mathematics

Review

Towards Sustainable Transportation: A Review of Fuzzy Decision Systems and Supply Chain Serviceability

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Abstract: Modern requirements dictate the need for sustainable transportation systems, given the substantial growth in transportation activities over recent years that is predicted to persist. This surge in transportation has brought about environmental concerns such as air pollution and noise. To deal with this crisis, municipal administrations are investing in sustainable, reliable, economical, and environmentally friendly transportation systems. This review examines the latest developments in fuzzy decision systems for sustainable transport supplements. By reviewing the literature, we assess the serviceability of the entire supply chain to maintain transport quality, remove degradation, and meet customer demands. The link between fuzzy decision systems and supply chain serviceability may not be immediately obvious, but there are many reasons why putting them together can be a valuable focus for companies. By leveraging the capabilities of fuzzy decision systems to optimize supply chain processes and improve service levels, companies can gain a competitive advantage and better meet customer demand.

Keywords: sustainable transportation systems; fuzzy decision systems; supply chain; environmental impact; customer demands

MSC: 90B06; 90B90; 90C70; 90B10

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1. Introduction

The transport sector has significantly affected the environmental, social, and economic aspects of human life. The analysis and planning practices of transport policies that support sustainable development are called sustainable transport planning [1–3]. Sustainable transportation systems are widely recognized to require the balance of current and future transportation quality, environmental preservation, and economic development [4–6]. In other words, sustainable transport aims to bring a careful balance between pollution, energy consumption, and accidents while improving the city's living and economic well-being as well. This is the goal of a city's sustainable transport [7,8]. In assessing transportation sustainability, measures are described regarding linguistic variables characterized by ambiguity and multi-possibility. Consequently, conventional assessment methods cannot handle such measurements efficiently and effectively [9]. Energy-efficient vehicles and clean fuel vehicles, including biodiesel and electric cars, are just a few examples of sustainable transportation methods. In 1997, the Center for Sustainable Transport defined a sustainable transportation system as one that safely and consistently meets the primary access needs of individuals and society, while also considering the health of humans and ecosystems and promoting intergenerational equity. Other sustainable transportation methods include carsharing, park and ride systems, and other environmentally friendly alternatives to traditional modes of transportation. Limiting emissions and waste based on the planet's ability to absorb emissions recycles its components and minimizes land use, noise production, and the use of non-renewable resources. Efficient decision-making methods are required to identify, compare, and select sustainable transportation systems. Intelligent decision making with real-time information processing is a valuable tool for companies to respond to changing sustainable transport conditions quickly. Inspection of fuzzy approaches is still underway in all this. This review aims to provide an overview of what has been done in the field so far, focusing on fuzzy-based processes, their restrictions, and their potential. Here, approaches based on fuzzy logic enter the picture. Fuzzy logic is a valuable tool for dealing with ambiguity, vagueness, and uncertainty. Recently, a survey on the technologies employed in modern decision systems for sustainable transport appeared, but some papers use a fuzzy approach. Therefore, the present mini-review aims to complement the Fuzzy Decision Systems for Sustainable Transport (FDSST) supplement. The remainder of the current study is structured as follows. In Section 2, a review of the literature on briefs is presented in this field. Section 3 offers commonly used approaches for sustainability assessment models and issues. An outline of the literature review is shown in Table 1. Section 4 will cover a discussion of the pros and cons of three decision-making methods: Analytic Hierarchy Process (AHP), Decision-Making Trial and Evaluation Laboratory (DEMATEL), and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). Section 5 is devoted to fuzzy-based techniques for FDSST. The Section 6 anticipates an exploration of fuzzy approaches against non-fuzzy approaches and the list of acronyms (see Table 2). Criteria for evaluating the sustainability of transportation systems are shown in Table 3. Section 7 covers the main discussion and perspectives of this research area. Following are the conclusion remarks provided in Section 8.

Table 1. An outline of the literature review.

Authors	Year	Contribution	Reference
Pourghasemi et al.	2012	Fuzzy theory and AHP	[10]
Ligmann-Zielinska and Jankowski	2014	Monte Carlo simulation and AHP	[11]
Razandi et al.	2015	ANP and frequency ratio	[12]
Fan et al.	2016	Fuzzy theory and AHP	[13]
Rajak et al.	2016	Fuzzy theory	[14]
Ha et al.	2017	Fuzzy theory and TOPSIS	[15]
Ghorbanzadeh et al.	2018	Geographic information system and ANP	[16]
Prasetyo et al.	2018	Fuzzy theory and AHP	[17]
Chen et al.	2018	Fuzzy theory and AHP	[18]
Grošelj and Zadnik Stirn	2018	Fuzzy Theory and AHP	[19]
Ghorbanzadeh et al.	2018	ANP and Monte Carlo simulation	[20]
Nazmfar et al.	2019	Fuzzy theory and ANP	[21]
Moslem et al.	2019	Fuzzy AHP	[22]
Awasthi and Omrani	2019	Fuzzy axiomatic design	[23]
Cabrera-Barona and Ghorbanzadeh	2019	Interval Calculus and AHP	[24]
Moslem et al.	2019	Fuzzy AHP and interval AHP	[25]
Tsang et al.	2020	Life cycle prediction based on fuzzy products	[26]
Pamucar et al.	2021	Neutrosophic fuzzy based measurement alternative options and ranking according to compromise solution	[27]

Table 1. *Cont.*

Authors	Year	Contribution	Reference
Ziemba	2021	Fuzzy TOPSIS, Fuzzy Simple Additive Weighting Method (SAW), and fuzzy preference ranking organism method for enrichment assessment	[28]
Zhang et.al.	2020	MAGDM fuzzy multi-granulation probabilistic models	[29]

Table 2. List of acronyms.

