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Research Paper

Policy strategies assessment for renewable-powered urban mobility investments: A novel fractional fuzzy decision support system

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ABSTRACT

Improving the performance of renewable-powered urban mobility projects requires well-defined strategies based on the most influential evaluation criteria. This study addresses the absence of a systematic approach in the literature by developing a novel hybrid decision support system that both determines and prioritizes these criteria, while also evaluating alternative strategies. The proposed model combines the simple weight calculation (SIWEC) method to assign precise importance weights to criteria with the alternative ranking using two-step logarithmic normalization (ARLON) technique to rank strategic options. To enhance robustness, p,q,r-Fractional fuzzy numbers are incorporated, enabling more effective management of uncertainty inherent in expert evaluations. The results highlight smart systems for urban mobility (weight: 0.176) and accessibility to mobility systems (weight: 0.173) as the most critical factors for investment decision-making. By applying the integrated SIWEC–ARLON framework, the decision-making process becomes more accurate, reliable, and adaptable to real-world policy environments. The findings offer practical guidance for policymakers and investors, enabling optimal resource allocation, minimization of investment risks, and the selection of strategies that can significantly enhance the sustainability and effectiveness of urban mobility solutions powered by renewable energy.

1. Introduction

Renewable-powered urban mobility investments indicate urban transportation projects supported by renewable energy sources. The ability to carry out public transportation with electric vehicles is an important example of this application. Rail systems such as trams and metros operating with renewable energy can be considered. Similarly, wind-powered charging units for electric bicycles are one of the applications aimed at this purpose (Jadhav et al., 2025). Owing to these projects, it is possible to reduce carbon emissions significantly. Transportation systems operating entirely with renewable energy compared to fossil-fueled vehicles support the reduction of air pollution. This contributes to the easier achievement of the goal of creating sustainable cities. Reducing countries' dependence on fossil fuel imports is one of these projects' most critical economic advantages. Since this will increase energy security, countries and businesses are less affected by

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price fluctuations. For these projects to be sustainable in the long term, their financial performance must be high (Wei et al., 2025). Otherwise, investors will not show interest in these projects. Moreover, smart systems for urban mobility play a critical role in increasing the performance of renewable-powered urban mobility projects. Smart charging infrastructures support more effective demand management.

According to the International Energy Agency (International Energy Agency, 2024), global investment in renewable-powered urban transport exceeded United States dollar (USD) 150 billion in 2023. Within this scope, annual growth rate of 8% through 2030 is projected. Similar to this issue, China have successfully transitioned their entire bus fleet to electric power. In addition to them, Norway aims to operate all public transport with renewable energy by 2028. However, many countries face challenges in this process. Insufficient charging infrastructure, high initial investment costs, and technological integration issues can create some difficulties. These challenges have been widely discussed within the frameworks of international agreements like the Paris Agreement and the European Green Deal. Low-carbon urban mobility is discussed as a key priority for achieving climate neutrality in these agreements. Incorporating these global developments into local decision-making is very significant for designing effective and sustainable renewable-powered urban mobility strategies.

It is very important to determine the most effective criteria to increase the performance of renewable-powered urban mobility projects. By focusing on important factors, limited resources such as budget and human resources are evaluated in the best way. Similarly, this situation is also very necessary to effectively manage project risks (Han et al., 2025). Determining the most critical factors to minimize technological, financial or infrastructural risks is important. If the most important criteria are not determined, serious problems may arise for the projects in terms of sustainability (Oladapo et al., 2025). Unplanned investment decisions may result in wrong technology selection or unnecessary infrastructure expenditures. In this case, projects may become economically unsustainable. Significant dissatisfaction may occur if projects are not designed according to user needs. Systematic analysis to determine the most effective criteria in renewable-powered urban mobility investments has not been sufficiently addressed in the literature. Existing studies generally emphasize the importance of urban mobility with renewable energy in a theoretical framework (Dai et al., 2025). Due to this situation, a new academic study is needed in this field. A new academic study can fill the gap in the literature by determining the most important criteria and guiding decision-makers.

Despite the growing global interest in renewable-powered urban mobility, existing studies largely emphasize descriptive trends, policy targets, or isolated technological applications. However, limited attention has been paid to systematically identifying and prioritizing the most influential evaluation criteria while simultaneously ranking policy alternatives within a unified decision-making framework. This gap becomes particularly critical in urban investment contexts where limited resources, high uncertainty, and multiple stakeholders coexist. To address this need, the present study proposes an integrated SIWEC–ARLON–p,q,r-Fractional fuzzy framework that enables objective criteria weighting and robust policy ranking under uncertainty. By directly linking global policy ambitions to a structured and operational decision-support approach, the study contributes a concise and actionable perspective to the literature on renewable-powered urban mobility investments. To address this gap, the study formulates the following research questions, which directly guide the methodology and analyses:

(1) *What are the most important evaluation criteria for renewable energy-based urban mobility investments, considering sustainability, accessibility, and technological integration?*
(2) *How can the most appropriate policy alternatives be systematically ranked according to these criteria to support effective decision-making?*

These research questions are designed to address the gap in the existing literature regarding systematic evaluation and prioritization in renewable-powered urban mobility investments. The first question focuses on identifying the most influential evaluation criteria, which is essential for ensuring that investment decisions are based on factors with the greatest impact on sustainability, accessibility, and technological advancement. The second question aims to determine how policy alternatives can be objectively ranked according to these criteria, ensuring that limited resources are allocated to the most effective strategies. Together, these questions form the foundation of the study's methodological approach, guiding the development of a hybrid decision support system that enhances decision accuracy, reduces uncertainty, and provides actionable guidance for policymakers and investors. The proposed hybrid decision support system addresses them through two main stages: the simple weight calculation (SIWEC) method for criteria weighting and the two-step logarithmic normalization (ARLON) method for ranking alternatives, supported by p,q,r-Fractional fuzzy numbers to better manage uncertainty.

This study contributes to the literature by introducing a novel hybrid decision support system that integrates the SIWEC and ARLON methods with p,q,r-Fractional fuzzy numbers to systematically identify and prioritize evaluation criteria for renewable-powered urban mobility investments. It further enriches the field by providing a structured framework that enhances decision-making accuracy, reduces uncertainty, and offers actionable policy guidance for sustainable urban mobility development. The main superiorities of the proposed model are given below. (1) Determining the most critical evaluation criteria in the context of urban mobility provides an important contribution to the literature. These criteria significantly guide investors in the strategic decision-making process. Thus, it is possible to make effective investment decisions. Considering the SIWEC method in this process provides an important contribution to the literature. There are many criteria weighting methods in the literature. However, the SIWEC technique has some advantages over other similar methods. SIWEC offers a more objective criteria weighting method instead of complex expert opinions. It can help to make more accurate decisions, especially in large-scale renewable energy projects. (2) Another contribution to the study is the systematic ranking of policy alternatives. In this way, concrete guidance can be provided for policy makers and investors. This situation allows businesses to use their resources more effectively. With the help of this situation, businesses can perform more effective cost analysis. The use of the ARLON technique in alternative ranking provides important contributions to the literature. ARLON's two-stage logarithmic normalization structure allows more effective results to be achieved, especially in large-scale decision problems. In methods such as TOPSIS, outliers can disrupt the ranking. In ARLON, the reliability of the ranking is increased by balancing the outliers. (3) The use of p,q,r-Fractional fuzzy numbers in the analysis process significantly contributes to the literature. Compared to traditional fuzzy number models, this new number system can model uncertainties more precisely. Traditional fuzzy numbers have simpler uncertainty models. On the other hand, these sets provide more detailed uncertainty analysis with p, q and r parameters. On the other hand, traditional sets are based on fixed functions and are usually specific to certain systems. However, p,q,r-Fractional fuzzy numbers can be adapted to different fuzzy systems thanks to the three-parameter structure.

