expert opinions into quantitative weights using fuzzy logic. This process effectively captures the inherent vagueness of human reasoning, ensuring that the resulting weights reflect real-world complexity and nuance. Building upon this, Fuzzy TOPSIS enables the ranking of alternatives based on their relative closeness to ideal and anti-ideal solutions. This dual-distance consideration enhances decision quality by incorporating both strengths and weaknesses of each alternative. Together, Fuzzy EW-AHP and Fuzzy TOPSIS provide a robust and holistic framework for partner evaluation across diverse operational dimensions.

The practical utility of these methods has been confirmed in multiple research studies and application domains. For instance, Ayadi et al. (2016) formulated a fuzzy collaborative evaluation framework to evaluate partner trust, emphasising the significance of relational elements in cooperation. Chen et al. (2020) integrated sustainability criteria into a hybrid rough-fuzzy DEMATEL-TOPSIS model, highlighting the increasing significance of environmental factors in partner selection. Shukla et al. (2014) used Fuzzy AHP and Fuzzy TOPSIS to simulate supply chain coordination, demonstrating its suitability for intricate logistical contexts. Fuzzy MCDM approaches are utilised across several sectors, including manufacturing, electronics, automotive, and humanitarian missions. Beyond theoretical validation, fuzzy MCDM techniques have found applications across a broad range of sectors (Gazi et al., 2023; Ghorui et al., 2023; Momena et al., 2023; Chakraborty et al., 2022; Ghosh et al., 2021). In manufacturing, these techniques have been employed to enhance supplier relationships by reconciling cost effectiveness with operational agility (Lin & Chen, 2004). Wu et al. (2020) utilised a fuzzy ensemble learning model in the electronics sector to categorise and prioritize potential partners according to sustainability indicators. In humanitarian logistics, where uncertainty and urgency are prominent, Venkatesh et al. (2018) utilised a Fuzzy AHP-TOPSIS model to identify supply partners for disaster relief missions, addressing the unique constraints of such operations.

The primary advantage of fuzzy MCDM procedures is their capacity to amalgamate several assessment criteria into organised decision-making frameworks. Economic considerations, including cost minimisation and profit distribution, are frequently emphasised in conjunction with social issues like as reliability and reputation. Environmental factors, such as greenhouse gas emissions and resource efficiency, have become increasingly significant as firms seek to align their operations with sustainability objectives.

Soysal et al. (2018) showed that horizontal collaboration solutions that integrate environmental criteria may markedly diminish carbon footprints while improving logistical efficiency. Mishra et al. (2015) included agility measurements into a fuzzy MULTIMOORA model to tackle dynamic market situations, demonstrating the flexibility of fuzzy methodologies in response to changing priorities.

2.4. Research gap and contribution

Horizontal collaboration has become a crucial approach in the transportation and logistics industry, providing opportunities to improve network efficiency, optimise resource use, and decrease total transportation expenses (Ferrell et al., 2020; Soysal et al., 2018). Horizontal collaboration enhances logistics system performance and improves service reliability and flexibility by allowing companies at the same supply chain level—such as logistics service providers, carriers, or distribution centres—to share assets and synchronise transport operations (Mrabti et al., 2022). Notwithstanding its acknowledged benefits, several deficiencies remain in the approaches and frameworks established to facilitate its application.

A notable shortcoming is the inadequate incorporation of economic, social, and environmental variables into cohesive evaluation frameworks. Current research frequently emphasises singular elements of cooperation, neglecting to thoroughly examine the complex structure of transportation collaborations. This gap impairs the capacity to develop comprehensive models that consider varied stakeholder objectives and fluctuating market conditions.

A further problem resides in the absence of empirical validation for theoretical models inside extensive datasets. Although several frameworks are accompanied by illustrative examples or restricted case studies, their relevance to real-world situations remains ambiguous. The lack of substantial empirical data limits the generalizability of these models and their use by practitioners in search of dependable decision-making aids.

Furthermore, several current frameworks inadequately account for the dynamic characteristics of transportation networks. Logistics networks function under extremely dynamic settings, shaped by variable demand, changing regulatory environments, and technological progress. Static decision models fail to encapsulate the intrinsic complexity of real-world transportation collaboration scenarios, hence constraining their capacity to provide prompt and robust recommendations for partnership decisions.

This study proposes an integrated fuzzy MCDM framework that combines Fuzzy EW-AHP and Fuzzy TOPSIS to address key gaps in partner selection for horizontal cooperation. The method systematically determines the weights of selection criteria based on expert input and evaluates potential partners under uncertainty, covering economic, social, and environmental aspects. This hybrid approach merges the strengths of Fuzzy EW-AHP for weighting subjective assessments with the ranking capability of Fuzzy TOPSIS, effectively managing ambiguity in decision-making. The framework has been empirically validated through computational experiments and sensitivity analysis, demonstrating its robustness and practical value for supporting sustainable and informed collaboration decisions.

3. Proposed methodology for partner selection

This paper provides an integrated fuzzy MCDM framework to tackle the intricacies of partner selection in horizontal collaboration. The approach integrates Fuzzy EW-AHP and TOPSIS to systematically assess and rank prospective partners. This hybrid methodology utilises fuzzy logic to address ambiguity and subjective assessments while maintaining a systematic evaluation procedure. The framework integrates these methodologies to establish a rigorous methodology for discovering ideal partner combinations that correspond with strategic objectives and improve transportation performance.

3.1. Identifying the evaluation criteria

Selecting appropriate evaluation criteria for partner selection in horizontal cooperation is crucial to ensure the success and sustainability of such partnerships (Franco, 2010). This paper builds its evaluation index system based on an extensive review of the literature, focusing on key factors relevant to horizontal cooperation. Drawing from various studies, the evaluation framework encompasses economic, social, and environmental factors, reflecting the multifaceted nature of transportation collaborations. The final criteria system contains 10 criteria (Fig.). Figure 1 schematically presents the hierarchical structure of the evaluation criteria, demonstrating the systematic organisation and interconnection of the economic, social, and environmental dimensions essential for a robust partner selection process in horizontal cooperation.

Profit sharing (C1) is a critical economic sub-criterion in horizontal cooperation within transportation and logistics networks (Ponte et al., 2016). Differences in the interpretation of the value of contributions and participation can lead to conflicts and delays in collaboration. Effective negotiations on the division of benefits and costs require mutual understanding and mechanisms that ensure a fair and acceptable distribution. A consistent profit-sharing strategy is essential to maintaining motivation among partners, as the lack of such a strategy can negatively impact the willingness to cooperate, thereby limiting the potential benefits and overall success of the collaboration (Basso et al., 2019). Additionally, cost reduction (C2) is a significant benefit of horizontal cooperation in the transportation system (Audy et al., 2012).

