Journal of Quality Engineering and Production Optimization

Volume 10, Issue 2, Summer & Autumn 2025

http://jqepo.shahed.ac.ir

Research Paper

DOI: 10.22070/jqepo.2026.21715.1326

Risk assessment of public-private partnership projects for electric vehicle charging through an extended MCDM method with interval type-2 fuzzy sets

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Abstract –*Due to the growing global attention to clean energy in the world, projects of electric vehicles (EVs) have greatly increased all around the world. The lack of charging infrastructure in developing countries has become a major problem. In this situation, governments engage the private sector to improve the charging infrastructure. Assessing the risk factors (RFs) under these circumstances is essential. In this paper, the important RFs are detected. Moreover, the weights of important RFs are identified through an extended version of the BWM approach. Furthermore, the overall risk levels of public-private partnership (PPP) charging projects are specified by using an integrated ELECTRE-VIKOR approach. To address uncertainty in risk identification, weighting, and ranking in practical situations, interval type-2 fuzzy sets (IT2FSs) are employed. IT2FSs provide more space for experts to cope with the uncertainty. Extended weighting and ranking methods are developed under IT2FSs. Finally, an example in the field of EV charging projects (EVCPs) is provided. The proposed framework was further validated through a comparative analysis with fuzzy VIKOR, fuzzy ELECTRE, and BWM–TOPSIS. The results demonstrated high consistency across the methods, supporting the credibility of the proposed approach.*

Keywords*– Electric vehicle charging projects; IT2FSs; Public-private partnership (PPP); Risk assessment.*

I. INTRODUCTION

In recent years, sustainability and clean energy have attracted a lot of attention. Electric vehicles (EVs), due to their lack of pollution, have absorbed a great deal of attention. Due to the shortage of charging infrastructure and the very fast growth of EVs, charging infrastructure is essential. In these situations, the public-private partnership (PPP) mode is applied to use the advantages of the private sector. Nguyen et al. (2024) examined the major risks affecting public–private partnership (PPP) smart transportation infrastructure projects. They find that political, financial, legal, and demand risks are the most critical and emphasize that effective risk allocation, strong contractual frameworks, stakeholder coordination, and government support are essential to improve project performance and reduce uncertainty. DeCorla-Souza & Hossain (2025) presented a screening tool to evaluate the financial viability of alternative PPP models for EV charging infrastructure. It shows that appropriate risk allocation, realistic demand forecasts, revenue design, and government support are key to attracting private investment and ensuring project sustainability. Because of the nature of PPP projects, evaluating risks and uncertainty is essential (Liu & Wei, 2018; Demirel, 2022).

Manuscript Received: 11-Apr-2025 & Revised:4-Jul-2025 & Accepted: 6-Sep-2025
ISSN: 2423-3781

To cope with the uncertainty of practical situations, type-1 fuzzy sets (T1FSs) theory was defined by Zadeh (1965). Risk assessment has been successfully applied in a fuzzy environment in the last decade (Budayan et al., 2018; Awodi et al., 2023). It has been argued that expressing the membership degree of T1FSs as an exact number is more challenging for decision-makers (Jahangirzadeh et al., 2020). In these conditions, type-2 fuzzy sets (T2FSs) are an enhancement of the T1FSs presented by Zadeh (1975). In comparison of T1FSs and T2FSs, the membership degree of the T1FSs is expressed by an exact number, and the membership degree of the T2FSs is explained by a T1FS (Barzegari & Mousavi, 2026). Therefore, the T2FSs provide more degrees of freedom to tackle the uncertainty (Dorfeshan et al., 2018). T2FSs are properly applied in many risk assessment problems (Asan et al., 2016; Debnath & Biswas, 2018).

Khan et al. (2024) developed an integrated IT2F and Bayesian network model to assess risks in hazardous cargo handling at seaports. It identifies human errors, equipment failures, and management shortcomings as the most critical risks and shows that the approach improves uncertainty handling for safer and more effective port operations. Mutlu et al. (2024) proposed an advanced risk evaluation method for open-cast coal mines using hybrid MCDM models with IT2FSs. A case study in Türkiye shows that safety hazards, equipment failure, and environmental risks are the most critical, and the approach effectively handles uncertainty to support better decision-making in mine risk management. Li et al. (2025) presented a combined method integrating scenario deduction and T2FS-based Bayesian networks to assess failure risks in solar tower power plants. The study highlights that equipment faults, operational errors, and environmental factors are the main risk drivers, and the approach enhances uncertainty modeling to improve risk management and decision-making in solar energy projects.

Regarding ranking the alternatives or projects based on the risk factors (RFs), Safari et al. (2016) identified and assessed the risks through the Vlsekriterijumska Optimizacija I KOmpromisno Resenje (VIKOR) method. Govindan & Jepsen (2016) presented a new Elimination and Choice Expressing Reality (ELECTRE) approach for supplier risk evaluation. Wang et al. (2018) evaluated construction risks using a VIKOR model based on projection. Peng et al. (2019) introduced an integration of regret theory and the ELECTRE method for investment risk assessment. Sarwar et al. (2023) developed an improved risk assessment model for intelligent manufacturing using rough interconnected clouds and the ELECTRE-II approach.

Alves & Pereira (2025) applied ELECTRE Tri-nC to improve clinical and non-clinical risk mitigation in healthcare. The case study demonstrates that the method effectively prioritizes risks, supports decision-making, and enhances patient safety and operational efficiency. Kan et al. (2024) provided a risk evaluation model for submarine pipelines using FMEA combined with gray relation projection and the VIKOR approach. Liu et al. (2025) extended an integrated entropy–AHP–VIKOR methodology to analyze risks in anti-money laundering (AML). The approach combines objective and subjective weighting to prioritize RFs, showing that transaction anomalies, customer profiling, and regulatory compliance gaps are the most critical risks for effective AML management. ELECTRE and VIKOR are two useful methods in the literature.

The VIKOR approach is particularly useful for ranking alternatives under conflicting criteria and uncertainty (Ahıskalı et al., 2025). Its main advantages include the ability to identify a solution closest to the ideal, to incorporate both individual and group decision-maker perspectives, and to provide a compromise solution (Naz et al., 2024). By computing the distances to the positive and negative ideal solutions, VIKOR offers flexibility in ranking alternatives with different units and importance levels. Overall, it helps decision-makers select the best option while considering relative priorities and real-world constraints (Seikh & Dey, 2025).