The second section reviews similar studies in the literature to define missing part. The recommended model is explained in the next section. The main findings are highlighted in the fourth section. The discussion will take place in the following section. The main concluding remarks are given in the final section.

2. Literature review

2.1. Renewable-powered urban mobility investments: key challenges and criteria

Existing studies on renewable-powered urban mobility investments primarily emphasize a set of recurring performance criteria that determine the long-term success of such projects. One dominant research direction focuses on economic viability, particularly revenue generation potential. Sustainable revenue streams are considered essential for covering operational and maintenance costs and for reducing dependency on external financing, thereby increasing investor attractiveness (Renga and Meo, 2024; Shamsuddoha et al., 2025). Revenue generation has also been linked to service quality and overall project sustainability (Hajjaji and Cristofari, 2024).

A second major research stream highlights accessibility to mobility systems as a core determinant of project performance. Studies consistently show that improved accessibility increases user participation, enhances social acceptance, and contributes to emission reduction by discouraging private vehicle use (Abdelhady and Shaban, 2024; Thompson et al., 2025). Accessibility is therefore treated not only as a social dimension but also as a mechanism that amplifies environmental and economic benefits.

Another group of studies concentrates on infrastructure-related criteria, including integration with existing urban infrastructure and flexibility for future expansion. Harmonization with current technological and physical infrastructures reduces implementation time and investment costs, while insufficient integration may lead to delays and additional expenditures (Iamtrakul et al., 2025; Gao et al., 2025). Flexibility and modularity are particularly emphasized as responses to urban growth and evolving mobility demand, allowing systems to adapt without excessive initial investments (Carramiñana et al., 2024; Huang et al., 2024).

Recent literature increasingly underscores the role of smart systems and climate resilience in renewable-powered urban mobility. Smart transportation technologies improve operational efficiency through real-time traffic management, demand forecasting, and optimized energy use, mitigating intermittency issues associated with renewable energy sources (Li et al., 2024; Liu et al., 2024). In parallel, resilience to climate change has emerged as a critical criterion, as climate-induced disruptions can significantly affect infrastructure reliability and maintenance costs (Syla et al., 2024; Han et al., 2025).

Overall, the literature identifies a consistent set of economic, infrastructural, technological, and environmental criteria, yet these studies predominantly remain descriptive and do not systematically prioritize the relative importance of these factors.

2.2. Decision support systems in renewable energy investment evaluation

To address the complexity of renewable energy investment decisions, a substantial body of literature applies multi-criteria decision-making techniques. One research stream employs causal analysis methods such as DEMATEL to explore interdependencies among performance criteria (Yüksel et al., 2025; Çelikbilek, 2025). These studies provide valuable insights into cause–effect relationships but do not directly yield priority weights for strategic decision-making.

Another stream relies on hierarchical weighting approaches, most notably AHP, to rank renewable energy investment strategies based on expert judgments (Akusta et al., 2025; Luhaniwal et al., 2025). While these methods are widely accepted, they depend heavily on pairwise comparisons and may suffer from consistency and subjectivity issues in large-scale or expert-intensive applications.

Ranking-based methods such as TOPSIS and CoCoSo have also been applied to evaluate renewable energy investments across different national contexts (Şahin and Deliktaş, 2025). These techniques offer straightforward ranking mechanisms but are often sensitive to normalization procedures and outliers. More recent studies introduce advanced fuzzy and hybrid models, such as linear diophantine fuzzy sets, to better capture uncertainty in investment evaluations. However, many of these approaches focus on either criteria weighting or alternative ranking in isolation rather than integrating both stages within a unified analytical framework.

2.3. Gaps in existing literature

Despite the growing volume of research on renewable-powered urban mobility investments, a critical gap remains in systematically determining and prioritizing the most influential evaluation criteria. Existing studies extensively discuss relevant factors such as revenue generation, accessibility, infrastructure integration, flexibility, smart systems, and climate resilience, yet few provide an objective mechanism to assess their relative importance. Moreover, while decision support systems are frequently employed, most studies apply conventional methods that are either highly subjective, sensitive to outliers, or limited to a single stage of decision-making. The lack of integrated frameworks that simultaneously address criteria weighting, alternative ranking, and uncertainty modeling restricts the practical applicability of existing research. To address this gap, the present study focuses on prioritizing smart systems for urban mobility and accessibility to mobility systems through a novel integrated decision support framework.

3. Methodology

In this paper, a novel hybrid decision support system is developed, and policy alternatives for renewable-powered urban mobility investments are proposed. The developed hybrid decision support system prioritizes the evaluation criteria for renewable-powered urban mobility investments with SIWEC and ranks the policy recommendations with ARLON. The hybrid decision support system includes $p,q,r-$ Fractional fuzzy numbers (FFN) for uncertainty analysis. The steps of a novel hybrid decision support system are presented in Fig. 1.

3.1. Methodological novelty and comparative advantages of the proposed framework

The methodological novelty of the proposed SIWEC–ARLON–p,q,r-Fractional fuzzy framework lies in its integrated and complementary structure, which addresses several limitations of conventional multi-criteria decision-making approaches. Unlike traditional weighting methods such as analytical hierarchy process (AHP) or Entropy, SIWEC assigns criterion weights by jointly considering normalized expert evaluations and their dispersion, enabling a more objective and data-driven weighting mechanism without relying on pairwise comparisons. This feature significantly reduces subjectivity and inconsistency, particularly in complex decision environments with multiple experts. In addition, the ARLON method enhances the robustness of alternative ranking by employing a two-step logarithmic normalization and Heron mean aggregation, which effectively mitigates the distortion caused by outliers that commonly affect distance-based methods such as Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The integration of p,q,r-Fractional fuzzy numbers further strengthens the framework by allowing a more flexible and precise representation of uncertainty through a three-parameter structure, surpassing the descriptive capacity of conventional fuzzy and intuitionistic fuzzy sets. Taken together, these methodological components form a coherent and scalable decision support system that offers superior stability, transparency, and interpretability compared to classical decision-making models.