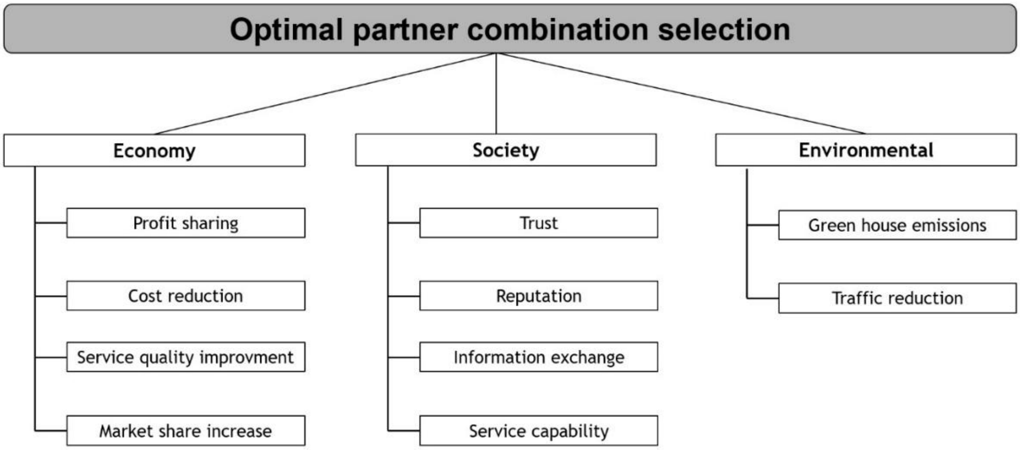

Fig. 1. Hierarchy of the partner combination selection for horizontal cooperation. Source: own work

By sharing resources, optimising logistics, and streamlining operations, partners can achieve substantial savings. These cost efficiencies not only improve operational profitability but also bolster network resilience, enabling enterprises to maximise load factors, minimise empty miles, and more effectively respond to variable transport needs (Flisberg et al., 2015). Furthermore, service quality improvement (C3) is a key benefit of horizontal cooperation in transportation and logistics. The integration of activities and joint coordination among participants enhances processes, leading to higher quality products and services (Lehoux et al., 2014). Horizontal collaboration improves the consistency and responsiveness of logistics systems by integrating transport activities across enterprises, hence enhancing customer satisfaction and strengthening competitive advantage. Moreover, market share increase (C4) is a critical economic sub-criterion in horizontal cooperation. Coordinated and integrated actions among partners achieve greater scale, enabling the offering of a larger volume of products or services to the market (Allen et al., 2014). Partners can assist each other in expanding into new geographical areas, customer segments, or distribution channels. This collaborative effort not only broadens market reach but also strengthens competitive positioning, allowing all participants to benefit from increased sales and market presence.

Trust (C5) is a crucial social sub-criterion in horizontal cooperation, aimed at establishing stable and enduring relationships between partners (Kwon & Suh, 2004). Building trust fosters long-term collaboration by facilitating problem-solving and conflict resolution, leading to more effective coordination and mutual benefits (Kwon & Suh, 2005). Trust reduces perceived risks, enhances information sharing, and aligns partners' goals and strategies. High levels of trust encourage open communication, resource sharing, and collaborative innovation, contributing significantly to the overall efficiency and success of the transportation network (Pomponi et al., 2015). Establishing trust requires consistent, reliable behavior, transparency, and a commitment to mutual interests, strengthening and sustaining the partnership over time (Sheffi et al., 2019). In addition to trust, reputation (C6) plays a significant role as a driver of horizontal cooperation, reflecting partners' reliability and trustworthiness (Badea et al., 2014). A strong reputation enhances collaboration by strengthening relationships, reducing risks, and generating mutual benefits. It encourages firms to engage in cooperative efforts, knowing their partners are committed to shared goals and ethical standards. This trust, built on reputation, mitigates opportunistic behavior and enhances the stability and effectiveness of the transportation network. Another critical driver is information sharing (C7), which significantly enhances partners' operational efficiency and performance (Basso et al., 2019). Open exchange of data and knowledge enables firms to better align their strategies and actions with rapidly changing market conditions. This alignment not only improves responsiveness and flexibility but also fosters stronger collaborative relationships, ensuring that all parties can optimize their operations and achieve mutual benefits (Daudi et al., 2016). Effective information sharing reduces uncertainties and facilitates coordinated decision-making, contributing to the overall success and stability of the transportation network. Another crucial social sub-criterion is service capability (C8), which reflects a partner's capacity to uphold high service standards despite the presence of a variety of operating situations. When it comes to transportation partnerships, service competency is frequently evaluated based on factors such as the performance of on-time delivery, the flexibility of capacity, and the technical experience in fleet management. When it comes to shared logistics operations, having a high service capacity is a must for attaining the appropriate service levels and maintaining standards of quality that are constant.

Besides economic and social factors, horizontal collaboration significantly enhances environmental sustainability. A significant quantifiable ecological advantage is the diminution of greenhouse gas emissions (C9). Collaborative transport strategies—such as route optimization, increased vehicle occupancy, and shared utilization of distribution centers—decrease total vehicle kilometers traveled, thereby reducing CO_2 emissions and aiding regulatory compliance (Soysal et al., 2018).

Traffic reduction (C10) is a significant ecologically and operationally pertinent sub-criterion in horizontal cooperation. Coordinated transportation initiatives allow collaborators to minimize vehicle fleets, eradicate duplicate deliveries, and alleviate congestion in both urban and interurban regions (Montoya-Torres et al., 2016). Effective traffic management through collaboration not only mitigates environmental damage but also facilitates smoother transportation flows, diminishes infrastructure degradation, and improves delivery dependability for all stakeholders.

3.2. The integrated fuzzy EW-AHP and TOPSIS method for partner combination selection

The integrated fuzzy EW-AHP and TOPSIS approach constitutes a thorough framework for systematically assessing and choosing optimal partner combinations in horizontal collaboration. This methodology integrates the advantages of Fuzzy Extent Analysis inside the Analytic Hierarchy Process (Fuzzy EW-AHP) for establishing criterion weights and employs the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for evaluating and ranking alternatives according to their performance. The approach employs triangular fuzzy numbers to effectively manage uncertainty and subjective judgments in decision-making, hence providing robust and informed partner selection. This section delineates the transformation rules, computational procedures, and implementation of this integrated technique.