The ELECTRE method is an MCDM approach designed to handle complicated decision problems with conflicting criteria (Fei et al., 2024). Its main advantages include the ability to perform outranking comparisons rather than relying solely on aggregate scores, which allows decision-makers to identify alternatives that are dominant or non-dominated relative to others (Martin & Smith, 2025). ELECTRE can handle both quantitative and qualitative criteria, incorporate thresholds for preference, indifference, and veto, and provide robust rankings or classifications even under uncertainty. Overall, it is particularly useful for complex, real-world decisions where trade-offs among multiple, sometimes incommensurable, criteria must be carefully evaluated (Fernández et al., 2025).

ELECTRE is a well-established outranking method that evaluates alternatives through concordance and discordance analyses. Its main advantage is the ability to identify dominance relationships among alternatives while effectively handling conflicting criteria, making it particularly suitable for complex risk assessment problems (Yu et al., 2018; Cusanno et al., 2026). Also, VIKOR is a compromise-ranking method that identifies alternatives closest to the ideal solution. It simultaneously considers overall group utility and individual regret, providing balanced and practical solutions in decision-making environments with conflicting criteria (Xu et al., 2026). Since ELECTRE focuses on outranking relationships and VIKOR emphasizes compromise solutions, integrating these methods enables decision-makers to benefit from the strengths of both approaches, resulting in more robust and reliable risk assessment outcomes. Moreover, while ELECTRE is capable of determining outranking relations among alternatives, it does not directly provide a complete final ranking. Therefore, VIKOR is integrated to generate a compromise-based ranking, allowing the decision-making process to produce a clear and comprehensive final result (Zandi & Roghanian, 2013). To achieve a comprehensive risk assessment, the weight of RF should be determined.

Many weighting methods have been extended in manifold areas. Kokangül et al. (2017) expressed a risk approximation approach according to the analytic hierarchy process (AHP) method. Fattahi & Khalilzadeh (2018) proposed an extended MULTIMOORA and AHP method for evaluating risks under a fuzzy environment. Pairwise comparisons among a large number of criteria or RFs are time-consuming. In such conditions, large-scale problems exhibit a higher degree of inconsistency among criteria. To mitigate this problem, the best-worst method (BWM) was defined by Rezaei (2016). In recent years, this method has been widely employed across various fields (Mohaghar et al., 2017; Amoozad Mahdiraji et al., 2018; Li et al., 2019).

Masudin et al. (2024) applied a fuzzy BWM and Risk Mitigation Number (RMN) to appraise and address risks across the halal meat supply chain. The study identifies contamination, supply disruption, and regulatory non-compliance as the most critical risks. It demonstrates that the integrated approach effectively prioritizes risks and supports targeted mitigation strategies to ensure halal compliance and supply chain resilience. Ahmadpour et al. (2025) developed a hybrid Fuzzy BWM model to evaluate companies' financial risk. The approach combines fuzzy logic with BWM to handle uncertainty and expert judgment, identifying liquidity, credit, and market risks as the most critical factors, and providing a structured framework for more accurate and reliable financial risk evaluation. To take advantage of the BWM method, this paper extends it using T2FSs to cope with uncertainty.

Although numerous risk assessment methods have been proposed in the literature, their application to EV charging infrastructure PPP projects remains challenging. These projects involve multiple stakeholders, conflicting evaluation criteria, and significant uncertainty arising from technological evolution, policy changes, and market dynamics. Many existing approaches rely on a single MCDM technique, which may not fully capture both the dominance relationships among alternatives and the compromise solutions required for complex decision-making. Moreover, conventional weighting methods often require numerous pairwise comparisons, while crisp or type-1 fuzzy approaches may not adequately represent the uncertainty and ambiguity inherent in expert judgments. These limitations highlight the need for a more comprehensive risk assessment framework capable of integrating efficient weighting, robust ranking, and advanced uncertainty modeling.

All in all, the research gaps of the literature review are presented as follows:

- Limited integration of compromise and outranking methods: Existing risk assessment studies rarely combine compromise-based methods (e.g., VIKOR) with outranking approaches (e.g., ELECTRE), despite their potential to improve the robustness and stability of ranking results.
- Underutilization of BWM in risk assessment: Although BWM requires fewer pairwise comparisons and offers higher consistency than AHP, its application in risk assessment studies remains relatively limited.

- Limited use of IT2FSs for uncertainty modeling in risk assessment: Most risk assessment studies employ crisp or type-1 fuzzy approaches, while the potential of IT2FSs to capture higher levels of uncertainty and ambiguity remains insufficiently explored.

Uncertainties are inherent in the decision-making and risk assessment environment. The linguistic variables are utilized to assess the projects according to the RFs. Linguistic variables have different meanings for different experts (Li et al., 2019; Hakam & Wasesa, 2025). When linguistic variables are used to cope with uncertainty, IT2FSs are applied because the membership degree of T2FSs is a T1FS. Furthermore, to use the advantages of the ELECTRE-based VIKOR method and BWM, a novel overall risk appraisal model is extended with the IT2FSs.

The main innovations of the current paper are clarified as follows:

1. The existing ELECTRE–VIKOR approach from the literature has been extended to the interval type-2 fuzzy environment to better model the uncertainty and ambiguity associated with expert judgments.
2. The Best–Worst Method (BWM) has also been formulated under interval type-2 fuzzy sets to derive RFs weights more reliably.
3. The main methodological contribution of the study is the integration of IT2F-BWM with the IT2F ELECTRE–VIKOR framework into a unified risk assessment model for EV charging PPP projects.

The structure of this paper is explained as follows: Section 2 provides the fundamental concepts used in this study. Section 3 introduces the suggested overall risk level assessment method. Section 4 presents a case study to better illustrate the profitability of the suggested method. Section 5 explains the comparative analysis of the proposed approach with the TOPSIS approach. Section 5 represents the conclusion and recommendations.