3.2. SIWEC with $\boldsymbol{p},\boldsymbol{q},\boldsymbol{r}-$ FFN

The SIWEC method is a decision-making method that weights

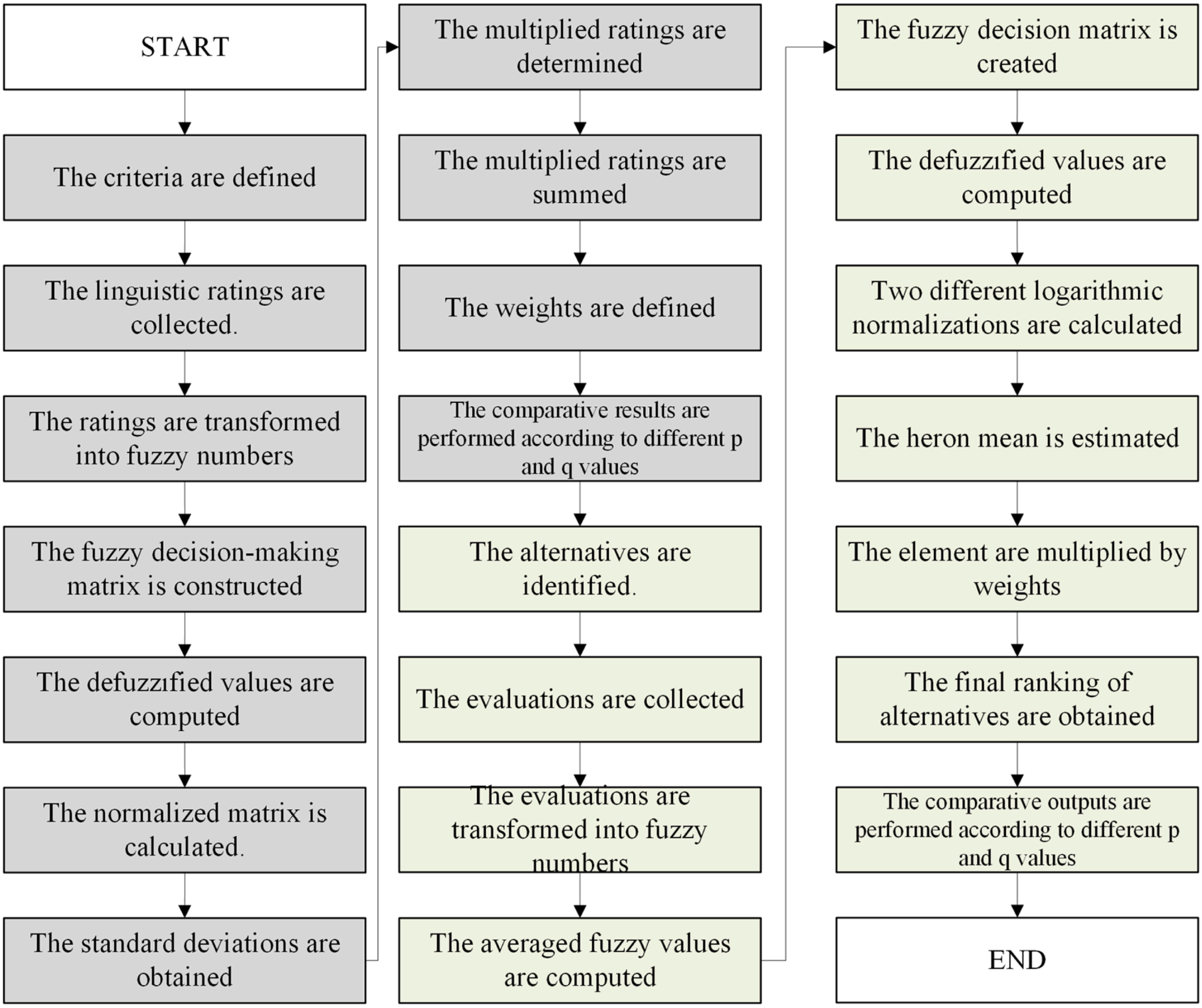

Fig. 1. The Steps of a Novel Hybrid Decision Support System.

criteria and assigns importance coefficients according to the common ratings of decision makers (DMs). In the method, the higher the standard deviation in the DMs' ratings, the more important the DM's rating becomes. This allows for more accurate and detailed ratings of DMs. The calculation of criteria weights with $p,q,r-$ FF SIWEC is presented below (Cao et al., 2025).

First, the importance of the criteria from the DMs to the target is rated. The rating is transformed to $p,q,r-$ FFN which has a degree of membership (μ), neutral (β) and non-membership (γ). The fuzzy initial decision-making matrix in Eq. (1) is constructed with these fuzzy numbers.

$$\widetilde{A} = [\widetilde{a}_{ij}]_{d\times n} \quad (1)$$

Where the number of DMs is d, and the number of criteria is n. $\widetilde{a}_{ij} = (\mu_{\widetilde{a}_{ij}}, \ \beta_{\widetilde{a}_{ij}}, \ \gamma_{\widetilde{a}_{ij}})$ means the fuzzy rating of DM_i for j^{th} criterion and has the condition in Eq. (2).

$$0 \le \frac{1}{p}\mu_{\widetilde{a}_{ij}} + \frac{1}{r}\beta_{\widetilde{a}_{ij}} + \frac{1}{q}\gamma_{\widetilde{a}_{ij}} \le 1 \quad (2)$$

Where p and q are positive integer numbers and $r = LCM(p,q)$. Next, the elements in Eq. (1) are defuzzified using Eq. (3).

$$a_{ij} = \frac{1 + \frac{1}{p}\mu_{\widetilde{a}_{ij}} + \frac{1}{r}\beta_{\widetilde{a}_{ij}} - \frac{1}{q}\gamma_{\widetilde{a}_{ij}}}{3} \quad (3)$$

Afterward, the normalization of the matrix is created with the help of Eq. (4).

$$\mathscr{n}_{ij} = \frac{a_{ij}}{\max(a_{ij})} \quad (4)$$

After creating the normalized matrix, the standard deviation is computed for each DM using the normalized ratings. Later, the normalized ratings are multiplied by standard deviations with Eq. (5).

$$v_{ij} = \mathscr{n}_{ij} \times sd_i \quad (5)$$

Where sd_i refers to the standard deviation for DM_i. In the other step, multiplied ratings are summed using Eq. (6).

$$s_j = \sum_{i=1}^{d} v_{ij} \quad (6)$$

Finally, the weight values are calculated by Eq. (7).

$$w_j = \frac{s_j}{\sum_{j=1}^{n} s_j} \tag{7}$$

3.3. ARLON with $\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{r} - FFN$

ARLON ranks the alternatives using logarithmic normalizations. The method is based on computing Heron mean of two different normalizations. The calculation of ranking results of alternatives with p,q,r − FF ARLON is detailed below (Yalçın et al., 2025).

First, the evaluations of alternatives are collected from DMs. The evaluations are transformed to p, q, r − FFN and computed averaged fuzzy numbers. The fuzzy decision matrix in Eq. (8) is created with fuzzy values.

$$\widetilde{X} = \left[\widetilde{x}_{ij}\right]_{m\times n} \tag{8}$$

Where the number of alternatives is m. Next, the values in Eq. (8) are defuzzified using Eq. (3). Two different logarithmic normalizations are calculated using Eqs. (9) and (10).

$$N_{ij}^{1} = \begin{cases} \dfrac{\ln(x_{ij})}{\ln\left(\prod_{i=1}^{m} x_{ij}\right)} & for\ B \\ \dfrac{1 - \dfrac{\ln(x_{ij})}{\ln\left(\prod_{i=1}^{m} x_{ij}\right)}}{m-1} & for\ C \end{cases} \tag{9}$$

$$N_{ij}^{2} = \begin{cases} \dfrac{\log_2(x_{ij})}{\sum_{i=1}^{m}\log_2(x_{ij})} & for\ B \\ 1 - \dfrac{\log_2(x_{ij})}{\sum_{i=1}^{m}\log_2(x_{ij})} & for\ C \end{cases} \tag{10}$$

Afterwards, the heron mean is computed with the help of Eq. (11).

$$h_{ij} = (1-\lambda)\sqrt{N_{ij}^{1}N_{ij}^{2}} + \lambda\frac{N_{ij}^{1}+N_{ij}^{2}}{2} \tag{11}$$

Where λ is the impact of normalizations, next, the weighted normalized decision matrix is obtained by Eq. (12).

$$k_{ij} = h_{ij} \times w_j \tag{12}$$

The weighted normalized benefit and cost criteria values are summed with Eqs. (13) and (14).

$$B_i = \sum_{j\in B} k_{ij} \tag{13}$$

$$C_i = \sum_{j\in C} k_{ij} \tag{14}$$

Finally, the final ranking of alternatives is defined by Eq. (15).

$$R_i = B_i^{\Psi} + C_i^{1-\Psi} \tag{15}$$

Where Ψ is equal to ratio of the number of benefit criteria to the number of criteria.

4. Analysis

To enhance the practical relevance of the proposed framework, this study further contextualizes the analysis by aligning the evaluated policy alternatives and criteria with real-world urban mobility investment conditions. The selected criteria and strategic alternatives reflect commonly reported indicators in publicly available urban transportation investment reports, including energy efficiency targets, accessibility indicators, infrastructure integration levels, and smart mobility deployment practices observed in large metropolitan areas. Recent electric bus deployment programs and charging infrastructure planning initiatives reported by major cities provide a realistic reference for the evaluation structure adopted in this study. Although primary project-level financial and operational datasets are often restricted due to confidentiality, the expert-based assessments in this research are grounded in empirical evidence derived from real investment practices, policy documents, and operational benchmarks. Therefore, the proposed SIWEC–ARLON–p,q,r-Fractional fuzzy framework offers a semi-realistic decision-support application that bridges theoretical modeling and practical urban mobility investment planning. The outputs of assessments of policy alternatives for renewable-powered urban mobility investments are summarized in this section. The tables are the outputs for the case where p and q are equal to 3.

