

Article

TOPSIS Evaluation of Prefabricated Building Construction Based on Interval-Valued Picture Fuzzy Sets and Cumulative Prospect Theory

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Abstract

Prefabricated construction is increasingly adopted worldwide because of its advantages in sustainability and construction efficiency. Nevertheless, the construction phase still faces substantial and multifaceted risks. These risks are characterized by high uncertainty and strong dependence on the subjective judgments of decision-makers, which may limit the wider promotion and application of prefabricated construction. Existing risk assessment methods often struggle to represent neutral and refusal attitudes in expert evaluations with sufficient precision. They also do not fully account for the psychological and behavioral mechanisms of decision-makers under risk. To address these limitations, this study proposes an integrated evaluation framework that combines interval-valued picture fuzzy sets (IVPFSs), cumulative prospect theory (CPT), and TOPSIS. The decision objective is to rank alternative construction-stage risk-control schemes and identify the relatively important risk factors influencing the ranking results. IVPFSs are used to represent support, opposition, neutrality, and refusal degrees in expert evaluations. CPT is incorporated to capture decision-makers' risk preferences, reference dependence, and loss-aversion behavior. A comprehensive risk indicator system is developed from five dimensions: personnel, management, technology, environment, and materials/equipment. Attribute weights are determined using a coordinated AHP–entropy weighting scheme to balance subjective expert judgment with objective information contained in the evaluation data. The proposed framework is applied to a prefabricated building project in Shanghai. The results indicate that personnel-related factors, especially the technical proficiency of construction workers, are relatively important risk sources in the examined case. The model also provides a structured ranking of alternative risk-control schemes. Overall, this study offers an exploratory case-based decision-support framework for construction-stage risk management in prefabricated building projects and demonstrates the potential value of incorporating behavioral preferences into fuzzy multi-criteria risk assessment.

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1. Introduction

Prefabricated buildings are composed of components manufactured in factories and then transported to the construction site, where they are connected and assembled using cast-in-place concrete [1]. In the context of urgent global targets for energy conservation and emissions reduction, this construction approach has been drawing increasing attention from governments and local communities around the world, owing to its marked advantages in efficiency, resource sustainability, and environmental performance [2]. To further accelerate its adoption, relevant authorities have introduced a series of incentive measures, including financial subsidies, simplified regulatory procedures, mandatory usage quotas, and public awareness campaigns [3]. However, despite these advantages and the presence of supportive policies, prefabricated buildings are still frequently perceived as less cost-effective than traditional cast-in-place structures [4]. This perception is largely attributable to the distinctive construction process of prefabricated buildings, and Figure 1 illustrates an indicative workflow for these stages.