II. BASIC KNOWLEDGE OF INTERVAL TYPE-2 FUZZY SETS

T2FSs were first presented by Zadeh (1975) as a development of T1FSs. Compared with T1FSs, T2FSs have a significantly greater capability to represent and handle uncertainty. They are particularly useful in situations where assigning a precise membership degree to a fuzzy number is difficult, such as when one or more criteria are expressed qualitatively through linguistic variables (LVs) or expert judgments (Mendel, 2017). This advantage arises from the structure of their membership grades. In T1FSs, the membership grade is defined as a deterministic value within the interval [0,1]. In contrast, in T2FSs, the membership degree is characterized by a T1FS, enabling a more flexible representation of uncertainty (Mendel, 2017). The selection of IT2FSs is motivated by the nature of the risk assessment problem considered in this study. EV charging PPP projects involve evaluations that are largely based on expert judgments regarding political, economic, technical, and social risks. In such situations, uncertainty arises not only from the imprecision of linguistic assessments (e.g., “high risk” or “medium risk”) but also from variations in how different experts interpret the same linguistic terms. Type-1 fuzzy sets can model the first level of uncertainty by assigning a membership function to each linguistic term. However, they assume that the membership function itself is precisely known. In contrast, IT2FSs allow uncertainty in the membership function through the footprint of uncertainty (FOU), making them more suitable for representing variations among experts and ambiguity in linguistic evaluations (Mendel, 2017).

Compared with intuitionistic fuzzy sets (IFSs), Pythagorean fuzzy sets (PFSs), and q-rung orthopair fuzzy sets (q-ROFSs), which primarily enhance the representation of membership, non-membership, and hesitation degrees, IT2FSs focus on modeling uncertainty associated with the membership functions themselves. Since the present study relies heavily on group-based linguistic judgments with potentially different interpretations among experts, capturing uncertainty in the membership functions is particularly important (Mendel, 2017). However, due to the computational complexity associated with T2FSs, their practical application can be challenging. To address this issue, IT2FSs were introduced as a simplified and more computationally efficient form of T2FSs (Kilic & Kaya, 2015). A T2F number is defined as follows:

$$\tilde{\tilde{\theta}} = \int_{g\in G}\int_{y\in j_G} \mu_{\tilde{\tilde{\theta}}}(g,y)/(g,y) \tag{1}$$

where $j_G \subseteq [0,1]$ and $\iint$ are the overall acceptable regions of g and y. When $\mu_{\tilde{\tilde{\theta}}}(g,y) = 1$ then $\tilde{\tilde{\theta}}$ defined as an IT2FS (Mendel, 2017). Equivalently, IT2FSs represent a particular form of T2FSs characterized by interval-valued secondary membership functions, and are specified as below (Mendel, 2017).

$$\tilde{\tilde{\theta}} = \int_{g\in G}\int_{y\in j_G} 1/(g,y) \quad \text{where } j_G \subseteq [0,1] \tag{2}$$

In this study, a particular type of these sets, known as interval trapezoidal T2FS, is employed, as illustrated below (Chen & Lee, 2010):

$$\tilde{\tilde{\theta}}_i = (\tilde{\theta}_i^U, \tilde{\theta}_i^L) = ((\theta_{i1}^U, \theta_{i2}^U, \theta_{i3}^U, \theta_{i4}^U; H_1(\tilde{\theta}_i^U), H_2(\tilde{\theta}_i^U)), (\theta_{i1}^L, \theta_{i2}^L, \theta_{i3}^L, \theta_{i4}^L; H_1(\tilde{\theta}_i^L), H_2(\tilde{\theta}_i^L))) \tag{3}$$

where, $\tilde{\theta}_i^L$ and $\tilde{\theta}_i^U$ are T1FSs. $H_j(\tilde{\theta}_i^U)$ clarifies the membership degree of the upper limit $\tilde{\theta}_i^U$. $H_j(\tilde{\theta}_i^L)$ explains the membership degree of the lower limit $\tilde{\theta}_i^L$ and $1 \le j \le 2$. Furthermore, the following relations need to be considered (Chen & Lee, 2010).

Fig. 1 demonstrates an IT2F number $\tilde{\tilde{A}}_i$

$$H_1(\tilde{\theta}_i^L) \in [0,1],\ H_2(\tilde{\theta}_i^L) \in [0,1],\ H_1(\tilde{\theta}_i^U) \in [0,1],\ H_2(\tilde{\theta}_i^U) \in [0,1],\ 1 \le i \le n \tag{4}$$

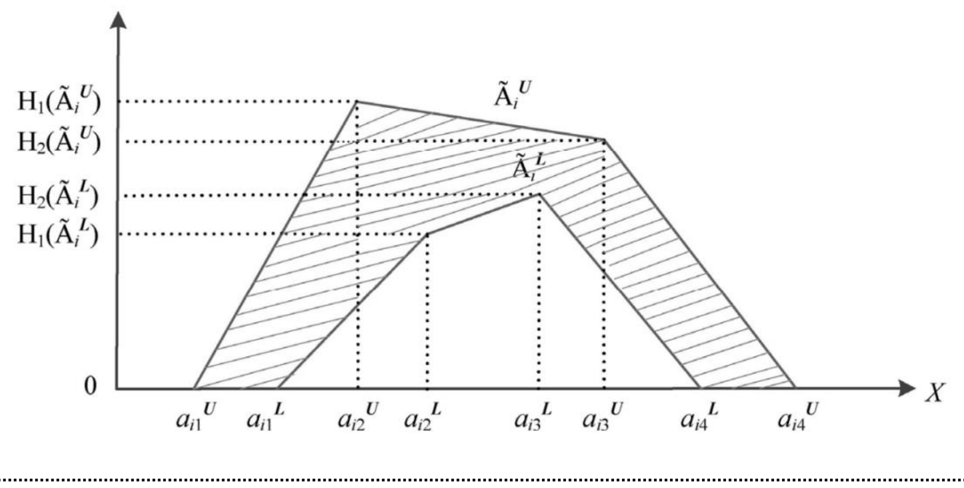

Fig. 1. An IT2F number

If $\tilde{\tilde{\lambda}}_1$ and $\tilde{\tilde{\lambda}}_2$ be formulated by using the following:

$$\tilde{\tilde{\lambda}}_1 = (\tilde{\lambda}_1^U . \tilde{\lambda}_1^L) = ((\lambda_{11}^U . \lambda_{12}^U . \lambda_{13}^U . \lambda_{14}^U; H_1(\tilde{\lambda}_1^U) . H_2(\tilde{\lambda}_1^U)). \tag{5}$$

$$(\lambda_{11}^{L}.\lambda_{12}^{L}.\lambda_{13}^{L}.\lambda_{14}^{L};H_1(\tilde{\lambda}_1^{L}).H_2(\tilde{\lambda}_1^{L})))$$
$$\tilde{\tilde{\lambda}}_2=(\tilde{\lambda}_2^{U}.\tilde{\lambda}_2^{L})=((\lambda_{21}^{U}.\lambda_{22}^{U}.\lambda_{23}^{U}.\lambda_{24}^{U};H_1(\tilde{\lambda}_2^{U}).H_2(\tilde{\lambda}_2^{U})).$$
$$(\lambda_{21}^{L}.\lambda_{22}^{L}.\lambda_{23}^{L}.\lambda_{24}^{L};H_1(\tilde{\lambda}_2^{L}).H_2(\tilde{\lambda}_2^{L}))) \tag{6}$$