4.1. Weighting the criteria for evaluating the renewable-powered urban mobility investments

The criteria for evaluating the renewable-powered urban mobility investments are defined from literature review and shared in Table 1.

The TR ratings are collected from seven DMs and illustrated in Table 2.

Afterwards, these ratings are transformed into fuzzy numbers. In this process, the equivalents of linguistic expressions are determined according to Fig. 2 (Kara et al., 2024a). That is, the equivalent of MG (medium good) is (.51,.135,.25).

By transforming all the experts' evaluations into the corresponding ones in Fig. 2, the fuzzy initial decision-making matrix is constructed. The matrix in Eq. (1) is displayed in Table 3.

Next, the defuzzified values are computed by Eq. (3). The defuzzified matrix is shown in Table 4.

The normalized matrix is calculated with the help of Eq. (4). Later, the standard deviations are obtained. The normalized number and standard deviations are exhibited in Table 5.

The multiplied ratings are determined by Eq. (5). The normalized numbers are multiplied by standard deviations. The output is given in Table 6.

Later, the multiplied ratings are summed with Eq. (6). Finally, the weight values are defined by Eq. (7). The weight values are illustrated in Table 7.

According to values in Table 7, the most important criteria for evaluating the renewable-powered urban mobility investments are smart systems for urban mobility and accessibility to mobility systems. While these two criteria have the highest weights, other factors such as revenue generation potential, integration with urban infrastructure, flexibility for possible expansion, and resilience to climate change also play important roles in ensuring the long-term sustainability and adaptability of renewable-powered urban mobility projects. Although their relative weights are lower in the current analysis, considering these additional dimensions could provide a more holistic and comprehensive decision-making framework, enabling policymakers to address a wider range of economic, infrastructural, and environmental challenges. For

Table 1
The Criteria Sets.

Criteria for evaluating the renewable-powered urban mobility investments	Codes
Revenue generation potential	RGP
Accessibility to mobility systems	AMS
Integration with urban infrastructure	IUI
Flexibility for the possible expansion	FPE
Smart systems for urban mobility	SSUM
Resilience to Climate Change	RCC

Table 2
The Linguistic Ratings.

	RGP	AMS	IUI	FPE	SSUM	RCC
DM1	MG	VVG	VG	MG	EG	VG
DM2	MG	VG	G	MG	VVG	G
DM3	M	VVG	G	G	VVG	VG
DM4	MG	VVG	G	G	VG	VG
DM5	G	VVG	MG	VG	VVG	VG
DM6	MG	VG	VG	G	VVG	MG
DM7	G	VG	G	MG	EG	VG

the reliability of the results, the analyses are repeated with different p and q values. According to different p and q values, the comparison results are summarized in Fig. 2.

When Fig. 3 is examined, the priority order of the criteria is the same for different p and q values.

4.2. *Ranking alternatives for the policy recommendations*

The alternative sets for the policy recommendations are shared in Table 8.

First, the evaluations are collected from DMs. The evaluations are displayed in Table 9.

The evaluations are transformed into fuzzy numbers, and the averaged fuzzy numbers are computed. The fuzzy decision matrix is exhibited in Table 10.

Next, the values are defuzzified using Eq. (3). The defuzzified values are shown in Table 11.

Afterwards, two different logarithmic normalizations are calculated using Eqs. (9) and (10). Two logarithmic normalizations are shared in Table 12.

In another step, the heron mean is computed with the help of Eq.

Table 4
The Defuzzified Matrix.

	RGP	AMS	IUI	FPE	SSUM	RCC
DM1	.377	.425	.416	.377	.444	.416
DM2	.377	.416	.405	.377	.425	.405
DM3	.362	.425	.405	.405	.425	.416
DM4	.377	.425	.405	.405	.416	.416
DM5	.405	.425	.377	.416	.425	.416
DM6	.377	.416	.416	.405	.425	.377
DM7	.405	.416	.405	.377	.444	.416

Table 5
The Normalized Numbers and Standard Deviations.

	RGP	AMS	IUI	FPE	SSUM	RCC	*sd*
DM1	.850	.957	.938	.850	1.000	.938	.06
DM2	.850	.938	.912	.850	.957	.912	.04
DM3	.816	.957	.912	.912	.957	.938	.05
DM4	.850	.957	.912	.912	.938	.938	.03
DM5	.912	.957	.850	.938	.957	.938	.04
DM6	.850	.938	.938	.912	.957	.850	.04
DM7	.912	.938	.912	.850	1.000	.938	.04

Table 6
The Multiplied Ratings.

	RGP	AMS	IUI	FPE	SSUM	RCC
DM1	.047	.053	.052	.047	.055	.052
DM2	.035	.038	.037	.035	.039	.037
DM3	.039	.046	.044	.044	.046	.045
DM4	.029	.033	.031	.031	.032	.032
DM5	.034	.036	.032	.035	.036	.035
DM6	.036	.040	.040	.039	.041	.036
DM7	.041	.042	.041	.038	.045	.042

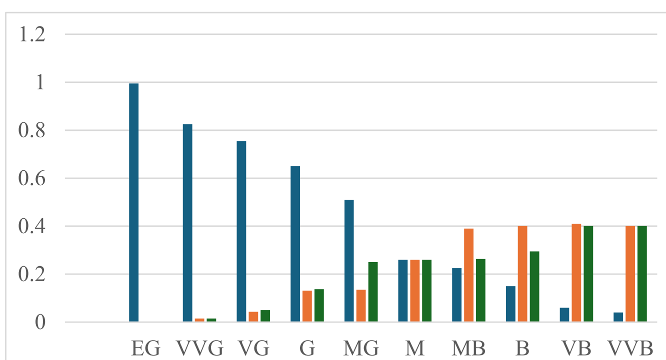

Fig. 2. Linguistic Terms and Their Corresponding Fractional Fuzzy Representations.

Table 3
The Fuzzy Initial Decision-making Matrix.

	RGP			AMS			IUI		
DM1	.510	.135	.250	.825	.015	.015	.755	.043	.050
DM2	.510	.135	.250	.755	.043	.050	.650	.131	.137
DM3	.260	.260	.260	.825	.015	.015	.650	.131	.137
DM4	.510	.135	.250	.825	.015	.015	.650	.131	.137
DM5	.650	.131	.137	.825	.015	.015	.510	.135	.250
DM6	.510	.135	.250	.755	.043	.050	.755	.043	.050
DM7	.650	.131	.137	.755	.043	.050	.650	.131	.137
	FPE			SSUM			RCC		
DM1	.510	.135	.250	.995	.000	.000	.755	.043	.050
DM2	.510	.135	.250	.825	.015	.015	.650	.131	.137
DM3	.650	.131	.137	.825	.015	.015	.755	.043	.050
DM4	.650	.131	.137	.755	.043	.050	.755	.043	.050
DM5	.755	.043	.050	.825	.015	.015	.755	.043	.050
DM6	.650	.131	.137	.825	.015	.015	.510	.135	.250
DM7	.510	.135	.250	.995	.000	.000	.755	.043	.050

(11). The heron mean values are displayed in Fig. 4. When λ is equal to 0, only the first logarithmic normalization produces results. If λ is equal to 1, the analysis is based on the second logarithmic normalization. A λ of 0.5 makes both logarithmic normalizations equally important. Therefore, a λ of 0.5 is selected (Kara et al. 2024b).

Later, the elements are multiplied by weight values in Table 7 with Eq. (12). Matrix K is shown in Fig. 5.

Finally, the final ranking of alternatives for the policy recommendations is calculated using Eqs. (13) – (15). The output is given in Fig. 6.

