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Innovative solution suggestions for financing electric vehicle charging infrastructure investments with a novel artificial intelligence-based fuzzy decision-making modelling

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Abstract

The right methods for effective financing of electric vehicle charging infrastructure investments should be identified. However, in the literature, there is no consensus on which funding source would be right for these projects. There is a need for a new study to recommend the most appropriate financing strategy for these projects. Accordingly, the purpose of this study is to identify innovative solutions for financing electric vehicle charging infrastructure investments. A novel fuzzy decision-making model is introduced to reach this objective. Firstly, the weights of experts are calculated using dimension reduction. Secondly, Spherical fuzzy decision matrix is obtained. Thirdly, the criteria in charging infrastructure for electric vehicles are weighted using Spherical fuzzy criteria importance through intercriteria correlation (CRITIC). Fourthly, innovative solutions for financing electric vehicles charging infrastructure are ranked via Spherical fuzzy ranking technique by geometric mean of similarity ratio to optimal solution (RATGOS). The main contribution of this study is that effective strategies can be identified for financing electric vehicle charging infrastructure investments by establishing a novel decision-making model. Most of the existing models in the literature could not consider the weights of the experts. This condition is criticized by different scholar because these experts can have different qualifications. To satisfy this problem, in this study, dimension reduction algorithm with machine learning is taken into consideration to compute thee weights of the experts. The findings demonstrate that the most effective criterion in the innovative financial solution for the charging infrastructure of electric vehicles is determined as "potential income". According to the ranking results, it is also defined that the most sustainable solution among the innovative strategies for financing the charging infrastructure of electric vehicles is "blockchain technology".

Keywords Electric vehicles · Charging · Infrastructure investments · Artificial intelligence

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1 Introduction

The effectiveness of charging stations is very important for the success of electric vehicles. In this context, it is important to have charging stations in sufficient numbers and in suitable locations. This contributes to a significant increase in customer satisfaction. Thus, these tools will be much more preferred by users. On the other hand, the effectiveness of the charging station also allows vehicles to be charged in a short time. Fast charging enables users to wait less during long-distance journeys (Zhang et al. 2024). Thus, customer expectations can be met more effectively. To increase the performance of charging stations, costs must be low. This contributes significantly to increasing the competitiveness of projects. Moreover, necessary security measures must be taken to ensure the effectiveness of charging station investments. Thus, the possibility of possible technical problems can be minimized. As a result, an effective charging infrastructure is critical for the successful adoption of electric vehicles (Zhao et al. 2024).

It is extremely important to choose the right methods for effective financing of electric vehicle charging infrastructure investments. Determining the correct financing methods is very critical for the successful implementation of the project. Similarly, this is important to ensure the sustainability of these projects. In this context, failure to determine the correct financing method causes many problems in terms of the sustainability of this project (Mittal et al. 2024). First, failure to determine the correct financing method may cause the project to remain in financial uncertainty. Since the uncertainty environment will make investors uneasy, investments may decrease. On the other hand, wrong financing methods may also cause the costs of the project to increase. Since this situation will cause a decrease in profitability, the sustainability of the projects may not be possible. Moreover, financing problems may result in the project resulting in poor quality or inadequate infrastructure. This issue may negatively affect the performance of projects (Jagani et al. 2024).

In summary, finding the right financing method is very important to increase the performance of these investments. In the literature, the importance of electric vehicle charging infrastructure investments is discussed by many researchers. In these studies, it is generally emphasized that these projects will contribute to the sustainable economic development of countries. In addition, a significant part of the studies underline that the right financing technique must be found to increase the effectiveness of these projects. However, there is no consensus on which funding source would be right for these projects. Similarly, studies determining the most appropriate financing sources for these investments are also very limited. Considering these issues, there is a need for a new study to recommend the most appropriate financing strategy for these projects.

Accordingly, in this study, it is aimed to evaluate innovative solutions for financing electric vehicle charging infrastructure investments. Hence, the main research question is which innovative solutions play the most critical role to provide effective financing for electric vehicle charging infrastructure investments. For this purpose, a novel fuzzy decision-making model is constructed while integrating AI technique with Spherical fuzzy sets. This novel model consists of four different stages. Firstly, the weights of experts are calculated using dimension reduction. Secondly, Spherical fuzzy decision matrix is obtained. Thirdly, the criteria in charging infrastructure for electric vehicles are weighted using Spherical fuzzy criteria importance through intercriteria correlation (CRITIC). Fourthly, innovative solutions for financing electric vehicles charging infrastructure are ranked via Spherical fuzzy ranking technique by geometric mean of similarity ratio to optimal solution (RATGOS). In addition to them, these alternatives are also ranked by using TOPSIS technique. Similarly, a comparative evaluation is also conducted by using Pythagorean fuzzy numbers to validate the accuracy of the findings of the proposed model. The main motivation of this study is that there is no consensus in the literature on how to provide effective financing of charging investments for electric vehicles. Electric vehicles and charging infrastructure are becoming increasingly important. On the other hand, there are some difficulties in financing these infrastructures. The increase in the use of electric vehicles is of critical importance in terms of reducing carbon emissions. However, the charging infrastructure for these vehicles is not developing in parallel. This situation constitutes a very serious obstacle to the development of these vehicles. The installation and development of charging infrastructure requires significant financing. Because of this issue, innovative financing solutions are necessary for the development of these investments. In this process, there is a great need to determine effective financing processes for this issue. Multi-criteria decision-making analysis can be taken into consideration to achieve this goal. In addition to this issue, there is a strong need for a new decision-making model to make evaluations with respect to the innovative solutions for financing electric vehicle charging infrastructure investments. The main reason behind this situation is that most of the existing models in the literature could not consider the weights of the experts. In other words, arithmetic mean of different evaluations is calculated. This condition is criticized by different scholar because these experts can have different qualifications. To satisfy this problem, in this study, dimension reduction algorithm with machine learning is taken into consideration to compute thee weights of the experts.

The main contribution of this study is that effective strategies can be identified for financing electric vehicle charging infrastructure investments by establishing a novel decision-making model. Therefore, this study has both theoretical and methodological contributions. With respect to the theoretical contributions, policy recommendations can be developed to find solutions for a significant problem. The lack of sufficient charging infrastructure is a major obstacle to the development of electric vehicle projects. This inadequacy creates significant customer dissatisfaction. In other words, customers are anxious about using electric vehicles due to this problem. This situation also constitutes a significant barrier to the development of projects. The development of charging infrastructure is of vital importance in this process. On the other hand, the cost of these projects is also quite high. In this context, the financing source needed for the sustainability of these projects must be provided. With the results to be obtained in this study, it is possible to determine the right strategies for the effective solution of this problem. On the other side, regarding the methodological contributions, the proposed decision-making model of this study has some advantages. The main superiorities of this proposed model are explained as follows. (i) RATGOS methodology is taken into consideration in the ranking of alternatives. Ranking techniques existing in the literature are criticized in many aspects. For instance, in the calculation steps of technique for order preference by similarity to ideal solution (TOPSIS), Euclidean distance is taken into consideration to define the distances to the optimal values. However, lots of scholars criticize this issue in the process of computing the distances to the negative ideal solutions. Similar to this condition, additive ratio assessment (ARAS) technique considers the ratio of similarities in the normalization process. Due to these criticisms, it is understood that a new ranking model is needed. RATGOS technique is developed to satisfy the problems stated in these criticisms. In the analysis process carried out with this method, the geometric mean is taken into consideration. In this way, it is aimed to perform more effective and accurate analyses (Liu et al. 2024). It is vital to determine the appropriate financing technique for the effectiveness of charging station investments for electric vehicles. In this context, determining the most accurate innovative solution is very critical. Therefore, it is necessary to choose the most appropriate ranking technique. Taking these issues into consideration, it is understood that the RATGOS technique is the most suitable method for this analysis (Yüksel et al. 2024). (ii) Preferring the CRTIC technique in determining the weights of the criteria will also contribute to the literature in many ways. The most important advantage of the CRITIC method over other similar techniques is that the correlation relationship between factors is considered during the analysis process (Simic et al. 2022; Aytekin et al. 2024). Some indicators need to be analyzed in determining the appropriate financing technique for electric vehicle charging station investments. However, these factors can also influence each other. For example, ensuring effective risk management can also reduce costs. Therefore, it is important to consider this correlation relationship in determining the most appropriate criteria. In this context, using the CRITIC technique in this analysis process helps to make a more accurate analysis. There are different decision-making techniques to compute the weights of the criteria, such as analytical network process (ANP) and analytical hierarchy process (AHP). However, with these approaches, it is not possible to identify the causal directions between the criteria (Abdul et al. 2024). Therefore, sensitive evaluations cannot be conducted with these techniques to compute the weights of the determinants of charging infrastructure for electric vehicles. (iii) In this study, a new decision-making model is developed. In this model, the importance weights of the experts whose opinions are obtained are determined. In this process, the AI application is integrated into the decision-making model. In this way, the importance weights of the experts are calculated by taking into consideration variables such as the education level and work experience of the experts. It is seen that this situation contributes to the literature in many ways. In traditional decision-making models, the weights of the experts are usually determined subjectively. In this study, a more objective method is developed using AI. Considering factors such as the education level and work experience of the experts in weighting can make the decisions more accurate and reliable. Similarly, the integration of the AI application into the decision-making model provides a significant innovation in the model creation process. Thanks to the AI integration, expert evaluations can be optimized by effectively analyzing large data sets. Variables such as the education level and work experience can change dynamically in the decision-making processes. Therefore, this model can optimize the effect of these variables. Thus, the decision-making process can be made more dynamic. (iv) Analysis with spherical fuzzy numbers also provides some advantages to the model. These numbers are one of the new generation fuzzy set theory structures used in multi-criteria decision-making processes. Spherical fuzzy numbers offer a more flexible and powerful structure compared to classical fuzzy sets and their advanced types such as intuitionistic fuzzy sets and Pythagorean fuzzy sets (Bonab et al. 2023). Unlike others, spherical fuzzy numbers can simultaneously define the membership degree, non-membership and hesitancy degrees of an element. In contrast, in classical fuzzy sets, only the membership degree is expressed as uncertainty (Haseli et al. 2024). In intuitionistic and Pythagorean fuzzy sets, anti-membership is taken into consideration. In this way, spherical fuzzy numbers can manage the uncertainty process much more effectively. In other words, spherical fuzzy sets are more powerful for modeling more complex relationships and uncertainties in decision-making processes. Therefore, spherical fuzzy numbers can offer a wider range of solutions in cases where other fuzzy set approaches are lacking.