Subsequently, the fundamental operation between them can be formulated by using the following:

1. Addition

$$\tilde{\tilde{\lambda}}_1\oplus\tilde{\tilde{\lambda}}_2=(\tilde{\lambda}_1^{U},\tilde{\lambda}_1^{L})+(\tilde{\lambda}_2^{U},\tilde{\lambda}_2^{L})=((\lambda_{11}^{U}+\lambda_{21}^{U},\lambda_{12}^{U}+\lambda_{22}^{U},\lambda_{13}^{U}+\lambda_{23}^{U},\lambda_{14}^{U}+\lambda_{24}^{U}$$
$$;min(H_1(\tilde{\lambda}_1^{U}),H_1(\tilde{\lambda}_2^{U})),min(H_2(\tilde{\lambda}_1^{U}),H_2(\tilde{\lambda}_2^{U}))),\lambda_{11}^{L}+\lambda_{21}^{L},\lambda_{12}^{L}+\lambda_{22}^{L},\lambda_{13}^{L}$$
$$+\lambda_{23}^{L},\lambda_{14}^{L}+\lambda_{24}^{L};min(H_1(\tilde{\lambda}_1^{L}),H_1(\tilde{\lambda}_2^{L})),min(H_2(\tilde{\lambda}_1^{L}),H_2(\tilde{\lambda}_2^{L})))). \tag{7}$$

2. Subtraction

$$\tilde{\tilde{\lambda}}_1\Theta\tilde{\tilde{\lambda}}_2=(\tilde{\lambda}_1^{U},\tilde{\lambda}_1^{L})-(\tilde{\lambda}_2^{U},\tilde{\lambda}_2^{L})=((\lambda_{11}^{U}-\lambda_{24}^{U},\lambda_{12}^{U}-\lambda_{23}^{U},\lambda_{13}^{U}-\lambda_{22}^{U},\lambda_{14}^{U}+\lambda_{21}^{U};$$
$$min(H_1(\tilde{\lambda}_1^{U}),H_1(\tilde{\lambda}_2^{U})),min(H_2(\tilde{\lambda}_1^{U}),H_2(\tilde{\lambda}_2^{U}))),\lambda_{11}^{L}-\lambda_{24}^{L},\lambda_{12}^{L}-\lambda_{23}^{L},\lambda_{13}^{L}$$
$$-\lambda_{22}^{L},\lambda_{14}^{L}-\lambda_{21}^{L};min(H_1(\tilde{\lambda}_1^{L}),H_1(\tilde{\lambda}_2^{L})),min(H_2(\tilde{\lambda}_1^{L}),H_2(\tilde{\lambda}_2^{L})))). \tag{8}$$

3. Multiplication

$$\tilde{\tilde{\lambda}}_1\otimes\tilde{\tilde{\lambda}}_2=(\tilde{\lambda}_1^{U}\ \tilde{\lambda}_1^{L})\otimes(\tilde{\lambda}_2^{U}\ \tilde{\lambda}_2^{L})=((R_{11}^{U},R_{12}^{U},R_{13}^{U},R_{14}^{U};min(H_1(\tilde{\lambda}_1^{U}),$$
$$H_1(\tilde{\lambda}_2^{U})),min(H_2(\tilde{\lambda}_1^{U}),H_2(\tilde{\lambda}_2^{U}))),R_{11}^{L},R_{12}^{L},R_{13}^{L},R_{14}^{L};min(H_1(\tilde{\lambda}_1^{L}),$$
$$H_1(\tilde{\lambda}_2^{L})),min(H_2(\tilde{\lambda}_1^{L}),H_2(\tilde{\lambda}_2^{L})))). \tag{9}$$

where:

$$R_i^T=\begin{cases}min(\lambda_{1i}^{T}\lambda_{2i}^{T},\lambda_{1i}^{T}\lambda_{2(5-i)}^{T},\lambda_{1(5-i)}^{T}\lambda_{2i}^{T},\lambda_{1(5-i)}^{T}\lambda_{2(5-i)}^{T}) & if\ \ i=1,2\\ max(\lambda_{1i}^{T}\lambda_{2i}^{T},\lambda_{1i}^{T}\lambda_{2(5-i)}^{T},\lambda_{1(5-i)}^{T}\lambda_{2i}^{T},\lambda_{1(5-i)}^{T}\lambda_{2(5-i)}^{T}) & if\ \ i=3,4\end{cases}$$

and $T\in\{U,L\}$.

4. Division

$$\frac{\tilde{\tilde{\lambda}}_1}{\tilde{\tilde{\lambda}}_2}=((P_{11}^{U},P_{12}^{U},P_{13}^{U},P_{14}^{U};min(H_1(\tilde{\lambda}_1^{U}),H_1(\tilde{\lambda}_2^{U})),min(H_2(\tilde{\lambda}_1^{U}),H_2(\tilde{\lambda}_2^{U}))),$$
$$P_{11}^{L},P_{12}^{L},P_{13}^{L},P_{14}^{L};min(H_1(\tilde{\lambda}_1^{L}),H_1(\tilde{\lambda}_2^{L})),min(H_2(\tilde{\lambda}_1^{L}),H_2(\tilde{\lambda}_2^{L})))), \tag{10}$$

where P_i^T is as follows.

$$P_i^T=\begin{cases}\min\left(\frac{\lambda_{1i}^{T}}{\lambda_{2i}^{T}},\frac{\lambda_{1i}^{T}}{\lambda_{2(5-i)}^{T}},\frac{\lambda_{1(5-i)}^{T}}{\lambda_{2i}^{T}},\frac{\lambda_{1(5-i)}^{T}}{\lambda_{2(5-i)}^{T}}\right) & if\ \ i=1,2\\ \max\left(\frac{\lambda_{1i}^{T}}{\lambda_{2i}^{T}},\frac{\lambda_{1i}^{T}}{\lambda_{2(5-i)}^{T}},\frac{\lambda_{1(5-i)}^{T}}{\lambda_{2i}^{T}},\frac{\lambda_{1(5-i)}^{T}}{\lambda_{2(5-i)}^{T}}\right) & if\ \ i=3,4\end{cases}$$

Also $\lambda_{2j}^{T}\neq 0$, $j=1.2.3.4$, and $T\in\{U.L\}$.