Acronym	Definition
AHP	Analytic Hierarchy Process
AIM	Assessment indicator models
AI	Artificial Intelligence
ANP	Analytic Network Process
BMW	Best-Worst Method
CBA	Cost-benefit analysis
CEA	Cost-effectiveness analysis
DEMATEL	The Decision Making Trial and Evaluation Laboratory
EIA	Environmental Impact Assessment
FDSST	Fuzzy Decision Systems for Sustainable Transport
FAHP	Fuzzy Analytic Hierarchy Process
AIM	Assessment indicator models
LCA	Life Cycle Analysis
OM	Optimization Model
MADM	Multiple Attribute Decision Making
MCDM	Multi-Criteria Decision Making
MAVT	Multi-Attribute Value Function Theory
MAUT	Multi-Attribute Utility Function Theory
SDM	System Dynamics Model
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution

Table 3. I (cost), II (benefit). Criteria for evaluating the sustainability of transportation systems.

Criteria	Definition	Category
Operating costs	Costs to administer the transport service for the service	I
Safety	Safety of transportation system	II
Security	Reliability of the transportation system	II
Reliability	Ability to perform the assured service accurately	II
Air pollutants	Transportation system’s air pollution	II
Noise	Transportation system’s environmental noise	II
GHG emissions	GHG emissions from the transportation system	II
Usage of fossil fuels	Use of hydrocarbon-containing material	II
Travel costs	Costs for travel between any given stations	II

Table 3. *Cont.*

Criteria	Definition	Category
Waste from road transport	Waste from transport on roads	II
Energy consumption	Energy consumption by the transportation system	II
Land usage	Land space used for running the transportation service	II
Accessibility	Access to residential areas	I
Benefits to economy	Benefits to the economy from the transportation model	I
Competency	State-of-the-art technology	I
Equity	Equal opportunity for dissimilar people	I
Possibility of expansion	Capacity to expand the service if required	I
Mobility	Ability to service over the transportation area	I
Productivity	Ability to achieve thresholds	I
Rate of occupation	Capacity usage of transportation mode	I
Share in public transit	Public transport's share	I
Convenience to use	Satisfaction in using the service of transport	I
Quality of service	Quality of service supplied by the transportation staff	I

2. Literature Review

Up to now, several research studies have been dedicated to developing principles, definitions, and evaluations of sustainable transportation [30–32]. Furthermore, a barrier assessment to achieving sustainable transportation has been offered in [33,34]. Richardson [6] proposed a framework to interact with the factors that influence indicators of the sustainability of transport. In [35], four critical pillars are defined for sustainable transportation, including effective land use and transportation; financial considerations; infrastructures; and interaction between neighborhoods. Black and Sato [36] investigated the effects of global warming and other factors that make transport unsustainable, including injuries and deaths from vehicle incidents, air quality problems, and depletion of petroleum resources. Bongardt et al. [37] reviewed the key challenges in the transport sector and the existing set of sustainable roles to address them [37]. In their study, Boschmann and Kwan [38] conducted a review of research on social sustainable urban transportation (SSUT) and concluded that urban transportation has a significant impact on achieving social sustainability in urban areas, including issues related to social justice, social exclusion, and overall quality of life. Castillo and Pitfield [39], on the other hand, developed a framework to aid in selecting a small subset of indicators for sustainable transportation. Lastly, Shay and Khattak [40] classified and discussed a range of transportation-related tools and strategies across several domains, including finance, technology, policies, and social groups. Rajak et al. [14] proposed a fuzzy approach to assess the sustainability performance of urban transportation by considering 60 attributes. Considering geographically based socioeconomic data and demand flow, Ignaccolo et al. [41] offered a methodology to assess an indicator of 'transportation energy dependence' of an urban area. Industry [4] prepared the context for cyber-physical systems. Within cyber-physical systems, a priority is developing smart cities that have as one of their goals sustainable transport. Cyber-physical systems also suppose the development of a digital twin, a cyber representation of the physical system that must be controlled. The models presented in this paper help the decision-making process in sustainable transportation, being useful in the cyber representation of the transportation specific to a smart city. This fits with the process of achieving complete autonomy. AHP is an effective way to solve complex decision problems. As a pioneer study, fuzzy AHP has been conducted in [42], where fuzzy ratios are described and compared by triangular membership functions. The Decision Making Trial and Evaluation Laboratory (DEMATEL) is considered a methodical method to identify the cause–effect relationship of multiplex systems and was first introduced in [43].

In the real world, multi-attribute group decision making (MAGDM) and granular computing (GrC) are complicated cognitive processes that involve presentation, fusion, and analysis of multi-source uncertain information [29,44,45]. GrC is a soft computing tool that efficiently handles multi-source uncertain information. Still, it often needs more convincing semantic interpretations for MAGDM due to information fusion rules and analysis mechanism instability. The proposed approach in [29,45] uses a GrC framework called multi-granulation probabilistic models to construct MAGDM-oriented models that use dual hesitant fuzzy (DHF) information. The approach is designed using the MULTIMOORA method and is applied in the context of person–job (P–J) fit.

A fuzzy decision system is a mathematical model that uses fuzzy logic to make decisions based on uncertain or vague data. It is commonly used in decision-making situations where traditional binary logic may not be sufficient to represent the complex relationships and uncertainties involved. On the other hand, supply chain serviceability refers to the ability of a supply chain to meet customer demand for a product or service while maintaining certain levels of efficiency and cost-effectiveness. There are several ways in which fuzzy decision systems can be used to improve supply chain serviceability. For example:

1. Demand forecasting: Fuzzy decision systems can be used to forecast product demand, taking into account factors such as seasonality, customer preferences, and market trends. This can help supply chain managers plan production and inventory levels more accurately, improving serviceability by ensuring that products are available when customers need them.
2. Inventory management: Fuzzy decision systems can be used to optimize inventory levels based on factors such as lead time, demand variability, and cost. This can help to reduce stockouts and overstocking, which can both have a negative impact on serviceability.
3. Supplier selection: Fuzzy decision systems can evaluate potential suppliers based on various criteria, such as quality, reliability, and cost. This can help supply chain managers make more informed decisions about which suppliers to use, improving serviceability by ensuring that high-quality materials and components are delivered on time.

Overall, fuzzy decision systems can help to improve supply chain serviceability by providing more accurate and reliable decision-making tools in situations where traditional binary logic may not be sufficient.