The following section includes literature review. After that, proposed methodology is explained. Analysis results are presented in the next part. Discussion and conclusion are given in the final parts.

2 Literature review on innovative financial solutions

The main indicators of effective innovative financial solutions are evaluated in this section. The summary of this literature review is indicated in Table 8. Blockchain technology is one of the effective financing techniques for electric vehicle charging infrastructure investments. Blockchain is an immutable, verifiable, and distributed ledger that allows trustless entities to transact with each other without trusting a central third party and without the issue of a single point of failure (Duong et al. 2024; Baza et al. 2021). Since blockchain technology uses cryptographic public keys to identify users, it provides the anonymous identity of users to other participating users for security purposes and offers many benefits to electric vehicles in terms of data security, privacy, transparency, visibility, and immutability for the provision of energy trading services (Akanfe et al. 2024; Zhu et al. 2024). As a matter of fact, this technology has shown great potential in transforming and improving the transportation industry by ensuring the security and control of P2P-based transactions of electric vehicles (Al-Saif et al. 2021). Salmani et al. (2022) proposes a bi-directional electric charging approach based on the blockchain mechanism for participation in the P2P energy market and the provision of ancillary services to the grid, while taking into account the preferences of electric vehicle users makes the proposed planning model suitable for changing operating conditions. Ressi et al. (2024) and Xu et al. (2021) propose an anonymous blockchain-based system for charging-connected electric vehicles while ensuring the establishment of a multilateral security system between electric vehicles and electric vehicle charging service providers (EVSPs).

Another effective financing technique that is important for determining effective financing techniques for electric vehicle charging infrastructure investments is green bonds (Hu et al. 2024). While green bonds emerge as a new financial instrument to direct finance to sustainable investments, they are fixed-income securities whose proceeds are used to finance new and existing suitable projects that only contribute to environmental sustainability (Jain et al. 2024; Cicchiello et al. 2022). In addition, there is a secondary market where supply and demand determine the price of the green bond (Torvanger et al. 2021). Ma et al. (2024) aimed to investigate the impact of green bonds and green loans on CO2 emissions associated with Electric Vehicle (EV) minerals, with a special emphasis on Asia-Pacific Economic Cooperation (APEC) countries, and accordingly, green bond issuance is important in reducing CO2 emissions. It is concluded that there is a driving force. Likewise, Xu et al. (2023) and Cheng and Wu (2024) also confirmed that the issuance of green bonds and green economic growth in the sector can accelerate the green economic growth rate of agriculture.

Public-private partnership (PPP), one of the effective financing techniques for electric vehicle charging infrastructure investments, covers a wide range of public sector infrastructure while expressing an approach adopted to increase the economic value of infrastructure outputs (Almeile et al. 2024). In addition, the PPP model can also be considered an effective way to strengthen capital, reduce uncertainties related to operation and construction, and achieve a country's sustainable development goals (Sheng et al. 2020). In other words, the public-private partnership model is an important tool for the government to advocate the exploration of sustainable business models in the charging facilities sector, which not only reduces the financial pressure of the government but also benefits from the advanced management experience of private enterprises to improve service and charging performance (Hossin et al. 2024; Cui et al. 2018). Huang et al. (2022) tried to design a mechanism called "electric vehicle charging infrastructure/public-private partnership" for the operation of charging facilities, while also clarifying the responsibilities of the relevant actors, analyzing their willingness to cooperate, and examining the economics of the mechanism design. Tahir et al. (2024) and Song et al. (2021) emphasized the importance of coordinated charging facilities with the rapid growth of electric vehicles, while using an integrated system dynamics model that simulates the use of flexible concession periods in electric vehicle charging infrastructure public-private partnership projects.

Global funds are another important potential innovative solution for effective financing of electric vehicle charging infrastructure investments, while charging infrastructure in many geographies requires continuous support through public-private partnerships and various publicly financed subsidies (LaMonaca and Ryan 2022). While global funds have an impact on electric vehicle charging infrastructure investments in many ways. These are steps such as performing risk and return analyzes of projects and raising awareness among fund managers and investments. Resosudarmo et al. (2023) assessed Indonesia's potential to achieve energy transition goals and examines carbon market and pricing-related programs that are important in generating funds to support energy transition goals. Loans received from financial institutions are another important tool for effective financing of electric vehicle charging infrastructure investments. Because government cash refunds or discounted loans can help electric vehicle users cover electric vehicle supply equipment and installation costs (Gonzalez et al. 2024; Lopez-Behar et al. 2019). In other words, while financing the activities is a real challenge, alternatives are being sought to finance the activities, and here we encounter loans from financial institutions (Bohnsack et al. 2014). Sun and Tang (2022) examined the relationship between digital inclusive finance and sustainable economic growth and argue that digital inclusive finance; It is concluded that it supports sustainable economic growth by increasing the loans received from financial institutions, the consumption amount of residents and the savings amount of residents.

Venture capital financing is another important tool for financing electric vehicle charging infrastructure. The effect of this innovative method can be increased in some cases. Examples of these situations include increasing the number of funds, improving incentives, and creating platforms such as sharing information and experience. As a matter of fact, the interaction of project developers with the remaining stakeholders, including the government, is a very important element when making decisions regarding the financing approach (Mele et al. 2024; Lam and Law 2018). In addition, venture capital shows a demand-side assessment of technology evolution, focusing more on the background of the innovation process, and the involvement of venture capitalists; It can have positive effects on a company's product marketing, strategic decisions and management control systems (Fang et al. 2024; Kou et al. 2020). Yi et al. (2023) aimed to empirically examine the effect of venture (risk) capital on the open innovation of Chinese enterprises, they concluded that venture capital can significantly promote the open innovation of enterprises. While Shao and Sun

(2021) evaluated how entrepreneurs' social capital facilitates venture capital financing for their start-ups, they do so by incorporating three dimensions of social capital (structural, cognitive, and relational dimensions) and three stages of the financing decision (access, negotiation, and action stages) are taken into consideration.

As a result of the literature review, it is possible to reach some important points. The effectiveness of charging stations helps increase the use of electric vehicles. Therefore, it is important to ensure the effectiveness of these projects. In this context, effective financing should be provided for these projects to solve the high-cost problem. Thus, it is necessary to determine which financing techniques are more suitable for these projects. However, the number of studies in this field in the literature is quite low. Hence, a new study is needed to determine the most appropriate financing methods for charging station investments of electric vehicles. It is understood that this issue is an important missing part in the literature. This study aims to determine the most appropriate financing method for these investments with an original fuzzy decision-making model. Thus, it will be possible to satisfy this gap mentioned in the literature.

