INFORMATICA, 2026, Vol. 0, No. 0, 1–43

DOI: https://doi.org/10.15388/26-INFOR641

Hyperbolic Fuzzy Decision Analytics-Driven Supplier Selection with Circular Economy Principles in the Aerated Concrete Industry

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Received: April 2026; accepted: July 2026

Abstract. The research introduces a credible decision-support tool for dealing with uncertainty for supplier selection in the aerated concrete industry. The developed framework includes criteria selection, determination of expert and criterion weights, and alternative ranking within a hyperbolic fuzzy environment. Criteria selection is done via the Laplacian score. Expert weights are methodically determined via entropy measure. Criteria are weighted using the LOPCOW and RANCOM methods, and alternatives are ranked using the hyperbolic extension of the DEPART method. The model is employed to solve a circular supplier selection problem in the aerated concrete industry. Comprehensive sensitivity and comparison checks are conducted.

Key words: supplier selection, construction management, circular economy, hyperbolic fuzzy sets, MCDM, sustainable building, construction supply chain.

1. Introduction

Buildings are responsible for an important portion of global energy consumption and carbon emissions. Energy consumption is related to the construction, operation, renovation, and demolition processes of buildings, as well as the production of building materials and various systems (Abass and Muthulingam, 2025). Rapid population growth and migration from rural areas to cities have made the construction sector one of the most

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energy-intensive and waste-producing sectors (Llantoy *et al.*, 2020; Movaffaghi and Yitmen, 2023), making environmental impact management challenging in the construction industry (Tushar *et al.*, 2022). Based on the Global Alliance for Buildings and Construction (GABC) 2024/25 global status report, in 2023, buildings accounted for 32% of global energy demand and 34% of CO_2 emissions. It also notes that despite a small reduction in carbon emissions and a slight increase in the use of renewable energy, these gains are insufficient to meet the Paris Agreement targets (GABC, 2025).

With the abandonment of the traditional "take-make-dispose" approach (Attri *et al.*, 2025; Wahyu Adi and Wibowo, 2020), the circular economy (CE) perspective, focusing on material circularity, waste reduction, and efficient resource use has also emerged as a strategic framework for the transformation of the construction industry, like other industries (Tan *et al.*, 2025; Gupta *et al.*, 2025; Jain *et al.*, 2025). CE intends to preserve the value of products, materials, and resources throughout their life cycle and to decrease wastes via useful techniques such as reuse, recycling, refurbishment, recovery, and cleaner production (Nayeri *et al.*, 2025; Hasheminezhad *et al.*, 2024; Salman and Hasar, 2023). In this way, CE aims to maximize the effective and efficient use of production elements, thereby extending their lifespan (Govindan *et al.*, 2020). In the construction industry, this could be achieved by using recycled or reusable materials (Melikoglu, 2025; Timm *et al.*, 2023), making modular designs (Abdelmageed and Zayed, 2020; Oteng *et al.*, 2025), realizing energy-efficient production (Ferreira Junior *et al.*, 2025; Ludger Bernsmann and Schleifenbaum, 2025), reducing carbon footprint (Almusaed *et al.*, 2024; Iqbal *et al.*, 2025), using reverse logistics (Mishra *et al.*, 2022), gathering environmental certification systems, and considering life cycle management (Llantoy *et al.*, 2020; Manu, 2024).

Sustainability has become a major concern in supply chain management due to increasing environmental pressures, resource scarcity, climate change, and rigourous environmental regulations (Govindan *et al.*, 2020). It is evident that supply chains exert a direct influence on various key performance indicators, including energy consumption, waste generation, carbon emissions, transportation activities, and resource efficiency throughout the life cycle of products and materials (Tushar *et al.*, 2022). There is an increasing expectation that firms will integrate sustainability considerations into purchasing, logistics, production, and supplier selection processes (Kannan *et al.*, 2020). In the construction industry, where material-intensive production and transportation activities create substantial environmental impacts, sustainable supply chain management plays a critical role in reducing waste, improving resource efficiency, lowering carbon emissions, and supporting the circular economy practices (Tushar *et al.*, 2022). For this reason, supplier selection decisions are no longer based solely on traditional factors such as cost, quality, and delivery performance, but also increasingly include environmental and circularity-related considerations (Kusi-Sarpong *et al.*, 2023; Tramarico *et al.*, 2025).

Aerated concrete is frequently preferred in the construction industry for its light weight, satisfactory thermal insulation, and material savings (Gyurkó *et al.*, 2019). Collaboration with suppliers who possess those competencies significantly enables aerated concrete companies to support CE. Consequently, supplier selection in the construction supply chain for the aerated concrete industry is crucial for successful CE applications

(Tushar *et al.*, 2022). Additionally, selecting the right suppliers may reduce costs and increase supply chain efficiency, thereby enhancing the firms' profitability and ability to meet customer expectations (Ecer *et al.*, 2024). Whereas traditional supplier selection processes prioritize factors such as cost, quality, delivery, and financial flexibility (Paul and Pal, 2025), CE-focused supplier selection could consider environmental and social criteria, including waste management, energy efficiency, carbon emissions, environmental compatibility, recyclable raw materials, social responsibility, clean technology, life cycle impacts, etc. (Ulutaş *et al.*, 2025; Tramarico *et al.*, 2025). Such a broad assessment involves a multi-dimensional decision-making process with inherent uncertainty.

Although there is some research on circular supplier selection in the available literature, many focus on automotive (Govindan *et al.*, 2020), electronics (Kannan *et al.*, 2020; Menon and Ravi, 2022), manufacturing (Liu *et al.*, 2022; Tong *et al.*, 2022), textile (Kusi-Sarpong *et al.*, 2023; Ecer and Torkayesh, 2022), and chemical (Mina *et al.*, 2021; Tramarico *et al.*, 2025) industries. However, in the construction sector, supplier selection models that comprehensively incorporate CE principles are limited, and most evaluations are restricted to environmental drivers (Amarasinghe *et al.*, 2024; Demirbağ *et al.*, 2025). Furthermore, there are a few studies in which CE criteria have been systematically determined in conjunction with expert opinions to cope with uncertainty and actual industry practices. As far as the authors' knowledge goes, there is no work on supplier selection in the aerated concrete industry. Besides, the existing literature shows that available circular supplier selection works largely focus on developed industrial sectors and global-scale examples. In developing countries, such as Türkiye, applied research on the construction sector and building materials is very scarce. For building materials like aerated concrete, which provides energy efficiency in buildings, has low carbon emissions, and is easy to transport due to its lightness, there is almost no circular supplier evaluation model in the literature. Circular supplier selection also involves managing uncertainty based on expert judgments and evaluations. In the construction industry, where many project-based, simultaneous, or sequential processes are carried out together, it is very difficult to measure supplier performance accurately and objectively. Therefore, decision-makers often rely on judgments based on their experiences or perceptions. In such an environment, supplier selection becomes a decision problem involving intensive uncertainty, and this problem needs to be addressed with reliable and powerful decision support systems. These research gaps stand out as critical for both practical applications and decision-makers for supplier selection in the construction supply chains to achieve sustainable development. This study, therefore, aims to fill those gaps by introducing a supplier selection methodology concerning CE principles. 16 drivers are determined by searching the literature and the opinions of experts. Five large companies operating in the aerated concrete sector in Türkiye are considered alternatives by experts using those drivers. To obtain trustworthy results under uncertainty, a comprehensive fuzzy hyperbolic (HyF) multi-criteria decision-making (MCDM) approach is developed. Criteria weights are decided using the Logarithmic Percentage Change-Driven Objective Weighting (LOPCOW) and Ranking Comparison (RANCOM) methods, balancing objective and subjective information, while alternatives are ranked using the hyperbolic extension of the Deviation-Based Pairwise Assessment

Ratio Technique (DEPART) method with hyperbolic fuzzy information. Thus, a cutting-edge decision support system, named HyF-LOPCOW-RANCOM-DEPART, is introduced for the first time.

The research presents significant novelties and contributions in terms of contextual and methodological aspects. It makes significant contributions to the literature on CE-focused supplier selection, specifically in the construction sector. First, addressing supplier selection in the aerated concrete industry within the framework of CE principles fills a notable gap in the literature. The 16 evaluation criteria presented in this study encompass economic, environmental, social, and technological dimensions. These criteria were developed based on both a comprehensive literature review and expert opinions. The research offers an innovative approach by basing the evaluation set not only on theory but also on industry-specific information. The ranking of Türkiye's leading aerated concrete manufacturers based on expert opinions has enabled the creation of a robust model based on real-world field data. This also increases the applicability of the findings to industry decision-making processes. Furthermore, expanding the CE criteria to include environmental indicators as well as waste management, life cycle assessment, carbon footprint, and technological capabilities enriches the perspective on supplier selection. With all these features, the study integrates theory and practice, producing an innovative approach and providing a significant reference for establishing a circular supply chain in the construction industry. Further, the novel methodological novelties and contributions of this research include:

- ✓ Utilization of a flexible orthopair variant for data interpretation allows decision experts to consider both membership and non-membership grades of a qualitative term, which otherwise is not possible. Moreover, considering a hyperbolic fuzzy set (HyFS) leverages the flexibility in expressing a choice, which is restricted in other variants.
- ✓ Determination of decision experts' weights (importance) is lacking in extant models, but the proposed framework calculates weights of experts by extending the entropy measure to HyFS and capturing hesitation in the preference distribution for weight calculation.
- ✓ Though criteria weights are calculated, the determination of both subjective and objective weights is usually lacking in the literature. This issue is resolved by this framework, which extends the LOPCOW and RANCOM multi-criteria methods to HyFS, and enables an aggregated weight (importance) for CE criteria.
- ✓ Finally, to rank construction material suppliers, the recently developed DEPART method is extended to HyFS, which determines ranks through relative comparison and duly considers the pairwise values of alternative suppliers, which are lacking in other ranking techniques. Besides, the ranks of suppliers are determined both at the individualistic level and the holistic level by combining the Copeland strategy with DEPART.

The rationale for choosing these decision methods to develop a decision framework is given below:

- ✓ First, rating data from experts is interpreted as HyFS (Dutta and Borah, 2023), which offers two benefits to decision experts, i.e., an orthopair format that enables understanding of both preference and non-preference grades for an option in the decision matrix.

Further, the flexibility of choice expression, which is restricted in other orthopair forms, is clarified in the methodology section for readers. These two benefits encouraged authors to utilize HyFS for the interpretation of rating data.

✓ Second, criteria selection is performed in order to reduce the complexity of the decision process. For this purpose, the Laplacian score is put forward, which selects criteria in such a manner that the structural semantics of the decision problem remains intact and the complexity is reduced significantly. Rather than reducing the feature (criteria) by transforming the feature set to new spaces, the Laplacian score carefully selects criteria by retaining structural semantics. Later, we deploy an entropy measure for determining the weights of experts, which is not adequately explored in the literature on construction supplier selection.

✓ Third, the weights of the criteria are methodically determined, which essentially reduces inaccuracies and subjectivity. As a result, we considered both objective and subjective weighting procedures for obtaining the holistic weights of criteria, both from rating as well as from the ranking of criteria by experts. LOPCOW (Ecer and Pamucar, 2022) was extended in the objective context after considering its merits with respect to nullify the effects of extreme values through a logarithmic function and determining weights with better discriminative abilities, which are otherwise lacking in standard objective methods such as entropy and SAW. In the subjective weight context, we extended the RANCOM (Więckowski *et al.*, 2023) method that showcased its superiority in comparison with other subjective weight methods in the study from Więckowski *et al.* (2023).

✓ Finally, we ranked alternative suppliers by extending the DEPART method (Keshavarz-Ghorabaee *et al.*, 2025) that considers the deviation ratio from ideal and anti-ideal points in order to find the rank order of alternatives. Some notable merits of DEPART that make it more effective than other rank methods are: (i) it determines deviation ratios that enable pairwise alternative comparison rather than distinctive alternative comparison; (ii) decision philosophy of DEPART follows the ideal, anti-ideal, and deviations that can be readily associated with human-driven decision logic and, as a result, the method becomes useful in practical sense and explainable to practitioners during complex decision-making process.

It must be noted that hyperbolic fuzzy MCDM is considered a crucial research topic because the HyFS is an emerging orthopair variant that considers both preference (membership) and non-preference (non-membership) grades and has flexible constraints, which allow decision experts to effectively utilize this fuzzy variant for modeling uncertainty during the rating of decision entities. Since the HyFS was recently proposed, its exploration in decision frameworks and solving decision problems has just started, and so it is seen as a promising research topic for researchers to develop decision frameworks under HyFS for rational decision-making. In this paper, we are considering a problem of selecting a suitable supplier in the construction field by focusing on CE principles within the aerated concrete industry. Since the problem has a clear structure of MCDM with different alternative suppliers rated by decision experts on different criteria, we extend this problem into the HyFS-based MCDM construct and attempt to solve the decision problem through a structured methodical framework.

The remaining part of the study is organized as follows. The second section contains a literature review. Within this scope, studies related to CE-focused supplier selection is included. Subsequently, studies employing different methods related to the subject are listed, and research gaps are conveyed. The third section introduces the research methodology. The fourth section presents the application section. The fifth and sixth sections respectively present the discussion, theoretical and practical implications, and conclusions.