A triangular fuzzy number can be represented as a triplet

$$\tilde{a} = [a^L, a^M, a^R] \tag{1}$$

where a^L, a^M, a^R are the minimum and maximum limits of the available area for the evaluation data, respectively. In order to convert the linguistic variables provided by decision-makers and experts into triangular fuzzy numbers, it is necessary to establish the transformation rules first, as shown in Table 2 and Table 3 (Awasthi et al., 2015).

Table 2. Transformation rules of lingustic ratings of decision makers for criteria weight. Source: own work

Linguistic term	Fuzzy number
Of little importance (LI)	(1,1,3)
Moderately important (MI)	(1,3,5)
Important (I)	(3,5,7)
Very important (VI)	(5,7,9)
Absolutely important (AI)	(7,9,9)

Table 3. Transformation rules of lingustic ratings of experts for criteria combination performance of partner combination. Source: own work

Lingustic term	Fuzzy number
Very low (VL)	(1,1,3)
Low (L)	(1,3,5)
Medium (M)	(3,5,7)
High (H)	(5,7,9)
Very high (VH)	(7,9,9)

The specific steps of fuzzy EW-AHP methods are as described below, following the approach proposed by He et al. (2016).

Step 1. Define $r_{jk} = \left(r_{jk}^L, r_{jk}^M, r_{jk}^R\right)$ for $j = 1,2, \dots, n$ and $k = 1,2, \dots, r$ as the linguistic ratings for criteria weights assigned by decision-maker D_k to criterion C_j. Convert r_{jk} to r_{jk}^s, and compute the fuzzy entropy e_j as follows:

$$r_{jk}^s = \frac{r_{jk}}{\sum_{k=1}^{r} r_{jk}} \quad (2)$$

$$e_j = -\frac{1}{lnr} \sum_{k=1}^{r} r_{jk}^s lnr_{jk}^s \quad (3)$$

Step 2. Calculate the fuzzy EW:

$$w_j^1 = \frac{1 - e_j}{n - \sum_{j=1}^{n} e_j} \quad (4)$$

Step 3. Determine the criteria weight w_j^2 using fuzzy AHP, considering subjective factors, as detailed in He et al. (2016).

Step 4. Compute the final weight w_j by integrating fuzzy EW and fuzzy AHP:

$$w_j = \frac{w_j^1 \times w_j^2}{\sum_{j=1}^{n} w_j^1 \times w_j^2} \quad (5)$$

where $w_j = \left(w_j^L, w_j^M, w_j^R\right)$.

The Fuzzy TOPSIS method is an MCDM technique that selects the best alternative by minimizing the distance to a positive ideal solution and maximizing the distance from a negative ideal solution. This approach uses triangular fuzzy numbers to handle uncertainty in the decision matrix. The steps are as follows:

Step 1. Aggregate fuzzy linguistic ratings for the performance of alternatives. Consider m alternatives $A = \{A_1, A_2, \dots, A_m\}$ and n criteria $C = \{C_1, C_2, \dots, C_n\}$. The fuzzy linguistic ratings $r_{aij} = \left(a_{ij}^L, a_{ij}^M, a_{ij}^R\right)$, is calculated by averaging the experts' ratings:

$$r_{aij} = \left(\frac{\sum_{k=1}^{r} a_{ijk}^L}{r}, \frac{\sum_{k=1}^{r} a_{ijk}^M}{r}, \frac{\sum_{k=1}^{r} a_{ijk}^R}{r}\right) \quad (6)$$

Step 2. Construct the initial fuzzy decision matrix A using the aggregated fuzzy ratings.

$$A = \begin{bmatrix} \left(a_{11}^L, a_{11}^M, a_{11}^R\right) & \cdots & \left(a_{1n}^L, a_{1n}^M, a_{1n}^R\right) \\ \vdots & \ddots & \vdots \\ \left(a_{m1}^L, a_{m1}^M, a_{m1}^R\right) & \cdots & \left(a_{mn}^L, a_{mn}^M, a_{mn}^R\right) \end{bmatrix} \quad (7)$$

Step 3. Normalize the fuzzy decision matrix.
For benefit-type criteria, normalization is performed as:

$$r_{ij}^b = \frac{r_{aij} - \min\left(r_{aij}, i = 1,2,\dots,m\right)}{\max\left(r_{aij}, i = 1,2,\dots,m\right) - \min\left(r_{aij}, i = 1,2,\dots,m\right)} \quad (8)$$
$$\forall j = 1,2, \dots, n$$

For cost-type criteria, normalization is:

$$r_{ij}^b = \frac{ma\,x\left(r_{aij}, i = 1,2,\dots,m\right) - r_{aij}}{\max\left(r_{aij}, i = 1,2,\dots,m\right) - \min\,\left(r_{aij}, i = 1,2,\dots,m\right)} \quad (9)$$
$$\forall j = 1,2, \dots, n$$

After normalization, the normalized fuzzy decision matrix B is obtained:

$$B = \left[r_{ij}^b\right]_{m \times n} = \begin{bmatrix} \left(b_{11}^L, b_{11}^M, b_{11}^R\right) & \cdots & \left(b_{1n}^L, b_{1n}^M, b_{1n}^R\right) \\ \vdots & \ddots & \vdots \\ \left(b_{m1}^L, b_{m1}^M, b_{m1}^R\right) & \cdots & \left(b_{mn}^L, b_{mn}^M, b_{mn}^R\right) \end{bmatrix} \quad (10)$$

Step 4. Calculate the integrated fuzzy weights of the criteria.
The integrated fuzzy weights w_j for each criterion are determined using the procedures described in Equations (2)–(5).