As can be seen in Fig. 6, the most suitable alternatives for the policy recommendations are funding projects with high energy efficiency and focusing on public-private partnerships.

4.3. Comparative outputs

For the reliability of the results, the analyses are repeated with different p and q values. According to different p and q values, the comparison outputs are summarized in Fig. 7.

When Fig. 7 is examined, it is seen that the ranking of the alternatives is similar. In addition, the first two ranks do not change according to different p and q values. This shows that these two alternatives are the most suitable under all conditions.

4.4. Sensitivity analysis

Sensitivity analysis is recommended for the validation of analyses. Sensitivity analysis demonstrates the impact of minimal changes in criterion weights on the ranking of alternatives. In other words, sensitivity analysis helps examine the situation of alternatives when the criteria weights differ from the current situation. Sensitivity analysis provides preliminary information about possible changes. Many different methods are available for simulating this change. In this manuscript, scenarios are generated with criterion weights increasing by simulation. In other words, the criterion weights are updated by generating numbers between −2 and + 2 using Monte Carlo simulation. The criterion weight is multiplied by (1 + 0.2) for + 2. The criterion weight is multiplied by (1–0.2) for −2. In this way, different scenarios are randomly generated. Then, weights are normalized so that the sum of all weights is 1. The random values for each scenario are summarized in Table 13.

The ranking of alternatives for the policy recommendations in the twenty scenarios constructed in this way is shown in Table 14.

As can be seen in Table 14, the ranking of the alternatives does not change in the sensitivity analysis conducted based on SIWEC. This demonstrates the robustness of the ranking of the alternatives for the policy recommended based on the criterion weights obtained with the SIWEC method. To demonstrate the superiority of this proposed model, results are obtained using the second weighting method. At the same time, a sensitivity analysis is also performed using the second weighting method. At this stage, the second weighting method for this manuscript is determined as AHP. The AHP method is a well-established method in literature. Table 15 summarizes the results of the AHP and AHP-based

Table 7
The Weight Values.

	RGP	AMS	IUI	FPE	SSUM	RCC
S	.261	.288	.277	.269	.294	.280
w	.157	.173	.166	.161	.176	.168

Table 8
The Alternative Sets.

Alternatives for the policy recommendations	Codes
Funding the projects with high energy efficiency	FND
Focusing on Public-private partnerships	FCS
Integration of IoT technologies in urban mobility systems	ITCH
Implementing dynamic pricing policies for the services	IMP
Promoting the performance-based incentives	PRM

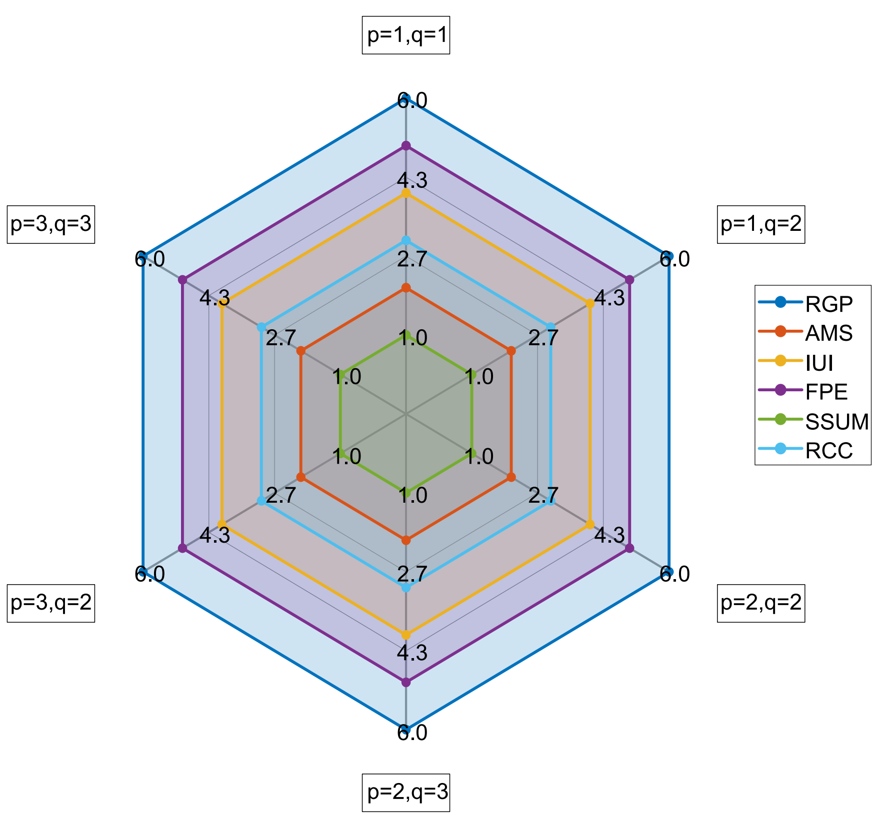

Fig. 3. Comparative Weighting Results of Evaluation Criteria under Different p and q Values.

Table 9
The Evaluations.

DM1	RGP	AMS	IUI	FPE	SSUM	RCC
FND	VVG	VVG	EG	EG	VVG	EG
FCS	VVG	G	VVG	VVG	G	G
ITCH	VG	M	VG	M	VG	G
IMP	MG	MG	M	G	M	M
PRM	M	VG	VG	M	M	G
DM2	RGP	AMS	IUI	FPE	SSUM	RCC
FND	VG	EG	EG	VVG	VVG	EG
FCS	G	VG	VG	G	VG	VVG
ITCH	VG	G	M	MG	MG	G
IMP	VG	G	M	G	M	MG
PRM	VG	M	MG	MG	M	G
DM3	RGP	AMS	IUI	FPE	SSUM	RCC
FND	VVG	VVG	VG	VVG	VVG	VVG
FCS	VVG	VG	VG	G	VVG	G
ITCH	VG	VG	VG	M	MG	MG
IMP	G	G	MG	G	G	MG
PRM	VG	M	VG	VG	MG	M
DM4	RGP	AMS	IUI	FPE	SSUM	RCC
FND	EG	EG	VVG	VVG	VG	VG
FCS	G	VG	G	VVG	G	VVG
ITCH	VG	MG	VG	G	M	G
IMP	G	MG	G	G	MG	VG
PRM	MG	M	G	G	MG	VG
DM5	RGP	AMS	IUI	FPE	SSUM	RCC
FND	VVG	EG	VG	VG	VVG	VG
FCS	G	G	G	VVG	VVG	G
ITCH	G	M	M	G	G	VG
IMP	M	MG	MG	VG	MG	MG
PRM	MG	MG	G	VG	G	M
DM6	RGP	AMS	IUI	FPE	SSUM	RCC
FND	VG	VG	EG	EG	VVG	VG
FCS	VVG	VVG	VVG	G	VVG	VG
ITCH	M	M	M	VG	MG	VG
IMP	MG	MG	M	G	M	VG
PRM	VG	M	M	G	VG	G
DM7	RGP	AMS	IUI	FPE	SSUM	RCC
FND	VG	VVG	VG	EG	VVG	VG
FCS	G	VVG	VVG	VG	VG	VVG
ITCH	VG	M	G	VG	G	MG
IMP	G	VG	VG	MG	MG	G
PRM	VG	M	VG	VG	G	VG

sensitivity analysis. The first column of the table shows the ranking of the alternatives according to their AHP weights, while the other columns of the table contain the sensitivity analysis.

An examination of Table 15 reveals that the ranking in the AHP column is the same as the SIWEC-based ranking. In other words, the results of the two analyses are consistent, demonstrating the reliability of the results. However, the rankings change in the sensitivity analysis performed using the criterion weights obtained from the AHP. In other words, a minimal change in the criterion weights changes the ranking of the alternatives for the policy recommendations according to the AHP. These results demonstrate that the proposed method is robust and superior to the AHP. This superiority is one of the advantages of the proposed method.