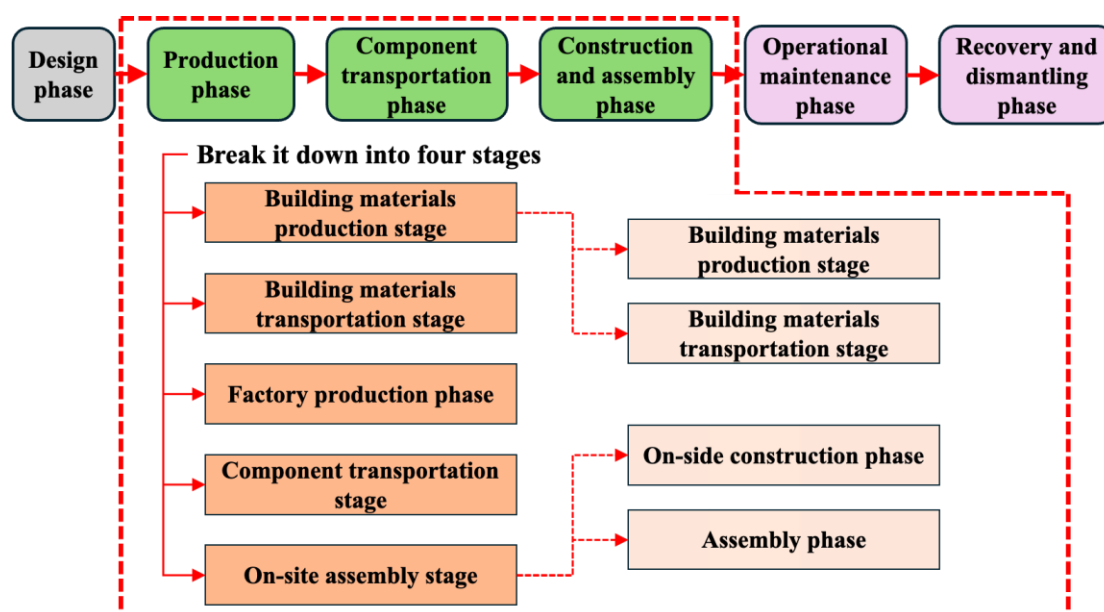


Figure 1. Main construction stages of prefabricated housing.

At present, mainstream evaluation approaches for prefabricated construction—such as the fuzzy Delphi method [5], SEM–SDM models [6], simulation-based analysis [7], DC-LCSA frameworks [8], and Bayesian network models [9]—still have some limitations. Meanwhile, both in China and internationally, existing studies have mainly concentrated on issues such as supply chain management [10], health management of workers in prefabrication plants [11], evacuation planning on construction sites [12], and cost control [13]. However, there remains a substantial gap in the literature concerning risks that are specific to the construction phase of prefabricated buildings—risks that often require a high level of technical expertise from construction personnel [14]. Moreover, since the implementation maturity of prefabricated construction still varies across regions in China, the implementation of such projects may entail potential risks that are difficult to foresee.

In recent years, a growing number of scholars have analyzed and discussed construction risks in prefabricated buildings, as summarized in Table 1. As can be seen from this body of work, most existing studies either overlook the psychological dimension of risk or fail to distinguish, in a nuanced way, between neutrality and refusal in expert judgments. Against this backdrop, the present paper adopts an IVPFS–CPT framework to compensate for these shortcomings in terms of expressive capacity and behavioral consistency, while at the same time making parameter calibration and model complexity control as transparent as possible.

Table 1. Comparison of related studies on prefabricated construction risk assessment.

Reference	Method	Findings	Limitations	Advantages of IVPFS–CPT
Li et al. [15]	SEM path analysis + cloud-model grading	Identifies key influence chains and completes project safety level classification.	A single membership function/cloud parameter cannot clearly distinguish “neutral” from “refusal”	IVPFS explicitly separates positive, neutral, negative, and refusal attitudes, avoiding parameter mixing in cloud models.
Luo et al. [16]	Hybrid MCDM (Delphi + entropy weighting/comprehensive evaluation)	Overall risk is relatively low; human–machine–method factors dominate.	Relies on bi-dimensional or one-dimensional membership processing, making it difficult to represent coexisting positive–neutral–negative–refusal risk perceptions	IVPFS helps represent positive, neutral, negative, and refusal information, while entropy-based weighting supports the extraction of objective discriminatory information.
Chang et al. [17]	IVPYFN–PT–TOPSIS	Can capture risk preferences and improve consistency of rankings.	Pythagorean fuzzy numbers do not explicitly distinguish neutrality from refusal	IVPFS explicitly distinguishes neutrality from refusal.
Chang & Zhao [2]	PTF-VIKOR (prospect theory + Pythagorean fuzzy model)	Rankings can vary with risk attitude and better align with behavioral regularities.	Still does not explicitly distinguish neutrality from refusal	IVPFS separates neutrality and refusal.
Liu et al. [18]	Cloud model (expectation–entropy–hyper-entropy)	Provides an operational grading scheme under imprecise data conditions.	Difficult to represent multi-polar hesitation (positive/neutral/negative/refusal) and risk psychology	The interval four-pole structure of IVPFS expresses multi-source hesitation and helps represent divergent expert judgments under uncertainty.