Step 5. Compute the weight normalized fuzzy decision matrix.
Using Equation (11), the weight normalized fuzzy decision matrix C is obtained by multiplying each element of the normalized fuzzy decision matrix B by the corresponding integrated fuzzy weight w_j:

$$C = \left[w_j \times r_{ij}^b\right]_{m \times n} \quad (11)$$

Step 6. Calculate distances to fuzzy ideal solutions.
Step 6.1. Identify the fuzzy positive ideal solution (C^+) and fuzzy negative ideal solution (C^+).
For benefit-type criteria set J_1 and cost-type criteria set J_2, the fuzzy ideal solutions are defined as:

$$C^{+} = (max c_{ij} \mid j \in J_1, min c_{ij} \mid j \in J_2) \tag{12}$$

$$C^{-} = (min c_{ij} \mid j \in J_1, max c_{ij} \mid j \in J_2) \tag{13}$$

Step 6.2. Compute Distances
A modified geometrical distance method is utilized to capture the uncertainty more effectively than the standard Euclidean distance.

$$d(a, b) = \frac{|a^L - b^L| + |a^M - b^M| + |a^R - R| + |pr_a - pr_b|}{3} \tag{14}$$

Thus, the distance of alternative ii from the fuzzy positive ideal solution (d_i^+) and negative ideal solution (d_i^-) can be computed as:

$$d_i^+ = \frac{\sum_{j=1}^{n}(|c_{ij}^L - c_j^{+L}| + |c_{ij}^M - c_j^{+M}| + |c_{ij}^R - c_j^{+R}| + |pr_{cij} - pr_{c_j^+}|)}{3n} \tag{15}$$

$$d_i^- = \frac{\sum_{j=1}^{n}(|c_{ij}^L - c_j^{-L}| + |c_{ij}^M - c_j^{-M}| + |c_{ij}^R - c_j^{-R}| + |pr_{cij} - pr_{c_j^-}|)}{3n} \tag{16}$$

Step 7. Compute Relative Closeness
Calculate the relative closeness RC_i of each alternative A_i to the ideal solution:

$$RC_i = \frac{d_i^-}{d_i^- + d_i^+}, \quad 0 \le RC_i \le 1 \tag{17}$$

Step 8. Rank Alternatives
Rank the alternatives based on their relative closeness RC_i. The alternative with the highest RC_i is chosen as the optimal partner combination.
The merged fuzzy EW-AHP and TOPSIS approach offers a systematic and efficient framework for tackling the intricacies of partner selection in horizontal collaboration. This approach utilises fuzzy logic to address uncertainty and integrates systematic multi-criteria decision-making approaches, ensuring a robust and adaptive assessment procedure for many circumstances. A brief consideration of the computational aspects indicates that the overall time complexity of the integrated fuzzy EW-AHP and TOPSIS approach remains polynomial in relation to the number of criteria and alternatives evaluated. The primary computational burden arises from constructing the fuzzy pairwise comparison matrices and performing the distance calculations for ranking alternatives. This ensures that the proposed framework is not only methodologically rigorous but also computationally feasible and scalable for practical applications involving larger sets of partners and criteria.

4. Computational experiments

This study addresses a decision-making scenario involving a fourth-party logistics (4PL) chain coalition tasked with evaluating four potential partner alternatives. The coalition is considering two manufacturers, labelled A and B, and two suppliers, labelled C and D. The objective is to enhance operational efficiency and customer service by selecting one manufacturer and one supplier from these options. Consequently, the 4PL must assess four possible partner combinations: {A, C}, {A, D}, {B, C}, and {B, D}. To guarantee a meticulous and methodical selection process, the merged fuzzy EW-AHP and TOPSIS methodologies are utilised. This hybrid paradigm enables the evaluation of partner combinations by integrating subjective expert assessments into a systematic decision-making process. The system utilises triangular fuzzy numbers to successfully manage uncertainties in linguistic assessments, guaranteeing that the chosen combination ideally balances economic, social, and environmental objectives. The outcomes of the computational experiments corroborate the proposed framework, emphasising its ability to facilitate partner selection decisions that enhance transport network performance, optimise resource utilization, and bolster the operational resilience of horizontal logistics collaborations. The main procedures are as follows:
Step 1. To acquire the linguistic ratings, four panels of experts ($k = 1, 2, 3, 4$) were established, each specializing in different domains: economy, environment, society, and logistics. These panels provided linguistic rating judgments for the criteria weights and the performance of each partner combination alternative. The resulting evaluations are detailed in Table 4 and Table 5.
Step 2. This involves calculating the integrated weights of the criteria using the data presented in Table 3 and applying Equations (2)–(5). The results of these calculations are shown in Table 6.
Step 3. This utilises the information in Table 2 and Equations (6) and (7) to derive the initial fuzzy decision matrix A (see Table 7). This matrix forms the basis for further analysis in the evaluation process.

Table 4. Linguistic ratings for the criteria weights. Source: own work

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
EP1	LI	VI	VI	MI	AI	I	MI	AI	I	LI
EP2	MI	I	MI	VI	AI	VI	AI	VI	LI	VI
EP3	I	VI	AI	AI	LI	AI	I	AI	AI	I
EP4	MI	I	LI	VI	AI	MI	AI	VI	VI	MI

Table 5. Linguistic ratings for partner combination performance for each criterion. Source: own work

		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
EP1	PC1	VL	H	L	L	H	M	M	VH	H	H
	PC2	L	M	L	H	L	VH	VL	H	L	M
	PC3	M	H	VH	VH	VH	H	VH	VH	VH	H
	PC4	L	M	VL	H	L	L	H	H	VL	M
EP2	PC1	L	L	H	VH	VL	L	H	VH	VL	L
	PC2	VH	H	L	H	L	M	VH	H	L	H
	PC3	M	VH	VH	VH	M	H	M	VH	M	VH
	PC4	VH	H	VL	H	L	M	VH	H	L	H
EP3	PC1	M	H	L	M	L	VH	H	H	M	L
	PC2	VL	M	VH	L	VH	H	L	M	VL	H
	PC3	L	H	M	VH	M	VH	VH	H	VH	L
	PC4	L	M	VH	L	M	H	VL	M	H	H
EP4	PC1	L	M	H	VL	VL	M	M	VL	L	M
	PC2	VH	L	L	H	L	H	VL	H	VH	H
	PC3	M	VH	VH	M	L	VH	VH	L	M	VH
	PC4	VH	L	VL	L	L	L	H	L	VH	L