2. Literature Review

2.1. *Studies on Circular Supplier Selection Criteria*

The CE is an important research area as an approach aimed at using resources more efficiently, increasing the lifespan of products, and consequently reducing waste generation (Lieder and Rashid, 2016). Kirchherr *et al.* (2017) defined CE as a transformation model leading to sustainable development and proposed a broad systems approach encompassing the process from design to post-use through the 3R-9R concepts. Based on this, material circularity, less carbon emissions in production processes, life cycle design, reverse logistics, and closed-loop supply chain have become important topics in the CE literature (Almusaed *et al.*, 2024; Mishra *et al.*, 2022).

The construction industry is critical for CE applications because it is a resource-intensive industry with high material consumption and, consequently, a high level of waste generation. While prominent themes related to the construction industry includes waste management, life cycle assessment (LCA), and the use of recycled materials (Jeon *et al.*, 2025), carbon emissions (Iqbal *et al.*, 2025), and clean production technologies (Alam *et al.*, 2024; Giannetti *et al.*, 2023), circularity is not limited to these themes. Prefabrication, modular construction, and off-site construction practices (Obi *et al.*, 2025) enable the reduction of material waste and the improvement of energy efficiency, and are seen as important steps in line with these circular economy principles. In addition, aerated concrete, steel, and composite materials play a strategic role in supplier selection processes in terms of material-based circularity due to their recyclability and low carbon levels (Ghisellini *et al.*, 2018). Aerated concrete, in particular, is a significant alternative in sustainable building applications due to its energy efficiency, lightness, thermal performance, and recycling potential (Rafiza *et al.*, 2022). These studies demonstrate that circularity is not limited to design and material selection, but encompasses a holistic structure, including production methods and logistics processes.

In supplier selection studies conducted during periods when sustainable development is not given the necessary importance, they fully concentrated on operational criteria such as cost, quality, and delivery. However, increasing sustainability pressures broadened this framework in later stages. Today, circular supplier selection groups drivers under economic, operational, environmental, social, and organizational headings. Factors such as cost, quality, and flexibility remain key drivers in almost all supplier selection work, whether traditional or circular (Alavi *et al.*, 2021; Liu *et al.*, 2022). Similarly, criteria such as delivery performance, on-time delivery, and capacity efficiency stand out as parameters reflecting operational performance and are commonly used in many studies (Govindan *et al.*, 2020; Tushar *et al.*, 2022). These criteria remain highly important and are still considered even under the pressures of sustainability. Environmental criteria, which are critical for the circular economy, are among the most extensively discussed topics in the supplier selection literature. Drivers, including eco-design, modularity, product disassembly, use of recyclable materials, energy efficiency, reduction of carbon emissions, waste management, and integration of green technology, are frequently preferred as circular indicators (Khalili Nasr *et al.*, 2021; Kusi-Sarpong *et al.*, 2023; Masoomi *et al.*, 2022). They are the most decisive components of circular supplier selection, as they aim to increase resource use efficiency in the process from production to distribution. Besides, reverse logistics, remanufacturing, take-back systems, and processes aimed at closing the product cycle are other drivers that reveal the extent to which suppliers aid circular economy principles (Koc *et al.*, 2023; Tramarico *et al.*, 2025). The literature indicates that they are utilized to measure a supplier's involvement in post-lifecycle processes, how they manage the recovery process, and their adaptation to closed-loop systems (Bai *et al.*, 2024; Demirbağ *et al.*, 2025). However, the social dimension is less emphasized than the other dimensions and is considered in a limited number of works. Some drivers, including occupational health and safety, employee welfare, and social responsibility, are usually included in the social sustainability aspect of circular supplier evaluation (Laosirihongthong *et al.*, 2019; Luthra *et al.*, 2017). Besides, organizational readiness, environmental management systems (EMS), level of LCA usage, and circular economy awareness are highlighted in the literature as key drivers (Amarasinghe *et al.*, 2024; Bai *et al.*, 2024). Consequently, Table 1 presents a summary of the criteria used.

2.2. *Literature Review on Methodology*

The subsection presents a method-oriented literature survey. For this purpose, we consider HyFS-based decision models, LOPCOW, RANCOM, and DEPART studies from the literature.

2.2.1. *Hyperbolic Fuzzy Sets (HyFSs)-Based Decision Models*

The HyFS emerged as an orthopair fuzzy form, which served as a variant of fuzzy set and joined the family of orthopair fuzzy sets, i.e. intuitionistic fuzzy set (IFS), Pythagorean fuzzy set (PFS), Fermatean fuzzy set (FFS), and q-rung orthopair fuzzy set (qROFS). The restrictions in the earlier orthopair fuzzy forms are additive in nature, and the restriction in HyFS is multiplicative in nature (hyperbolic geometric boundary). Recently, Dutta and Borah (2023) have developed HyFS and clarified that this variant is more flexible and promotes improved interpretation of ratings and expression of choices.

Soon after, different decision applications considered HyFS for decision-making. Divsalar *et al.* (2023) presented new operational laws for HyFSs and extended TODIM with Kano modeling for decision-making. Agriculture 4.0 decision support systems are evaluated by extending WZIC and CODAS combination to HyFS (Alamoodi *et al.*, 2024).

Table 1
Extant studies on criteria within CE.

	Kannan *et al.* (2020)	Feng and Gong (2020)	Govindan *et al.* (2020)	Alavi *et al.* (2021)	Haleem *et al.* (2021)	Khalili Nasr *et al.* (2021)	Mina *et al.* (2021)	Perçin (2022)	Liu *et al.* (2022)	Tushar *et al.* (2022)	Menon and Ravi (2022)	Tong *et al.* (2022)	Masoomi *et al.* (2022)	Luthra *et al.* (2017)	Kusi-Sarpong *et al.* (2023)	Bai *et al.* (2024)	Demirbağ *et al.* (2025)	Tramarico *et al.* (2025)	Koc *et al.* (2023)	Amarasinghe *et al.* (2024)	Laosirihongthong *et al.* (2019)
Cost	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓	✓	✓							✓
Quality	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓			✓		✓	✓	✓
Flexibility	✓	✓		✓		✓			✓	✓	✓	✓		✓					✓		
Delivery	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓		✓					✓		✓
Reputation	✓			✓	✓	✓				✓									✓		
Recyclable / Eco-friendly Materials	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓						✓	✓	✓	✓	✓	
Green Packaging	✓	✓		✓	✓	✓	✓			✓		✓		✓					✓		
Air / Pollution Control	✓	✓	✓	✓		✓			✓	✓	✓		✓						✓		✓
Environmental Standards and Compliance	✓	✓	✓	✓	✓	✓		✓		✓								✓	✓		
Clean / Green Technology	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓				✓			✓	✓		✓	
Energy Consumption / Efficiency					✓				✓												✓
Carbon Emissions		✓					✓					✓									
Waste Management				✓	✓	✓								✓			✓	✓	✓	✓	
Reverse Logistics / Take-back				✓	✓													✓			
Remanufacturing / Reuse Capability						✓										✓	✓		✓		
Eco-design / Modularity / Disassembly			✓		✓			✓	✓		✓	✓	✓	✓			✓	✓		✓	
EMS		✓		✓		✓			✓	✓	✓		✓	✓					✓		✓
LCA / Lifecycle Information					✓										✓	✓	✓		✓		
Resource Consumption Reduction		✓							✓		✓		✓		✓		✓				
Social and Occupational H&S	✓			✓		✓		✓	✓		✓			✓			✓		✓		✓
Organizational readiness / CE awareness					✓										✓	✓	✓		✓	✓	

Banik and Dutta (2024) proposed a new score function and applied a HyFS-based decision framework for identifying crime-prone zones in Dibrugarh city.

Recently, Zavadskas *et al.* (2025) handled disputes in construction contracts by presenting the CRITIC and WASPAS combination under HyFS. Dutta and Bahrami (2025) investigated the effectiveness of HyFS by comparing it with other orthopair forms and extended the WASPAS method for renewable energy selection. Dutta *et al.* (2025) presented HyFS-based TOPSIS for facilitating the cryptocurrency investment process.

2.2.2. *Overview of the LOPCOW, RANCOM, and DEPART Methods*

LOPCOW (Ecer and Pamucar, 2022) is a weight determination method that follows a log function to nullify the effects of extreme values. Driven by its straightforward approach and effectiveness in calculating weights, researchers adopted the method to diverse decision fields. Lukić (2023) ranked the Western Balkan countries based on their economic position using LOPCOW and EDAS. The performance of the Romanian banking sector was determined by extending the WISP and LOPCOW methods (Yilmaz, 2023). Setiawansyah (2024) selected restaurants by using the LOPCOW-MOORA combination. A Fermatean fuzzy LOPCOW and CoCoSo methodology was presented for ranking cloud vendors within the healthcare sector (Dhruva *et al.*, 2024). Rong *et al.* (2024) considered LOPCOW and ARAS methods under an interval variant of the Fermatean fuzzy context for risk assessment in the R&D project. Organic food selection is done as part of consumer decision-making by extending LOPCOW and EDAS within a full consistency framework (Sanyal *et al.*, 2024). Using LOPCOW-MABAC integration, Aşan *et al.* (2025) analysed the project performance of regional development agencies. Öztaş (2026) determined the cybersecurity levels of BRICS countries using the LOPCOW and MARCOS methods. Food waste treatment methods were evaluated utilizing the LOPCOW-COPRAS combination in a generalized orthopair context by Dhruva *et al.* (2025). Wang (2025) chose the best employee based on LOPCOW and ARAS. Dey *et al.* (2025) evaluated firm performance based on merger/acquisition effects using PIV and LOPCOW methods. Gopisetty *et al.* (2025) applied LOPCOW and RAM methods with double normalization for the rational selection of sustainable EVs. Kannan *et al.* (2026) presented LOPCOW with PROMETHEE for effective selection of a site for sustainable emergency services. Özekenci (2026) compared the logistics performance of Central and Eastern European countries by using the combined LOPCOW and RAWEC methods. Kahreman (2026) recently compared the performance of European Union countries in terms of their productive capacity by considering the impact of COVID-19 and decision methods such as LOPCOW and SPC for weight calculation and MACONT for ranking countries.

Więckowski *et al.* (2023) presented a new subjective weight method, named Ranking Comparison (RANCOM). Soon after, researchers utilized the method for diverse decision problems. Więckowski *et al.* (2024) compared AHP with RANCOM and showed that RANCOM performs better and yields stable results for decision-making. Barriers hindering logistic 4.0 were prioritized using polytopic fuzzy RANCOM based on a field study (Korucuk and Aytekin, 2024). A fuzzy variant of RANCOM was proposed by Więckowski *et al.* (2025) for uncertainty modeling in the decision process. Bitarafan *et al.* (2025) evaluated earthquake resilience within urban areas using fuzzy RANCOM. Shekhovtsov *et al.* (2025) determined the liveability within a city by using RANCOM and RAM combination. Provinces are ranked based on business losses as a result of the aftermath of the earthquake by using the RANCOM and KEMIRA combination (Toktaş, 2025). Chatterjee and Seikh (2025) proposed a decision model with circular Fermatean fuzzy numbers as rating data, RANCOM and OWCM as weight procedure, and AROMAN as ranking procedure for selecting a suitable technique to treat wastewater from industry. Uzun *et al.* (2026) presented RANCOM with GIS for identifying a suitable location for debris storage post-disaster. El Fadli *et al.* (2026) presented the RANCOM and CoCoSo combination for identifying a suitable location to set up offshore wind turbines on the Atlantic coast (Morocco).

Keshavarz-Ghorabaee *et al.* (2025) gave the inception of the DEPART method, which follows the pairwise comparison construct and determines ranks based on the ratio method. The DEPART method recently appeared in the literature, and some researchers adopted the method for decision problems. Shamsi *et al.* (2025) developed a decision model with DEPART and other methods for evaluating green concrete technologies for retaining walls and pavements. Yalçın *et al.* (2025) presented the RANCOM, MEREC, and DEPART combination for ranking advertising videos of brand activists via spherical fuzzy information. Balo *et al.* (2026) used the DEPART method to evaluate sustainable thermal insulation alternatives.

2.3. *Insights from the Literature Survey*

A review of the current literature reveals that research on supplier selection within the scope of CE has been conducted in the fields of electronics (Kannan *et al.*, 2020; Menon and Ravi, 2022), chemistry (Alavi *et al.*, 2021), automotive (Haleem *et al.*, 2021), textile (Khalili Nasr *et al.*, 2021; Kusi-Sarpong *et al.*, 2023), and manufacturing (Liu *et al.*, 2022; Tong *et al.*, 2022) sectors using multidimensional fuzzy MCDM approaches. Moreover, most current studies on supplier selection in the construction sector focus on sustainability indicators such as environmental certification, occupational health and safety, green design, and the use of recyclable materials. However, CE's more technical sub-components, including material cycles, component recovery, modularity, and material passports, are generally overlooked (Perçin, 2022; Tushar *et al.*, 2022). In a recent study, Demirbağ *et al.* (2025) addressed CE in terms of functional, product, component, material, and energy circularity dimensions, presenting a comprehensive model aimed at addressing one of the significant gaps in this field. However, there is still very little literature on the application of this approach at the level of construction materials, particularly materials with high circularity potential such as aerated concrete. Particularly in material-intensive sectors such as construction, there are very few studies that address supplier and material selection in an integrated manner with CE principles. Furthermore, there are almost no examples in the literature of applied supplier selection models focusing on critical building materials such as aerated concrete in terms of energy efficiency and environmental performance. Consequently, this study aims to fill this gap and provide a concrete framework for how the circular economy can be integrated into the construction material supply chain. On the other hand, a significant portion of existing studies limit their evaluation criteria to environmental indicators only, failing to sufficiently integrate economic, technological, and managerial dimensions. The number of studies in which the CE criteria are systematically determined based on the opinions of industry experts and tested in real-world applications is also quite limited. Furthermore, it is observed that studies on CE-based supplier selection in the literature are largely addressed in the context of developed countries and general building materials. However, in developing countries such as Türkiye, there are very few models for building materials of strategic importance for sustainable building applications, particularly aerated concrete, due to its energy efficiency, light weight, and low carbon potential.