Compared with existing studies based on CPT or fuzzy TOPSIS, this study goes beyond simply combining several decision-making techniques. It develops an integrated evaluation framework that links information representation, behavioral decision-making, and alternative ranking in the context of construction-stage risk assessment for prefabricated buildings. By introducing interval-valued picture fuzzy sets (IVPFSs), the proposed model can represent four types of expert judgment information: support, neutrality, opposition, and refusal. This is particularly useful in prefabricated construction risk assessment, where experts may not only support or oppose a judgment, but may also remain neutral or refuse to provide a definite evaluation because of incomplete information or uncertain project conditions.

The research problem addressed in this study is how to evaluate construction-stage risks in prefabricated building projects when expert judgments involve uncertainty, neutrality, refusal information, and behavioral risk preferences. Accordingly, the decision ob-

jective is to rank alternative construction-stage risk-control schemes and identify the relatively important risk factors that influence the ranking results. To achieve this objective, CPT is incorporated into the TOPSIS procedure to reflect decision-makers' reference dependence, loss aversion, and different attitudes toward gains and losses. In addition, a coordinated AHP–entropy weighting procedure is used to combine subjective expert knowledge with objective information contained in the evaluation data.

On the practical side, this study provides a structured decision-support framework for risk management in prefabricated construction projects. The case study illustrates how the proposed model can be applied to compare alternative risk-control schemes and identify relatively important risk factors in a real project context. Rather than claiming universal validity, the study offers exploratory case-based evidence for the applicability of the IVPFS–CPT–TOPSIS framework. The scope of this study is confined to risk management during the construction phase of prefabricated buildings. Section 2 introduces the basic concepts and methodological foundations of IVPFSs and CPT. Section 3 presents the AHP–entropy weighting procedure. Section 4 develops the proposed IVPFS–CPT–TOPSIS risk assessment framework. Section 5 applies the model to the Shanghai case and conducts sensitivity, robustness, and comparative analyses. Section 6 summarizes the main findings and management implications, while Section 7 discusses the limitations and future research directions.

2. Methodology

2.1. Picture Fuzzy Sets

Picture fuzzy sets provide a useful tool for handling uncertain information in multi-attribute decision-making problems. By introducing three independent parameters—membership, neutrality, and non-membership—they enable a refined description of the complex attitudes of support, opposition, and neutrality that arise in cognitive and evaluative processes. The key constraint is that the sum of these three grades does not exceed 1, and the remaining part is interpreted as the degree of refusal. In this way, hesitant or incomplete information can be more explicitly represented. Owing to this feature, picture fuzzy sets exhibit strong capability in representing subjective judgments, conflicting information, and knowledge gaps, and are particularly well suited to multi-attribute decision-making and risk assessment in complex environments.

As shown in Table 2, the advantages of IVPFS do not amount to a single-dimensional refinement; instead, they constitute a systematic advance in cognitive structure, information granularity, and alignment with practical applications. Accordingly, this study adopts IVPFS as the basis for model evaluation.

Table 2. Summary of Fuzzy Linguistic Models.

Information Dimension		Advantages	Limitations
IFS	Two-dimensional (support/oppose)	Provides an initial description of hesitation	Cannot distinguish neutrality from refusal; relatively narrow domain of expression; inflexible point-valued form
PFS	Three-dimensional (support/neutral/oppose)	Explicitly depicts neutral attitudes	Point-valued form struggles to capture fluctuations in judgments and divergence of group opinions
PYFS	Two-dimensional (support/oppose)	Looser constraints and a wider domain of expression	Does not explicitly distinguish neutrality from refusal; point-valued form lacks flexibility

IVPYFS	Two-dimensional interval-valued (support/oppose)	Combines the wide domain of PYFS with the tolerance of interval values for fuzziness	Does not explicitly distinguish neutrality from refusal; three-way cognition is represented only indirectly
IVPFS	Three-dimensional (support/neutral/oppose)	Independent three-dimensional cognitive structure; strong interval-valued expressive power; more consistent with multi-attitude decision contexts	Computation is relatively complex

Definition 1 ([19]). Let X be a non-empty universe of discourse. A picture fuzzy set A on X is an object of the following form: $A = \{\langle x, \mu_A(x), \eta_A(x), \nu_A(x) \rangle | x \in X\}$, where $\mu_A(x) \in [0, 1]$, $\eta_A(x) \in [0, 1]$, $\nu_A(x) \in [0, 1]$ denote, respectively, the degrees of membership, neutrality, and non-membership. For all $x \in X$, these functions satisfy $0 \leq \mu_A(x) + \eta_A(x) + \nu_A(x) \leq 1$.