Table 6. Integrated weights of criteria. Source: own work

Fuzzy-EW	C1 [0,588; 0	C2 [0,318; 0,337; 0,345]	C3 [0,530; 0,347; 0,123]	C4 [0,312; 0,336; 0,353]	C5 [0,610; 0,296; 0,095]
	C6 [0,317; 0	C7 [0,449; 0,395; 0,156]	C8 [0,321; 0,333; 0,345]	C9 [0,520; 0,354; 0,126]	C10 [0,315; 0,338; 0,347]
FWA	C1 [0,214; 0	C2 [0,223; 0,338; 0,439]	C3 [0,231; 0,339; 0,430]	C4 [0,232; 0,341; 0,428]	C5 [0,202; 0,337; 0,462]
	C6 [0,233; 0,342; 0,425]	C7 [0,245; 0,338; 0,417]	C8 [0,240; 0,340; 0,420]	C9 [0,227; 0,336; 0,437]	C10 [0,223; 0,338; 0,439]
Integrated weights	C1 [0,056; 0,038; 0,015]	C2 [0,024; 0,024; 0,025]	C3 [0,051; 0,037; 0,017]	C4 [0,020; 0,022; 0,024]	C5 [0,039; 0,012; 0,016]
	C6 [0,013; 0,012; 0,016]	C7 [0,075; 0,061; 0,040]	C8 [0,033; 0,033; 0,037]	C9 [0,016; 0,013; 0,008]	C10 [0,046; 0,040; 0,041]

Table 7. Initial fuzzy decision matrix A. Source: own work

C1	C2	C3	C4	C5
$\begin{bmatrix}1,5 & 3,0 & 5,0\\4,0 & 5,5 & 6,5\\2,5 & 4,5 & 6,5\\4,0 & 6,0 & 7,0\end{bmatrix}$	$\begin{bmatrix}3,5 & 5,5 & 7,5\\3,0 & 5,0 & 7,0\\6,0 & 8,0 & 9,0\\3,0 & 5,0 & 7,0\end{bmatrix}$	$\begin{bmatrix}3,0 & 5,0 & 7,0\\2,5 & 4,5 & 6,0\\6,0 & 8,0 & 8,5\\2,5 & 3,0 & 4,5\end{bmatrix}$	$\begin{bmatrix}3,0 & 4,5 & 6,0\\4,0 & 6,0 & 8,0\\6,0 & 8,0 & 8,5\\3,0 & 5,0 & 7,0\end{bmatrix}$	$\begin{bmatrix}2,0 & 3,0 & 5,0\\2,5 & 4,5 & 6,0\\3,5 & 5,5 & 7,0\\2,5 & 4,5 & 6,0\end{bmatrix}$
C6	C7	C8	C9	C10
$\begin{bmatrix}3,5 & 5,5 & 7,0\\4,5 & 6,5 & 8,5\\6,5 & 8,5 & 9,0\\2,5 & 4,5 & 6,5\end{bmatrix}$	$\begin{bmatrix}4,0 & 6,0 & 8,0\\2,5 & 3,5 & 5,0\\6,0 & 8,0 & 8,5\\4,5 & 6,0 & 7,5\end{bmatrix}$	$\begin{bmatrix}5,0 & 6,5 & 7,5\\4,5 & 6,5 & 8,5\\5,0 & 7,0 & 8,0\\3,5 & 5,5 & 7,5\end{bmatrix}$	$\begin{bmatrix}2,5 & 4,0 & 6,0\\2,5 & 4,0 & 5,5\\5,0 & 7,0 & 8,0\\3,5 & 5,0 & 6,5\end{bmatrix}$	$\begin{bmatrix}2,5 & 4,5 & 6,5\\4,5 & 6,5 & 8,5\\5,0 & 7,0 & 8,0\\3,5 & 5,5 & 7,5\end{bmatrix}$

Step 4. The weighted normalised fuzzy decision matrix is calculated using Equations (8)–(11). Among the criteria, C1, C3, C4, C5, C6, C7, and C8 are benefit-type criteria; C2, C9, and C10 are cost-type criteria. To obtain the normalised fuzzy decision matrix B (see Table 7) and weighted normalised fuzzy decision matrix C (see Table 8), we use Equations (8)–(11).

Step 5. The distances between each alternative and both the fuzzy positive and negative ideal solutions are computed. Equations (12) and (13) are used to determine the fuzzy positive d_i^+ and negative d_i^- ideal solutions. The distances d_i^+ and d_i^- for each alternative i from these ideal solutions are calculated using Equations (14) to (16), resulting in:

$$d_1^+ = 0{,}020, d_2^+ = 0{,}010, d_3^+ = 0{,}014, d_4^+ = 0{,}017$$

$$d_1^- = 0{,}045, d_2^- = 0{,}043, d_3^- = 0{,}019, d_4^- = 0{,}042$$

Table 8. Normalize fuzzy decision matrix B. Source: own work

C1	C2	C3	C4	C5
$\begin{bmatrix}0,0 & 0,0 & 0,0\\1,0 & 0,8 & 0,8\\0,4 & 0,5 & 0,8\\1,0 & 1,0 & 1,0\end{bmatrix}$	$\begin{bmatrix}0,8 & 0,8 & 0,8\\1,0 & 1,0 & 1,0\\0,0 & 0,0 & 0,0\\1,0 & 1,0 & 1,0\end{bmatrix}$	$\begin{bmatrix}0,1 & 0,4 & 0,6\\0,0 & 0,3 & 0,4\\1,0 & 1,0 & 1,0\\0,0 & 0,0 & 0,0\end{bmatrix}$	$\begin{bmatrix}0,0 & 0,0 & 0,0\\0,3 & 0,4 & 0,8\\1,0 & 1,0 & 1,0\\0,0 & 0,1 & 0,4\end{bmatrix}$	$\begin{bmatrix}0,0 & 0,0 & 0,0\\0,3 & 0,6 & 0,5\\1,0 & 1,0 & 1,0\\0,3 & 0,6 & 0,5\end{bmatrix}$
C6	C7	C8	C9	C10
$\begin{bmatrix}0,3 & 0,3 & 0,2\\0,5 & 0,5 & 0,8\\1,0 & 1,0 & 1,0\\0,0 & 0,0 & 0,0\end{bmatrix}$	$\begin{bmatrix}0,4 & 0,6 & 0,9\\0,0 & 0,0 & 0,0\\1,0 & 1,0 & 1,0\\0,6 & 0,6 & 0,7\end{bmatrix}$	$\begin{bmatrix}1,0 & 0,7 & 0,0\\0,7 & 0,7 & 1,0\\1,0 & 1,0 & 0,5\\0,0 & 0,0 & 0,0\end{bmatrix}$	$\begin{bmatrix}1,0 & 1,0 & 0,8\\1,0 & 1,0 & 1,0\\0,0 & 0,0 & 0,0\\0,6 & 0,7 & 0,6\end{bmatrix}$	$\begin{bmatrix}1,0 & 1,0 & 1,0\\0,2 & 0,2 & 0,0\\0,0 & 0,0 & 0,3\\0,6 & 0,6 & 0,5\end{bmatrix}$