III. PROPOSED OVERALL RISK ASSESSMENT METHOD

In this research, firstly, the weight of the comprehensive set of RFs in EV charging PPP projects is specified by using the linear BWM method. Secondly, the projects are ranked based on the RFs by using the ELECTRE-VIKOR method. Thirdly, to use the merits of IT2FSs, the BWM and ELECTRE-VIKOR methods are extended under the IT2FSs. A visual representation of the proposed framework is depicted in Fig. 2. The symbols and notations used in this study are presented in Table I.

Table I. Notations

Notation	Description
n	Number of RFs
j	Number of RFs
m	Number of EVCP
$\tilde{\tilde{R}}_{MI}$	The vector of best to over RFs
$\tilde{\tilde{R}}_{LI}$	The vector of other RFs to the worst RF
$Def(\tilde{\tilde{R}}_1)$	Defuzzification of IT2F number $\tilde{\tilde{R}}_1$
λ	Consistency in BWM
s_j	Weight of RF j
$\tilde{\tilde{pr}}_{ij}$	Evaluation of EVCP i based on the RF j
$\tilde{\tilde{U}}_{ij}$	Normalized decision matrix
$\tilde{\tilde{G}}_{ij}$	Weighted normalized decision matrix
$\tilde{\tilde{C}}_{hf}$	Concordance set
$\tilde{\tilde{W}}_{hf}$	Discordance set
O_{hf}	Concordance matrix
T_{hf}	Discordance matrix
N_j	Regret measure
D_j	Utility measure
O_j	Aggregating concordance index
Z_j	Final values of EVCP
ν	Maximum group utility
$(1-\nu)$	Individual regret.

Step 1: For comparisons among RFs, first specify a set of RFs.
Step 2: Specify the best and worst RFs from the weight point of view.

In this step, the most important (best) and least important (worst) RFs from the weight point of view are specified.

Step 3: Explain the precedence of the most critical RF over the other identified RFs

The precedence of the best RF over the other RFs is gathered from specialists through the linguistic variables that are depicted in Table II. The vector of best to over RFs is described as follows:

$$\tilde{\tilde{R}}_{MI} = (\tilde{\tilde{R}}_{MI,1}, \tilde{\tilde{R}}_{MI,2}, \dots, \tilde{\tilde{R}}_{MI,n}) \tag{11}$$

Step 4: Express the precedence of other identified RFs over the worst RF.

The preference of other RFs over the worst RF is gathered from specialists through the linguistic variables that were given in Table I. The vector of other RFs to the worst RF is presented by using the following:

$$\tilde{\tilde{R}}_{LI} = (\tilde{\tilde{R}}_{LI,1}, \tilde{\tilde{R}}_{LI,2}, \dots, \tilde{\tilde{R}}_{LI,n}) \tag{12}$$

Table II. Definition and IT2F scales of the linguistic variables (Cevik Onar et al., 2014)

Linguistic variables	IT2F scales
Absolutely strong (AS)	((7,8,9,9;1,1),(7.2,8.2,8.8,9;0.9,0.9))
Very strong (VS)	((5,6,8,9;1,1),(5.2,6.2,7.8,8.8;0.9,0.9))
Fairly strong (FS)	((3,4,6,7;1,1),(3.2,4.2,5.8,6.8;0.9,0.9))
Slightly strong (SS)	((1,2,4,5;1,1),(1.2,2.2,3.8,4.8;0.9,0.9))
Exactly equal (E)	((1,1,1,1;1,1),(1,1,1,1;1,1))

The IT2F numbers are defuzzified by using:

$$Def(\tilde{\tilde{R}}_1) = \frac{1}{2}\left(\sum_{Q\in\{U\ L\}} \frac{R_{11}^Q + (1 + H_1(\tilde{R}_1^Q)R_{12}^Q + (1 + H_2(\tilde{R}_1^Q)R_{13}^Q + R_{14}^Q}{4 + H_1(\tilde{R}_1^Q) + H_2(\tilde{R}_1^Q)}\right) \tag{13}$$

Step 5: Obtain the most appropriate weights assigned to RFs.

The following linear model is utilized to generate a singular weight of RFs.

$$\begin{aligned} & min\,\lambda \\ & |s_{MI} - R_{MI\,j} * s_j| \le \lambda \qquad for\ all\ j \\ & |s_j - R_{j\,LI} * s_{LI}| \le \lambda \qquad for\ all\ j \\ & \sum_{j=1}^{n} s_j = 1\, s_j \ge 1 \qquad for\ all\ j \end{aligned} \tag{14}$$

Remarkably, λ reveals the consistency. The values close to zero indicate a higher level of consistency. In addition, the final weights $(s_1^*. s_2^*. \dots . s_n^*)$ are extracted from the above linear model.

Step 6: Construct decision matrix

The ratings of the electric vehicle charging project (EVCP) based on the RFs are gathered from an expert using the linguistic variables, defined by Chen & Lee (2010).