3. Commonly Used Approaches for Sustainability Evaluation: Models and Issues

The techniques commonly used for evaluating sustainability can be categorized into the following groups:

- Life cycle analysis (LCA) was initially developed for evaluating industrial processes but has increasingly been used to assess the environmental impact of transportation systems [46]. The core concept of LCA is to combine a range of criteria, such as polluting emissions and resource usage, into a few metrics that reflect the overall impact of the system over its entire life cycle. The method has undergone significant efforts to standardize impact assessment and interpretation of the results.
- Cost–benefit analysis (CBA) and cost-effectiveness analysis (CEA) are based on considering the budgetary equivalent of all positive and negative effects of a business project. Cost-effectiveness analysis is used when the value of the project is unmeasurable economically or when a degree of realization of the achieved result is given. With the CBA and CEA [47] approaches, it is challenging to quantify external and social costs directly (e.g., air pollution, noise pollution, accidents, congestion, and fuel costs).
- Environmental impact assessment (EIA) is a method designed to evaluate the ecological impact of new localized polluters, such as industries or highways, and their

surrounding areas [48–50]. When applied to transportation, EIA is utilized to investigate the environmental effects of specific transportation methods.
- Optimization models (OM) are mathematical models that consist of an objective function and a set of constraints represented in an equation or inequality network. Linear programming is commonly used to find an optimal solution that aligns with social, economic, and environmental objectives. An example of the application of OM in urban transport can be found in [51].
- System dynamics models (SDM) are used to model complex systems by representing the dynamics of the system. These models show the relationships between system elements over time through stocks, flows, and a feedback mechanism.
- Assessment indicator models (AIM) use indicators to assess the sustainability of transportation systems. These models can be classified into composite index models and multi-dimensional matrix models. Composite index models output a single index that represents the degree of satisfaction with economic, social, and environmental objectives. Examples of these models include ecological footprint and green gross national product. However, it is difficult to obtain a single universal composite index for sustainable transportation.
- Data analysis is a category of models that involves using statistical data and applying techniques such as surveys, hypothesis testing, and structural equation modeling to investigate sustainable transportation systems.
- Multi-Criteria Decision Analysis (MCDA) comprises various methods such as Multi-Attribute Value Function Theory (MATT), Multi-Attribute Utility Function Theory (MAUT), and Analytic Hierarchy Process (AHP). These methods offer a framework for integrating information from different disciplines to support decision making. MCDA has found numerous applications in the management environment for selecting the best alternative from a set of options. However, as multiple criteria are often involved, there is no single optimal solution. Therefore, trade-offs and compromises must be made to maximize the benefits of multiple criteria.

4. AHP, DEMATEL, TOPSIS, and Their Applications

The existing methods can be categorized based on the role of the methods in either calculating the weight of criteria or prioritizing alternatives. Pairwise comparison weighting methods are used to calculate the relative importance or weight of different criteria, while distance-based ranking methods are used to rank or prioritize different alternatives based on their similarity or distance to an ideal solution. AHP and DEMATEL are both pairwise comparison weighting methods. AHP is used to derive weights of criteria and alternatives through a pairwise comparison of criteria and alternatives against a common goal. On the other hand, DEMATEL is used to evaluate the interrelationships between criteria and identify the key criteria that have the most significant impact on the decision-making process. TOPSIS is a distance-based ranking method used to rank alternatives based on their closeness to the ideal solution. In summary, AHP and DEMATEL are weighting methods, while TOPSIS is a ranking method. Each method has its strengths and limitations, and the choice of appropriate method depends on the specific decision-making context and the decision-maker's preferences. In this section, AHP, DEMATEL, and TOPSIS are investigated, and in the next section, the fuzzy versions of these methods are studied.

4.1. AHP

AHP decomposes complex problems into several subproblems using hierarchical levels, each of which embodies a set of criteria or attributes relative to each subproblem. In this kind of multicriteria analysis method, the relative importance of several relevant characteristics is represented based on an additive weighing process. Through a paired comparison process, the extent of several features is determined. However, the AHP model suffers from various deficiencies [52]. The AHP is applicable in nearly crisp information decision applications; it makes and deals with a poorly balanced judgment scale; the uncertainty associated with human mapping judgment into a natural language is not considered in the AHP method; the classification of the AHP method is somewhat imprecise, and the results of the AHP are considerably affected by selection based on the preferences of the decision-maker [53]. To remedy some of these problems, the fuzzy theory has been integrated with AHP to improve uncertainty [54]. In recent research [25], the authors applied a methodology using the FAHP approach to assess the sustainability of the transportation system in Mersin city. The FAHP approach allowed for the use of fuzzy numbers in pairwise comparisons of stakeholders, including users, potential users, and decision-makers. The decision-makers, who were experts in the transportation field and officials in the Mersin municipality, established a hierarchy tree to compare the main three criteria and 21 sub-criteria. The resulting scores from the FAHP were aggregated using the geometric mean approach and prioritized.

Apart from AHP, other methods have been developed, such as the Analytical Network Process (ANP) method, which is a generalization of AHP. ANP can evaluate the interrelations and influences between the elements that make up the decision-making process and has been shown to provide excellent results when decision alternatives and criteria are strongly correlated [55,56].

4.2. DEMATEL

Although ANP allows us to assess influence and interdependence, it is sometimes not understandable by decision-makers. As a result, DEMATEL begins to play an important role. DEMATEL is a valuable technique that aims to develop and analyze a structural model based on causal relationships between complicated factors. It depicts a fundamental concept of textual relationships among the system's elements. DEMATEL is able to clearly understand the cause–effect relationship in a wide variety of problems [57]. Compared to AHP and ANP, DEMATEL, by examining elements in cause and effect relationships, provides a better understanding of influences [58,59]. Even though DEMATEL is a valuable and practical technique for evaluating problems, in this process of establishing a structural model, the interactions of the components of the system are generally given by crisp values. However, because in real-world applications evaluation criteria are integrated through uncertain factors, crisp values are inadequate. In other words, conveying human judgment about preferences using exact numerical values will result in inaccurate estimations and conclusions. One way to handle uncertainties is to apply fuzzy theory to the DEMATEL method; motivated by this, many researchers in this field of study have developed a fuzzy DEMATEL method to solve various problems [60–63].