Table 9. Weighted normalize fuzzy decision matrix C. Source: own work

C1	C2	C3	C4
$\begin{bmatrix}0,000 & 0,000 & 0,000\\0,047 & 0,042 & 0,036\\0,019 & 0,025 & 0,036\\0,047 & 0,050 & 0,047\end{bmatrix}$	$\begin{bmatrix}0,009 & 0,006 & 0,007\\0,010 & 0,008 & 0,010\\0,000 & 0,000 & 0,000\\0,010 & 0,008 & 0,010\end{bmatrix}$	$\begin{bmatrix}0,014 & 0,039 & 0,061\\0,000 & 0,029 & 0,037\\0,096 & 0,098 & 0,098\\0,000 & 0,000 & 0,000\end{bmatrix}$	$\begin{bmatrix}0,000 & 0,000 & 0,000\\0,016 & 0,015 & 0,030\\0,048 & 0,036 & 0,037\\0,000 & 0,005 & 0,015\end{bmatrix}$
C5	C6	C7	C8
$\begin{bmatrix}0,000 & 0,000 & 0,000\\0,017 & 0,036 & 0,031\\0,050 & 0,060 & 0,062\\0,017 & 0,036 & 0,031\end{bmatrix}$	$\begin{bmatrix}0,014 & 0,010 & 0,008\\0,028 & 0,021 & 0,031\\0,056 & 0,041 & 0,039\\0,000 & 0,000 & 0,000\end{bmatrix}$	$\begin{bmatrix}0,027 & 0,026 & 0,035\\0,000 & 0,000 & 0,000\\0,062 & 0,048 & 0,041\\0,036 & 0,026 & 0,029\end{bmatrix}$	$\begin{bmatrix}0,005 & 0,003 & 0,000\\0,003 & 0,003 & 0,000\\0,005 & 0,004 & 0,000\\0,000 & 0,000 & 0,000\end{bmatrix}$
C9	C10		
$\begin{bmatrix}0,056 & 0,066 & 0,054\\0,056 & 0,066 & 0,067\\0,000 & 0,000 & 0,000\\0,034 & 0,044 & 0,040\end{bmatrix}$	$\begin{bmatrix}0,071 & 0,074 & 0,077\\0,014 & 0,015 & 0,000\\0,000 & 0,000 & 0,019\\0,042 & 0,044 & 0,039\end{bmatrix}$		

Step 6. The relative closeness of each alternative to the ideal solution is then determined. This is calculated using Equation (17) for each alternative A_i:
$RC_1 = 0{,}694$,
$RC_2 = 0{,}809$,
$RC_3 = 0{,}584$,
$RC_4 = 0{,}707$

Step 7. Based on the relative closeness values, the four alternatives are ranked in the following order: $RC_2 > RC_4 > RC_1 > RC_3$. Therefore, the partner combination $PC2$ is identified as the optimal choice.

5. Discussion

5.1. Interpretation of findings

The partner combinations for the 4PL chain are ranked using the integrated fuzzy EW-AHP and FWA method. The results indicate that the partner combination PC2 is the optimal alternative. To test the robustness of this decision, a sensitivity analysis is performed to examine the impact of changes in criteria weights on the results. Figure 2 illustrates the sensitivity analysis results for the economy criteria, showing the effects of 5%, 10%, and 20% weight changes, both increasing and decreasing from the base weight. It is evident that as the weight of the economic criteria changes, the relative closeness of partner combinations PC3 and PC4 decreases slightly, while that of PC1 and PC2 increases slightly. Despite these variations, PC2 consistently maintains the highest relative closeness, indicating its robustness as the optimal partner combination.

Figure 3 presents the sensitivity analysis results for the society criteria. The analysis includes the same range of weight changes as the economic criteria. As the weight of the societal criteria increases, the relative closeness of PC3 and PC4 shows a slight increase, whereas PC2 remains the top choice due to its consistent performance. This reaffirms the robustness of the proposed methodology, as PC2 consistently emerges as the optimal partner combination regardless of changes in societal criteria weights. This figure confirms that the ranking stability is maintained, demonstrating that the proposed framework reliably accommodates adjustments in the weighting of societal criteria without significantly altering the final partner selection outcome.

Figure 4 shows the sensitivity analysis results for the environmental criteria. Similar to the previous analyses, the results indicate that the relative closeness of PC1 and PC2 slightly decreases with environmental criteria fluctuations, while PC3 and PC4 exhibit minimal changes. However, PC2 continues to be the optimal partner combination, demonstrating the stability and effectiveness of the proposed methodology. This figure further confirms that the model remains robust and reliable when environmental weighting factors are varied, underlining its practical suitability for real-world decision-making.