The decision matrix is defined below:

$$PR_{ij} = \begin{array}{c} \\ P_1 \\ \vdots \\ P_m \end{array} \begin{array}{c} \begin{array}{ccc} R_1 & \dots & R_n \end{array} \\ \begin{bmatrix} \tilde{\tilde{p}}r_{11} & \cdots & \tilde{\tilde{p}}r_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{\tilde{p}}r_{m1} & \cdots & \tilde{\tilde{p}}r_{mn} \end{bmatrix} \end{array} \tag{15}$$

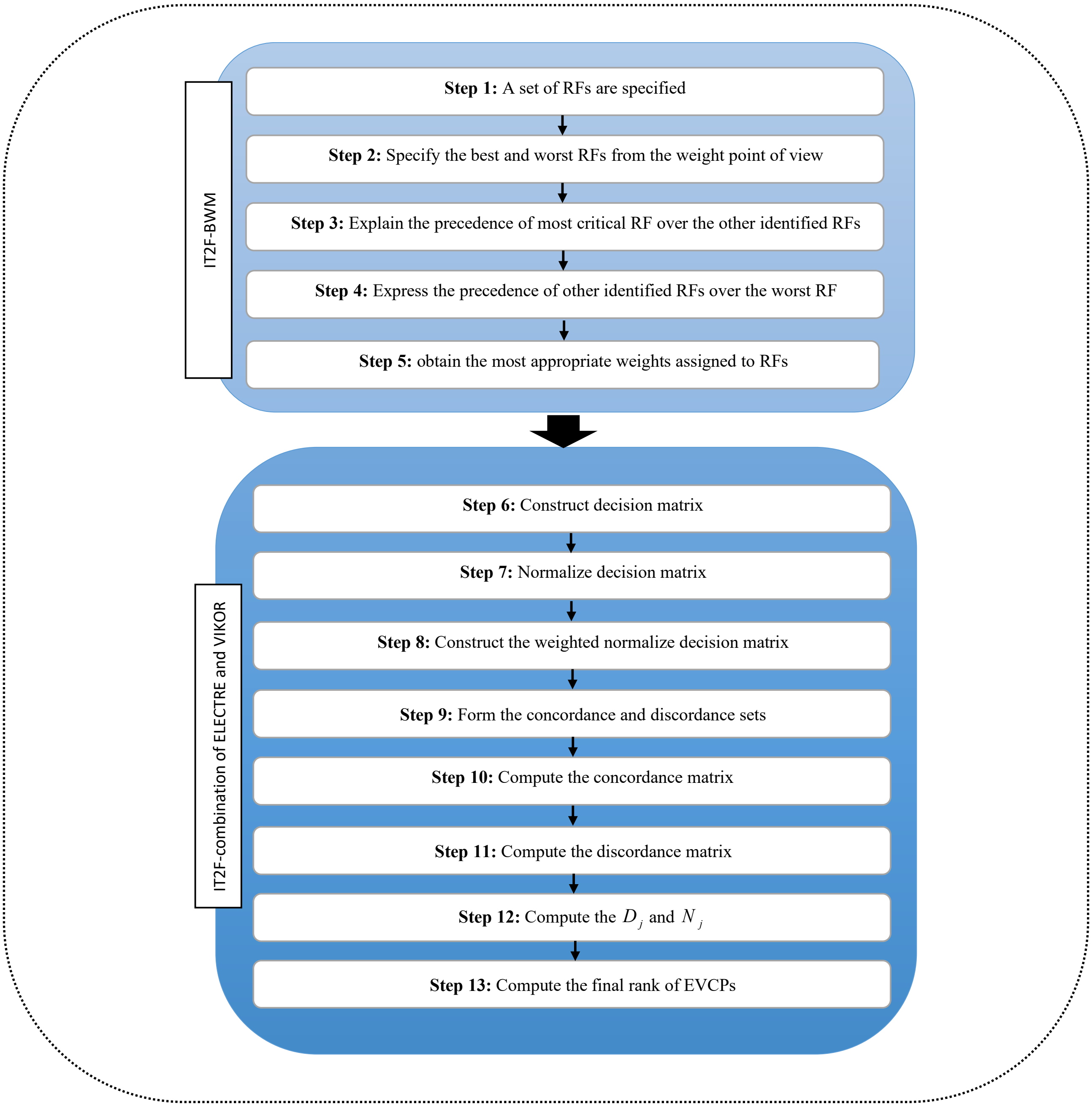

Fig. 2. Visual representation of the proposed framework

Step 7: Normalize the decision matrix

In this step, the benefit RFs are normalized below:

$$\tilde{\tilde{U}}_{ij} = \left[\begin{pmatrix} \frac{pr_{ij1}^U}{pr^+}, \frac{pr_{ij2}^U}{pr^+}, \frac{pr_{ij3}^U}{pr^+}, \frac{pr_{ij4}^U}{pr^+}; \\ H_1(\tilde{P}R^U), H_2(\tilde{P}R^U) \end{pmatrix}, \begin{pmatrix} \frac{pr_{ij1}^L}{pr^+}, \frac{pr_{ij2}^L}{pr^+}, \frac{pr_{ij3}^L}{pr^+}, \frac{pr_{ij4}^L}{pr^+}; \\ H_1(\tilde{P}R^L), H_2(\tilde{P}R^L) \end{pmatrix}\right] \tag{16}$$

The cost RFs are normalized by:

$$\tilde{\tilde{U}}_{ij} = \left[\begin{pmatrix} \frac{pr^-}{pr^U_{ij4}}, \frac{pr^-}{pr^U_{ij3}}, \frac{pr^-}{pr^U_{ij2}}, \frac{pr^-}{pr^U_{ij1}}; \\ H_1(\tilde{P}R^{UK}), H_2(\tilde{P}R^{UK}) \end{pmatrix}, \begin{pmatrix} \frac{pr^-}{pr^L_{ij4}}, \frac{pr^-}{pr^L_{ij3}}, \frac{pr^-}{pr^L_{ij2}}, \frac{pr^-}{pr^L_{ij1}}; \\ H_1(\tilde{P}R^{LK}), H_2(\tilde{P}R^{LK}) \end{pmatrix}\right] \tag{17}$$

Where, $pr^+ = \max_i\{pr^U_{ij4}\}, pr^- = \max_i\{pr^U_{ij1}\}$.
The normalized decision matrix is defined below:

$$(\tilde{\tilde{U}}_{ij})_{m\times n} = \begin{pmatrix} \tilde{\tilde{u}}_{11} & \cdots & \tilde{\tilde{u}}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{\tilde{u}}_{m1} & \cdots & \tilde{\tilde{u}}_{mn} \end{pmatrix} \tag{18}$$

Step 8: Construct the weighted normalized decision matrix.
In this step, the extracted importances of RFs in step 5, using the BWM approach, are multiplied by the normalized decision matrix.