3 Proposed methodology

In this article, innovative investment suggestions required to charging infrastructure for electric vehicles are aimed. A multi-criteria decision-making methodology is proposed to identify optimal innovative solution proposals. One of the data sources of this method is the evaluations of experts. Although giving equal distance to experts' evaluations is accepted in the literature, it has been criticized in recent years. The main reason for this is that experts' experiences and knowledge levels are different. Therefore, machine learning technique is recommended to objectively determine expert weights. In this technique, the feature matrix can be converted into a weight matrix with the help of the dimension reduction algorithm. Another stage of the proposed methodology is to include the uncertainty in expert opinions into the analysis. In mathematics, uncertainty measurement can be evaluated with fuzzy set theory. Therefore, spherical fuzzy numbers are used to integrate the uncertainty in expert opinions. The decision matrix is obtained with the fuzzy opinions of the experts. Afterwards, effective criteria must be determined in the charging infrastructure of electric vehicles. For this purpose, the criteria on the charging infrastructure are weighted objectively with the CRITIC method. CRITIC method is a statistics-based multi-criteria decision-making technique used in criterion weighting with correlation between criteria and standard deviation values. In the final stage of the proposed methodology, RATGOS, one of the current ranking methods in the multi-criteria decision-making literature, is used to determine the optimal alternative. In ranking methods, calculating metric distance based on expert opinions is criticized. Therefore, the RATGOS method, which takes the similarity ratio into account, is preferred. The proposed methodology, which consists of 4 stages, is detailed, and summarized in Fig. 1.

The steps and formulations of the proposed methodology shown in Fig. 1 are presented under subheadings. In the proposed methodology, spherical fuzzy sets are preferred. In spherical fuzzy sets, an element has membership (μ), non-membership (v) and hesitancy (π) degrees. Accordingly, A SFS must satisfy in Eq. (1).

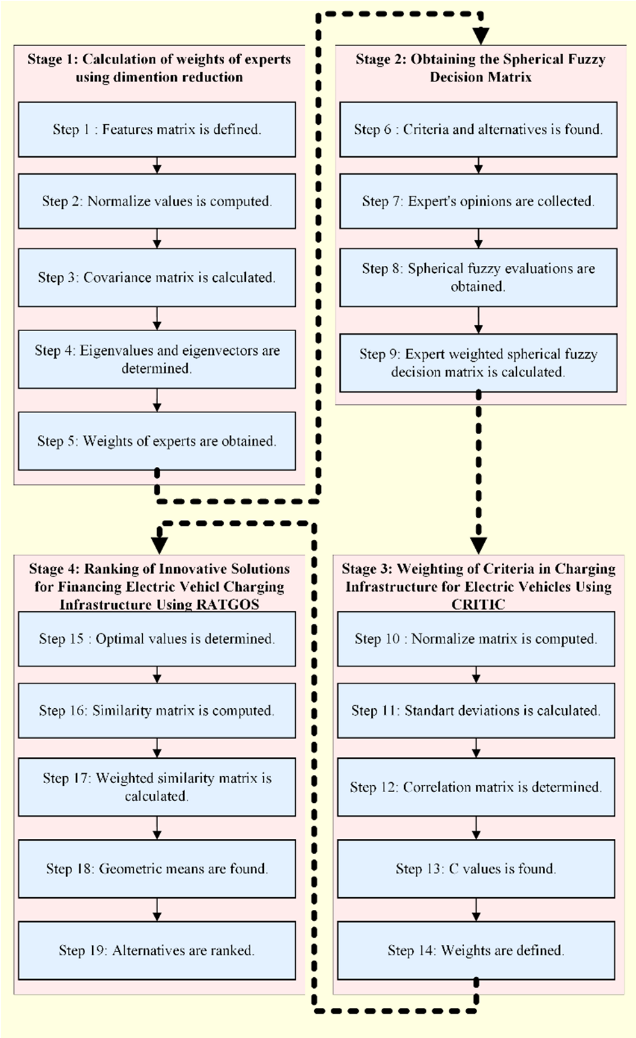

Fig. 1 Flowchart of proposed methodology

$$0 \leq \mu^{2} + v^{2} + \pi^{2} \leq 1 \tag{1}$$

Basic operations, distance measures and aggregation operators are formulated in Eq. (2).

$$\begin{aligned}
D\left(\tilde{A}, \tilde{B}\right) &= \arccos\left\{1 - \tfrac{1}{2}\left(\left(\mu_{\tilde{A}} - \mu_{\tilde{B}}\right)^2 + \left(v_{\tilde{A}} - v_{\tilde{B}}\right)^2 + \left(\pi_{\tilde{A}} - \pi_{\tilde{B}}\right)^2\right)\right\} \\
\tilde{A} + \tilde{B} &= \left\{\left(\mu_{\tilde{A}}^2 + \mu_{\tilde{B}}^2 - \mu_{\tilde{A}}^2\mu_{\tilde{B}}^2\right)^{0.5}, v_{\tilde{A}}^2 v_{\tilde{B}}^2, \left(\left(1 - \mu_{\tilde{B}}^2\right)\pi_{\tilde{A}}^2 + \left(1 - \mu_{\tilde{A}}^2\right)\pi_{\tilde{B}}^2 - \pi_{\tilde{A}}^2\pi_{\tilde{B}}^2\right)^{0.5}\right\} \\
\tilde{A} \times \tilde{B} &= \left\{\mu_{\tilde{A}}^2\mu_{\tilde{B}}^2, \left(v_{\tilde{A}}^2 + v_{\tilde{B}}^2 - v_{\tilde{A}}^2 v_{\tilde{B}}^2\right)^{0.5}, \left(\left(1 - v_{\tilde{B}}^2\right)\pi_{\tilde{A}}^2 + \left(1 - v_{\tilde{A}}^2\right)\pi_{\tilde{B}}^2 - \pi_{\tilde{A}}^2\pi_{\tilde{B}}^2\right)^{0.5}\right\} \\
\lambda\, \tilde{A} &= \left\{\left(1 - \left(1 - \mu_{\tilde{A}}^2\right)^{\lambda}\right)^{0.5}, v_{\tilde{A}}^{\lambda}, \left(\left(1 - \mu_{\tilde{A}}^2\right)^{\lambda} - \left(1 - \mu_{\tilde{A}}^2 - \pi_{\tilde{A}}^2\right)^{\lambda}\right)^{0.5}\right\} \\
\tilde{A}^{\lambda} &= \left\{\mu_{\tilde{A}}^{\lambda}, \left(1 - \left(1 - v_{\tilde{A}}^2\right)^{\lambda}\right)^{0.5}, \left(\left(1 - v_{\tilde{A}}^2\right)^{\lambda} - \left(1 - v_{\tilde{A}}^2 - \pi_{\tilde{A}}^2\right)^{\lambda}\right)^{0.5}\right\}
\end{aligned} \tag{2}$$

3.1 Dimension reduction algorithm with machine learning

Machine learning is a subset of artificial intelligence that creates systems that learn from a data set. Its main purpose is to gain the ability to learn and recognize patterns by using data related to a specific problem. Dimension reduction algorithms are techniques that help reduce the size of a data set by reducing the number of variables in a data set. In connection with machine learning, dimension reduction algorithms are preferred to better understand and model the features of a data set. There is more than one feature in a data set containing demographic information of experts. It is possible to reduce this data set to a single variable with the dimension reduction algorithm. The new score for each expert contains information based on demographic information. Therefore, it is suggested that the new scores be used as experts' importance weights. Calculating experts' weights using dimensionality reduction is outlined below (Vieira Sobrinho et al. 2024).

In *Step 1*, the feature matrix (F) is defined, which accepts the demographic information of experts as elements. What is meant by demographic information is variables such as the age, experience and educational status of the experts (Berahmand et al. 2024). Since these characteristics of experts affect their level of knowledge, they play an important role in prioritizing their evaluations. The feature matrix is defined in Eq. (3).

$$F = \begin{bmatrix} f_{11} & \cdots & f_{1n} \\ \vdots & \ddots & \vdots \\ f_{m1} & \cdots & f_{mn} \end{bmatrix} \tag{3}$$

Step 2 is concerned with computing normalized values. The feature matrix is centralized using Eqs. (4) and (5). Afterwards, a normalized matrix (N) is obtained from the centralized values (c) with the help of Eqs. (6) and (7).

$$c_{ij} = f_{ij} - \bar{f}_j \tag{4}$$

$$\bar{f}_j = \frac{\sum_{i=1}^{m} f_{ij}}{m} \tag{5}$$

$$N = \begin{bmatrix} n_{11} & \cdots & n_{1n} \\ \vdots & \ddots & \vdots \\ n_{m1} & \cdots & n_{mn} \end{bmatrix} \tag{6}$$

$$n_{ij} = \frac{c_{ij}}{\sqrt{\sum_{i=1}^{m} c_{ij}^2}} \tag{7}$$

Step 3 involves calculating the covariance matrix (*CM*). By using Eqs. (8)-(11), covariance values between variables are calculated.