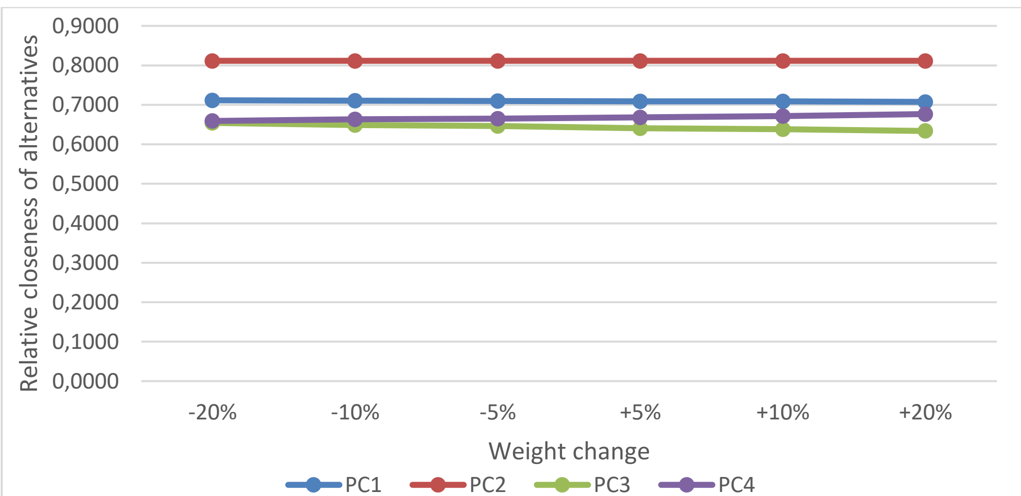

Figure 2. Sensitivity analysis result of economic criteria. Source: own work

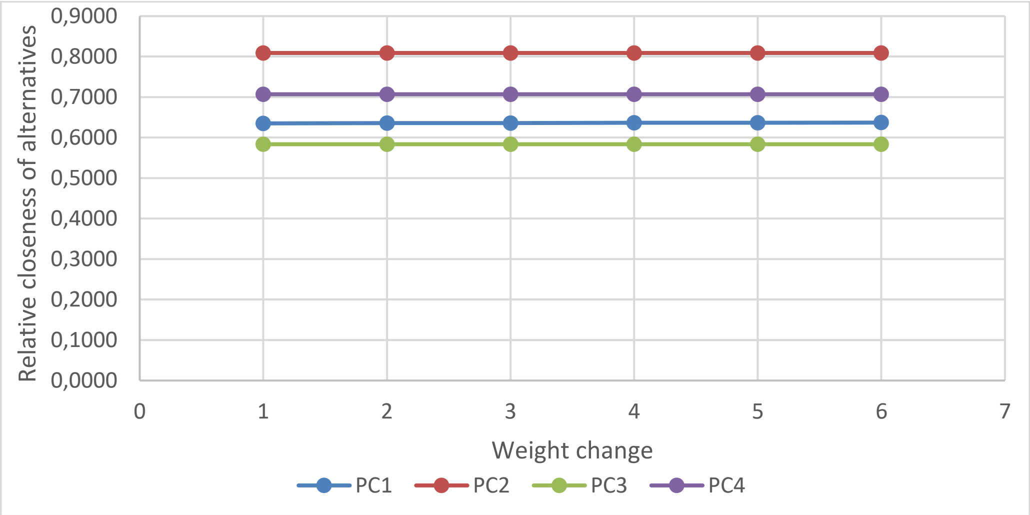

Figure 3. Sensitivity analysis result of the society criteria. Source: own work.

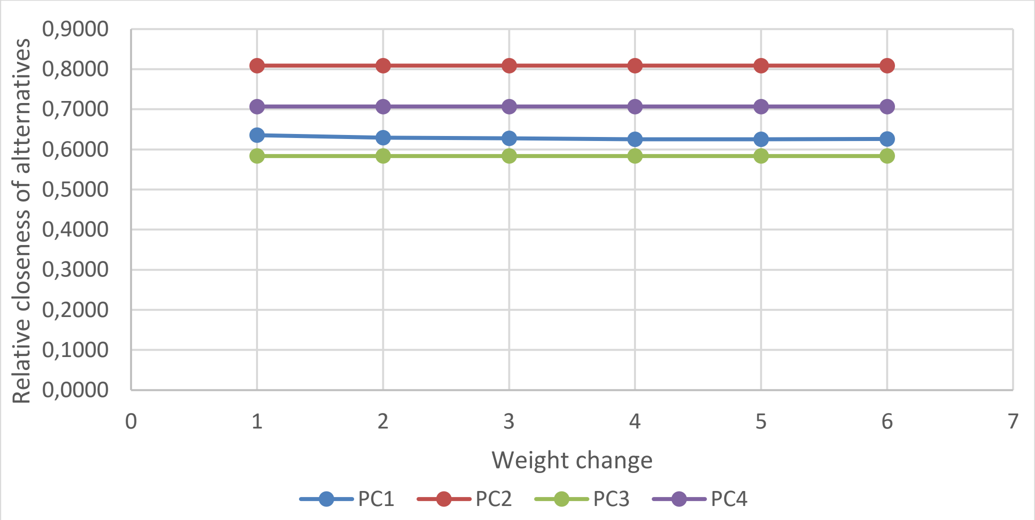

Figure 4. Sensitivity analysis result of environ-mental criteria. Source: own work

The sensitivity analysis confirms that the partner combination PC2 consistently ranks highest across different criteria weight scenarios. This indicates the robustness and effectiveness of the integrated fuzzy EW-AHP and FWA methodology for partner selection in a 4PL chain. Future research could explore additional criteria and extend this model to other industries to further validate its applicability.

5.2. Contribution to knowledge and practice

This research significantly enhances academic understanding and practical applications in horizontal collaboration by presenting an integrated fuzzy multi-criteria decision-making framework for partner selection. The study identifies significant deficiencies in current methodologies by integrating Fuzzy EW-AHP with TOPSIS, thus offering a

comprehensive and systematic framework for assessing and prioritising potential partners.
The research enhances the comprehension of partner choosing by introducing a complete framework that integrates economic, social, and environmental aspects. This research highlights the necessity of a comprehensive approach to partnership selection in transportation and logistics networks, contrasting with traditional models that often focus on isolated aspects of collaboration rather than addressing the integrated nature of joint transport operations. The use of fuzzy logic in the decision-making process signifies a methodological advancement, as it adeptly tackles the intrinsic ambiguity and subjectivity linked to partner assessment. The empirical validation of the model via computational experiments with a fourth-party logistics (4PL) coalition connects theoretical components to real-world applications, showcasing the practicality and dependability of the proposed framework.
In addition to its theoretical significance, this study advances the mathematical foundations of multi-criteria decision-making within the context of logistics cooperation. By extending and integrating the traditional Fuzzy EW-AHP and TOPSIS methods, the research demonstrates how established techniques can be systematically adapted and refined for the complex task of partner selection in horizontal alliances. In particular, the framework elaborates the fuzzy entropy-based weighting procedure and customizes the distance metrics in the Fuzzy TOPSIS approach to better capture the inherent uncertainty and interdependencies among evaluation criteria. This refined mathematical formulation enhances the accuracy and flexibility of the decision model, providing both scholars and practitioners with a replicable, adaptable tool suitable for diverse collaborative contexts where partner evaluation must account for multiple, and often conflicting, quantitative and qualitative dimensions.
This study also offers as well managers a systematic decision-making instrument that improves their capacity to identify suitable partners for horizontal collaboration. The approach guarantees goal alignment, resource complementarity, and mutual trust—essential elements for successful collaboration—by methodically assessing potential partners against several criteria. The incorporation of environmental factors, including greenhouse gas emissions and traffic reduction, bolsters sustainable transportation operations, aligning with modern corporate goals and regulatory mandates. The sensitivity analysis performed in this work provides significant insights into the stability of partner selection outcomes under different settings, hence enhancing the robustness of the technique.
The results of this research have ramifications that extend beyond the immediate context of 4PL coalitions. The suggested framework's scalability and versatility render it suitable for many sectors aiming to enhance horizontal collaboration initiatives. This study addresses theoretical gaps and practical obstacles, contributing to the growth of cooperation methods and providing concrete answers for practitioners seeking to improve operational efficiency and competitive advantage.