4.3. TOPSIS

The multicriteria decision analysis method, known as the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), was initially developed by Hwang and Yoon in 1981. Hwang, C.L. and Yoon, K. (1981), Multiple Attribute Decision-Making Methods and Application. New York: Springer-Verlag, with further developments in 1993. The advantages of TOPSIS are simplicity of use, consideration of distances to an ideal solution, and universality. The traditional TOPSIS model has some main disadvantages such as correlations between criteria, uncertainty in obtaining the weights using only objective or subjective methods, and the possibility of an alternative being close to the ideal point and the nadir point simultaneously [64]. To address these issues, several versions of TOPSIS have been proposed in the literature.

4.4. Advantages and Disadvantages of AHP, DEMATEL, and TOPSIS

In Table 4, pros and cons of this methods are summarized and mentioned. However, it is important to note that the comparison between these methods should not be based solely on their roles in MCDM but also on their ability to handle different types of data and decision-making scenarios. For instance, while DEMATEL is useful in identifying causal relationships, it may not be appropriate for situations where there are many criteria and alternatives. Similarly, while TOPSIS is effective in ranking alternatives, it may not be appropriate for situations where there are complex relationships between criteria. Ultimately, the choice of method should be based on the specific needs of the decision-making problem at hand.

Table 4. Pros and cons of AHP, DEMATEL, and TOPSIS Methods.

Method	Pros	Cons
AHP	• Simple to understand and use • Can handle complex decision-making problems with multiple criteria • Provides a systematic approach to prioritize alternatives	• Requires the use of pairwise comparisons, which can be time-consuming and subject to bias • Does not account for interactions between criteria • The results can be sensitive to the input data and decision-makers' preferences
DEMATEL	• Accounts for interactions between criteria • Provides a visual representation of the problem structure • Can handle both qualitative and quantitative data	• Requires the use of expert knowledge to define the causal relationships between criteria • Can be difficult to interpret the results • The number of iterations needed to achieve convergence can be high
TOPSIS	• Accounts for both positive and negative deviations from the ideal solution • Provides a simple and intuitive way to rank alternatives • Can handle both quantitative and qualitative data	• Assumes that the criteria are equally important and independent • Does not account for interactions between criteria • The results can be sensitive to the choice of weights and the normalization method

5. Fuzzy Based Techniques: State of the Art

In the context of FDSST, sustainability issues were tackled using fuzzy techniques as described in [48], where the implementation of sustainable initiatives was investigated. The primary decision-making techniques used to solve transport selection problems, including those in other sectors, are the fuzzy Analytical Hierarchy Process (FAHP) and Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [65]. However, like other methods, these have their pros and cons, as outlined in [15]. The process of analytical hierarchy is considered one of the most robust decision-making methodologies, developed by Saaty in the 1980s to simplify complex decision-making problems [66]. AHP is based on an additive weighting process that represents several relevant criteria by their correlative importance. AHP has been extensively applied in various areas and problems, particularly in engineering fields such as transport engineering [67,68], construction engineering, accuracy evaluation, and many other engineering fields [69–71]. However, AHP has limitations, which researchers have attempted to overcome by integrating fuzzy theories to improve its results [18,72].

Fuzzy logic and fuzzy set theory are used to mimic human reasoning and deal with uncertainty and imprecise knowledge in decision making [73]. Unlike Boolean logic, where an element is either true or false, fuzzy logic assigns a degree of truth between 0 and 1. This allows each element to also belong to its complement to a certain degree, which makes it more flexible and realistic [74]. Fuzzy sets were introduced by Zadeh to handle vague concepts precisely, and they have been successfully applied to complex problems in various fields due to their ability to handle vagueness [74]. When mapping out criteria based on their importance in a decision-making problem, decision-makers' perceptions are the primary source, and these perceptions can be represented using linguistic variables. To quantify these perceptions, a fuzzy set is needed along with its respective membership function.

To calculate the relative closeness of each alternative to the ideal solution, TOPSIS uses a similarity measure, which can be the Euclidean distance or the Manhattan distance. The alternatives are then ranked based on their relative closeness to the ideal solution. One of the advantages of TOPSIS is that it is a simple and easy-to-use method that can handle both quantitative and qualitative criteria. However, as mentioned earlier, there are some limitations to the traditional TOPSIS method, which have led to the development of various modified versions of the method in the literature.

Additionally, one of the advantages of Fuzzy AHP over Fuzzy TOPSIS is that Fuzzy AHP allows for the allocation of weights to the criteria using both objective and subjective methods. This helps to address the uncertainty in obtaining weights in a more comprehensive manner. However, Fuzzy AHP also has some limitations, such as the assumption of independence between criteria, which may not always hold in real-world decision-making problems. Another disadvantage of Fuzzy AHP is that it requires pairwise comparison between criteria, which can be time-consuming and complex (Figure 1).