The weighted normalized decision matrix is expressed by:

$$\tilde{\tilde{G}}_{ij} = (\tilde{\tilde{g}}_{ij})_{m\times n} = \tilde{\tilde{U}}_{ij} * s_j = \begin{pmatrix} \tilde{\tilde{u}}_{11} * s_1 & \cdots & \tilde{\tilde{u}}_{1n} * s_n \\ \vdots & \ddots & \vdots \\ \tilde{\tilde{u}}_{m1} * s_1 & \cdots & \tilde{\tilde{u}}_{mn} * s_n \end{pmatrix} \tag{19}$$

Step 9: Form the concordance and discordance sets.
In this stage, the matrix $\tilde{\tilde{G}}_{ij}$is transformed into a deterministic number through Eq. (13). Then, the sets of concordance and discordance for each pair of h and f alternatives are determined. Notably, $h = 1,2,\dots,m; h \neq f$. Concordance set ($\tilde{\tilde{C}}_{hf}$) including all indices that P_h are superior to P_f and discordance sets are defined as:

$$\tilde{\tilde{C}}_{hf} = \{j|[\tilde{\tilde{g}}_{hj}] \geq [\tilde{\tilde{g}}_{fj}]\},\ \tilde{\tilde{W}}_{hf} = \{j|[\tilde{\tilde{g}}_{hj}] \prec [\tilde{\tilde{g}}_{fj}]\} = J - \tilde{\tilde{C}}_{hf} \tag{20}$$

Step 10: Compute the concordance matrix.
The concordance index is computed through the members of $\tilde{\tilde{C}}_{hf}$. Thus, the concordance index is obtained as follows:

$$O_{hf} = \sum_{j\in\tilde{\tilde{C}}_{hf}}^{n} S_j \tag{21}$$

Step 11: Compute the discordance matrix.
The discordance index is computed based on the members of $\tilde{\tilde{W}}_{hf}$. Thus, the discordance indicator is obtained as follows:

$$T_{hf} = \frac{\max_{j\in w_{hf}}|\tilde{\tilde{g}}_{hj} - \tilde{\tilde{g}}_{fj}|}{\max_{j\in J}|\tilde{\tilde{g}}_{hj} - \tilde{\tilde{g}}_{fj}|} \tag{22}$$

Step 12: Compute the D_j and N_j

$$N_j = T_j * max\ s_i \qquad D_j = 1 - O_j \qquad where\ O_j = \sum_{j\neq m}^{J} o_{jm}/J - 1 \tag{23}$$

Step 13: Compute the final rank of EVCPs

$$Z_j = \nu(D_j - D^*)/(D^- - D^*) + (1-\nu)(N_j - N^*)/(N^- - N^*) \tag{24}$$

where, $D^* = min\, D_j\,, D^- = max\, D_j\,, N^* = min\, N_j\,, N^- = max\, N_j$.
ν represents the weight of maximum group utility and $(1-\nu)$ illustrates the weight of individual regret. Notably, because of the negative nature of RFs, the final value of alternatives is ranked in descending order.

IV. CASE STUDY

In the case study, three defined EV charging station projects implemented under a public–private partnership (PPP) scheme in different regions of China were selected as decision alternatives and compared in terms of overall risk. In other words, the case study adopted from Liu & Wei (2018) is presented. The RFs used in the case study were also adopted from Liu & Wei (2018), where the risk identification process was conducted through a systematic and rigorous procedure. Specifically, the authors first performed a comprehensive literature review on PPP projects and EV charging infrastructure to establish an initial list of potential RFs. Subsequently, expert consultations were conducted to refine and validate the preliminary risk structure. To further ensure the relevance and significance of the identified risks, a two-round questionnaire survey involving domain experts was carried out. Based on the results of the literature review, expert judgments, and questionnaire surveys, the final set of 17 RFs was identified and classified into four main categories: political and legal risks (R1), economic and financial risks (R2), project and technical risks (R3), and social and environmental risks(R4). Then, the RFs for each main risk factor are explained. The profiles of experts are presented in Table III. Information on the best and worst RFs and project ratings based on the RFs is gathered from an experienced expert and is given in Table IV to Table IX.

Table III. Profile of experts

Organization	No.
Academic sector	10
Government	6
EV companies	2
Infrastructure construction firms	4
State grid and China southern power grid	4
Private sector firms	4

Table IV. Initial information of BWM for main risk factors evaluaiton

Main risk factors	R_1	R_2	R_3	R_4
Best RF: R_4	SS	FS	VS	E
		Worst RF: R_3		
	R_1	FS		
	R_2	SS		
	R_3	E		
	R_4	FS		

Table V. Initial information of BWM for political/legal risks evaluation

Political/legal risks	R_{11}	R_{12}	R_{13}	R_{14}
Best RF: R_{11}	E	E	FS	FS
		Worst RF: R_{14}		
	R_{11}	FS		
	R_{12}	FS		
	R_{13}	E		
	R_{14}	E		

Table VI. Initial information of BWM for economic risks evaluation

Economic risks	R_{21}	R_{22}	R_{23}	R_{24}
Best RF: R_{23}	E	E	E	FS
		Worst RF: R_{24}		
	R_{21}	FS		
	R_{22}	FS		
	R_{23}	FS		
	R_{24}	E		

Table VII. Initial information of BWM for social/environmental risks evaluation

Social/Environmental risks	R_{31}	R_{32}
Best RF: R_{31}	E	E
		Worst RF: R_{32}
	R_{31}	E
	R_{32}	E

Table VIII. Initial information of BWM for technical/operational risks evaluation

Technical/Operational risks	R_{41}	R_{42}	R_{43}	R_{44}	R_{45}	R_{46}	R_{47}
Best RF: R_{41}	E	E	SS	SS	SS	FS	FS
			Worst RF: R_{47}				
		R_{41}	FS				
		R_{42}	FS				
		R_{43}	SS				
		R_{44}	SS				
		R_{45}	SS				
		R_{46}	E				
		R_{47}	E				

Table IX. Linguistic information about ratings of projects based on the RFs

Risk factors	Risk description	P_1	P_2	P_3
R_{11}	Policy	M	H	VH
R_{12}	Government intervention	H	VH	H
R_{13}	Government credit	VH	H	MH
R_{14}	Corruption	MH	MH	M
R_{21}	Market	H	VH	MH
R_{22}	Interest rate fluctuation	VH	H	H
R_{23}	Revenue	MH	MH	M
R_{24}	Payment	M	MH	ML
R_{31}	Power price rise	VH	H	H
R_{32}	Shortage of supporting facility	H	VH	H
R_{41}	Operation	M	H	MH
R_{42}	High battery cost	H	VH	H
R_{43}	Long charging period	MH	H	M
R_{44}	Construction	MH	H	VH
R_{45}	Inadequate PPP project experience	VH	H	ML
R_{46}	Project uniqueness	VH	M	MH
R_{47}	Operating	H	VH	H

The weight of the main risk factors is computed using Eq. (14). The importance of each RF is determined using the same method. Afterward, the importance of each RF and the weight of the main risk factors are multiplied. The final importances of RFs are depicted in Table X. The final value and final ranks of projects are demonstrated in Table XII.