5.3. Advantages and limitations

Based on the integrated Fuzzy EW-AHP and FWA methodologies presented in this paper, a comprehensive framework for partner selection in horizontal cooperation within the transportation system has been developed. This approach combines the strengths of both methods to effectively account for the inherent uncertainties and subjective judgments that are characteristic of the partner selection process. By utilising a structured evaluation index system derived from a thorough review of relevant literature and expert input, the proposed model addresses multiple criteria, including economic, social, and environmental factors. The application of the model in a real-world setting demonstrates its robustness and effectiveness in identifying the most suitable partners for cooperation, thus enhancing the strategic decision-making process for managers.
Despite its strengths, the proposed methodology has certain limitations. One of the primary challenges lies in the requirement for decision-makers to possess a high level of proficiency in interpreting the criteria weights and integrating expert judgments, which may impact the accuracy of the results in scenarios where such expertise is lacking. Additionally, the model currently lacks a quantitative approach for evaluating the performance of different criteria combinations, which could further refine the selection process. Future research could focus on expanding the model to include a more dynamic and adaptable criteria evaluation system that accounts for changes in external environmental factors. Moreover, developing a computerised decision-support system could

facilitate a more user-friendly application of the model, promoting wider adoption and fostering more effective partnerships in diverse transportation contexts.

5.4. Future research directions

The key aim of future research should be to expand the current model to incorporate new advances and evolving objectives in transportation management. Integrating criteria related to digital transformation, resilience to disruptions, and sophisticated sustainability metrics will enhance the model's relevance in a rapidly evolving corporate context. The integration of machine learning algorithms that adjust criterion weights depending on real-time data can significantly improve the adaptability and accuracy of decision-making frameworks. Such advances would enable managers to respond more efficiently to changing market conditions and unforeseen disruptions.

Moreover, comparative studies done across other industries and geographical regions can provide valuable insights into the generalizability and scalability of the proposed strategy. To enhance the model's applicability across diverse contexts, these studies will aid in pinpointing sector-specific challenges and opportunities. The framework's robustness might be further substantiated by exploring potential collaborations with industries that heavily rely on horizontal collaboration, including the retail, manufacturing, and logistics sectors.

The development of a comprehensive decision-support system that integrates qualitative and quantitative data inputs is another compelling avenue for future research. To enhance transparency, traceability, and efficiency in the partner selection process, such systems may include advanced technologies such as artificial intelligence, blockchain, and the Internet of Things. Artificial intelligence-driven predictive analytics may yield deeper insights into partner performance trends, while blockchain technology might ensure that records of collaborative agreements are secure and immutable.

A practical extension of this research should apply the integrated fuzzy EW-AHP and TOPSIS framework to rank potential partners based on real locations. Incorporating real-world geographic data would allow decision-makers to test the model under actual market conditions, improving its applicability and supporting more informed strategic planning.

Furthermore, subsequent research may explore the integration of environmental, social, and governance factors into the criteria for selecting partners. As sustainability gains prominence in the global transportation system, models that advocate for ecological responsibility and ethical conduct will become progressively significant. This is due to the increasing necessity of sustainability. Research into aligning these factors with economic objectives might facilitate the development of more comprehensive decision-making frameworks.

This leads us to the subsequent point: the investigation of innovative methodologies, such as digital twins for simulating transportation situations or hybrid models that integrate established approaches with developing technologies, might advance the boundaries of present research. These strategies would enable managers to adeptly traverse complex interactions in an era characterised by heightened unpredictability and technological upheaval, enhancing their theoretical understanding while providing practical tools.

6. Conclusions

This study presented a comprehensive fuzzy multi-criteria decision-making framework for partner selection in horizontal collaboration, integrating Fuzzy Extent Analysis with the Analytic Hierarchy Process (Fuzzy EW-AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The suggested technique adeptly tackled the intricacies of partner selection by integrating economic, social, and environmental parameters while navigating the inherent uncertainties and subjective evaluations in decision-making processes. The methodology exhibited robustness and practical application by methodically establishing criterion weights using Fuzzy EW-AHP and evaluating alternatives according to their proximity to ideal solutions via Fuzzy TOPSIS.

The computational tests performed in a fourth-party logistics (4PL) coalition context confirmed the efficacy of the system. The findings consistently revealed the ideal partner combination, even within differing criteria weight circumstances, as validated by sensitivity analysis. These findings underscore the efficacy of the technique in promoting informed decision-making, guaranteeing strategy coherence among partners, and improving overall transportation efficiency.

This research's principal contribution is its methodological integration, providing a thorough and systematic approach to partner selection that considers various characteristics and uncertainty. This paradigm offers practical insights for managers aiming to enhance horizontal partnerships, hence increasing operational efficiency, sustainability, and competitive advantage.

Notwithstanding its merits, this study possesses specific drawbacks. The dependence on expert assessment for criterion weighting creates possible bias, and the model's fixed structure may restrict its responsiveness to changing market conditions. Future studies should emphasise the integration of quantitative methodologies, such as machine learning, to dynamically modify criterion weights depending on real-time data. Furthermore, broadening the framework to encompass additional sectors and geographical situations would improve its generalizability. Creating a decision-support system to enhance practical execution may increase its acceptance and effectiveness.

A promising direction for future research involves conducting a comparative assessment of the proposed framework with alternative Fuzzy MCDM methods, such as Fuzzy VIKOR or Fuzzy DEMATEL-TOPSIS, to verify its relative performance and methodological advantages. Further studies may also explore the integration of additional sustainability indicators, social responsibility dimensions, or sector-specific evaluation criteria to expand the scope and relevance of the model. Moreover, the application of the framework to larger and more complex partner networks, including multi-tier supply chains or international collaboration contexts, could test its scalability and adaptability. Extending the approach to dynamic partnership scenarios, such as temporary alliances or flexible contractual arrangements, may also offer valuable insights for practitioners seeking to enhance collaboration strategies under changing market conditions.

This research greatly enhances academic literature and practical applications by offering a comprehensive method for partner selection in horizontal cooperation. The suggested technique provides a framework for establishing more successful partnerships that correspond with economic objectives, social agendas, and environmental sustainability.

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