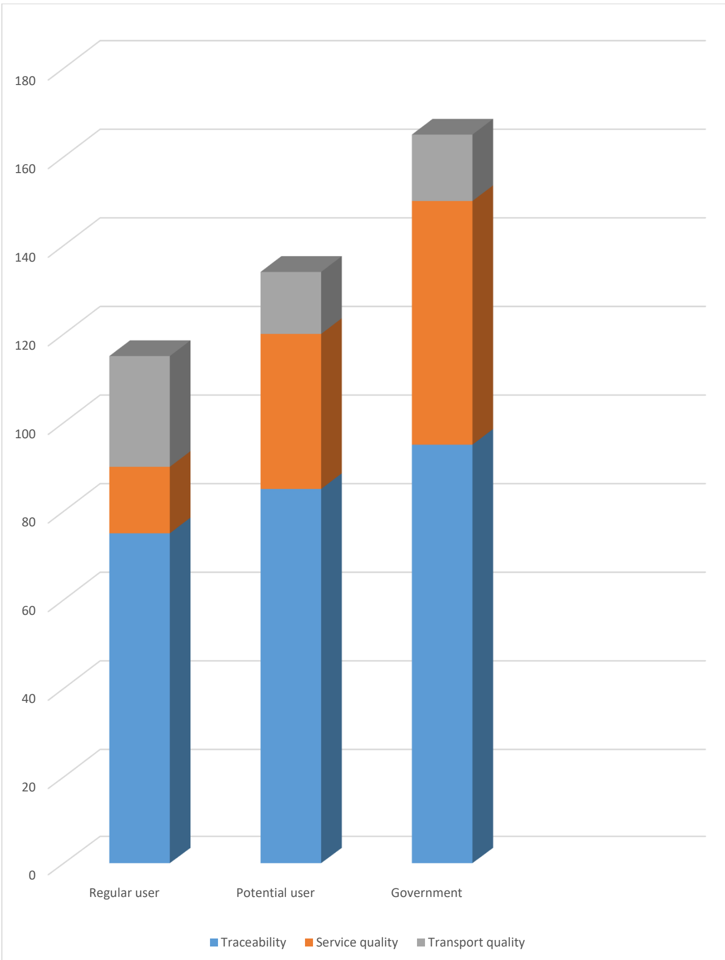

Figure 1. Comparison of the scores derived from FAHP for the first level of decision elements.

The FAHP approach was used as a technique in [25] to apply the TOPSIS model in the city of Mersin. The FAHP approach allowed the hierarchical analysis to be 'fuzzified' by incorporating fuzzy numbers in the pairwise comparisons (PC) conducted by collaborators such as users, potential users, and decision-makers. The hierarchical tree included three main criteria and twenty-one sub-criteria, and the data were collected through PC.

The geometric mean approach was then used to aggregate the analyzer responses, and the final scores were compiled and prioritized.

6. Fuzzy Decision-Making Techniques

This section begins with an overview of the different fuzzy structures that can be used in decision-making techniques, followed by a discussion of the fuzzy versions of the three techniques mentioned earlier.

6.1. Choice of Fuzzy Structure

The choice of fuzzy structure depends on the specific characteristics of the decision problem and the quality of data available [75]. Triangular and trapezoidal fuzzy structures are suitable for representing imprecise or vague data, where the degree of membership of an alternative to a criterion is represented by a triangular or trapezoidal membership function [76,77]. Spherical and ellipsoidal fuzzy structures are useful for dealing with more complex and uncertain data, where the degree of membership is represented by a spherical or ellipsoidal membership function [78]. The selection of the appropriate fuzzy structure for a specific problem requires careful consideration of the problem characteristics and the available data. In general, triangular and trapezoidal fuzzy structures are preferred for decision problems where the data are relatively simple and the degree of uncertainty is low, while spherical and ellipsoidal fuzzy structures are more suitable for complex decision problems with high levels of uncertainty and ambiguity. The choice between different fuzzy structures should be based on the specific requirements and constraints of the decision problem, as well as the available data and the degree of uncertainty involved. Below is a list of the advantages and disadvantages of each fuzzy set.

Advantages of Triangle Fuzzy Sets:

- *Simplicity:* Triangle fuzzy sets are simple to understand and easy to work with. They only require three parameters to define their shape: the left edge, the peak, and the right edge.
- *Intuitive interpretation:* The triangular shape of the membership function is intuitive and can be easily understood by non-experts.
- *Useful for modeling gradual change:* Triangle fuzzy sets are useful for modeling gradual change in a system, such as temperature or humidity levels.

Disadvantages of Triangle Fuzzy Sets:

- *Limited flexibility:* The triangular shape is restrictive and may not be suitable for modeling complex or nonlinear systems.
- *Limited accuracy:* The triangular shape may not accurately capture the degree of membership of an element in the set, especially if the shape of the data distribution is not triangular.

Advantages of Spherical Fuzzy Sets:

- *Flexibility:* Spherical fuzzy sets can take on any shape, making them more flexible for modeling complex and nonlinear systems.
- *Higher accuracy:* The spherical shape can accurately capture the degree of membership of an element in the set, even for non-triangular data distributions.

Disadvantages of Spherical Fuzzy Sets:

- *Complexity:* Spherical fuzzy sets require more parameters to define their shape, which can make them more difficult to work with.
- *Less intuitive interpretation:* The spherical shape is less intuitive than the triangular shape, which may make it more difficult for non-experts to understand.

While each setting has its own advantages, as mentioned above, the current study focuses specifically on triangle fuzzy sets. In the following, Fuzzy AHP, Fuzzy DEMATEL, and Fuzzy TOPSIS based on triangle fuzzy sets are delineated.

6.2. Fuzzy AHP

Fuzzy Analytic Hierarchy Process (Fuzzy-AHP) is a decision-making tool for various problems. Fuzzy AHP appeared in [42] for the first time, which compared fuzzy ratios described by triangular membership functions. As mentioned in Section 6.1, the choice of fuzzy set and membership function can have a significant impact on the results. For example, in the case of AHP, variants such as the triangular fuzzy AHP and the spherical fuzzy AHP use different types of membership functions and calculation procedures, resulting in different weights for criteria and rankings for alternatives. The triangular fuzzy AHP [79] assigns triangular membership functions to each criterion, while the spherical fuzzy AHP [80] assigns spherical membership functions. The choice of membership function can have implications for the sensitivity of the method to changes in input values, as well as the robustness of the results. Thus, it is important to carefully consider the choice of fuzzy set and membership function when integrating fuzzy theory with MADM methods. Here, we continue with triangular membership functions. Let $C_i = \{c_1, \ldots, c_i\}$ be the set of criteria and $P = [\hat{P}_{ij}]$ be the pairwise comparison matrix.

$$\hat{P}_{ij} = \begin{bmatrix} \hat{P}_{11} & \cdots & \hat{P}_{1n} \\ \vdots & \ddots & \vdots \\ \hat{P}_{n1} & \cdots & \hat{P}_{nn} \end{bmatrix} \tag{1}$$

The method follows the following steps.