From a methodological perspective, most existing studies address uncertainty in a limited manner; expert opinions are mostly evaluated with equal weight and rely on a single weighting approach. However, since the evaluation of supplier performance in the construction industry is largely based on experience and perception, uncertainty and differences in the level of knowledge among experts must be explicitly reflected in decision models. Besides, the interpretation of data in terms of an orthopair fuzzy construct is subtle, and the flexibility for expressing choices is restricted in earlier studies. Moreover, the weights or importance of decision experts are either neglected or assigned directly without methodical determinations. Also, the weights of criteria are calculated, but the determination of both subjective and objective weights is lacking in extant studies. Additionally, ranks are determined in extant frameworks, but due consideration to each expert's data for the rank determination of suppliers and the combined rank of suppliers is missing.

As a result, this research aims to fill the aforementioned gaps by: (i) focusing on the construction sector, (ii) addressing strategic building materials such as aerated concrete, and (iii) addressing uncertainty with hyperbolic fuzzy sets, integrating the LOPCOW, RANCOM, and DEPART methods, and incorporating expert weighting. Thus, this work presents a comprehensive circular supplier selection model.

3. Research Methodology

The evaluation data obtained based on the expert profiles and business structures defined in this section were used as input in multi-criteria decision-making techniques to solve the circular economy-based supplier selection problem. In our study, we developed a methodological framework based on hyperbolic fuzzy sets to account for the uncertainty arising from the nature of the criteria, the subjective nature of expert opinions, and the uncertainty in the performance of the alternatives. In this context, we explain step by step in the following subsections the hyperbolic fuzzy set structure used in the study, how the criteria and expert weights were determined, and how the alternatives were ranked.

3.1. *Preliminaries*

We review the hyperbolic fuzzy set and its operations here.

Definition 1 (Yager, 2016). R is a reference set. q-ROFS Q on R is given by,

$$Q = \big(r, \mu_Q(r), \upsilon_Q(r) \vee r \in R\big), \tag{1}$$

where $\mu_Q(r)$ is the degree of preference or membership, $\upsilon_Q(r)$ is the degree of non-preference or non-membership.

Note that $\mu_Q(r)$ and $\upsilon_Q(r)$ are in the unit interval. Also $0 \leqslant \mu_Q^q + \upsilon_Q^q \leqslant 1$ with $q \geqslant 1$.

We present the orthopair fuzzy conditions for clarity to readers in Eq. (2).

$$Conditions = \begin{cases} 0 \leqslant \mu_q^1 + \upsilon_Q^1 \leqslant 1 q = 1 & (\textit{Intuitionistic fuzzy set } (\textit{IFS})), \\ 0 \leqslant \mu_Q^2 + \upsilon_Q^2 \leqslant 1 q = 2 & (\textit{Pythagorean fuzzy set } (\textit{PFS})), \\ 0 \leqslant \mu_Q^3 + \upsilon_Q^3 \leqslant 1 q = 3 & (\textit{Fermatean fuzzy set } (\textit{FFS})). \end{cases} \tag{2}$$

Definition 2 (Dutta and Borah, 2023). R is a reference set. HyFS B on R is given by

$$B = \big(r, \mu_B(r), \upsilon_B(r) \vee r \in R\big), \tag{3}$$

where $\mu_Q(r)$ is the degree of preference or membership, $\upsilon_Q(r)$ is the degree of non-preference or non-membership. Also, $0 \leqslant \mu_B(r) \cdot \upsilon_B(r) \leqslant 1$.

Note 1: $B_i = (\mu_i, \upsilon_i)$, $\forall i = 1, 2, \dots, n$ is a hyperbolic fuzzy number (HyFN) and a collection of such numbers constitutes a HyFS.

In the orthopair fuzzy set family, HyFS is a recent inception that is gaining attention from researchers considering its flexibility in choice elicitation, which is restricted or constrained by certain inequalities in the predecessor forms, such as IFS, PFS, FFS, and, in general, q-ROFS. Such inequalities are relaxed in HyFS, and a broader window for choice expression is provided with a two-dimensional representation – both preference and non-preference grades. Driven by the flexibility, we consider HyFN for the study. It must be noted that the earlier fuzzy variants in the orthopair family followed additive constraints, while the HyFS followed multiplicative constraints, and it is based on the concept of a hyperbola as suggested by Dutta and Borah (2023). Specifically, Dutta and Bahrami (2025) argued that HyFS incorporates a hyperbolic geometric boundary that facilitates expressiveness and adaptability. Furthermore, it can be noted that in qROFS, there is a need to choose q a priori, which is a crucial tuning parameter. Choosing a lesser q blocks several orthopair values (membership and non-membership), while a larger q requires changing the semantic interpretation of all values simultaneously. As a result, it is more about robustness of representation rather than ranking accuracy when it comes to HyFS versus qROFS. The questions these two sets address are different. In qROFS, the question is 'what must be the value of q so that the expert's choice can be represented?', whereas in HyFS, the question is 'what is the expert's opinion?' From this, we gain clarity that it is about representational robustness rather than decision accuracy, which motivated authors to choose HyFS for data or rating interpretation. Methodical superiority of the proposed framework can be noticed in Section 1.

Definition 3 (Dutta and Borah, 2023; Divsalar *et al.*, 2023). Let B_1 and B_2 be two HyFNs. Some operations that can be performed are:

$$B_1 \oplus B_2 = (\mu_1 + \mu_2 - \mu_1 \cdot \mu_2, \upsilon_1 \cdot \upsilon_2), \tag{4}$$

$$\delta . B_2 = \big(1 - (1 - \mu_2)^\delta, \upsilon_1^\delta\big), \tag{5}$$

$$B_1^\delta = \left(\mu_1^\delta, 1 - (1 - \upsilon_1)^\delta\right), \tag{6}$$

$$B_1 \otimes B_2 = (\mu_1 \cdot \mu_2, \upsilon_1 + \upsilon_2 - \upsilon_1 \cdot \upsilon_2), \quad \text{where } \delta > 0. \tag{7}$$

Eqs. (4)–(7) refer to operations such as ring sum, scalar multiplication, power function, and ring product, respectively.

Definition 4 (Dutta and Borah, 2023; Divsalar *et al.*, 2023). Let B_1 and B_2 be any two HyFNs. Then, to compare these two HyFNs, we present the score and accuracy measure, which is given by

$$S(B_1) = 2\mu_1 - \mu_1 \cdot \upsilon_1, \tag{8}$$

$$A(B_2) = 2\upsilon_2 - \mu_2 \cdot \upsilon_2, \tag{9}$$

here, Eqs. (8) and (9) are the score and accuracy measures.

If two HyFNs must be compared, then do the following:

- Check the score, if $S(B_1) > S(B_2)$, then $B_1 > B_2$; If $S(B_1) = S(B_2)$, then go to accuracy measure.
- Check the accuracy, if $A(B_1) > A(B_2)$, then $B_1 < B_2$; If $A(B_1) = A(B_2)$, then $B_1 = B_2$.

3.2. *Feature Selection*

In this section, we present the feature reduction module by considering the Laplacian score. The presented procedure is capable of feature selection with no requirement for class labels. As a result, for decision problems, the Laplacian score is viable. Furthermore, the score retains the local structure or patterns, which mitigates information loss and efficiently reduces complexity or computational overhead.

This score considers alignment with the intrinsic geometry of data. Generally, criteria with low scores are preferred as they retain information about the neighborhood, and so, the top k criteria are selected based on the arrangement of the scores in ascending order. The method performs feature reduction that helps in reducing dimensionality.

The procedure for determining the reduced set of features is:

Input: Experts' rating criteria – $k \times n$ matrix

Process:

- Construct the similarity matrix
- Compute the degree matrix and Laplacian matrix
- Calculate the mean with respect to the degree matrix for each criterion
- Determine the Laplacian score by obtaining variation values
- Rank the criteria

End process

Output: A revised criteria set (feature reduced) – $k \times c$ where $c < n$.

It must be noted that each criterion is assigned a score, and based on the importance, the top k criteria are chosen. This helps in feature reduction and facilitates local structure intactness.

3.3. *Weight Calculation Module*

In this section, we present a detailed step-by-step procedure for determining the weights of the criteria and the experts involved in the decision process. It must be noted that the weights or relative importance of a decision entity are not equal, and methodical determination of such values reduces bias and subjectivity (Kao, 2010; Koksalmis and Kabak, 2019). Driven by these studies, we present a methodical setup for determining the weights of the criteria and experts.

In general, weights are determined either with partial a priori information or no such information. The former type incurs a certain level of additional overhead, which in many situations is not practically possible. As a result, the latter type is presented by researchers. In the latter context, objective and subjective weight types exist. Subjective types directly consider ranks or priority to determine the weights (importance), while objective types consider opinions from stakeholders to determine the weights. Since both these types have their own benefits, we consider both types in this study to determine the weights of the criteria. Further, experts' weights are determined objectively.

LOPCOW and RANCOM methods are extended to HyFS for determining the objective and subjective weights of criteria. LOPCOW follows a logarithmic function that is capable of reducing the scale-size effect, thus making the approach balanced without being affected by value spikes. Also, RANCOM considers ordinal data and pair-wise constructs, enabling careful consideration of each decision entity. Besides, it is intuitive, less impacted by inconsistencies, and computationally feasible. The combination of these two methods yields a holistic criterion weight, which can be further used for rank determination. The entropy approach is extended to HyFS for determining the weights of experts. Entropy determines the uniformity that exists in the construct or entity that is being measured. As a result, a high entropy value indicates high uniformity – less variability. So, there is a tendency for perceived consistency in the rating that would facilitate rational decision-making.

Detailed steps for the calculation are given below:

3.3.1. *Objective Weights*

Step 1: Consider a $d \times c$ matrix where d experts provide her/his rating on c criteria.

Step 2: Normalize the data by using Eq. (10). It must be noted that this normalization is irrespective of the criteria type, as the rating is with respect to the level of preference. A normalized $d \times c$ matrix is obtained.

$$na_{lj} = \frac{a_{lj} - a_{\min}}{a_{\max} - a_{\min}}, \tag{10}$$

where a_{ij} is the score value, $a_{\max}$ and $a_{\min}$ are maximum and minimum values.

Step 3: Determine the percentage value for the criterion to form a vector of $1 \times c$. This value indicates the information or discriminatory power of a criterion, and hence, the higher the PV, the higher the importance.

$$V_j = \ln\left(\frac{\sqrt{\frac{\sum_{l=1}^{d}(na_{lj})^2}{d}}}{\sigma}\right) \cdot 100, \tag{11}$$

where $\ln(.)$ is the natural log function and σ is the standard deviation.

Step 4: Normalize the vector from Eq. (11) to get the objective weights of the criteria. Apply Eq. (12) for obtaining the weights.

$$w_j = \frac{V_j}{\sum_{j=1}^{c} V_j}, \tag{12}$$

where w_j is the weight of the criterion j.

3.3.2. *Subjective Weights*

Step 1: Consider the $d \times c$ matrix as before. Determine the rank order based on score values.

Step 2: Determine the matrix of rank comparison (MAC) by using Eq. (13). This is a square matrix of order $c \times c$. Specifically, each element in the MAC is determined by a rule provided in Eq. (13).

$$\begin{cases} \text{If } f(c_1) < f(c_2), & \text{then } a_{ij} = 1, \\ \text{If } f(c_1) < f(c_2), & \text{then } a_{ij} = 0.5, \\ \text{Otherwise}, & a_{ij} = 0. \end{cases} \tag{13}$$

Here c_1 and c_2 are any two criteria and $f(.)$ It is a basic arithmetic function.

Step 3: Determine the net information and normalize the values to get subjective weights of criteria, which is a vector of $1 \times c$ order.

$$\lambda_j = \frac{\sum_j a_{ij}}{\sum_i \sum_j a_{ij}}, \tag{14}$$

where λ_j is the subjective weight of criterion j.

Combined weights are determined by taking a linear combination of vectors from Eq. (12) and Eq. (14), the objective and subjective weights of criteria. It is also a vector of $1 \times c$ order.

3.3.3. *Expert Weight*

We put forward an entropy measure for determining the weights of experts. The rationale is discussed above, and the steps for calculation are given below:

Step 1: Obtain the decision matrices from each expert.

Step 2: Determine the entropy of criteria with respect to each expert using Shanon entropy.

Step 3: Calculate the net entropy associated with expert rating.

Step 4: Normalize the values to obtain the weights of experts.