4.5. An application on developing and developed countries

Developing effective policies for renewable energy-supported urban transportation investments requires separate analyses of developed and developing countries. This requirement stems from significant differences in countries' economic capacity, existing infrastructure levels, policy priorities, social dynamics, and international obligations. Developed countries generally have larger public budgets, developed financial markets, and strong investor networks capable of supporting renewable energy projects. Consequently, they are able to subsidize long-term infrastructure investments and rapidly implement innovative technologies. In contrast, developing countries often face limited budgets, high debt burdens, and challenges accessing financing. This leads to a greater dependence on international funds and public-private partnerships in policy design. Significant differences also exist in terms of infrastructure and technological advancements. In developed countries, existing transportation infrastructure and energy grids are more suitable for the integration of renewable resources and the implementation of smart transportation systems. In contrast, in developing countries, infrastructure deficiencies, inadequate maintenance capacity, and technological adaptation challenges shape policy priorities. Consequently, conducting a differentiated analysis based on a country's level of development is critical for effective policy development, both in terms of applicability and success. For developed countries, policies focus on optimizing existing systems, integrating advanced technologies, and achieving carbon neutrality targets. For developing countries, accelerating basic

Table 11
The Defuzzified Values.

	RGP	AMS	IUI	FPE	SSUM	RCC
FND	.336	.337	.337	.337	.337	.336
FCS	.336	.337	.337	.336	.336	.337
ITCH	.336	.334	.335	.336	.336	.336
IMP	.336	.336	.336	.336	.335	.336
PRM	.336	.334	.336	.336	.336	.336

Table 12
Two Logarithmic Normalizations.

N_{ij}^{1}	RGP	AMS	IUI	FPE	SSUM	RCC
FND	.2000	.2001	.2001	.2001	.2001	.2000
FCS	.2000	.2001	.2001	.2000	.2001	.2001
ITCH	.2000	.1998	.1999	.2000	.2000	.1999
IMP	.1999	.2001	.2000	.1999	.1999	.2000
PRM	.2000	.1998	.2000	.2000	.2000	.2000
N_{ij}^{2}	RGP	AMS	IUI	FPE	SSUM	RC1C
FND	.8002	.8006	.8003	.8006	.8004	.8001
FCS	.8000	.8005	.8003	.8000	.8002	.8002
ITCH	.7999	.7993	.7997	.8000	.7999	.7997
IMP	.7998	.8002	.7999	.7996	.7995	.7999
PRM	.8001	.7993	.7999	.7999	.8000	.8000

Table 10
The Fuzzy Decision Matrix.

	RGP			AMS			IUI		
FND	.028	.000	.000	.030	.000	.000	.030	.000	.000
FCS	.025	.000	.000	.030	.000	.000	.030	.000	.000
ITCH	.023	.000	.000	.009	.000	.000	.019	.000	.000
IMP	.021	.000	.000	.024	.000	.000	.023	.000	.000
PRM	.027	.000	.000	.010	.000	.000	.023	.000	.000
	FPE			SSUM			RCC		
FND	.036	.000	.000	.030	.000	.000	.027	.000	.000
FCS	.027	.000	.000	.028	.000	.000	.029	.000	.000
ITCH	.027	.000	.000	.022	.000	.000	.021	.000	.000
IMP	.020	.000	.000	.016	.000	.000	.024	.000	.000
PRM	.026	.000	.000	.024	.000	.000	.025	.000	.000

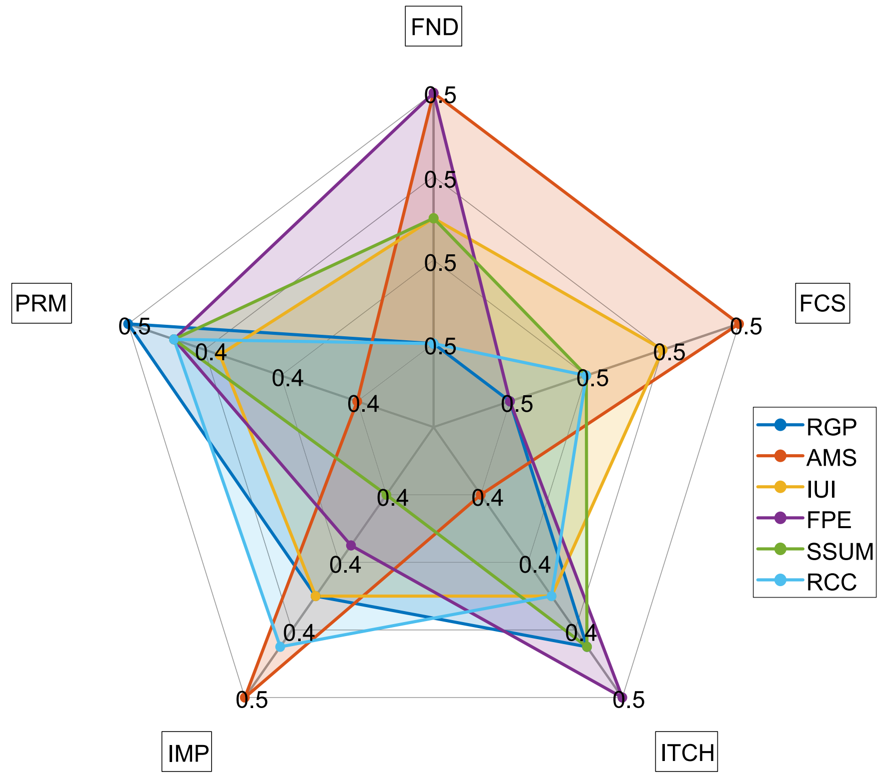

Fig. 4. Heron Matrix ($\lambda = 0.5$).

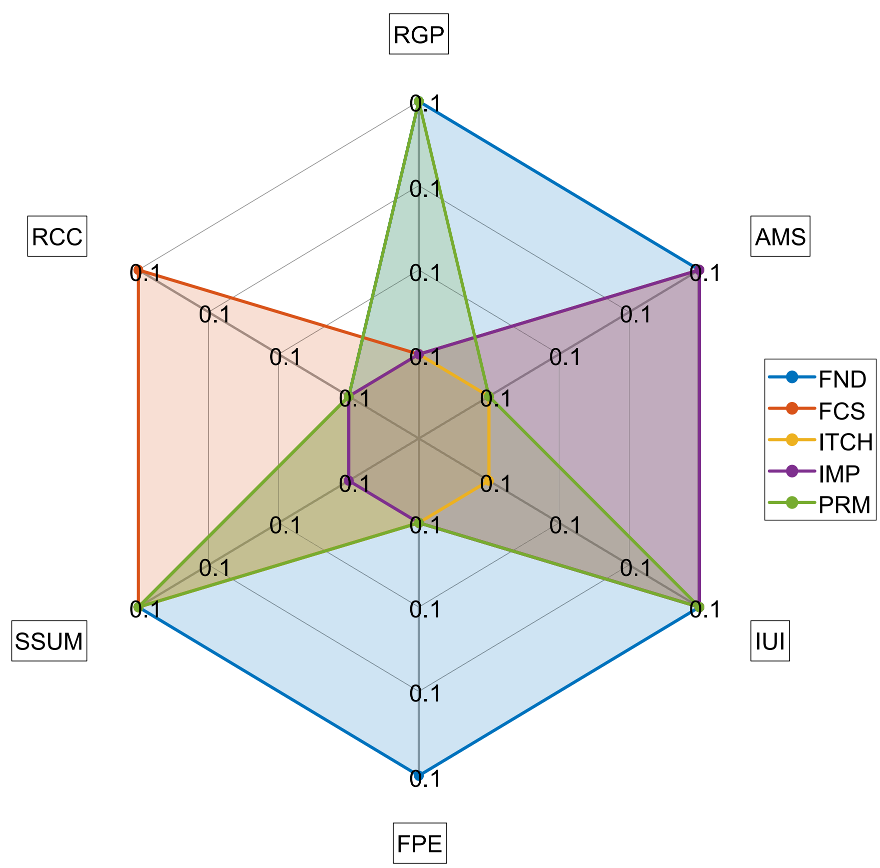

Fig. 5. K Matrix.