Table X. Final weights of RFs

Main risk factors	Primary weight	Consistency ratio	Risk factors	Primary weight	Consistency ratio	Final weights
Political/legal risks	0.23	0.19	R_{11}	0.375	0	0.08625
			R_{12}	0.375		0.08625
			R_{13}	0.125		0.02875
			R_{14}	0.125		0.02875
Economic risks	0.14		R_{21}	0.3	0	0.042
			R_{22}	0.3		0.042
			R_{23}	0.3		0.042
			R_{24}	0.1		0.014

Continue Table XI. Final weights of RFs

Main risk factors	Primary weight	Consistency ratio	Risk factors	Primary weight	Consistency ratio	Final weights
Social/ environmental risks	0.08	0.19	R_{31}	0.5	0	0.04
			R_{32}	0.5		0.04
Technical/ Operational risks	0.55		R_{41}	0.28	0.2	0.154
			R_{42}	0.28		0.154
			R_{43}	0.11		0.0605
			R_{44}	0.11		0.0605
			R_{45}	0.11		0.0605
			R_{46}	0.055		0.03025
			R_{47}	0.055		0.03025

Table XII. Final ranks of projects

Alternatives	Final value	Final ranking
P_1	1	1
P_2	0.5	2
P_3	0.13	3

A. Comparative analysis

Furthermore, the suggested approach is compared with BWM-TOPSIS, Fuzzy VIKOR, and fuzzy ELECTRE methods to indicate the validity of the proposed method. The final outcomes are presented in Table XIII.

Table XIII. Comparative analysis

Alternatives	Final value	Final ranking	Value of fuzzy BWM-TOPSIS method (Gupta, 2018)	Rankings by fuzzy BWM-TOPSIS method (Gupta, 2018)	Values of fuzzy VIKOR (Mahmudah et al., 2024)	Rankings by fuzzy VIKOR (Mahmudah et al., 2024)	Values of fuzzy ELECTRE (Kaya & Kahraman, 2011)	Rankings by fuzzy ELECTRE (Mahmudah et al., 2024)
P_1	1	1	0.21	1	0.34	1	1	1
P_2	0.5	2	0.61	2	0.62	2	0.68	2
P_3	0.13	3	0.73	3	0.76	3	0.46	3

The comparative analysis demonstrates that the rankings generated by the proposed framework are largely consistent with those obtained from fuzzy VIKOR, fuzzy ELECTRE, and fuzzy BWM–TOPSIS. This consistency indicates that the proposed methodology provides stable and reliable evaluation results. From a practical perspective, the identified high-priority risks can assist policymakers, investors, and project managers in allocating resources more effectively and developing targeted risk mitigation strategies. Furthermore, the integration of BWM, ELECTRE, and VIKOR within an interval type-2 fuzzy environment offers a comprehensive decision-support framework. This framework can effectively address uncertainty and conflicting evaluation criteria in EV charging infrastructure PPP projects.

B. Sensitivity analysis

In this section, a sensitivity analysis is conducted by varying the values of the maximum group utility and individual regret parameters in the VIKOR method. The objective is to examine the stability and robustness of the proposed IT2F-BWM–ELECTRE–VIKOR framework under different decision-making preferences. The results of the sensitivity analysis are presented in Table XIV.

Table XIV. Sensitivity analysis on parameters in the VIKOR method

Alternatives	$\nu = 0.5$	$\nu = 0.9$	$\nu = 0.7$	$\nu = 0.3$	$\nu = 0.1$
P_1	1	1	1	1	1
P_2	0.5	0.1	0.3	0.7	0.9
P_3	0.132296	0.238132	0.185214	0.079377	0.026459

As shown in Table XIV, the ranking results remain unchanged across all sensitivity analysis scenarios, except when the maximum group utility parameter is set to 0.9, where only the second and third-ranked alternatives exchange their positions. The top-ranked alternative remains unchanged in all scenarios. This indicates that the proposed IT2F-BWM–ELECTRE–VIKOR framework is robust and produces stable ranking results with respect to variations in the decision strategy parameters. This, in turn, demonstrates the reliability of the proposed approach.

V. CONCLUSION

This study proposed an integrated IT2F-BWM–ELECTRE–VIKOR framework for the risk assessment of electric vehicle (EV) charging infrastructure public–private partnership (PPP) projects. The framework combines the weighting capability of the Best–Worst Method (BWM) with the complementary strengths of ELECTRE and VIKOR for alternative evaluation and ranking under uncertainty. In addition, interval type-2 fuzzy sets (IT2FSs) were incorporated to better capture ambiguity and uncertainty in expert judgments. To illustrate the applicability of the proposed framework, a benchmark case study adopted from the literature was analyzed. The results showed that the proposed approach can prioritize risk factors and rank project alternatives in a structured and transparent manner. The findings indicate that integrating weighting and ranking techniques within an interval type-2 fuzzy environment can provide useful decision support for complex risk assessment problems characterized by uncertainty and multiple evaluation criteria.

The study contributes to the existing literature in three ways. First, it integrates compromise-based and outranking decision-making philosophies within a unified risk assessment framework. Second, it employs the Best–Worst Method, which requires fewer pairwise comparisons and generally provides higher consistency than many traditional weighting approaches. Third, it incorporates interval type-2 fuzzy sets to better represent uncertainty and ambiguity in experts' evaluations. Future research may also explore fully interval type-2 fuzzy weighting and ranking procedures, incorporate larger groups of experts, and examine the applicability of the proposed approach in other risk assessment and decision-making contexts.

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