3.4. *Ranking Method*

In this section, we present a HyFS extension of the DEPART method (Keshavarz-Ghorabaee *et al.*, 2025), which is a recently developed ranking approach for determining the priority of alternatives. The method follows relational pairwise comparison, which sets it apart from other popular methods in the decision-making field. Most extant methods follow distance measure or uni-directed utility measure, which lack careful consideration of the decision entities.

DEPART, in contrast, considers a pairwise approach and hence, every entity in the set is given due consideration. The main philosophy of DEPART is to calculate deviation from best and worst and determine ratios that are finally aggregated to form scores. As a result, DEPART is fully relative, unlike other rank methods that are either partially relative or non-relative.

Driven by these merit points, in this work, we extend DEPART to HyFS for ranking. The steps involved in the ranking are clarified below:

Step 1: Consider d experts who rate a alternatives over c criteria. The decision matrices are formed with qualitative ratings, and the entries are transformed to HyFN, and the score is determined by using Eq. (8).

Step 2: Form positive and negative deviation matrices by using Eqs. (15)–(16). These are matrices of order $a \times c$.

$$p_{ij} = \left|a_{ij} - a_j^+\right|, \tag{15}$$

$$n_{ij} = \left|a_{ij} - a_j^-\right|, \tag{16}$$

where a_{ij} is the score value.

Here, $a_j^+ = \max(a_{ij})$ for benefit and $\min(a_{ij})$ for cost. It is the opposite for a_j^-.

Step 3: Form a pairwise positive and negative ratio of deviation by using Eqs. (17)–(18). These are square matrices of order $a \times a$.

$$pd_{fg} = \sum_{j=1}^{c}\left(\frac{p_{gj} + P}{p_{fj} + P}\right), \tag{17}$$

$$nd_{fg} = \sum_{j=1}^{c}\left(\frac{p_{fj} + N}{p_{gj} + N}\right), \tag{18}$$

where f and g are any two alternatives.

Here, $P = \max(p_{ij})$ and $N = \max(n_{ij})$.

Step 4: Determine the net pairwise deviation by using Eq. (19). Determine the score and arrange alternatives in descending order of score.

$$D_{fg} = z \cdot pd_{fg} + (1 - z) \cdot nd_{fg}, \tag{19}$$

$$Score_i = \sum_g D_{fg}. \tag{20}$$

Arrange the score in descending order of values. A higher score is highly preferred, and so on.

From Eq. (20), d vectors of $1 \times a$ order are obtained. These are rank orders of alternatives based on data from each expert. To combine the ordering and obtain a net rank vector, the Copeland procedure is presented. Steps are given below:

- Consider a $a \times d$ matrix and $1 \times d$ vector as input;
- Obtain the weighted decision matrix of order $a \times d$ by multiplying the weights of the expert by every value in the decision matrix;
- Calculate the net score alternatively to obtain a vector of $1 \times a$;
- Identify the maximum value from the vector and subtract each value from the maximum to obtain a rank vector, which must be arranged in descending order to obtain the net rank of alternatives.

By applying the procedure mentioned above, a combined rank order is obtained that yields a vector of $1 \times a$ order. A single aggregated rank vector is obtained by considering rank vectors from d experts' rating data.

4. Application

The proposed HyF-LOPCOW-RANCOM-DEPART model is applied to address the CE-focused supplier selection problem in the aerated concrete industry. In this context, researchers designed a multi-layered research process to comprehensively solve the problem, as shown in Fig. 1.

The preparation process for this study was carried out in 3 stages. In the first step, a pool of criteria containing 22 main criteria was created through face-to-face interviews with relevant literature and experts. The experts consulted on the construction industry's circular economy-focused supplier selection was building construction, concrete manufacturing, and building market parts sales managers. These individuals were also involved in the data collection process in the third stage. Furthermore, the positions and experience of the industry experts were, respectively: building construction company owner (7 years), building materials store company owner (8 years), building materials store, and building construction company owner (25 years), building materials store marketing-sales manager (11 years), and construction materials supplier marketing-sales manager (11 years). Despite the fact that three of the participating experts are company owners or senior decision-makers, the study aimed to reduce potential individual bias by including experts from a

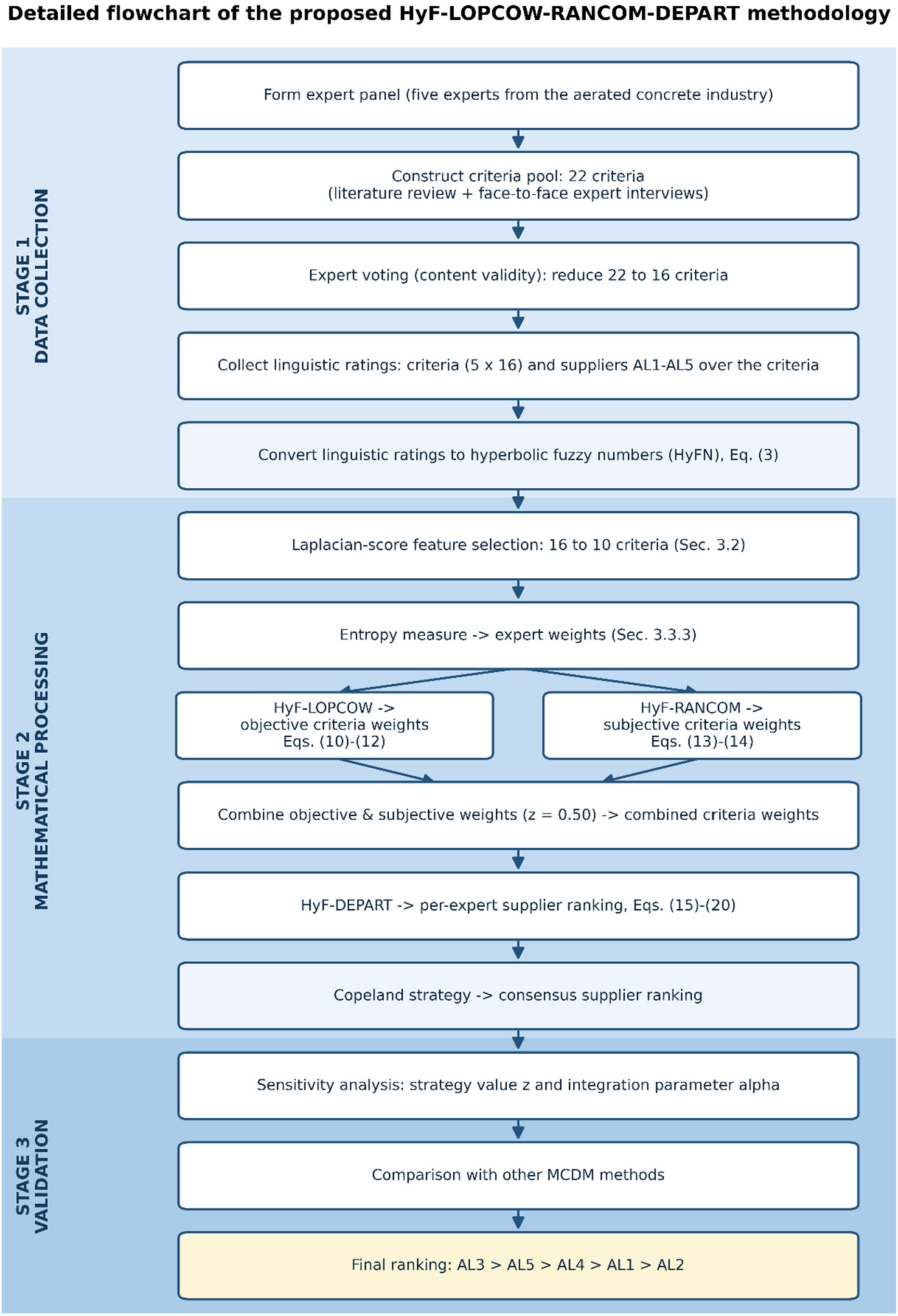

Fig. 1. Detailed flowchart of the proposed HyF-LOPCOW-RANCOM-DEPART methodology, organized into three stages: data collection, mathematical processing, and validation.

variety of professional backgrounds, including purchasing, accounting, operations, and management. Furthermore, the entropy-based expert weighting approach was utilized to minimize the dominance of highly uniform evaluations by considering the consistency and variation of expert judgments. Given that supplier selection decisions in the construction materials sector are influenced by both operational and financial considerations, it was considered important to include company owners in order to reflect real-world decision-making dynamics.

In the second stage, experts from academia and industry checked the suitability of the criteria pool for the study. These experts were also among the practitioners mentioned earlier.

Specifically, the suitability of the 22-criterion pool was assessed through a structured voting exercise: each candidate's criterion was put to the panel, and the experts voted on its relevance and appropriateness for circular-economy-based supplier selection in the aerated concrete industry. Criteria that did not attain the agreed majority support, chiefly those judged redundant with a retained criterion, not specific to the aerated concrete supply chain, or of limited practical measurability, were removed. As a result, six criteria were eliminated, and the remaining 16 criteria (Table 2) were carried forward to the data-collection survey in the next stage.

The criteria used in the study, along with their definitions and references, are shown in Table 2. The research data were collected in the third stage between October and November, 2025, from five experts (EXT1-EXT5). The participants consisted of company owners and managers in purchasing and marketing departments who were directly involved in the decision-making processes regarding supplier selection. Participants had between 7 and 25 years of experience, ensuring that supplier evaluations were based on both industry knowledge and field experience. Participants had at least a university degree, typically in business administration or accounting. Their age range was 30–45. Considering their industry experience and age, it is clear that they were directly involved in field work after their education. For evaluations in a multi-dimensional and in-depth field like the circular economy, this panel is considered a suitable data source.

Decision-makers evaluated five major firms that play an important role in the aerated concrete industry using the suggested framework in this research. In line with the principles of confidentiality and impartiality, the names of the companies included in the study are not explicitly stated; companies are referred to by codes AL1–AL5. Firms of varying scales and organizational structures operating in Türkiye's construction industry are involved in the production and distribution of aerated concrete. They include those with nationwide recognition as well as those active in specific regional markets. The circular supplier selection process is not based on a single profile but rather reflects the industry's overall structure.

The assessments obtained from the experts and businesses defined in this section were directly used in the application of the circular economy-based supplier selection model developed in the study. These data, based on expert opinions, were analysed within the framework of hyperbolic fuzzy sets to determine the criterion weights and alternative rankings. The steps followed during the application process are presented below.

Table 2
Criteria set used in the study.

Criteria	Criteria name	Definition	References
CRT1	Customer expectations	The product's level of meeting customer needs in terms of performance, durability, and delivery.	Expert opinion
CRT2	Quality	Product quality is quality consistency, quality management systems (ISO 9001, etc.).	(Alavi *et al.*, 2021; Feng and Gong, 2020; Govindan *et al.*, 2020; Kannan *et al.*, 2020; Khalili Nasr *et al.*, 2021; Liu *et al.*, 2022; Masoomi *et al.*, 2022; Menon and Ravi, 2022; Mina *et al.*, 2021; Perçin, 2022; Tong *et al.*, 2022; Tushar *et al.*, 2022)
CRT3	Cost	It includes topics such as product unit cost, production and logistics costs, and price competitiveness.	(Paul and Pal, 2025; Alavi *et al.*, 2021; Feng and Gong, 2020; Kannan *et al.*, 2020; Liu *et al.*, 2022; Masoomi *et al.*, 2022; Menon and Ravi, 2022; Perçin, 2022; Tong *et al.*, 2022; Tushar *et al.*, 2022)
CRT4	Constraints on the deferred payment option	Financial flexibility in sales terms refers to payment facilities.	Expert opinion
CRT5	Energy consumption inefficiency	The use of energy-saving technologies in production processes.	(Paul and Pal, 2025; Feng and Gong, 2020; Haleem *et al.*, 2021; Masoomi *et al.*, 2022; Menon and Ravi, 2022)
CRT6	Inefficiency in the use of recycled material use	The percentage of recycled content in raw material sourcing and production.	(Alavi *et al.*, 2021; Kannan *et al.*, 2020; Khalili Nasr *et al.*, 2021; Mina *et al.*, 2021; Perçin, 2022; Tushar *et al.*, 2022)
CRT7	Inefficiency in waste management and recovery	It refers to the reuse or recycling of production waste.	(Alavi *et al.*, 2021; Haleem *et al.*, 2021; Luthra *et al.*, 2017)
CRT8	Carbon footprint	The level of reduction in greenhouse gas emissions arising from production and transportation.	(Paul and Pal, 2025; Feng and Gong, 2020; Tong *et al.*, 2022)
CRT9	Non-compliance with environmental certification	It includes obtaining environmental management certifications such as CE, ISO 14001, LEED, etc.	(Feng and Gong, 2020; Haleem *et al.*, 2021; Khalili Nasr *et al.*, 2021; Tushar *et al.*, 2022)
CRT10	Gaps in green supply chain/logistics	It includes topics such as local supply advantages, emission reduction in transportation, and logistics efficiency.	(Kusi-Sarpong *et al.*, 2023)
CRT11	Technological capability limitation	It includes dimensions such as Rand D capacity, the level of innovation in production technologies, and digitalization.	(Alavi *et al.*, 2021; Feng and Gong, 2020; Haleem *et al.*, 2021; Khalili Nasr *et al.*, 2021; Liu *et al.*, 2022; Luthra *et al.*, 2017; Mina *et al.*, 2021; Perçin, 2022; Tushar *et al.*, 2022)
CRT12	Product life-cycle management	The product's lifespan is the management of its reuse and recycling potential.	
CRT13	Occupational health and safety	Worker safety and the prevention of workplace accidents in production facilities.	(Kannan *et al.*, 2020; Liu *et al.*, 2022; Luthra *et al.*, 2017; Menon and Ravi, 2022; Perçin, 2022)

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Table 2
(*continued*)

Criteria	Criteria name	Definition	References
CRT14	Social responsibility and ethics	Employee rights, transparency, contribution to society, and ethical trade principles.	(Alavi *et al.*, 2021; Kannan *et al.*, 2020; Khalili Nasr *et al.*, 2021; Liu *et al.*, 2022; Menon and Ravi, 2022; Perçin, 2022)
CRT15	Corporate reputation vulnerability	The company's reputation in the industry, past performance, and references.	(Alavi *et al.*, 2021; Haleem *et al.*, 2021; Khalili Nasr *et al.*, 2021; Tushar *et al.*, 2022)
CRT16	Insufficiency in managerial compliance and top management support	It includes administrative support for circular economy policies and sustainability strategies.	(Haleem *et al.*, 2021; Kusi-Sarpong *et al.*, 2023)

Table 3
Expert rating on criteria.