$$CM = \begin{bmatrix} cov(n_1, n_1) & \cdots & cov(n_1, n_n) \\ \vdots & \ddots & \vdots \\ cov(n_n, n_1) & \cdots & cov(n_n, n_n) \end{bmatrix} \tag{8}$$

$$cov(x, y) = \frac{\sum_{i=i}^{m} (x_i - \bar{x})(y_i - \bar{y})}{n} \tag{9}$$

$$\bar{x}_j = \frac{\sum_{i=1}^{m} x_{ij}}{m} \tag{10}$$

$$\bar{y}_j = \frac{\sum_{i=1}^{m} y_{ij}}{m} \tag{11}$$

In *Step 4*, the eigenvalues (λ) and eigenvectors (*V*) of the covariance matrix are determined. The solution set of Eq. (12) gives the eigenvalues of the covariance matrix.

$$Det(CM - \lambda I) = 0 \tag{12}$$

Where, *Det* denotes the determinant of the matrix, while *I* denotes the identity matrix. With Eq. (13), the biggest of the eigenvalues is found. Thus, the most important component of the feature matrix is obtained. In other words, it is ensured that the newly created dimension contains the biggest information in the feature matrix.

$$\lambda_{max} = \max_i \lambda_i \tag{13}$$

Equation (14) is also used to find the eigenvector.

$$(CM - \lambda_{max} I) * V = 0 \tag{14}$$

Step 5 is about obtaining the experts' weights. In Eq. (15), the feature matrix is multiplied by the eigenvectors. As a result of this multiplication, a new vector space (*H*) is obtained.

In other words, a new matrix is created that contains the information of the old matrix at the maximum level. The weights of the experts (*ew*) are computed by normalizing the elements of the new space matrix with Eq. (16).

$$H = F * V \tag{15}$$

$$ew_i = \frac{h_i}{\sum_{i=1}^{m} h_i} \tag{16}$$

where h_i are the elements of the H. There are some limitations to obtaining the weights of experts with this algorithm. First of all, there must be a data set containing at least two features. Thus, a one-dimensional structure can be obtained. In addition, the data must be numerical or quantifiable. Dimension reduction analysis cannot be performed with non-standardizable variables. In summary, the proposed approach can be used for data-based expert weighting.

3.2 Spherical fuzzy decision matrix

The process in multi-criteria decision-making methods begins with obtaining the decision matrix. In studies that accept expert opinions as data, the weighted average of expert opinions can be computed. To include the uncertainty in expert opinions in the analysis, the decision matrix must be obtained with fuzzy numbers. The steps of the relevant stage with spherical fuzzy sets are summarized below (Büyüközkan et al. 2024).

Step 6 includes criteria and alternatives. The literature on the subject is examined. A set of criteria and alternatives is created through literature review and field research. Afterwards, the obtained variables are evaluated by experts. If it is missing, research is done. This process continues until all the variables are determined. In *Step 7*, expert opinions are collected. The experts identified in the first section are evaluated alternatives on the basis of criteria. The linguistic expressions used in the evaluation are shown in Table 1.

In *Step 8*, spherical fuzzy evaluations are obtained. For each expert, each of their evaluations is replaced by their fuzzy number counterparts in Table 1. Where, μ, v and π values are membership, non-membership and hesitancy degrees, respectively. $0 \le \mu^2 + v^2 + \pi^2 \le 1$. *Step 9* is about calculating the expert weighted spherical fuzzy decision matrix. Using fuzzy expert opinions and expert weights, an expert-weighted spherical fuzzy decision matrix is calculated with the help of Eq. (17). The expert-weighted spherical fuzzy decision matrix (D) is shown in Eq. (18).

Table 1 Linguistic expressions

Term	μ	v	π
Absolutely more importance (AMI)	0.9	0.1	0.1
Very high importance (VHI)	0.8	0.2	0.2
High importance (HI)	0.7	0.3	0.3
Slightly more importance (SLI)	0.6	0.4	0.4
Equally importance (EI)	0.5	0.5	0.5
Slightly low importance (SLI)	0.4	0.6	0.4
Low importance (LI)	0.3	0.7	0.3
Very low importance (VLI)	0.2	0.8	0.2
Absolutely low importance (ALI)	0.1	0.9	0.1

$$SWAM = \left\{ \left[1 - \prod {}_{i=1}^{k} \left(1 - \mu {}_{i}^{2}\right)^{ew_i} \right]^{\frac{1}{2}}, \prod {}_{i=1}^{k} v_i^{ew_i}, \left[\prod {}_{i=1}^{k} \left(1 - \mu {}_{i}^{2}\right)^{ew_i} - \prod {}_{i=1}^{k} \left(1 - \mu {}_{i}^{2} - \pi {}_{i}^{2}\right)^{ew_i} \right]^{\frac{1}{2}} \right\} \tag{17}$$

$$D = \begin{bmatrix} d_{11} & \cdots & d_{m1} \\ \vdots & \ddots & \vdots \\ d_{1n} & \cdots & d_{mn} \end{bmatrix} \tag{18}$$

In this process, d is the element of the D and is a spherical fuzzy number.

3.3 Spherical fuzzy CRITIC

CRITIC method is used to weight criteria using the linear relationship coefficient. The main advantage of the method is that it uses statistical methods. In addition, it is accepted as an objective weighting method in the literature. This allows more realistic results to be obtained. The steps of the CRITIC method with spherical fuzzy numbers are as follows (Yan et al. 2024).

In *Step 1*, Normalize matrix (X) is computed. D is normalized using Eqs. (19) and (20).

$$X = \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{m1} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{1n} & \cdots & \tilde{x}_{mn} \end{bmatrix} \tag{19}$$

$$\widetilde{x}_{ij} = \begin{cases} \dfrac{1 - \frac{\mu {}_{ij}^{2} \mathrm{X} \mu {}_{-}^{2} + v_{ij}^{2} \mathrm{X} v_{-}^{2} + \pi {}_{ij}^{2} \mathrm{X} \pi {}_{-}^{2}}{\mu {}_{ij}^{2} \mathrm{V} \mu {}_{-}^{2} + v_{ij}^{2} \mathrm{V} v_{-}^{2} + \pi {}_{ij}^{2} \mathrm{V} \pi {}_{-}^{2}}}{1 - \frac{\mu {}_{-}^{2} \mathrm{X} \mu {}_{+}^{2} + v_{-}^{2} \mathrm{X} v_{+}^{2} + \pi {}_{-}^{2} \mathrm{X} \pi {}_{+}^{2}}{\mu {}_{-}^{2} \mathrm{V} \mu {}_{+}^{2} + v_{-}^{2} \mathrm{V} v_{+}^{2} + \pi {}_{-}^{2} \mathrm{V} \pi {}_{+}^{2}}} \; for\, benefit\, critera \\ \dfrac{1 - \frac{\mu {}_{ij}^{2} \mathrm{X} \mu {}_{+}^{2} + v_{ij}^{2} \mathrm{X} v_{+}^{2} + \pi {}_{ij}^{2} \mathrm{X} \pi {}_{+}^{2}}{\mu {}_{ij}^{2} \mathrm{V} \mu {}_{+}^{2} + v_{ij}^{2} \mathrm{V} v_{+}^{2} + \pi {}_{ij}^{2} \mathrm{V} \pi {}_{+}^{2}}}{1 - \frac{\mu {}_{-}^{2} \mathrm{X} \mu {}_{+}^{2} + v_{-}^{2} \mathrm{X} v_{+}^{2} + \pi {}_{-}^{2} \mathrm{X} \pi {}_{+}^{2}}{\mu {}_{-}^{2} \mathrm{V} \mu {}_{+}^{2} + v_{-}^{2} \mathrm{V} v_{+}^{2} + \pi {}_{-}^{2} \mathrm{V} \pi {}_{+}^{2}}} \; for\, cost\, criteria \end{cases} \tag{20}$$

Where $(\mu {}_{-}, v_{-}, \pi {}_{-})$ means the minimum optimal value, $(\mu {}_{+}, v_{+}, \pi {}_{+})$ is the maximum optimal value. The X notation represents the multiplication operation while the V notation defines the maximum operation. *Step 11* covers calculating standard deviations. With Eq. (21), the standard deviation $(\widetilde{\sigma} {}_{j})$ of each criterion is calculated.

$$\widetilde{\sigma} {}_{j} = \sqrt{\frac{1}{n-1} \sum {}_{j=1}^{n} \left(\widetilde{x}_{ij} - \overset{\sim}{\bar{x}}_{j} \right)^{2}} \quad i = 1, 2, \ldots, m \tag{21}$$

Step 12 is about determining the correlation matrix. The relationship coefficients $(\widetilde{\rho} {}_{jk})$ between the criteria are computed with Eqs. (22) and (23).