- **step 1** Compute $F_k = (F_{k,l}, F_{k,m}, F_{k,u})$ values for each row as follows:

$$F_k = \sum_{j=1}^{n} P_{kj} \times [\sum_{i=1}^{n}\sum_{j=1}^{n} P_{ij}]^{-1} \quad for\ k = 1, \ldots, n; \tag{2}$$

- **step 2** The following equations will determine the degree of possibility of $F_k \geq F'_k$ and $k \neq k'$. Let $F_1 = (F_{1,l}, F_{1,m}, F_{1,u})$ and $F_2 = (F_{2,l}, F_{2,m}, F_{2,u})$, then:

$$\begin{cases} D(F_1 \geq F_2) \quad if \ \ F_{1,m} \geq F_{2,m} \\ D(F_1 \geq F_2) = \frac{F_{1,u} - F_{2,l}}{(F_{1,u} - F_{2,l}) + (F_{2,m} - F_{1,m})} \end{cases} \tag{3}$$

- **step 3** Calculate the weight of the criteria by

$$W'(c_i) = \min\{D(F_i \geq F_k)\} \ \ k = 1, \ldots, n \quad and \ \ k \neq i. \tag{4}$$

and arranged in a vector;

$$W' = [W'(c_1), \ldots, W'(c_n)] \tag{5}$$

- **step 4** Compute the normalized weight.

$$W_i = \frac{W'(c_i)}{\sum_{i=1}^{n} W'(c_i)}. \tag{6}$$

6.3. Fuzzy DEMATEL

Decision-Making Trial and Evaluation Laboratories (DEMATELs) are considered effective methods to identify the causes and effects of complex systems. These are efficient methods. Additionally, they are used to assign importance weights to each variable. If a problem consists of n criteria, $C = \{C_1 2, \ldots, C_n\}$, by following the steps, we can calculate the weights of each criterion by DEMATELs.

- **step 1** The pairs of criteria that influence the matrix are as follows.

$$\widehat{IP}_{kh} = \begin{bmatrix} \widehat{IP}_{11} & \cdots & \widehat{IP}_{1n} \\ \vdots & \ddots & \vdots \\ \widehat{IP}_{n1} & \cdots & \widehat{IP}_{nn} \end{bmatrix} \tag{7}$$

- **step 2** Normalizing the IP influence matrix by equation and obtaining the NP normalized influence matrix:

$$\widehat{NP}_{kh} = \begin{bmatrix} \widehat{NP}_{11} & \cdots & \widehat{NP}_{1n} \\ \vdots & \ddots & \vdots \\ \widehat{NP}_{n1} & \cdots & \widehat{NP}_{nn} \end{bmatrix} \tag{8}$$

where, $\widehat{NP}_{kh} = \frac{\widehat{IP}_{kh}}{\hat{R}} = (\frac{\widehat{IP}_{kh,l}}{\hat{R}_l}, \frac{\widehat{IP}_{kh,m}}{\hat{R}_m}, \frac{\widehat{IP}_{kh,u}}{\hat{R}_u})$ and

$$\hat{R} = (\max(\widehat{IP}_{kh,l}), \max(\widehat{IP}_{kh,m}), \max(\widehat{IP}_{kh,u})).$$

- **step 3** Obtain the fuzzy matrix of the total relation $\hat{U}$ by:

$$\begin{aligned} \widehat{U}_{kh} = \lim_{w \to \infty} (\widehat{NP}^1_{kh} + \widehat{NP}^2_{kh} + \cdots + \widehat{NP}^w_{kh}) = \\ \widehat{NP}_{kh}(1 - \widehat{NP}_{kh})^{-1} \end{aligned} \tag{9}$$

where $\hat{U}_{kh}$ is a fuzzy number;

$$\hat{U}_{kh} = \begin{bmatrix} \hat{U}_{11} & \cdots & \hat{U}_{1n} \\ \vdots & \ddots & \vdots \\ \hat{U}_{n1} & \cdots & \hat{U}_{nn}. \end{bmatrix} \tag{10}$$

- **step 4** Computing the sum of rows and columns of the total relation matrix and calling them $\hat{D}_i$and$\hat{R}_i$.
- **step 5** Obtaining the weights $\hat{w}_i = (w_{i,l}, w_{i,m}, w_{i,u})$ through

$$w_{i,l} = \sqrt{(\hat{D}_{i,l} + \hat{R}_{i,l})^2 + (\hat{D}_{i,l} - \hat{R}_{i,l})^2} \tag{11}$$

$$w_{i,m} = \sqrt{(\hat{D}_{i,m} + \hat{R}_{i,m})^2 + (\hat{D}_{i,m} - \hat{R}_{i,m})^2} \tag{12}$$

$$w_{i,u} = \sqrt{(\hat{D}_{i,u} + \hat{R}_{i,u})^2 + (\hat{D}_{i,u} - \hat{R}_{i,u})^2} \tag{13}$$

- **step 6** Defuzzification of fuzzy weights using the equation:

$$w_i = \frac{w_{i,l} + 2w_{i,m} + w_{i,u}}{4}. \tag{14}$$

6.4. Fuzzy TOPSIS

The fuzzy TOPSIS approach involves fuzzy assessment evaluations of the criteria and alternatives in TOPSIS (Hwang and Yoon et al., 1981). The TOPSIS approach chooses the option that is closest to the positive ideal solution and farthest from the negative perfect solution [81]. Positive ideal solutions are made up of excellent performance values for each criterion, and negative ideal solutions are made up of the worst performance values.

- **step 1** Rating assignments to criteria and alternatives. Assume that there are possible alternatives called $A = \{A_1, \cdots, A_j\}$ that will be assessed against the n criteria $B = \{B_1, \cdots, B_n\}$. The weights of the criteria are indicated by $W = \{w_1, \cdots, w_m\}$. The performance grading of each decision maker $D_k(k = 1, 2, \cdots, p)$ for each alternative $A_j(j = 1, 2, \cdots, n)$ with respect to criteria C are denoted by $\hat{R}_k = \hat{x}_{ijk}$, $(i = 1, \cdots, m, j = 1, \cdots, n, k = 1, \cdots, p)$ with the membership function $\mu_{\hat{R}_k(x)}$.
- **step 2** The total fuzzy rating is calculated and computed for criteria and alternatives. If the fuzzy rating of all decision makers is described as a triangular fuzzy number $\hat{R}_k = (x_k, y_k, y_k), k = 1, \cdots, p$, then the total fuzzy rating is given by $\hat{R} = (x, y, z)$, $k = 1, 2, \cdots, p$, where

$$x = \min_k\{x_k\}, \ \ y = \frac{1}{p}\sum_{k=1}^{p} y_k, \ \ z = \max_k\{z_k\}.$$