CW	EXT1	EXT2	EXT3	EXT4	EXT5
CRT1	6	6	4	6	6
CRT2	6	6	4	6	6
CRT3	5	7	5	6	7
CRT4	5	7	2	5	7
CRT5	6	6	4	3	7
CRT6	4	4	3	2	4
CRT7	4	4	3	2	4
CRT8	4	5	3	2	4
CRT9	6	6	3	3	4
CRT10	6	6	4	4	4
CRT11	6	6	4	5	7
CRT12	7	5	4	6	4
CRT13	6	7	4	6	5
CRT14	6	6	4	6	6
CRT15	6	7	4	6	7
CRT16	6	7	4	4	5

The steps for determining the values of decision entities are given below:

Step 1: Collect data from five experts (EXT) on 16 criteria. Each expert rates the criteria to form a 5×16 weight calculation matrix (Table 3).

Step 2: Considering the dimension of the data, the feature reduction algorithm is applied from Section 3.2 for determining the Laplacian score. From the algorithm, it is clear that a criterion with a low score gets a high preference, meaning that the criterion has greater representation ability compared to others.

Table 4 gives the similarity matrix and degree vector values that are calculated by using the Laplacian algorithm. The values 0 to 4 denote EXT1 to EXT5. A Laplacian matrix is determined by using these two results, and that is shown in Table 5. Finally, the score vector of each criterion is determined, and based on the ascending order of scores, the criteria are arranged. From the list, the best K criteria are chosen.

Table 4
Similarity matrix of criteria.

Similarity	0	1	2	3	4
0	0	0.571	0.324	0.373	0.378
1	0.571	0	0	0.136	0.523
2	0.324	0	0	0.514	0.283
3	0.373	0.136	0.514	0	0.339
4	0.378	0.523	0.283	0.339	0
Degree	0	1	2	3	4
0	1.647	0	0	0	0
1	0	1.229	0	0	0
2	0	0	1.122	0	0
3	0	0	0	1.362	0
4	0	0	0	0	1.523

Table 5
Laplacian matrix of criteria.

Laplacian matrix	0	1	2	3	4
0	1.647	−0.571	−0.324	−0.373	−0.378
1	−0.571	1.229	0	−0.136	−0.523
2	−0.324	0	1.122	−0.514	−0.283
3	−0.373	−0.136	−0.514	1.362	−0.339
4	−0.378	−0.523	−0.283	−0.339	1.523

The score value for each criterion is determined as CRT1: 1.183, CRT2: 1.183, CRT3: 1.139, CRT4: 0.99, CRT5: 1.019, CRT6: 1.018, CRT7: 1.018, CRT8: 0.923, CRT9: 0.94, CRT10: 1.034, CRT11: 1.047, CRT12: 1.297, CRT13: 1.133, CRT14: 1.183, CRT15: 1.012, and CRT16: 0.885 based on the values in Table 5. By arranging these values in ascending order, the top 10 criteria chosen are CRT4, CRT5, CRT6, CRT7, CRT8, CRT9, CRT10, CRT11, CRT15, and CRT16.

These ten criteria constitute the reduced set used for the subsequent criteria weighting and supplier ranking; the remaining six are retained in the validated framework but excluded from the computational evaluation in order to reduce dimensionality. Hence, the framework validates 16 criteria, of which 10 are used in the final evaluation. It is noted that the Laplacian score is applied to the 16 expert-validated criteria (not the original 22-criterion pool): the 22 to 16 reduction is the prior Stage-2 expert-voting step, whereas the Laplacian score performs this data-driven 16 to 10 reduction while preserving the local structure of the rating data. Figure 2 reports the Laplacian score of each of the 16 criteria and the top-10 (lowest-score) criteria that are retained.

Step 3: Collect data about alternatives from the experts. Five alternatives are rated based on 10 criteria (feature reduced) by five experts. So, five matrices of 5×10 are obtained (Table 6).

Step 4: Use the data from Step 3 (Table 6) and the procedure in Section 3.3 for determining the weights of experts. A vector of 1×5 is obtained (Table 7).

Table 6
Decision matrix from experts.

Criterion–Expert	AL1	AL2	AL3	AL4	AL5
CRT4–EXT1	4	4	4	4	4
CRT4–EXT2	7	5	6	7	7
CRT4–EXT3	3	2	3	3	4
CRT4–EXT4	4	4	5	4	5
CRT4–EXT5	4	4	4	4	4
CRT5–EXT1	6	4	4	4	6
CRT5–EXT2	5	5	4	5	5
CRT5–EXT3	4	5	4	6	3
CRT5–EXT4	7	7	5	5	7
CRT5–EXT5	4	4	5	4	4
CRT6–EXT1	4	4	4	4	4
CRT6–EXT2	4	4	4	4	5
CRT6–EXT3	3	6	4	5	2
CRT6–EXT4	7	7	5	4	6
CRT6–EXT5	5	6	5	5	4
CRT7–EXT1	4	4	4	4	4
CRT7–EXT2	6	7	6	5	6
CRT7–EXT3	3	7	5	5	1
CRT7–EXT4	6	6	4	4	6
CRT7–EXT5	5	6	4	5	5
CRT8–EXT1	4	4	4	4	4
CRT8–EXT2	7	7	6	6	7
CRT8–EXT3	3	6	3	4	2
CRT8–EXT4	6	6	5	5	5
CRT8–EXT5	4	6	5	5	5
CRT9–EXT1	5	4	4	4	5
CRT9–EXT2	7	7	7	7	7
CRT9–EXT3	5	6	4	5	3
CRT9–EXT4	6	7	5	4	6
CRT9–EXT5	4	6	4	5	5
CRT10–EXT1	5	4	4	4	5
CRT10–EXT2	6	7	5	5	7
CRT10–EXT3	5	6	4	5	3
CRT10–EXT4	4	6	4	5	6
CRT10–EXT5	5	6	4	4	5
CRT11–EXT1	5	4	4	4	5
CRT11–EXT2	6	7	6	6	6
CRT11–EXT3	5	7	5	6	4
CRT11–EXT4	6	7	4	4	6
CRT11–EXT5	5	7	4	6	6
CRT15–EXT1	6	4	4	4	6
CRT15–EXT2	7	7	7	7	7
CRT15–EXT3	5	7	3	4	5
CRT15–EXT4	5	7	5	4	4
CRT15–EXT5	6	6	6	6	6
CRT16–EXT1	6	4	4	4	6
CRT16–EXT2	7	5	6	7	7
CRT16–EXT3	3	6	4	5	4
CRT16–EXT4	6	7	4	4	5
CRT16–EXT5	7	7	5	5	5

Note: EXT1, EXT2, EXT3, EXT4, and EXT5 are experts; CRT4, CRT5, CRT6, CRT7, CRT8, CRT9, CRT10, CRT11, CRT15, and CRT16 are criteria; and AL1, AL2, AL3, AL4, and AL5 are alternative suppliers.

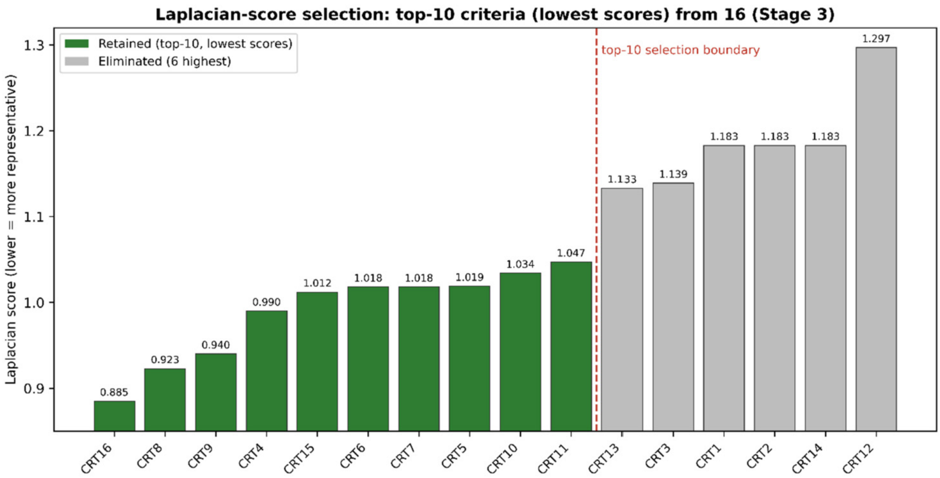

Fig. 2. Laplacian scores of the 16 criteria in ascending order. The top-10 criteria with the lowest scores (CRT16, CRT8, CRT9, CRT4, CRT15, CRT6, CRT7, CRT5, CRT10, CRT11) are retained; the six with the highest scores are eliminated.

Table 7
Entropy values of experts.

ENT EXT1	ENT EXT2	ENT EXT3	ENT EXT4	ENT EXT5
1.609438	1.578417	1.554161	1.579711	1.609438
1.468365	1.488357	1.457769	1.553098	1.586629
1.609438	1.652961	1.366196	1.520871	1.547699
1.609438	1.556763	1.486519	1.501412	1.547699
1.609438	1.399258	1.29921	1.565377	1.547699
1.579711	1.650291	1.481371	1.527846	1.522251
1.579711	1.715194	1.481371	1.500698	1.522251
1.579711	1.747302	1.517754	1.490963	1.527846
1.468365	1.837625	1.450043	1.492798	1.609438
1.468365	1.779347	1.457769	1.48296	1.541284

Use the procedure in the expert weight calculation section to determine the entropy (Table 7) associated with each expert rating, and by normalization, we get weights as: 0.201, 0.198, 0.188, 0.212, and 0.202, respectively.

Step 5: Consider the rating of 10 criteria by five experts to form a weight matrix of 5×10 order. By applying the criteria weight procedures from Section 3.3, the objective and subjective weights of the criteria are determined. Each weight yields a vector of 1×10. They are combined to form a single weight vector of 1×10.

Table 8 provides ratings from experts on the criteria that are considered for the study after feature reduction. Laplacian score supported the feature-reduction and facilitated dimensionality reduction, which, from the managerial context, corresponds to reduced complexity and computational overhead. Eqs. (10)–(12) corresponds to the determination of criteria weights by LOPCOW. Data in Table 8 is transformed to its corresponding

Table 8
Feature-reduced criteria set from Laplacian score.

Criteria	EXT1	EXT2	EXT3	EXT4	EXT5
CRT4	5	7	2	5	7
CRT5	6	6	4	3	7
CRT6	4	4	3	2	4
CRT7	4	4	3	2	4
CRT8	4	5	3	2	4
CRT9	6	6	3	3	4
CRT10	6	6	4	4	4
CRT11	6	6	4	5	7
CRT15	6	7	4	6	7
CRT16	6	7	4	4	5

Table 9
Normalized data.

Criteria	EXT1	EXT2	EXT3	EXT4	EXT5
CRT4	0.772870662	1	0	0.772870662	1
CRT5	0.871972318	0.871972318	0.269896194	0	1
CRT6	1	1	0.264150943	0	1
CRT7	1	1	0.264150943	0	1
CRT8	0.432653061	1	0.114285714	0	0.432653061
CRT9	1	1	0	0	0.30952381
CRT10	1	1	0	0	0
CRT11	0.82464455	0.82464455	0	0.658767773	1
CRT15	0.82464455	1	0	0.82464455	1
CRT16	0.82464455	1	0	0	0.658767773

Table 10
Objective weights by HyF-LOPCOW.

PV	Criteria weight
77.34229094	CRT4: 0.138671694
60.27494807	CRT5: 0.108070618
59.23576519	CRT6: 0.106207404
59.23576519	CRT7: 0.106207404
41.60836661	CRT8: 0.07460217
35.56630127	CRT9: 0.063768983
25.54128119	CRT10: 0.045794515
76.46759595	CRT11: 0.137103401
78.67431212	CRT15: 0.141059956
43.79005707	CRT16: 0.078513855

HyFSs, and scores are determined. Eq. (11) determines the percentage value, which maps to a logarithmic scale for nullifying the spikes in value due to extreme value rating and yields a weight vector upon normalization, which is a vector of 1×10 order (Table 9).