$$\widetilde{\rho} {}_{jk} = \sum {}_{i=1}^{m} \left(\widetilde{x}_{ij} - \overset{\sim}{\bar{x}}_{j} \right) \left(\widetilde{x}_{ik} - \overset{\sim}{\bar{x}}_{k} \right) / \sqrt{\sum {}_{i=1}^{m} \left(\widetilde{x}_{ij} - \overset{\sim}{\bar{x}}_{j} \right)^{2} \sum {}_{i=1}^{m} \left(\widetilde{x}_{ik} - \overset{\sim}{\bar{x}}_{k} \right)^{2}} \tag{22}$$

$$\bar{\tilde{x}}_j = \frac{1}{n}\sum\nolimits_{j=1}^{n}\tilde{x}_{ij} \quad i = 1,2,\ldots,m \tag{23}$$

In *Step 13*, *C* values are found. Equation (24) shows the calculation of *C* values.

$$\tilde{C}_j = \tilde{\sigma}_j \sum\nolimits_{k=1}^{n}(1 - \tilde{\rho}_{jk}) \quad j = 1,2,\ldots,n \tag{24}$$

With *Step 14*, the weights (*w*) are defined. Criterion weights are obtained by normalizing *C* values with Eq. (25).

$$\tilde{w}_j = \frac{\tilde{C}_j}{\sum\nolimits_{j=1}^{n}\tilde{C}_j} \tag{25}$$

3.4 Spherical fuzzy RATGOS

RATGOS is a multi-criteria decision-making technique that considers the geometric mean of similarities to the optimal value. The innovative aspect of the method is that it takes geometric ratio into account. Additionally, the biggest advantage of the method is that it does not use metric distances. The nature of linguistic expressions being ordinal measurement may cause errors in metric distance calculations. In this respect, the RATGOS method provides more realistic results than methods such as TOPSIS and VIKOR. The version of RATGOS integrated with spherical fuzzy numbers is described below (Dinçer et al. 2023).

In *Step 15*, the optimal values are determined with Eq. (26). Equation (27) is the score value of a spherical fuzzy number (Oflaz et al. 2023).

$$optimal = \begin{cases} \{(\mu, v, \pi)\,|\max(S(Z_i)\} \ \ for\ benefit \\ \{(\mu, v, \pi)\,|\min(S(Z_i)\} \ \ for\ cost \end{cases} \tag{26}$$

$$S(\{\mu,\ v,\ \pi\}) = (2\mu - \pi)^2 - (v - \pi)^2 \tag{27}$$

Step 16 is about computing the similarity matrix (*B*). The similarity matrix is obtained by dividing the elements of *D* by the optimal value. However, division is not defined in spherical fuzzy numbers (Yüksel et al. 2024). Therefore, the score value of the optimal value is calculated. Then, the product of the spherical fuzzy number and the positive number is applied with Eq. (28). The elements of the similarity matrix are calculated with Eq. (29) where λ is positive number.

$$\lambda\,\tilde{A} = \left\{\left(1 - \left(1 - \mu_A^2\right)^{\lambda}\right)^{0.5}, v_A^{\lambda}, \left(\left(1 - \mu_A^2\right)^{\lambda} - \left(1 - \mu_A^2 - \pi_A^2\right)^{\lambda}\right)^{0.5}\right\} \tag{28}$$

$$\tilde{b}_{ij} = \frac{1}{S\,(optimal)}\,\tilde{d}_{ij} \tag{29}$$

Step 17 involves calculating the weighted similarity matrix (*K*). *B* is multiplied by the criterion weights using Eq. (28). As a result of the multiplication, the *K* in Eq. (30) is obtained.

$$K = WB \tag{30}$$

With *Step 18*, geometric means (*Geo*) are found. For each alternative, spherical fuzzy geometric mean values (*SGM*) are calculated using Eqs. (31) and (32).

$$Geo = \sqrt[m]{\prod\nolimits_{j=1}^{m} k_{ij}} \tag{31}$$

$$SGM(A_1, A_2, \ldots, A_m) = \left\{\prod\nolimits_{i=1}^{m} \mu_{A_i}^{\frac{1}{m}}, \left[1 - \prod\nolimits_{i=1}^{m} \left(1 - v_{A_i}^2\right)^{\frac{1}{m}}\right]^{0.5}, \left[\prod\nolimits_{i=1}^{m} \left(1 - v_{A_i}^2\right)^{\frac{1}{m}} - \prod\nolimits_{i=1}^{m} \left(1 - v_{A_i}^2 - \pi_{A_i}^2\right)^{\frac{1}{m}}\right]^{0.5}\right\} \tag{32}$$

In *Step 19*, the alternatives are ranked. Score values of spherical fuzzy geometric means are obtained with Eq. (27). Finally, the score values are sorted from largest to smallest.

4 Analysis results

The results of the analyzes carried out to determine innovative financial solution strategies for charging infrastructures of electric vehicles are presented under subheadings.

4.1 Calculation of weights of experts using dimension reduction

The weighting of experts in multi-criteria decision-making techniques is an important issue. Machine learning technique is preferred for expert weighting in the study. First, people with academic studies on the infrastructure of electric vehicles or white-collar people with high field experience are determined. These experts are then contacted via e-mail and an interview invitation is sent. Interviews are held with experts who agree. While face-to-face meetings are planned with experts in geographical proximity, meetings are held online with remote experts. In these interviews, demographic information of the experts is obtained as part of *Step 1*. With Eq. (3), the feature matrix identified from the experts' demographic information is given in Table 2.

The experience periods of the three experts participating in the interview are 19, 16 and 18, respectively. All three experts are senior managers working in the field. As a result of *Step 2*, the values of the feature matrix are normalized using Eqs. (4)-(7). For analysis, the education variable is digitized. Coding is performed as 1 for Bachelor, 2 for MSc and 3 for doctorate. Calculations are made according to this coding. The normalized matrix is given in Table 9. Then, with the help of Eqs. (8)-(11), the covariance matrix of the variables mentioned in *Step 3* is calculated. The covariance matrix is shown in Table 10. In the *Step 4* process, the eigenvalues are determined with Eq. (12). Eigenvalue results are exhibited in

Table 2 Features matrix

	Age	Experience	Education	Salary
Expert 1	42	19	Bachelor	2200
Expert 2	40	16	MSc	2250
Expert 3	38	18	MSc	2000

Table 3 Weights of the experts

	Weights
Expert 1	0.342
Expert 2	0.348
Expert 3	0.31

Table 4 Criteria and alternatives for financing electric vehicle charging infrastructure

Criteria		Alternatives	
Define	Codes	Define	Codes
Risk Profile	RIPO	Blockchain technology	BLTE
Cost Evaluation	CSEV	Green bond	GRBN
Size of the Project	SIPR	Public-private partnerships	PPPS
Duration of the Project	PRPJ	Global funds	GLFS
Potential Income	PONC	Venture capital financing	VCFI
Government Policies	GVPC	Loans from financial institutions	LFIN

Table 11. The largest of the eigenvalues is found with Eq. (13) and the result is the second eigenvalue with a value of 0.832. The eigenvector corresponding to the second eigenvalue is obtained by Eq. (14). The results are detailed in Table 12. As a result of *Step 5*, expert weights are obtained by Eqs. (15) and (16). The weights of the experts are shared in Table 3.

According to Table 3, Expert 2's opinions are considered more important than other experts. Having both high income and education has brought the expert to the fore. Additionally, Expert 2 ranks second in terms of age. In addition, Expert 3 is the expert with the lowest importance rating. The importance weight of this expert, who has both a low income and a young age, is 0.31.

4.2 Obtaining the spherical fuzzy decision matrix

With *Step 6*, effective criteria and innovative financial solutions are found in the charging infrastructures of electric vehicles. The results obtained from the literature review are presented to experts. The alternatives and criteria approved by experts are presented in Table 4.

To determine the most suitable financial product for electric vehicle charging investments, some factors need to be taken into consideration. In this context, 6 different variables are determined by considering the points emphasized by similar studies in the literature. The risk status of the project is important in understanding the most effective financial product (Benmouna et al. 2024). On the other hand, the cost effectiveness of these projects is another factor that should be considered when choosing financial products (Ma et al. 2024). Moreover, the amount and duration of the projects can also affect the selection of financing products (Baek et al. 2024). Finally, the possible return of the project and government supports also enable the determination of more effective financial products (Cheng et al. 2024; Feng et al. 2024). Within the framework of *Step 7*, each alternative is evaluated separately by experts based on criteria. The evaluations of three experts are reported in Table 13. For *Step 8*, expert evaluations are converted into fuzzy numbers in Table 1. As a result of *Step 9*, the expert-weighted spherical fuzzy decision matrix is calculated by Eqs. (17) and (18).

The expert-weighted spherical fuzzy decision matrix (D) used for CRITIC and RATGOS is exhibited in Table 5.