infrastructure investments, facilitating access to financing, and increasing social acceptance are prioritized goals. Taking these

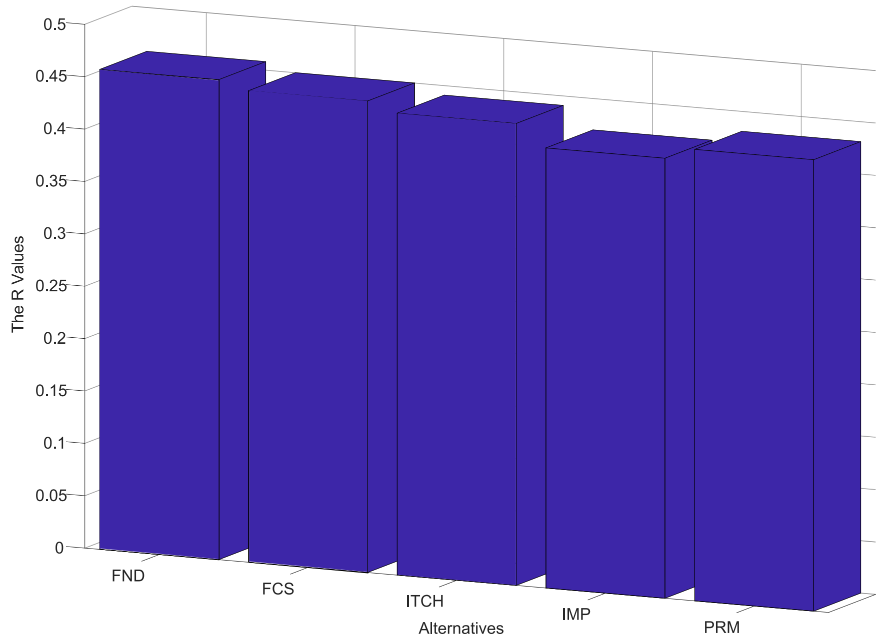

Fig. 6. The R Values.

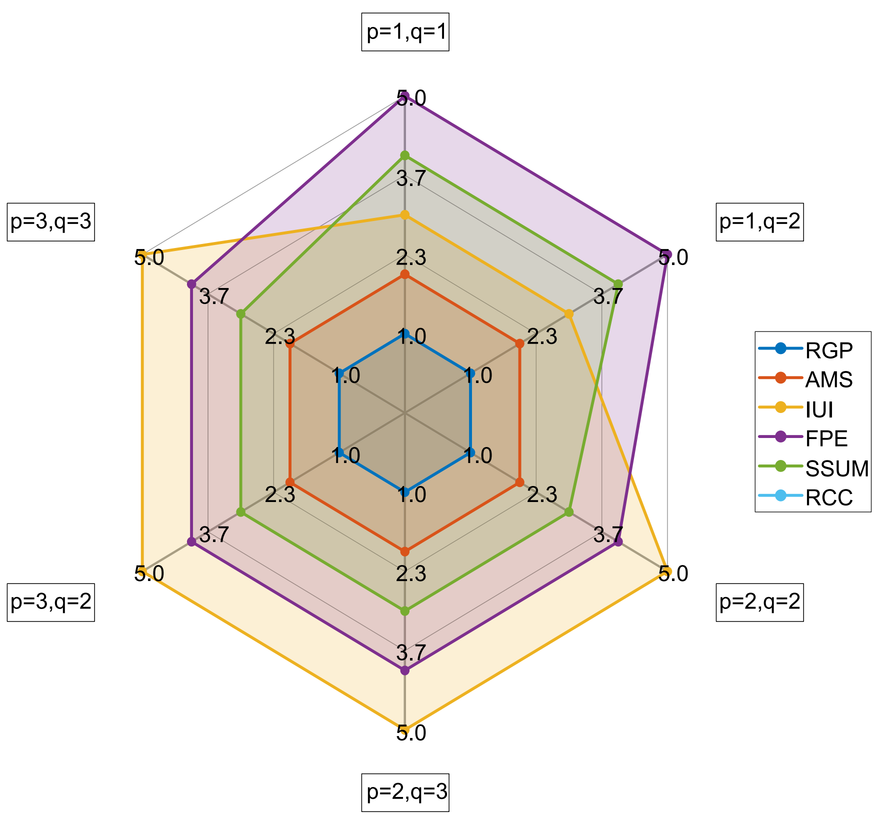

Fig. 7. Comparative Ranking Results of Policy Alternatives under Different p and q Values.

differences into account, this study conducts separate analyses for both developing and developed countries to identify the most effective strategies. Details of the analysis results are provided in Table 16.

Table 16 demonstrates that funding projects with high energy efficiency and prioritizing public–private partnerships are the most critical strategy alternatives for all country groups. The comparative analysis conducted separately for developing and developed countries revealed that the top two policy recommendations are identical for both groups. This outcome suggests that these strategies are not contingent on the structural differences between countries, such as economic capacity, infrastructure maturity, or governance models. Instead, they represent universally applicable approaches that address the fundamental requirements for enhancing the performance of renewable-powered urban mobility investments. High energy efficiency ensures optimal utilization of limited resources and maximizes environmental benefits, while public–private partnerships provide a robust mechanism for mobilizing

Table 13
Scenarios' Random Values.

	RGP	AMS	IUI	FPE	SSUM	RCC
SA1	.437	-.781	-.063	.621	1.784	1.116
SA2	.409	1.663	.239	1.889	1.691	−1.517
SA3	−1.483	1.953	−1.048	.513	1.953	1.307
SA4	-.686	-.379	1.087	-.515	−1.602	.909
SA5	-.686	.564	1.472	.721	-.726	1.293
SA6	-.555	1.576	.299	−1.952	1.418	−1.640
SA7	1.869	-.136	1.419	.933	1.627	−1.586
SA8	−1.830	-.840	-.227	.831	1.755	-.811
SA9	1.331	−1.491	.564	1.107	1.968	.110
SA10	−1.060	1.101	1.834	−1.824	−1.696	1.293
SA11	-.659	1.472	.098	1.787	.721	-.726
SA12	1.373	−1.763	1.006	−1.616	1.122	−1.455
SA13	.401	−1.729	.939	1.653	−1.375	1.033
SA14	1.127	.905	−1.331	−1.975	-.741	-.949
SA15	1.036	1.520	−1.604	1.708	-.091	1.287
SA16	−1.509	-.777	−1.579	-.555	−1.181	−1.035
SA17	-.862	-.050	-.570	−1.613	−1.770	−1.542
SA18	.344	1.828	1.585	.714	−1.394	1.352
SA19	-.849	-.425	.043	.704	1.270	1.228
SA20	−1.095	−1.569	-.581	.823	.917	.099

financial resources, sharing risks, and leveraging expertise across sectors. Therefore, these strategies can be considered core policy priorities that are relevant and effective regardless of a country's stage of development.

5. Discussion

A new transportation system that operates on clean energy requires a permanent solution to ensure accessibility. For example, if there are no portable chargers, there may be serious problems in industries such as transportation, communication, and emergency services. This situation also creates significant difficulties in meeting electricity demands (ur Rehman et al., 2025). When investments are made in these areas without developing strategies to address these challenges, it is inevitable that problems such as the lack of sufficient portable charging options and limited adaptability will arise. Therefore, an urgent action plan for reliable and versatile power solutions is also necessary to clean cities and transportation. Regarding sustainable and equitable cities, accessibility is one of the most important criteria. In addition, most accessibility-based assessments emphasize traveling to work by car or public transportation (Ryan et al., 2023; Soukhov et al., 2024). Shared mobility is an important step for the accessibility and equity of metro-based urban commercial travel. As a result, there is a continuing interest in the research of new metro-based transportation modes in urban transportation and planning. Accessibility, like a chain, also means access to many other things that societies need (Zhou et al., 2025; Mei et al., 2024). Accessibility also means equality in the distribution of social services. Thus, areas with accessibility have more social services, which paradoxically creates an unequal distribution (Sharma and Patil, 2024; Guo et al., 2024).