From Eqs. (11)–(12), the results in Tables 9 and 10 are depicted. From Table 9, data is given to the LOPCOW for calculating the objective criteria weights (refer to Table 10). Further, data in Table 8 is provided to Eqs. (13)–(14) for determining the subjective criteria weights using the RANCOM method (Table 11).

Table 11
MAC values – RANCOM method.

	CRT4	CRT5	CRT6	CRT7	CRT8	CRT9	CRT10	CRT11	CRT15	CRT16
EXT1 MAC										
CRT4	0.5	0	1	1	1	0	0	0	0	0
CRT5	1	0.5	1	1	1	0.5	0.5	0.5	0.5	0.5
CRT6	0	0	0.5	0.5	0.5	0	0	0	0	0
CRT7	0	0	0.5	0.5	0.5	0	0	0	0	0
CRT8	0	0	0.5	0.5	0.5	0	0	0	0	0
CRT9	1	0.5	1	1	1	0.5	0.5	0.5	0.5	0.5
CRT10	1	0.5	1	1	1	0.5	0.5	0.5	0.5	0.5
CRT11	1	0.5	1	1	1	0.5	0.5	0.5	0.5	0.5
CRT15	1	0.5	1	1	1	0.5	0.5	0.5	0.5	0.5
CRT16	1	0.5	1	1	1	0.5	0.5	0.5	0.5	0.5
EXT2 MAC										
CRT4	0.5	1	1	1	1	1	1	1	0.5	0.5
CRT5	0	0.5	1	1	1	0.5	0.5	0.5	0	0
CRT6	0	0	0.5	0.5	0	0	0	0	0	0
CRT7	0	0	0.5	0.5	0	0	0	0	0	0
CRT8	0	0	1	1	0.5	0	0	0	0	0
CRT9	0	0.5	1	1	1	0.5	0.5	0.5	0	0
CRT10	0	0.5	1	1	1	0.5	0.5	0.5	0	0
CRT11	0	0.5	1	1	1	0.5	0.5	0.5	0	0
CRT15	0.5	1	1	1	1	1	1	1	0.5	0.5
CRT16	0.5	1	1	1	1	1	1	1	0.5	0.5
EXT3 MAC										
CRT4	0.5	0	0	0	0	0	0	0	0	0
CRT5	1	0.5	1	1	1	1	0.5	0.5	0.5	0.5
CRT6	1	0	0.5	0.5	0.5	0.5	0	0	0	0
CRT7	1	0	0.5	0.5	0.5	0.5	0	0	0	0
CRT8	1	0	0.5	0.5	0.5	0.5	0	0	0	0
CRT9	1	0	0.5	0.5	0.5	0.5	0	0	0	0
CRT10	1	0.5	1	1	1	1	0.5	0.5	0.5	0.5
CRT11	1	0.5	1	1	1	1	0.5	0.5	0.5	0.5
CRT15	1	0.5	1	1	1	1	0.5	0.5	0.5	0.5
CRT16	1	0.5	1	1	1	1	0.5	0.5	0.5	0.5
EXT4 MAC										
CRT4	0.5	1	1	1	1	1	1	0.5	0	1
CRT5	0	0.5	1	1	1	0.5	0	0	0	0
CRT6	0	0	0.5	0.5	0.5	0	0	0	0	0
CRT7	0	0	0.5	0.5	0.5	0	0	0	0	0
CRT8	0	0	0.5	0.5	0.5	0	0	0	0	0
CRT9	0	0.5	1	1	1	0.5	0	0	0	0
CRT10	0	1	1	1	1	1	0.5	0	0	0.5
CRT11	0.5	1	1	1	1	1	1	0.5	0	1
CRT15	1	1	1	1	1	1	1	1	0.5	1
CRT16	0	1	1	1	1	1	0.5	0	0	0.5
EXT5 MAC										
CRT4	0.5	0.5	1	1	1	1	1	0.5	0.5	1
CRT5	0.5	0.5	1	1	1	1	1	0.5	0.5	1
CRT6	0	0	0.5	0.5	0.5	0.5	0.5	0	0	0
CRT7	0	0	0.5	0.5	0.5	0.5	0.5	0	0	0
CRT8	0	0	0.5	0.5	0.5	0.5	0.5	0	0	0
CRT9	0	0	0.5	0.5	0.5	0.5	0.5	0	0	0
CRT10	0	0	0.5	0.5	0.5	0.5	0.5	0	0	0
CRT11	0.5	0.5	1	1	1	1	1	0.5	0.5	1
CRT15	0.5	0.5	1	1	1	1	1	0.5	0.5	1
CRT16	0	0	1	1	1	1	1	0	0	0.5

Table 12
Subjective criteria weights by HyF-RANCOM.

Criteria	EXT1	EXT2	EXT3	EXT4	EXT5	Average
CRT4	0.07	0.17	0.01	0.16	0.16	0.114
CRT5	0.14	0.1	0.15	0.08	0.16	0.126
CRT6	0.03	0.02	0.06	0.03	0.05	0.038
CRT7	0.03	0.02	0.06	0.03	0.05	0.038
CRT8	0.03	0.05	0.06	0.03	0.05	0.044
CRT9	0.14	0.1	0.06	0.08	0.05	0.086
CRT10	0.14	0.1	0.15	0.12	0.05	0.112
CRT11	0.14	0.1	0.15	0.16	0.16	0.142
CRT15	0.14	0.17	0.15	0.19	0.16	0.162
CRT16	0.14	0.17	0.15	0.12	0.11	0.138

Table 12 presents the subjective weight values from each expert, which are further used for determining the subjective weights of criteria. Eq. (14) determines the weights, and it is shown in Table 13.

The results in Table 10 and Table 12 are used for determining the combined weights of criteria by considering the step size as 0.50. The weights are calculated as: CRT4: 0.126, CRT5: 0.117, CRT6: 0.072, CRT7: 0.072, CRT8: 0.059, CRT9: 0.075, CRT10: 0.079, CRT11: 0.140, CRT15: 0.152, and CRT16: 0.108, respectively.

Step 6: Apply the procedure in Section 3.4 for determining the individualistic and combined ranks of alternatives by considering data from Step 3. A rank vector of 1×5 is obtained.

Eqs. (15)–(20) are applied for determining the ranks of alternative suppliers. Note that the ranks from each expert's data are obtained, and the combined ranks are also determined using the Copeland strategy. We present the results from the DEPART method for one expert, and the combined ranks of alternative suppliers are presented from Eq. (20) and the Copeland strategy.

Table 13 depicts the results of the DEPART method by considering the rating from expert EXT1. Likewise, results are determined for other experts' rating data, and the ranks at 0.50 are depicted in Table 14 for all five experts. Eq. (15)–(19) is used on the rating data provided in Table 7. Each parameter of DEPART is determined and shown in Table 14. Table 15 shows the rank values of alternative suppliers by considering data from each expert and strategy value at 0.50.

From Table 14, it is clear that supplier 'AL2' is the least preferred by five experts, and the conclusion on the top alternative supplier varies across experts. To arrive at a consensus, we apply the Copeland strategy, and the results are shown in Table 15.

From Table 15, the combined ranks of alternative suppliers are clear. Alternative 'AL3' is most preferred, while 'AL2' is least preferred. From the Copeland strategy, we are able to arrive at a consensus on the top priority and the least priority alternative. In the earlier situation, it was difficult as each expert's ranking provided a new rank order that led to non-consensus in the final priority of alternatives. Besides, this approach facilitates the understanding of ranking by each expert, which otherwise ceases to exist. This improvement in rank determination is lacking in extant models.

Table 13
DEPART decision parameters for rating from EXT1.

	AL1	AL2	AL3	AL4	AL5
Normalized matrix					
CRT4	0.1618	0.31623	0.31623	0.31623	0.1618
CRT5	0.47837	0.31623	0.31623	0.31623	0.47837
CRT6	0.1618	0.31623	0.31623	0.31623	0.1618
CRT7	0.1618	0.31623	0.31623	0.31623	0.1618
CRT8	0.1618	0.31623	0.31623	0.31623	0.1618
CRT9	0.26381	0.31623	0.31623	0.31623	0.26381
CRT10	0.26381	0.31623	0.31623	0.31623	0.26381
CRT11	0.26381	0.31623	0.31623	0.31623	0.26381
CRT15	0.47837	0.31623	0.31623	0.31623	0.47837
CRT16	0.47837	0.31623	0.31623	0.31623	0.47837
d_plus					
CRT4	0	0	0	0	0
CRT5	0.31657	0	0	0	0.31657
CRT6	0	0	0	0	0
CRT7	0	0	0	0	0
CRT8	0	0	0	0	0
CRT9	0.10201	0	0	0	0.10201
CRT10	0.10201	0	0	0	0.10201
CRT11	0.10201	0	0	0	0.10201
CRT15	0.31657	0	0	0	0.31657
CRT16	0.31657	0	0	0	0.31657
d_minus					
CRT4	0.31657	0	0	0	0.31657
CRT5	0	0	0	0	0
CRT6	0.31657	0	0	0	0.31657
CRT7	0.31657	0	0	0	0.31657
CRT8	0.31657	0	0	0	0.31657
CRT9	0.21456	0	0	0	0.21456
CRT10	0.21456	0	0	0	0.21456
CRT11	0.21456	0	0	0	0.21456
CRT15	0	0	0	0	0
CRT16	0	0	0	0	0
e_plus					
AL1	1	0.7401	0.7401	0.7401	1
AL2	1.47134	1	1	1	1.47134
AL3	1.47134	1	1	1	1.47134
AL4	1.47134	1	1	1	1.47134
AL5	1	0.7401	0.7401	0.7401	1
e_minus					
AL1	1	1.52866	1.52866	1.52866	1
AL2	0.71658	1	1	1	0.71658
AL3	0.71658	1	1	1	0.71658
AL4	0.71658	1	1	1	0.71658
AL5	1	1.52866	1.52866	1.52866	1
e_eta_0.5					
AL1	1	1.13438	1.13438	1.13438	1
AL2	1.09396	1	1	1	1.09396
AL3	1.09396	1	1	1	1.09396
AL4	1.09396	1	1	1	1.09396
AL5	1	1.13438	1.13438	1.13438	1

Table 14
Expert-wise ranking of alternative suppliers.

EW	0.201	0.198	0.188	0.212	0.202
Comb-factor (0.50)	EXT1	EXT2	EXT3	EXT4	EXT5
AL1	0.204913	0.188721	0.198582	0.195679	0.212133
AL2	0.196725	0.206215	0.174003	0.16984	0.173641
AL3	0.196725	0.204595	0.206566	0.201943	0.221191
AL4	0.196725	0.200265	0.200513	0.230497	0.196585
AL5	0.204913	0.200204	0.220337	0.202042	0.196449
Order	AL1 > AL5 > AL2 > AL3 > AL4	AL2 > AL3 > AL4 > AL5 > AL1	AL5 > AL3 > AL4 > AL1 > AL2	AL4 > AL5 > AL3 > AL1 > AL2	AL3 > AL1 > AL4 > AL5 > AL2

Table 15
Combined ranking of alternative suppliers by HyF-DEPART.

Wcomb	EXT1	EXT2	EXT3	EXT4	EXT5	M	max-M	FinalR
AL1	0.201	0.990	0.752	0.848	0.404	3.195	0.616	RANK 4
AL2	0.603	0.198	0.940	1.060	1.010	3.811	0	RANK 5
AL3	0.804	0.396	0.376	0.636	0.202	2.414	1.397	RANK 1
AL4	1.005	0.594	0.564	0.212	0.606	2.981	0.830	RANK 3
AL5	0.402	0.792	0.188	0.424	0.808	2.614	1.197	RANK 2

4.1. *Illustration of the Computational Steps (Worked Example)*

To illustrate how the framework operates, the principal computational steps are demonstrated below using the case-study data; the complete intermediate values are reported in Tables 3–16.

(a) From linguistic rating to a normalized score. Each linguistic rating is converted to a hyperbolic fuzzy number (HyFN) and then to a crisp score using the score function in Eq. (8). The resulting score vector of every criterion is rescaled by the min–max normalization in Eq. (10). For criterion CRT4, the five expert ratings (5, 7, 2, 5, 7) give, after the HyFN transformation and Eq. (10), the normalized vector (0.773, 1.000, 0.000, 0.773, 1.000), as reported in Table 9.

(b) Objective weights (LOPCOW). For each criterion, the percentage value is obtained from Eq. (11), with d = 5 experts and σ_j the standard deviation. The percentage values of the ten criteria are 77.342, 60.275, 59.236, 59.236, 41.608, 35.566, 25.541, 76.468, 78.674, and 43.790, summing to 557.736. Normalizing with Eq. (12), gives, for example, w(CRT4) = 77.342 / 557.736 = 0.139 and w(CRT15) = 78.674 / 557.736 = 0.141, the largest objective weight.

(c) Subjective weights (RANCOM). Each expert ranks the criteria, and the pairwise ranking-comparison matrix (MAC) is formed by Eq. (13) with entries 1, 0.5, or 0. Summing each criterion's row and normalizing by Eq. (14), and averaging over the five experts, yields the subjective weights in Table 12; for instance, CRT15 attains the highest value (0.162), and CRT6 and CRT7 attain the lowest (0.038).