4.3 Weighting of criteria in charging infrastructure for electric vehicles using spherical fuzzy CRITIC

By *Step 10*, D is normalized using Eqs. (19) and (20). All criteria are benefit criteria. The normalized matrix is given in Table 14. For *Step 11*, Eq. (21) is used, and the standard deviation of each criterion is calculated. Standard deviations for the criteria are shown in Table 15. In *Step 12*, Eqs. (22) and (23) gives the result of the correlation matrix of the criteria. The correlation matrix is depicted in Table 16. In *Step 13*, Eq. (24) is used, and the C values are found as a result. Finally, at the end of *Step 14*, the weights are defined. Equation (25) is used to calculate the criterion weights. C values and criterion weights are summarized in Table 6.

According to the weights in Table 6, the order of importance of the criteria is graphed in Fig. 2.

According to Table 6; Fig. 2, the most effective criterion in the innovative financial solution for the charging infrastructure of electric vehicles is determined as “potential income” because it is the criterion with the greatest weight. When the importance level is examined, it is determined that the “risk profile” criterion is in second place with the importance weight of 0.179. According to these results, potential income should be taken into consideration when determining the financial product in the charging infrastructure of electric vehicles. Investments with high potential income should be preferred. At the same time, the investor’s risk profile is also important. Risk preference affects the financial solution to be chosen.

4.4 Ranking of innovative solutions for financing electric vehicles charging infrastructure using spherical fuzzy RATGOS

The RATGOS method starts with determining the optimal values in *Step 15*. Equations (26) and (27) are used to find the optimal values of D. With *Step 16*, Eqs. (28) and (29) are used and the similarity matrix is calculated. The similarity matrix is detailed in Table 17. At the end of *Step 17*, the weighted similarity matrix is calculated. The results are displayed in Table 18. With *Step 18*, geometric means are found by Eqs. (31) and (32). The spherical fuzzy geometric mean of each alternative is given in Table 7. Additionally, by Eq. (27), spherical fuzzy geometric means are defuzzified.

Considering the *GEO* values in Table 7, the alternatives are ranked in *Step 19*. The rankings of the alternatives are shown in Fig. 3.

As seen in Table 7; Fig. 3, the most sustainable solution among the innovative strategies for financing the charging infrastructure of electric vehicles is “blockchain technology” because it has the highest *GEO* value. The solution with the second highest *GEO* value is “public-private partnerships”. According to the ranking result, blockchain technology is the alternative with higher potential income and risk. Moreover, partnership is another optimal solution in innovative financing solution according to the risk profile. Infrastructure financing of electric vehicles can be provided through public or private partnerships.

Table 5 The expert-weighted spherical fuzzy decision matrix

	RIPO			CSEV			SIPR			PRPJ			PONC			GVPC		
BLTE	0.73	0.29	0.28	0.39	0.62	0.41	0.77	0.23	0.23	0.49	0.52	0.42	0.38	0.68	0.29	0.83	0.18	0.22
GRBN	0.24	0.76	0.24	0.72	0.30	0.29	0.32	0.72	0.35	0.77	0.25	0.19	0.78	0.25	0.15	0.60	0.44	0.28
PPPS	0.56	0.47	0.33	0.86	0.15	0.16	0.78	0.25	0.15	0.80	0.20	0.23	0.14	0.87	0.14	0.67	0.33	0.33
GLFS	0.43	0.59	0.35	0.67	0.33	0.33	0.45	0.57	0.36	0.39	0.63	0.40	0.53	0.50	0.37	0.69	0.35	0.23
VCFI	0.73	0.27	0.30	0.35	0.66	0.36	0.74	0.29	0.20	0.29	0.73	0.30	0.68	0.38	0.19	0.58	0.45	0.30
LFIN	0.72	0.29	0.26	0.33	0.71	0.36	0.27	0.75	0.28	0.46	0.57	0.40	0.67	0.34	0.36	0.70	0.32	0.21

4.5 Comparative sensitivity analyses

In the multi-criteria decision-making methodology, the consistency and validity of the ranking of alternatives are tested. This test is usually in the form of comparing the results of the analyses made with a second ranking method or with different number systems. In this context, the TOPSIS method is preferred as a second method for comparing the results. In addition, Pythagorean fuzzy numbers are selected for different number systems. Thus, the analysis is repeated with binary combinations and the ranking results are obtained. The ranking results are visualized in Fig. 4.

As can be seen in Fig. 4, the rankings are consistent even though the method and numbering system have changed. In addition to the comparison results, sensitivity analysis is also performed. Thus, it is desired to examine the change in the ranking of the alternatives due to the change in the weights of the criteria. In this context, the SF-RATGOS method is repeated with small changes in the weights of the criteria. The alternative rankings obtained with ten different criteria weight scenarios are presented in Fig. 5.

In Fig. 5, it is seen that the ranking of the alternatives does not change in different criterion weight scenarios.

5 Discussion

As a result of the analysis, the most important factor affecting electric vehicle charging infrastructure investment financing is found to be potential income. The increase in demand for electric vehicles also increases the demand for charging these vehicles. Therefore, an increase in revenue can also be observed. Apart from this, the correct location of charging stations is important in terms of potential income. In addition, the scope of government incentives and regulations may influence the decision to invest. This contributes to an increase in potential income. Zhou et al. (2023a) examined the electric vehicle system in Japan and the impact of battery charging on system performance. The results of the study using the agent-based simulation method show that potential return is important for the investment process. Zhou et al. (2023a) evaluated the profitability of electric vehicle fast charging stations. It is argued that with the recent growth in demand for electric vehicles, there has been an increase in potential revenue. Eltamaly (2023) stated that there is a relationship between investments in electric vehicles and potential returns.

Risk profile is found to be another important factor affecting investment in electric vehicle charging infrastructure. High-risk profile investors tend to invest in innovative projects. In this context, innovative projects have higher return potential as well as higher risk. This may directly affect the investment decision. Furthermore, the risk profile and the return period of the investment should be compatible. A higher risk profile requires a longer return on investment. Schulz-Mönninghoff and Evans (2023) conducted a study on the reuse and recycling of electric vehicle batteries in Germany. It is underlined that the net present value of the project may change depending on the risk profile. Al-obaidi and Farag (2023) inves-

Table 6 C values and criterion weights

Criteria	C	W
RIPO	2.483	0.179
CSEV	2.271	0.164
SIPR	2.358	0.170
PRPJ	2.170	0.157
PONC	2.624	0.189
GVPC	1.948	0.141

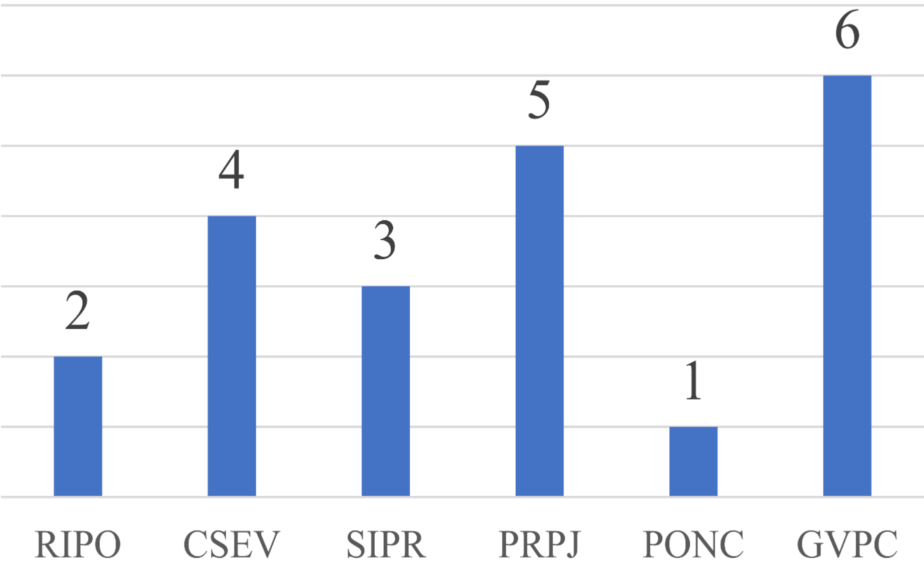

Fig. 2 Results of weighting

Table 7 Geometric means

Alternatives	Spherical Fuzzy Geometric Means			GEO
BLTE	0.189	0.930	0.132	-0.577
GRBN	0.171	0.939	0.107	-0.637
PPPS	0.188	0.927	0.096	-0.612
GLFS	0.163	0.942	0.128	-0.624
VCFI	0.172	0.939	0.111	-0.632
LFIN	0.157	0.946	0.123	-0.640

tigated the charging problems of electric vehicles. It is stated that the risk profile is a determinant of the return on investment.