If the fuzzy rating and importance weight of the kth decision maker are $\hat{x}_{ijk} = (x_{ijk}, y_{ijk}, z_{ijk})$ and $\hat{w}_{ijk} = (w_{jk1}, w_{jk2}, w_{jk3}), i = 1, \cdots, m, j = 1, \cdots n$, respectively, then the aggregated fuzzy rating $(\hat{x}_{ij})$ of alternatives with respect to each criterion is given by $\hat{x}_{ij} = (x_{ij}, y_{ij}, z_{ij})$, where

$$x_{ij} = \min_k\{x_{ijk}\}, \ \ y_{ij} = \frac{1}{p}\sum_{k=1}^{p} y_{ijk}, \ \ z_{ij} = \max_k\{z_{ijk}\}. \tag{15}$$

The aggregated fuzzy weights $(\hat{w}_{ij})$ of each criterion are calculated as $\hat{w}_j = (w_{j1}, w_{j2}, w_{j3})$, where

$$w_{j1} = \min_k\{w_{jk1}\}, \ \ w_{j2} = \frac{1}{p}\sum_{k=1}^{p} b_{jk2}, \ \ w_{j3} = \max_k\{w_{jk3}\}. \tag{16}$$

- **step 3** Determine the fuzzy decision matrix. The fuzzy decision matrix for alternatives $(\hat{D})$ and criteria $(\hat{w})$ is constructed as follows:

$$\hat{D} = \begin{bmatrix} \hat{x}_{11} & \cdots & \hat{x}_{1n} \\ \vdots & \ddots & \vdots \\ \hat{x}_{m1} & \cdots & \hat{x}_{mn} \end{bmatrix} \tag{17}$$

$i = 1, \ldots, m; j = 1, \ldots, n, \ \ \hat{w} = (\hat{w}_1, \cdots, \hat{w}_n)$.

- **step 4** Normalization of the fuzzy decision matrix. By using linear scale transformation, the raw data can be normalized to various criteria scale. The normalized fuzzy decision matrix $\hat{N}$ is given by:

$$\hat{N} = [\hat{n}_{ij}]_{m \times n}, i = 1, \cdots, m, j = 1, \cdots, n, \tag{18}$$

where

$$\hat{n}_{ij} = (\frac{x_{ij}}{z_j^*}, \frac{y_{ij}}{z_j^*}, \frac{z_{ij}}{z_j^*}) \tag{19}$$

and $c_j^* = \max_i\{c_{ij}\}$, (benefit)

$$\hat{n}_{ij} = (\frac{x_j^-}{z_{ij}}, \frac{x_j^-}{y_{ij}}, \frac{x_j^-}{x_{ij}}) \tag{20}$$

and $x_j^- = \min_i\{x_{ij}\}$, (cost criteria)

- **step 5** Compute the weighted normalized matrix. The weighted normalized matrix $\hat{V}$ for the criteria is calculated by multiplying the weights $(\hat{w}_j)$ of the evaluation criteria with the normalized fuzzy decision matrix $\hat{n}_{ij}$ $\hat{V} = [\hat{v}_{ij}]_{m\times n}, i = 1, \ldots, m, j = 1, \ldots, n,$ where $\hat{v}_{ij} = \hat{n}_{ij}.\hat{w}_j$.

- **step 6** Determine the ideal fuzzy positive and negative solutions. These are computed as follows: $A^+ = (\hat{v_1}^+, \hat{v_2}^+, \ldots, \hat{v_n}^+)$ where

$$\hat{v_j}^+ = \max_i v_{ij3}, i = 1, \ldots, m, j = 1, \ldots, n. \tag{21}$$

$A^- = (\hat{v_1}^-, \hat{v_2}^-, \ldots, \hat{v_n}^-)$

$$\hat{v_j}^- = \min_i v_{ij1}, i = 1, \ldots, m, j = 1, \ldots, n. \tag{22}$$

- **step 7** Compute the distance of each alternative from positive and negative solutions. The distance (d^+, d^-) of each weighted alternative $i = 1, \ldots, m$ is calculated as follows: $d_i^+ = \sum_{j=1}^n d_v(\hat{v}_{ij}, \hat{v}_j^+), i = 1, \ldots, m$, $d_i^- = \sum_{j=1}^n d_v(\hat{v}_{ij}, \hat{v}_j^-), i = 1, \ldots, m$, where $d_v(\hat{a}, \hat{b})$ is the distance measurement between two fuzzy numbers $\hat{a}$ and $\hat{b}$.
- **step 8** Compute the closeness coefficient (CC_i) of each alternative. The closeness coefficient CC_i represents the distances between the fuzzy positive ideal solution (A^-) and the fuzzy negative ideal solution (A^+) simultaneously. The closeness coefficient of each alternative is calculated as: $CC_i = \frac{d_i^-}{d_i^- + d_i^+}, i = 1, \ldots, m$.
- **step 9** The different alternatives are ranked according to the closeness coefficient (CC_i) in decreasing order. The best choice is closest to the positive and farthest from the negative.

6.5. Hybrid Fuzzy Approaches

The trend of integrating or combining classical MADM methods has become more popular in recent studies. This approach has been shown to increase the effectiveness and accuracy of decision-making processes. For instance, the combination of DEMATEL and TOPSIS has been utilized to determine the weight of criteria and rank alternatives in a variety of decision-making contexts [82–84]. Another combination that has been explored is AHP and DEMATEL. This integration has been used to calculate the importance of criteria and to identify the causal relationships between criteria [85–87]. Additionally, the combination of AHP and TOPSIS has also been studied, which allows for the calculation of criteria weights and alternative ranking simultaneously [88,89]. Overall, the integration or combination of classical methods provides a more comprehensive approach to decision-making and should be considered in future MADM research.