This study aims to determine policies for developing transportation systems with renewable energy integration. In this context, some criteria have come to the forefront for creating a new hybrid decision support system for renewable energy urban mobility investments. These criteria include revenue generation potential, accessibility to mobility systems, integration with urban infrastructure, flexibility for possible expansion, smart systems for urban mobility, and resilience to climate change. The analysis of this study has brought two more criteria to the forefront. The first was observed as smart systems for urban mobility and the other as accessibility to mobility systems. Although all the criteria have individual importance, as stated by Elassy et al. (2024), with the widespread use of intelligent transportation systems (ITSs), it is possible to build urban transportation systems more efficiently and resiliently. The research that used smart urban energy systems (SUES) and smart grids

Table 14
Sensitivity Analysis based on SIWEC.

	SA1	SA2	SA3	SA4	SA5	SA6	SA7	SA8	SA9	SA10	SA11	SA12	SA13	SA14	SA15	SA16	SA17	SA18	SA19	SA20
FND	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
FCS	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
ITCH	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
IMP	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
PRM	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4

Table 15
Sensitivity Analysis based on AHP.

	AHP	SA1	SA2	SA3	SA4	SA5	SA6	SA7	SA8	SA9	SA10	SA11	SA12	SA13	SA14	SA15	SA16	SA17	SA18	SA19	SA20
FND	1	1	2	1	2	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
FCS	2	2	3	2	1	2	3	3	3	3	3	3	2	3	3	3	5	4	3	3	2
ITCH	3	3	1	4	3	1	2	2	2	2	2	2	3	4	2	2	2	2	2	2	3
IMP	5	4	5	5	5	4	4	4	4	4	4	4	4	2	4	5	4	3	4	5	4
PRM	4	5	4	3	4	5	5	5	5	5	5	5	5	5	5	4	3	5	5	4	5

Table 16
The Results of Developing and Developed Countries.

	Developing	Developed
FND	1	1
FCS	2	2
ITCH	5	3
IMP	3	4
PRM	4	5

(SG) to understand integrative energy management explained that integrating SG technologies into urban areas fosters innovative perspectives on the value of urban infrastructure.

On the other hand, incorporating SG technologies into urban energy systems fosters the modernization of old urban energy infrastructures (Zheng et al., 2024). Esfandi et al. (2024) pointed out that after the period that combined technology with sustainability and governance and determined the impact of smart transportation on energy and environmental planning, the period between 2009 and 2017 saw the emergence of artificial intelligence, energy storage, smart grids, and EVs in addition to technology. According to Yang and Li (2024), the provision of smart city infrastructure will require adopting renewable energy and efficient resource management, which will necessarily lead to the widespread use of green transportation systems, including electric vehicles and advanced public transportation. Additionally, the idea of smart cities has gained significant interest due to incorporating advanced technology into transportation systems (Manirathinam et al., 2024). The findings from the studies also reveal that artificial intelligence technologies, apart from the doubt of data security and ethical decision-making, have the potential to multiply energy differently, reducing emissions and saving money in transportation (Mirindi et al., 2025; Yan and Lv, 2024).

6. Conclusion

This study uses a novel model to evaluate policy alternatives for renewable-powered urban mobility investments. The study contributes to the literature by integrating the SIWEC method for objective criteria weighting and the ARLON technique for ranking policy alternatives. Furthermore, the use of p,q,r-Fractional fuzzy numbers allows for a more precise modeling of uncertainties compared to traditional fuzzy sets. Regarding the first research question *"What are the most important evaluation criteria for renewable energy-based urban mobility investments?"*, the analysis identified smart systems for urban mobility (weight: 0.176) and accessibility to mobility systems (weight: 0.173) as the most significant criteria. On the other side, for the second research question *"How can the most appropriate policy alternatives be ranked in line with these criteria?"*, the findings indicate that funding projects with high energy efficiency and prioritizing public–private partnerships are the most suitable policy recommendations.

However, the successful implementation of the identified strategies and policy alternatives may face various practical challenges, especially in diverse urban contexts. These challenges include significant initial capital requirements, regulatory and bureaucratic constraints, a lack of technical expertise for integrating advanced smart systems, and potential resistance from stakeholders due to social or cultural factors. Differences in infrastructure readiness and financial capacity among cities can also affect the feasibility and speed of adoption. To address these issues, tailored financing mechanisms should be developed to meet the specific needs of each urban environment. Stakeholder engagement strategies can help build collaboration and support. In addition, supportive policy frameworks are needed to facilitate the transition to sustainable urban mobility. By addressing these barriers with a holistic and strategic approach, the proposed recommendations can be turned into practical outcomes that improve urban transportation systems.

From a policy perspective, the findings provide clear guidance for urban decision-makers seeking to accelerate renewable-powered mobility transitions. The results indicate that investments prioritizing smart mobility systems and accessibility should be placed at the core of urban transportation policies, as these dimensions generate the highest systemic impact across economic, environmental, and operational objectives. Policymakers can use the proposed framework to support evidence-based prioritization of limited public resources, particularly when designing funding schemes, public–private partnership structures, and technology adoption strategies. Moreover, the robustness of the results across different parameter settings suggests that the recommended policy directions remain valid under varying uncertainty conditions, making the framework suitable for both developed and developing urban contexts. By translating complex expert evaluations into transparent and structured decision outputs, the proposed approach supports more consistent, defensible, and scalable urban mobility investment policies.

The main limitation is that a fixed criteria set is taken into consideration in this study. However, the performance indicators of these projects can evolve over time because of economic fluctuations and technological advancements. Future research can develop a dynamic evaluation model that adapts to technological improvements. Another limitation is that all experts' evaluations are considered with the same significance weight. For future research direction, the weights of the experts can be computed according to their demographical factors. In addition, future studies could expand the analysis by incorporating additional evaluation criteria such as revenue generation potential, integration with urban infrastructure, flexibility for possible expansion, and resilience to climate change. Including these factors would allow for a more comprehensive and holistic decision-making framework, better reflecting the multifaceted nature of renewable-powered urban mobility projects.

Abbreviations

AHP	analytical hierarchy process
AMS	Accessibility to mobility systems
ARLON	alternative ranking using two-step logarithmic normalization
DEMATEL	decision making trial and evaluation laboratory
DM	decision maker
FCS	Focusing on Public-private partnerships
FFN	Fractional fuzzy numbers
FND	Funding the projects with high energy efficiency
FPE	Flexibility for the possible expansion
IEA	International Energy Agency
IMP	Implementing dynamic pricing policies for the services
ITCH	Integration of IoT technologies in urban mobility systems
IUI	Integration with urban infrastructure
PRM	Promoting the performance-based incentives
RCC	Resilience to Climate Change
RGP	Revenue generation potential
SIWEC	simple weight calculation
SSUM	Smart systems for urban mobility
TOPSIS	technique for order preference by similarity to ideal solution
USD	American dollar

Authors contribution

All authors contributed equally.

CRediT authorship contribution statement

Serhat Yüksel: Writing – review & editing, Writing – original draft, Methodology. **Dragan Pamucar:** Writing – review & editing. **Vladimir Simic:** Writing – review & editing. **Serkan Eti:** Writing – review & editing, Writing – original draft. **Ceren Demir:** Writing – review & editing, Writing – original draft. **Hasan Dinçer:** Writing – review & editing, Writing – original draft.

Informed consent

Informed consent was obtained from all individual participants included in the
study.

Ethical approval

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Data availability

Data will be made available on request.

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