(d) Combined weights. The objective and subjective weights are merged through a convex combination with $z = 0.50$, $w_j(comb) = z \cdot w_j(obj) + (1 - z) \cdot w_j(sub)$, giving CRT4 = 0.126, CRT5 = 0.117, CRT6 = 0.072, CRT7 = 0.072, CRT8 = 0.059, CRT9 = 0.075, CRT10 = 0.079, CRT11 = 0.140, CRT15 = 0.152 and CRT16 = 0.108.

(e) Expert weights (entropy). The Shannon entropy of each expert's rating distribution is computed as in Section 3.3.3 and normalized across experts, giving the expert-weight vector (0.201, 0.198, 0.188, 0.212, 0.202) for EXT1–EXT5 (Table 14).

(f) Ranking by HyF-DEPART and aggregation. For each expert, the positive and negative deviation matrices follow from Eqs. (15)–(16); the pairwise deviation ratios from Eqs. (17)–(18); and the net pairwise value with z = 0.50 from Eq. (19). The alternative score is the normalized row sum in Eq. (20). Using the data of EXT1 (Table 13), the row sums are 5.403 for AL1 and AL5 and 5.188 for AL2, AL3 and AL4 (total 26.370), so the normalized score of AL1 is 5.403 / 26.370 = 0.205. Aggregating the five expert rankings with the Copeland strategy and the expert weights gives the consensus order AL3 > AL5 > AL4 > AL1 > AL2, i.e. AL3 is the most and AL2 the least preferred supplier, in agreement with Table 15.

5. Validation Checks

5.1. *Sensitivity Analysis*

This section determines the effect of a change in strategy values on the ranking of alternative suppliers. Likewise, we also infer the effect of the change of criteria weights on the ranking of alternative suppliers. We refer to these two types as intra-sensitivity analysis and inter-sensitivity analysis. In the former, we vary the strategy values in the unit interval with a step size of 0.10. Hence, we consider nine episodes from 0.10 to 0.90 for the rank value of alternative suppliers based on data from each expert. Table 16 shows the results of the sensitivity analysis of strategy values.

Table 16 shows the results of the intra-sensitivity analysis – strategy values are altered from 0.10 to 0.90, and it is inferred that for data from EXT1: AL1, AL2; EXT2: AL2, AL5; EXT3: AL5; EXT4: AL4; and EXT5: AL3 are the best suppliers. This information is crucial in a decision process, and extant models cannot reveal this insight. So, each expert yields different preferences for different suppliers, and it is evident from Table 16. As a result, understanding the ranking from each expert's viewpoint is crucial.

5.1.1. *Sensitivity to the Criteria Weighting*

In addition to the strategy-value sensitivity reported above, the robustness of the combined criteria weights is examined with respect to the parameter that balances the objective (LOPCOW) and subjective (RANCOM) weights. Writing the combined weight as $w_j(comb) = \alpha \cdot w_j(obj) + (1 - \alpha) \cdot w_j(sub)$, with the main analysis using $\alpha = 0.50$, the parameter α is varied from 0 (purely subjective) to 1 (purely objective) in steps of

Table 16
Sensitivity analysis of strategy values.

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
EXT1									
AL1	0.238	0.23017	0.22166	0.21327	0.20491	0.196529	0.188055	0.17943	0.17059
AL2	0.174	0.17989	0.18556	0.19115	0.19673	0.202314	0.207963	0.213713	0.2196
AL3	0.174	0.17989	0.18556	0.19115	0.19673	0.202314	0.207963	0.213713	0.2196
AL4	0.174	0.17989	0.18556	0.19115	0.19673	0.202314	0.207963	0.213713	0.2196
AL5	0.238	0.23017	0.22166	0.21327	0.20491	0.196529	0.188055	0.17943	0.1705
#	AL1 > AL5 > AL2 > AL3 > AL4	AL1 > AL5 > AL2 > AL3 > AL4	AL1 > AL5 > AL2 > AL3 > AL4	AL1 > AL5 > AL2 > AL3 > AL4	AL1 > AL5 > AL2 > AL3 > AL4	AL2 > AL3 > AL4 > AL1 > AL5	AL2 > AL3 > AL4 > AL1 > AL5	AL2 > AL3 > AL4 > AL1 > AL5	AL2 > AL3 > AL4 > AL1 > AL5
EXT2									
AL1	0.188	0.18866	0.18868	0.1887	0.18872	0.188741	0.188761	0.188782	0.18880
AL2	0.209	0.20835	0.20764	0.20693	0.20622	0.205504	0.204793	0.204079	0.20336
AL3	0.21	0.20865	0.2073	0.20595	0.2046	0.203241	0.201885	0.200526	0.19916
AL4	0.204	0.20373	0.20257	0.20142	0.20027	0.19911	0.197953	0.196794	0.19563
AL5	0.187	0.19062	0.19381	0.19701	0.2002	0.203404	0.206608	0.209819	0.21303
#	AL3 > AL2 > AL4 > AL1 > AL5	AL3 > AL2 > AL4 > AL5 > AL1	AL2 > AL3 > AL4 > AL5 > AL1	AL2 > AL3 > AL4 > AL5 > AL1	AL2 > AL3 > AL4 > AL5 > AL1	AL2 > AL5 > AL3 > AL4 > AL1	AL5 > AL2 > AL3 > AL4 > AL1	AL5 > AL2 > AL3 > AL4 > AL1	AL5 > AL2 > AL3 > AL4 > AL1
EXT3									
AL1	0.187	0.19062	0.19328	0.19593	0.198582	0.201237	0.203898	0.206567	0.2092
AL2	0.170	0.17138	0.172255	0.17312	0.174003	0.174879	0.175756	0.176635	0.1775
AL3	0.199	0.20103	0.202877	0.20472	0.206566	0.208412	0.210262	0.212116	0.2139
AL4	0.204	0.20348	0.202495	0.20150	0.200513	0.19952	0.198525	0.197527	0.1965
AL5	0.237	0.23347	0.229093	0.22471	0.220337	0.215953	0.21156	0.207155	0.2027
#	AL5 > AL4 > AL3 > AL1 > AL2	AL5 > AL4 > AL3 > AL1 > AL2	AL5 > AL3 > AL4 > AL1 > AL2	AL5 > AL3 > AL4 > AL1 > AL2	AL5 > AL3 > AL4 > AL1 > AL2	AL5 > AL3 > AL1 > AL4 > AL2	AL5 > AL3 > AL1 > AL4 > AL2	AL3 > AL5 > AL1 > AL4 > AL2	AL3 > AL1 > AL5 > AL4
EXT4									
AL1	0.206	0.20377	0.20106	0.19837	0.19568	0.192995	0.190313	0.187628	0.18493
AL2	0.172	0.17172	0.17109	0.17047	0.16984	0.169217	0.168596	0.167974	0.16735
AL3	0.186	0.19063	0.19442	0.19819	0.20194	0.205691	0.209437	0.213186	0.21694
AL4	0.217	0.22093	0.22413	0.22732	0.2305	0.233671	0.236845	0.240023	0.24320
AL5	0.216	0.21295	0.2093	0.20566	0.20204	0.198425	0.194809	0.191189	0.18756
#	AL4 > AL5 > AL1 > AL3 > AL2	AL4 > AL5 > AL1 > AL3 > AL2	AL4 > AL5 > AL1 > AL3 > AL2	AL4 > AL5 > AL1 > AL3 > AL2	AL4 > AL5 > AL3 > AL1 > AL2	AL4 > AL3 > AL5 > AL1 > AL2	AL4 > AL3 > AL5 > AL1 > AL2	AL4 > AL3 > AL5 > AL1 > AL2	AL4 > AL3 > AL5 > AL1 > AL2
EXT5									
AL1	0.219	0.21751	0.21572	0.21393	0.21213	0.210337	0.208539	0.206737	0.20493
AL2	0.165	0.16747	0.16953	0.17158	0.17364	0.175702	0.177766	0.179834	0.18190
AL3	0.226	0.2248	0.2236	0.22239	0.22119	0.219988	0.218784	0.217579	0.21637
AL4	0.194	0.19518	0.19565	0.19612	0.19659	0.197054	0.197524	0.197994	0.19846
AL5	0.194	0.19505	0.19551	0.19598	0.19645	0.196917	0.197386	0.197856	0.19832
#	AL3 > AL1 > AL4 > AL5 > AL2	AL3 > AL1 > AL4 > AL5 > AL2	AL3 > AL1 > AL4 > AL5 > AL2	AL3 > AL1 > AL4 > AL5 > AL2	AL3 > AL1 > AL4 > AL5 > AL2	AL3 > AL1 > AL4 > AL5 > AL2	AL3 > AL1 > AL4 > AL5 > AL2	AL3 > AL1 > AL4 > AL5 > AL2	AL3 > AL1 > AL4 > AL5 > AL2

0.10, and the criteria weights and their ranking are recomputed at each value. As shown in Fig. 3, corporate reputation and reliability (CRT15) remains the highest-weighted criterion for every value of α, and technological capability and innovation (CRT11) is the second-highest over almost the entire range; only very close to the purely objective extreme (α greater than about 0.95) does the deferred-payment criterion (CRT4) marginally overtake CRT11. The importance ordering is therefore stable, with Spearman rank correlations between 0.71 and 1.00 relative to the $\alpha = 0.50$ baseline (Fig. 4). Hence, varying the balance between objective and subjective information does not alter the leading circular-economy criteria, confirming the robustness of the combined weighting.

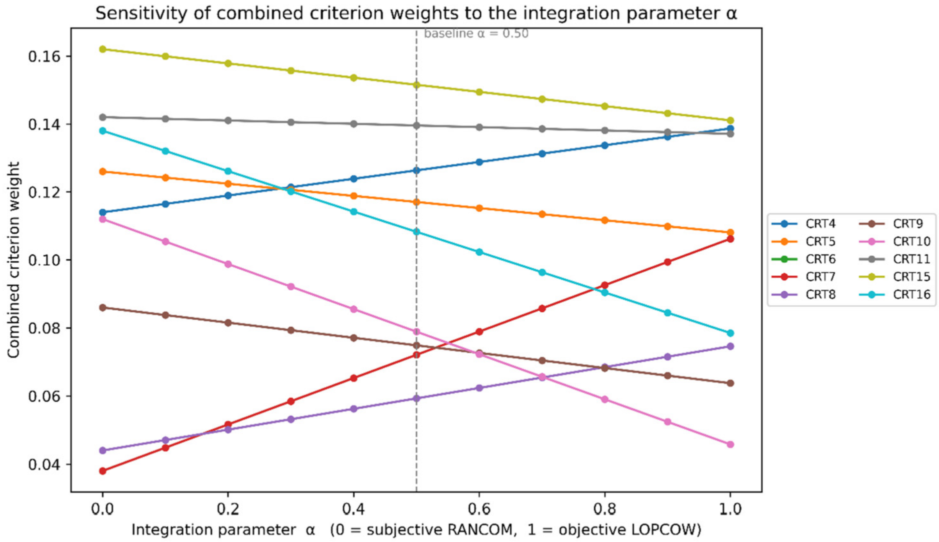

Fig. 3. Sensitivity of the combined criterion weights to the integration parameter α ($\alpha = 0$ corresponds to purely subjective RANCOM weights and $\alpha = 1$ to purely objective LOPCOW weights).

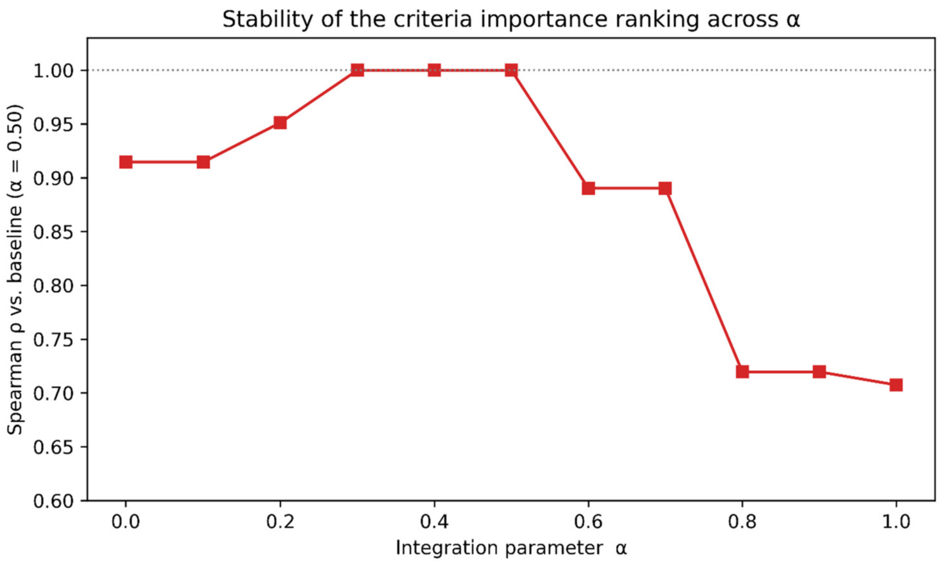

Fig. 4. Stability of the criteria importance ranking: Spearman rank correlation between the ranking at each α and the ranking at the baseline $\alpha = 0.50$.