The results of the analysis show that the solution for the most optimal innovative investment is Blockchain Technology. Financing with blockchain technologies has several advantages. First, it has lower transaction costs compared to traditional methods. Furthermore,

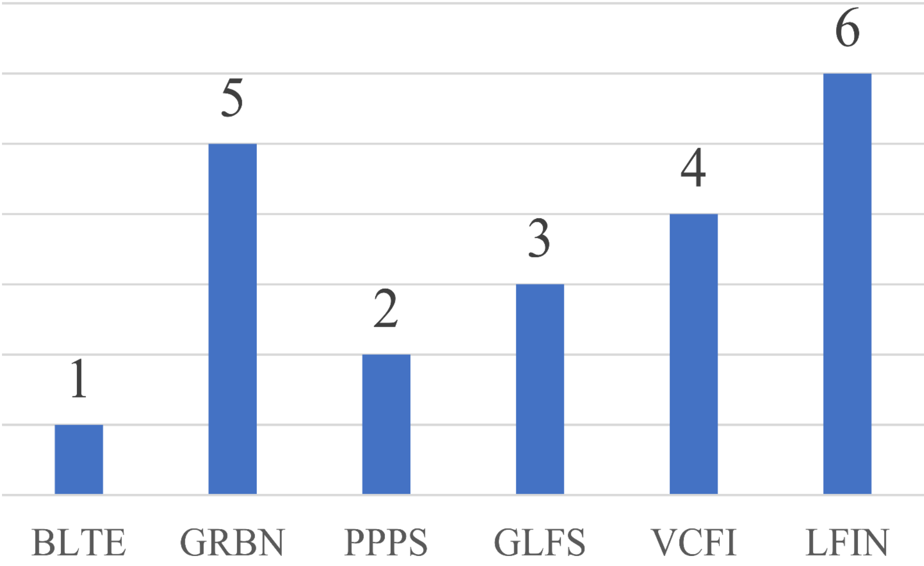

Fig. 3 Results of ranking

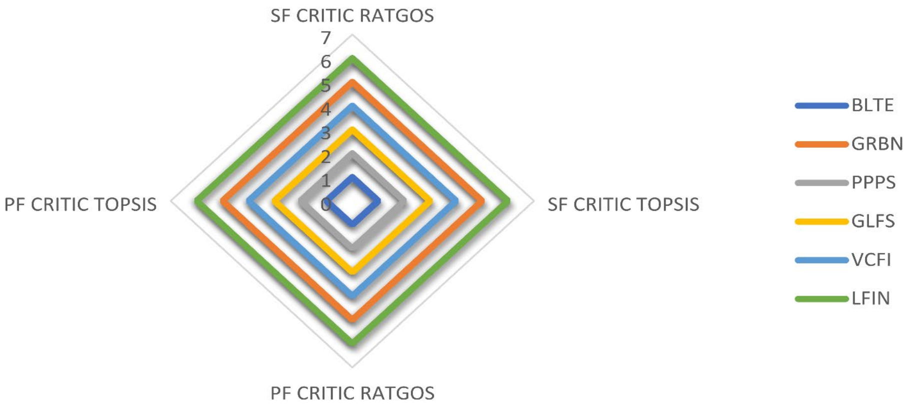

Fig. 4 Comparative ranking results

it allows investors to reach larger audiences by removing geographical boundaries. Faster execution of transactions is possible thanks to these technologies. It also makes it possible to track all transactions transparently. Zhao et al. (2023) examined the role of blockchain technology in the inclusion of the new energy vehicle industry in carbon trading. It is stated that Blockchain technologies, which have a strong technological infrastructure and transparency features, are suitable tools for this situation. Cavalcante et al. (2023) argued that excess photovoltaic energy can be used to charge electric vehicles. Furthermore, it is suggested that this process between energy producers and electric vehicle owners can be carried out based on Blockchain.

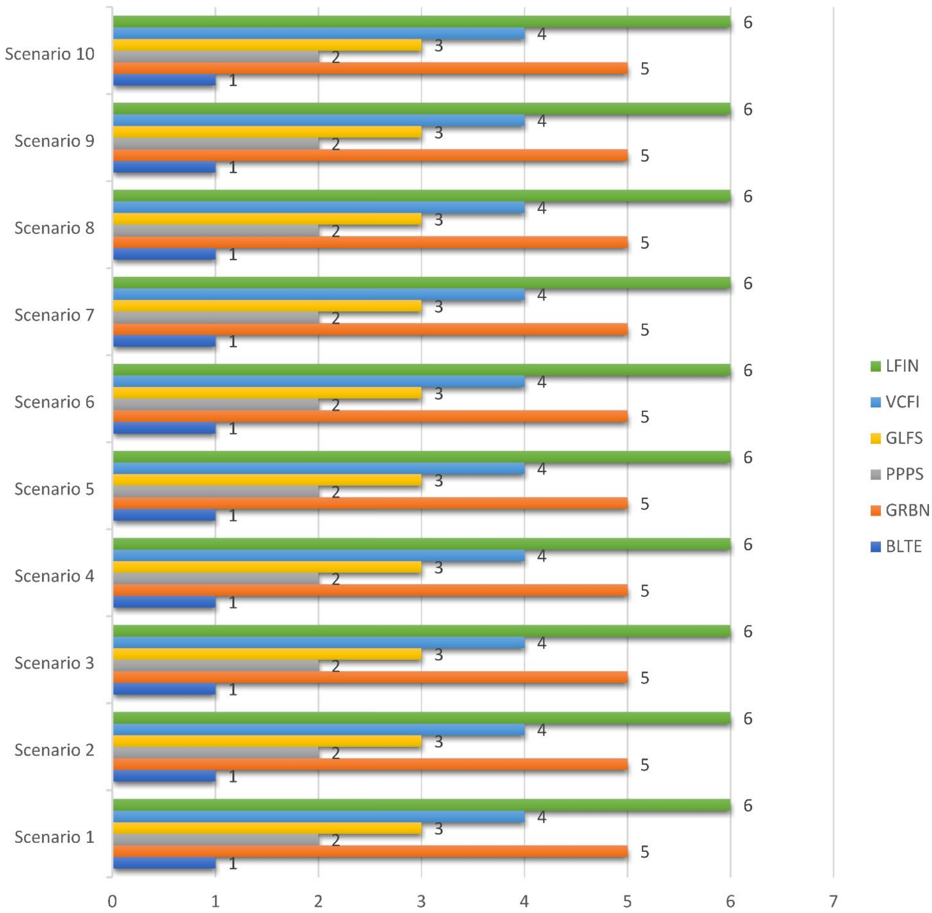

Fig. 5 Sensitivity analysis results

6 Conclusion

6.1 Concluding remarks

This study investigates innovative solutions for financing electric vehicle charging infrastructure investments. In this process, a novel fuzzy decision-making model is proposed by integrating AI technique with Spherical fuzzy sets. In the first stage, the weights of experts are calculated using dimension reduction. Secondly, Spherical fuzzy decision matrix is created. Thirdly, the criteria in charging infrastructure for electric vehicles are weighted using Spherical fuzzy CRITIC. Fourthly, innovative solutions for financing electric vehicles charging infrastructure are ranked via Spherical fuzzy RATGOS. It is concluded that the most effective criterion in the innovative financial solution for the charging infrastructure of electric vehicles is determined as "potential income". According to the ranking results, it is also defined that the most sustainable solution among the innovative strategies for financing the charging infrastructure of electric vehicles is "blockchain technology". The main contribution of this study to the literature is that RATGOS methodology is considered in the ranking of alternatives. The RATGOS technique was developed to satisfy the problems about the criticisms to the existing ranking methods. In the analysis process carried out with this method, the geometric mean is considered. In this way, it is aimed to perform more effective and accurate analyses.

6.2 Policy implications

Increasing the efficiency of charging infrastructure investments for electric vehicles is necessary for environmental sustainability. This is also important in terms of energy security. Improvements to be made regarding financial issues play a critical role in the success of these investments. It is possible to determine some policy recommendations and practices to achieve this goal. Providing state incentives is an application that can be considered in this process. In this context, direct financial incentives can be offered to companies investing in charging infrastructure. Providing low-interest loans is one of the most important application examples that can be given in this regard. Due to this situation, businesses can achieve significant cost efficiency. Similarly, tax deductions can be applied for investments in electric vehicle charging stations. This situation also supports the reduction of costs for investors. Establishing energy cooperatives is also a necessary policy recommendation to ensure the financial efficiency of charging infrastructure investments for electric vehicles. These cooperatives can be considered as an alternative model for financing charging infrastructure investments. Thanks to this advantage, communities can access sustainable energy much more easily. Crowdfunding is another policy that can be considered in this process. Community-based funding platforms can be used for charging infrastructure investments. Because of this issue, businesses can access the funds they need both at a lower cost and more easily. Similarly, digital technologies and artificial intelligence can be used to increase the efficiency of charging infrastructure. By taking these technologies into account, the capacity utilization of charging stations can be optimized. This allows for more accurate management of energy demand. Blockchain technology is another important issue for increasing the effectiveness of these investments. Some policy applications can be presented for these technologies to be used more effectively. This technology has many advantages such as secure data sharing and decentralized structure. More comprehensive regulations can be created to increase the performance of this process. Thanks to these regulations, it is possible to increase the confidence of investors in these projects and the market. This situation also contributes significantly to increasing the performance of these investments. On the other hand, the curricula for blockchain technology in universities should be updated. Similarly, governments can organize campaigns to introduce the benefits and application areas of blockchain technology to the public. This situation supports the increase of people's confidence in these technologies.