7. Discussion and Future Directions

To summarize the literature review, Fuzzy TOPSIS is generally more agile than Fuzzy AHP in the decision-making process, except for situations with few criteria and suppliers. However, Fuzzy TOPSIS lacks the ability to integrate requirements into sub-criteria, which limits its use in supplier selection. Fuzzy AHP has a lower time complexity, but the advantage is reduced if a decision matrix consistency test is performed. Fuzzy decision-making techniques are commonly used for FDSSTs due to their complexity and uncertainty, and fuzzy set theory is well-suited for solving problems in uncertain environments. However, there is a lack of comparison between fuzzy and classical techniques in the FDSST domain. In most fuzzy controllers, trial and error are considered a stable structure. Applying self-regulated fuzzy structures and efficient training algorithms requires more research. The number of publications dealing with the design of Type-2 fuzzy systems has recently increased significantly. Since Type-2 fuzzy systems are stronger than their Type-1 counterparts, this trend could continue in the future [90–102]. On the contrary, research studies on type-2 fuzzy sustainable transport are rare. From this point of view, the advantages of type-2 fuzzy engines are completely ignored in sustainable transportation applications. Therefore, an open direction in this field is to study the application of type-2 fuzzy systems for sustainable transportation. Figure 2 displays the hierarchical structure of the supply quality criteria in relation to public bus transportation. To automatically implement fuzzy systems, research should focus on using bioinspired algorithms to find optimal values of membership functions and the number of alpha planes. Some recent studies have explored the use of artificial neural networks in sustainable transport systems, but combining them with fuzzy systems can lead to complex and challenging results. It is recommended to use combinations of both approaches to enhance sustainable transport systems. Additionally, more applications of fuzzy techniques at the data-driven model level are needed to improve decision-making and productivity, although challenges related to data storage and collection may arise.

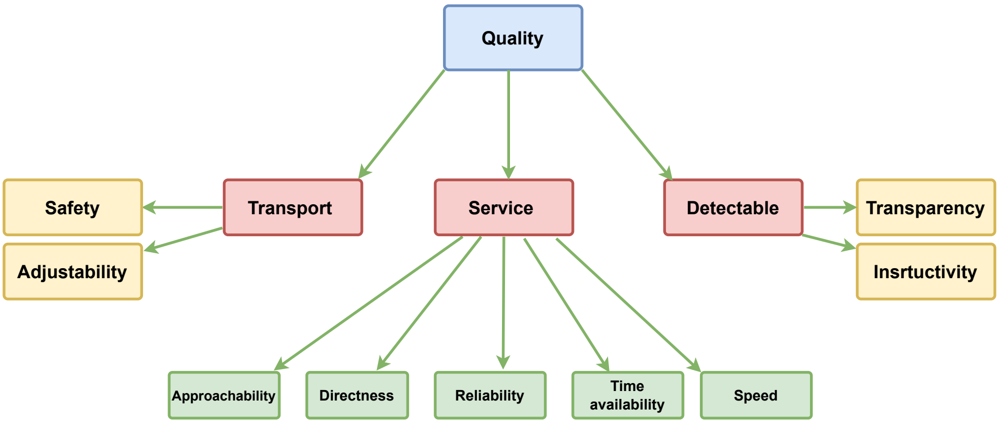

Figure 2. The hierarchical architecture of the supply quality in public transport [68].

To achieve sustainable transportation, several strategies can be adopted, including:

- Promoting the use of public transportation: Encouraging people to use buses, trains, and subways instead of private cars can reduce congestion, air pollution, and carbon emissions. Governments can also invest in expanding public transportation infrastructure to improve its accessibility and convenience.
- Encouraging cycling and walking: Encouraging people to cycle or walk instead of driving can reduce greenhouse gas emissions, improve public health, and reduce traffic congestion. Governments can invest in building cycling and walking paths, improving pedestrian infrastructure, and creating incentives for people to use these modes of transportation.
- Promoting electric vehicles: Electric vehicles emit fewer greenhouse gases than traditional gasoline-powered vehicles. Governments can incentivize people to purchase electric cars and invest in charging infrastructure to support their use.
- Implementing smart mobility solutions: Smart mobility solutions such as car-sharing, ride-sharing, and on-demand public transportation can improve accessibility and reduce the need for private cars. Governments can also invest in intelligent transportation systems to improve traffic flow and reduce congestion.
- Adopting sustainable urban planning: Sustainable urban planning can reduce the need for transportation by creating mixed-use developments that integrate residential, commercial, and recreational areas. This can reduce the need for long-distance commuting and promote sustainable transportation modes.

The future of sustainable transportation will require a combination of these strategies and others that emerge as technology advances. For example, autonomous vehicles may reduce traffic congestion and improve safety, but their environmental impact and impact on urban form still need to be made clear. Additionally, using renewable energy sources such as solar, wind, and geothermal for transportation may become more prevalent. To ensure a sustainable transportation future, governments, businesses, and individuals must work together to reduce the negative impacts of transportation on the environment, economy, and society. This will require policy and regulatory changes, investment in sustainable infrastructure, and a shift towards more sustainable modes of transportation.

8. Conclusions

Up to now, many researchers have tried to develop decision algorithms for sustainable transportation. The current study includes a review of essential studies applying fuzzy decision systems for sustainable transport. In this regard, the role of decision systems in sustainable transportation was investigated, including the most critical steps taken to date, their limits, and their potential to solve the most vital problems and issues. The present models and commonly used approaches for sustainability evaluation were delineated. Then, fuzzy-based techniques for FDSST were investigated. Finally, a discussion of existing fuzzy methods against non-fuzzy practices was presented, and possible future directions were listed. Our literature review illustrates many areas for improving the fuzzy decision algorithm applied to sustainable transportation. The focus of the current study was on AHP, DEMATEL, and TOPSIS methods due to their widespread usage and popularity in the MCDM literature. These methods have been extensively researched and applied in various fields, demonstrating their effectiveness in decision-making processes. However, in recent years, newer methods such as the Best-Worst Method (BWM), an extension of AHP designed to address its limitations, have emerged. In future studies, we aim to explore the effectiveness and limitations of these advanced methods to provide a more comprehensive analysis of the latest developments in MCDM techniques.

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