5.2. *Comparison with Other Ranking Methods*

To further validate the proposed framework, the supplier ranking obtained from HyF-DEPART with Copeland aggregation is compared with five established MCDM methods:

Table 17
Comparison of supplier rankings (1 = best) by the proposed method and five established MCDM methods (per-expert ranking fused by Copeland).

Supplier	Proposed	TOPSIS	WASPAS	ARAS	CoCoSo	SAW
AL1	4	3	3	3	3	3
AL2	5	4	5	5	5	5
AL3	1	1	1	1	1	1
AL4	3	2	2	2	2	2
AL5	2	5	4	4	4	4
Spearman ρ vs proposed	1.00	0.40	0.70	0.70	0.70	0.70

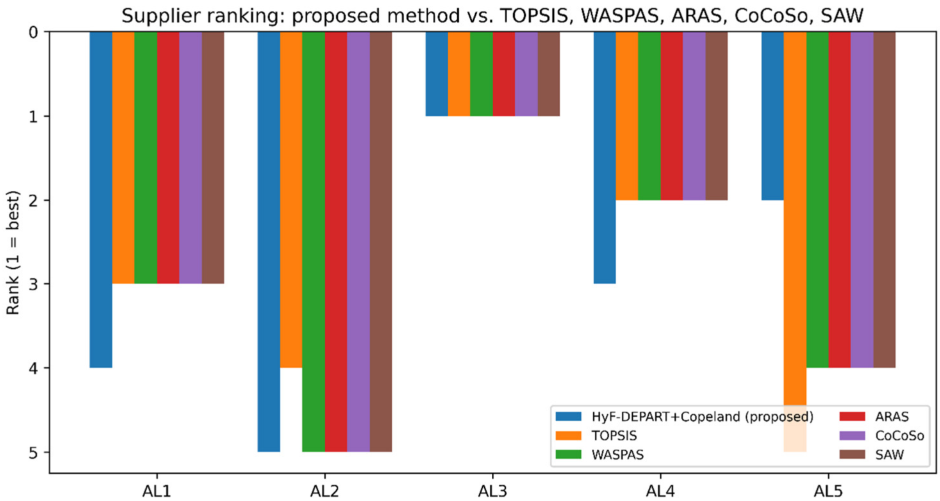

Fig. 5. Supplier rankings (1 = best) from the proposed HyF-DEPART+Copeland method compared with TOPSIS, WASPAS, ARAS, CoCoSo and SAW.

TOPSIS, WASPAS, ARAS, CoCoSo, and SAW, computed from the complete decision matrix over the ten retained criteria with the combined criteria weights. As in the proposed framework, each method ranks the suppliers for every expert, and the five per-expert rankings are fused by the Copeland strategy with the expert weights; all ten criteria are treated as cost-type, consistent with their definitions in Table 2. Table 17 and Fig. 5 report the resulting rankings. All six methods identify AL3 as the best supplier and rank AL4 second or third, while AL1, AL2, and AL5 occupy the lower positions. The Spearman rank correlations with the proposed ranking range from 0.40 (TOPSIS) to 0.70 (WASPAS, ARAS, CoCoSo, and SAW), with the agreement strongest at the top and the divergences confined to the middle and lower ranks. The unanimous selection of AL3 as the best supplier across all methods confirms the robustness and reliability of the proposed supplier ranking.

5.3. *Discussion*

In this study, a practical and flexible decision-support system has been developed for supplier evaluation in circular economy-based supply chains under uncertainty. The proposed approach is based on the LOPCOW–RANCOM and DEPART-based MCDM methodology integrated under a hyperbolic fuzzy set structure. This multi-layered structure provides a more balanced and reliable supplier selection model in selection processes where subjective evaluations and uncertainty are high.

The driver weights clearly indicate the effect of circular economy principles on the supplier selection for building construction processes. More clearly, corporate reputation and reliability (CRT15) is the foremost driver (0.152). This means that, in terms of long-term business relationships, supply continuity, and risk reduction, reliability is still a decisive factor in the construction industry. Some papers emphasized that supplier reliability plays a critical role in sustainable supply chains (Kannan *et al.*, 2020; Luthra *et al.*, 2017). Technological capability and innovation (CRT11) is the second-crucial driver (0.140), meaning that in building materials with technology-intensive production processes, such as aerated concrete, clean production technologies, process optimization, and innovative applications play a central role in aiding the circular economy. This finding is also consistent with previous studies (Haleem *et al.*, 2021). The third-highest priority belongs to the deferred payment option (CRT4; 0.126), indicating that supplier selection decisions are shaped by economic and environmental sustainability concerns, particularly in emerging markets such as Türkiye, in which financing costs are high. Furthermore, circular economy-based supplier selection does not completely exclude traditional economic drivers; rather, it offers a holistic approach that considers these criteria together with environmental and managerial factors.

The findings present that energy efficiency (CRT5) and managerial compliance and top management support (CRT16) have medium-high weights. Thus, energy consumption, operational control, and corporate ownership are perceived as key factors in circular economy applications in the aerated concrete sector. As a result, energy-focused environmental policies and managerial commitment are becoming increasingly crucial in the production of building materials (GABC, 2025).

Furthermore, the relatively high weight of the green supply chain and logistics practices (CRT10) remarks that the CE approach is addressed holistically, encompassing production processes, logistics, and distribution stages together (Mishra *et al.*, 2022). Regarding the findings, using recycled materials (CRT6) and waste management and recovery (CRT7) are given relatively lower weight than others. Though material circularity is considered a core concept in CE research, in practice, decision-makers prioritize other drivers, such as energy efficiency, technological competence, and regulatory compliance, over CRT 6 and CRT 7. Studies supporting this finding depict that drivers such as recycling and waste management could be prioritized lower due to structural, technical, and especially economic constraints (Ghisellini *et al.*, 2018; Timm *et al.*, 2023). This finding could also reveal that material-based circularity has not yet matured sufficiently.

The combined ranking obtained using the Copeland technique brought together the different situations that emerged in expert opinion-based rankings, thereby achieving consensus. The different rankings obtained with each expert's evaluation in the previous steps made it difficult to determine the final priority, but with Copeland, the relative advantages of the alternatives are presented more clearly and comparably. This process shows that in decision-making processes involving subjective evaluations, the ranking technique is as important as weighting. The fact that AL3 ranked first illustrates the importance of considering not only environmental criteria but also multidimensional factors such as governance compliance, operational stability, and balanced performance. In contrast, AL2's relatively low performance indicates that strong corporate perception, brand awareness, or technical advantages alone are not sufficient. This finding reveals that supplier selection focused on the circular economy can produce different results than conventional selection models.

6. Implications

6.1. *Managerial Implications*

As discussed above, the proposed framework helps a real-world logistics manager make better decisions. This study also has crucial managerial implications for companies operating in the aerated concrete industry and their supplier decision-makers. Firstly, the selection of suppliers based on a CE approach should not be limited to environmental indicators alone, but should also consider factors such as corporate reputation, technological competence, and financial flexibility. In other words, the flexibility a company offers in payment, its position within the sector, and its technological capabilities are as important as environmental indicators in aerated concrete supply. Therefore, companies should increase their technological capacity and demonstrate a strong corporate stance to establish sustainable business relationships. Additionally, the high importance of criteria such as energy efficiency and compliance with environmental regulations will require manufacturing companies to revise their production processes to produce energy-efficient and regulatory-compliant products. Companies that implement this will both gain a cost advantage and become an important link in the supply chain. Companies operating in compliance with environmental regulations and legislation will both overcome increasing public pressure and position themselves well in the face of legal regulations, and be preferred due to the trust they build. The research results also show an increasing importance of green supply chain and logistics processes. In this situation, manufacturers need to consider environmental impacts not only during the product's manufacturing phase but also during its delivery to the customer. Optimal route selection in logistics processes, and the use of gasoline, hybrid, or electric vehicles instead of diesel vehicles, stand out as elements that strengthen CE performance in the supply chain. However, the fact that criteria such as recycling of material or waste management are given less importance compared to others indicates a lack of sufficient awareness in this area. Therefore, suppliers prioritizing this area will help decision-makers achieve circular economy goals. Furthermore, the proposed framework helps a real-world logistics manager make better decisions.

6.2. *Policy Implications*

This study offers important insights for public authorities and regulators on how to more effectively implement CE-focused criteria in building construction processes. Firstly, the importance of criteria such as energy efficiency and environmental compliance has begun to influence current selection decisions. This necessitates a firm commitment to achieving public goals such as energy efficiency and carbon emission reduction, and the strengthening of regulations in this direction. The significant role of certification and regulatory compliance criteria in supplier selection suggests that policymakers can guide suppliers by developing standards in this area. Labelling systems that measure and numerically compare the circular performance of building materials can be an incentive for companies to achieve these goals. Once such regulations are implemented, a more transparent market environment will be created, and environmentally friendly companies will gain a competitive advantage under increasing cost pressures. Besides, the research findings show that areas such as the use of recycled materials or waste management are not yet sufficiently emphasized in supplier selection. This creates an important area for intervention for authorities. Through regulations, authorities can implement incentives, tax breaks, or priority in public procurement for the use of such materials. This could pave the way for the development of these areas through public means.

6.3. *Theoretical Implications*

The framework proposed in this work combines different decision methods to arrive at a rational decision by reducing human intervention. Specifically, decision parameters such as weights or importance of experts, weights or importance of criteria, and ranks of alternative suppliers are determined methodically, which eventually reduces inaccuracies and bias in value assignment to decision parameters. By extending a decision method to the HyFS, we make the choice to extend considering the merit value it adds to the decision process. Entropy is used for expert weight calculation, as it captures hesitation and the depth of information an expert offers to the decision process. Likewise, LOPCOW and RANCOM are extended for determining the combined criteria weights, as LOPCOW has the ability to nullify extreme values and offers effective discrimination of criteria. RANCOM is a simple and straightforward subjective method, which outperforms different state-of-the-art subjective methods as clarified by Wieckowski *et al.* (2023). Finally, suppliers are ranked based on expert-wise data and combined grading by HyF-DEPART, which offers both individualistic and cumulative sense of ranking of alternative suppliers.

By calculating key decision parameters, we not only reduce subjectivity/bias but also make the process explainable, which is currently essential in AI systems. The step-by-step procedure offers transparency in the process, and stakeholders can readily apply changes to realize its impact on the final choices. Such perturbations are computationally viable given the flexible design of the proposed framework, which is both scalable and logically connected to yield rational decisions.

7. Conclusion

This research focuses on supplier selection in the construction supply chain for the aerated concrete industry, considering CE drivers. To do this, we introduced the HyF-LOPCOW-

RANCOM-DEPART framework, which allows for a more systematic and transparent approach to supplier selection, addressing uncertainty and subjective evaluations. The study contributes to the supply chain process by providing a practical tool for incorporating CE applications into the decision-making process in the construction materials industry. Another significant contribution of the study is that it clearly demonstrates that CE-based supplier selection is not solely based on environmental indicators. The research results emphasize that factors such as technological capability, management structure, and corporate reputation are at least as important as environmental criteria. The proposed HyF-LOPCOW-RANCOM-DEPART decision support approach for CE-focused supplier selection produces more systematic and balanced results by considering the characteristics of experts. Thanks to this model, which makes a significant methodological contribution to the literature, intuitive decisions are replaced by consistent evaluations. In this respect, the proposed model can be used not only for the aerated concrete sector but also for other sectors with similar characteristics.

Whereas the research offers valuable contributions, it also has some limitations. First, the study is based on the assessments of a limited number of experts. Although the expert panel consisted of individuals with extensive field experience, increasing the number of experts could strengthen the representativeness of the results. Another limitation is that the research was conducted within a specific industry and a limited number of firms. This limits generalization to other construction materials or different sub-industries. Although the present study focuses on the aerated concrete sector in Türkiye, the proposed decision-making framework is flexible and can be adapted to different geographic and industrial contexts. The methodology is not limited to a specific country or market structure, and the evaluation criteria may be revised according to regional regulations, environmental policies, supply chain characteristics, and market conditions. Future studies may apply the proposed framework to different construction material sectors, such as insulation materials or prefabricated building components, and compare circular economy priorities across developed and developing countries. Furthermore, applications in different developed and developing countries and regional contexts could reveal the impact of regulatory frameworks and market conditions on supplier selection outcomes. Third, this research provides a static assessment and does not consider changes in supplier performance over time. Future research could analyse the development of suppliers' CE performance over the years using dynamic evaluation models. Fourth, the proposed framework assumes that the data is fully available, which might not always be practically viable. In such cases, the present model cannot handle the non-availability of data. Partial information about decision parameters, such as criteria and alternatives, cannot be embedded in the present framework. These limitations will be handled in the future. Furthermore, plans are made to extend the proposed framework for other decision applications in the field of logistic service providers, renewable energy-based transit mode selection, technology intervention assessment in supply chains, resilience, and humanitarian supply chain evaluation. Novel fuzzy variants, such as pentagonal fuzzy set, bipolar fuzzy set, quantum fuzzy set, etc., may also be explored for data interpretation, and novel decision models can be developed under these fuzzy constructs for rational decision-making with better modelling of uncertainty. Finally, plans are made to integrate machine learning methods with a decision support system for carrying out data-driven decision activities with the help of a larger volume of data.

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