6.3 Limitations and future research directions

The main limitation of this study is that only charging investments of the electrical vehicles are evaluated. However, some other factors may affect the effectiveness of these projects, such as technological infrastructure. Thus, in the future studies, this situation can also be examined. The proposed model has also some limitations. In this scope, CRITIC methodology is used to weight the determinants. Although this technique has some advantages, there are also some criticisms regarding this methodology. Thus, in the following studies, a novel weighting technique can be introduced to overcome these problems. In the literature, there are also some new weighting techniques to weight the indicators. For instance, criteria importance assessment (CIMAS) methodology is proposed to reach this objective (Kara et al. 2024a, b, c). The main superiority of this methodology is that the validity of the results can be checked. Similarly, instead of a pairwise comparison, each expert evaluates the criteria. This allows for a more objective assessment. In this context, an analysis can be performed by taking this technique into account in future studies. The security of this method can be tested by performing a sensitivity analysis of the analysis results.

Appendix

Table 8 Summary of literature review

Authors	Results
(Duong et al. 2024) (Baza et al. 2021) (Akanfe et al. 2024) (Zhu et al. 2024) (Al-Saif et al. 2021)	Blockchain technology is one of the effective financing techniques for electric vehicle charging infrastructure investments.
(Hu et al. 2024) (Jain et al. 2024) (Cicchiello et al. 2022) (Torvanger et al. 2021) (Xu et al. 2023)	Another effective financing technique that is important for determining effective financing techniques for electric vehicle charging infrastructure investments is green bonds.
(Almeile et al. 2024) (Sheng et al. 2020) (Hossin et al. 2024) (Cui et al. 2018) (Huang et al. 2022)	Public-private partnership (PPP) covers a wide range of public sector infrastructure while expressing an approach adopted to increase the economic value of infrastructure outputs
(LaMonaca and Ryan 2022) (Resosudarmo et al. 2023) (Gonzalez et al. 2024) (Lopez-Behar et al. 2019) (Bohnsack et al. 2014)	Global funds are another important potential innovative solution for effective financing of electric vehicle charging infrastructure investments,
(Mele et al. 2024) (Lam and Law 2018) (Fang et al. 2024) (Kou et al. 2020) (Shao and Sun 2021)	Venture capital financing is another important tool for financing electric vehicle charging infrastructure.

Table 9 Normalize matrix

	Age	Experience	Education	Salary
Expert 1	0.71	0.62	-0.82	0.27
Expert 2	0	-0.77	0.41	0.54
Expert 3	-0.71	0.15	0.41	-0.8

Table 10 Covariance matrix

	Age	Experience	Education	Salary
Age	0.33	0.11	-0.29	0.25
Experience	0.11	0.33	-0.25	-0.12
Education	-0.29	-0.25	0.33	-0.11
Salary	0.25	-0.12	-0.11	0.33

Table 11 Eigenvalues

Eigenvalues	Value
1	0
2	0.832
3	0.502
4	0

Table 12 Eigenvector

Eigenvector
-0.612
-0.355
0.612
-0.355

Table 13 Experts opinions

Expert 1						
	RIPO	CSEV	SIPR	PRPJ	PONC	GVPC
BLTE	9	5	8	6	6	9
GRBN	3	4	1	3	8	7
PPPS	6	9	8	9	1	7
GLFS	3	7	2	4	2	4
VCFI	5	4	9	1	9	3
LFIN	4	1	4	1	8	8
Expert 2						
	RIPO	CSEV	SIPR	PRPJ	PONC	GVPC
BLTE	4	2	7	3	1	5
GRBN	2	6	2	8	9	1
PPPS	2	7	9	6	1	7
GLFS	3	7	6	2	5	9
VCFI	8	4	2	3	2	4
LFIN	8	5	2	5	5	2
Expert 3						
	RIPO	CSEV	SIPR	PRPJ	PONC	GVPC
BLTE	6	4	8	5	1	9
GRBN	2	9	5	9	1	7
PPPS	7	9	1	8	2	6
GLFS	6	6	4	5	7	2
VCFI	8	2	7	4	3	8
LFIN	8	2	1	6	6	8

Table 14 Normalize matrix of D

	RIPO	CSEV	SIPR	PRPJ	PONC	GVPC
BLTE	0.010	0.935	0.029	0.752	0.850	0.000
GRBN	1.000	0.345	0.966	0.095	0.000	0.941
PPPS	0.504	0.000	0.000	0.000	1.000	0.667
GLFS	0.776	0.451	0.801	0.902	0.626	0.598
VCFI	0.000	0.974	0.116	1.000	0.279	1.000
LFIN	0.048	1.000	1.000	0.802	0.317	0.550

Table 15 Standard deviations

Criteria	Std. Dev.
RIPO	0.4354
CSEV	0.4141
SIPR	0.4849
PRPJ	0.4311
PONC	0.3795
GVPC	0.3577

Table 16 Correlation matrix

	RIPO	CSEV	SIPR	PRPJ	PONC	GVPC
RIPO	1.000	-0.767	0.475	-0.578	-0.222	0.391
CSEV	-0.767	1.000	0.036	0.813	-0.294	-0.272
SIPR	0.475	0.036	1.000	0.029	-0.669	0.266
PRPJ	-0.578	0.813	0.029	1.000	-0.099	-0.199
PONC	-0.222	-0.294	-0.669	-0.099	1.000	-0.632
GVPC	0.391	-0.272	0.266	-0.199	-0.632	1.000

Table 17 Similarity matrix

	RIPO			CSEV			SIPR			PRPJ			PONC			GVPC		
BLTE	0.65	0.41	0.26	0.26	0.82	0.29	0.61	0.47	0.21	0.37	0.71	0.33	0.28	0.82	0.22	0.66	0.43	0.21
GRBN	0.20	0.83	0.21	0.51	0.60	0.24	0.23	0.85	0.26	0.61	0.48	0.17	0.62	0.49	0.14	0.44	0.67	0.22
PPPS	0.48	0.58	0.30	0.65	0.45	0.16	0.62	0.49	0.14	0.65	0.43	0.21	0.10	0.93	0.10	0.50	0.59	0.28
GLFS	0.37	0.69	0.31	0.47	0.63	0.26	0.33	0.75	0.28	0.29	0.78	0.31	0.39	0.70	0.30	0.52	0.61	0.19
VCFI	0.65	0.40	0.29	0.23	0.84	0.25	0.58	0.53	0.18	0.21	0.85	0.23	0.52	0.61	0.16	0.42	0.68	0.24
LFIN	0.64	0.42	0.24	0.22	0.87	0.25	0.20	0.86	0.21	0.34	0.75	0.32	0.51	0.58	0.31	0.53	0.58	0.18

Table 18 Weighted similarity matrix

	RIPO			CSEV			SIPR			PRPJ			PONC			GVPC		
BLTE	0.31	0.85	0.14	0.11	0.97	0.12	0.27	0.88	0.11	0.15	0.95	0.14	0.12	0.96	0.10	0.28	0.89	0.10
GRBN	0.09	0.97	0.09	0.22	0.92	0.11	0.10	0.97	0.11	0.27	0.89	0.08	0.29	0.87	0.07	0.17	0.95	0.09
PPPS	0.22	0.91	0.14	0.29	0.88	0.08	0.28	0.89	0.07	0.29	0.88	0.11	0.04	0.99	0.04	0.20	0.93	0.12
GLFS	0.16	0.93	0.14	0.20	0.93	0.12	0.14	0.95	0.12	0.12	0.96	0.13	0.18	0.94	0.14	0.21	0.93	0.08
VCFI	0.31	0.85	0.16	0.10	0.97	0.10	0.26	0.90	0.09	0.09	0.97	0.09	0.24	0.91	0.08	0.17	0.95	0.10
LFIN	0.30	0.85	0.13	0.09	0.98	0.10	0.08	0.98	0.09	0.14	0.96	0.14	0.24	0.90	0.16	0.21	0.93	0.08

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Declarations

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