2.2. Interval-Valued Picture Fuzzy Sets

IVPFS can be regarded as an important extension of picture fuzzy sets for dealing with imprecise information. IVPFS assigns interval-valued parameters to membership, neutrality, and non-membership. This structure provides a richer framework for describing uncertainty and hesitation in complex environments. A key strength of this model lies in its ability to accommodate the fluctuation range in decision-makers' judgments. At the same time, it explicitly treats the remaining, unclassifiable part as an interval-valued refusal degree. Owing to this property, IVPFS offer greater practical usefulness and flexibility than conventional fuzzy sets, especially in risk evaluation contexts and multi-attribute decision-making contexts where subjective assessments are prevalent and data are often incomplete.

Definition 2 ([20]). An interval-valued picture fuzzy set is defined as follows: $A = \{\langle x, \mu_A(x), \eta_A(x), \nu_A(x) \rangle | x \in X\}$, where $\mu_A(x) = [\mu_A^-(x), \mu_A^+(x)]$, $\eta_A(x) = [\eta_A^-(x), \eta_A^+(x)]$, $\nu_A(x) = [\nu_A^-(x), \nu_A^+(x)]$ are intervals in $[0, 1]$ representing, respectively, the membership, neutrality, and non-membership degrees of the element x . For all $x \in X$, they satisfy $0 \leq \mu_A(x) + \eta_A(x) + \nu_A(x) \leq 1$ and the refusal degree is defined by $\Omega_A(x) = 1 - \mu_A(x) - \eta_A(x) - \nu_A(x)$, where $\Omega_A(x) = [\Omega_A^-(x), \Omega_A^+(x)] = [1 - (\mu_A^+(x) + \eta_A^+(x) + \nu_A^+(x)), 1 - (\mu_A^-(x) + \eta_A^-(x) + \nu_A^-(x))]$ denotes the interval-valued refusal degree of $x \in X$. For convenience, an IVPFN is written as $\alpha = ([a, b], [c, d], [e, f])$.

Definition 3 ([21]). Let $\alpha_1 = ([a_1, b_1], [c_1, d_1], [e_1, f_1])$ and $\alpha_2 = ([a_2, b_2], [c_2, d_2], [e_2, f_2])$ be two IVPFNs, and let $\lambda > 0$ be a real scalar. Then the basic algebraic operations on IVPFNs are defined as follows:

$$\begin{aligned}\alpha_1 \oplus \alpha_2 &= ([a_1 + a_2 - a_1 a_2, b_1 + b_2 - b_1 b_2], [c_1 c_2, d_1 d_2], [e_1 e_2, f_1 f_2]); \\ \alpha_1 \otimes \alpha_2 &= ([a_1 a_2, b_1 b_2], [c_1 + c_2 - c_1 c_2, d_1 + d_2 - d_1 d_2], [e_1 + e_2 - e_1 e_2, f_1 + f_2 - f_1 f_2]); \\ \lambda \alpha_1 &= ([1 - (1 - a_1)^\lambda, 1 - (1 - b_1)^\lambda], [c_1^\lambda, d_1^\lambda], [e_1^\lambda, f_1^\lambda]); \\ \alpha_1^\lambda &= ([a_1^\lambda, b_1^\lambda], [1 - (1 - c_1)^\lambda, 1 - (1 - d_1)^\lambda], [1 - (1 - e_1)^\lambda, 1 - (1 - f_1)^\lambda]).\end{aligned}$$

Definition 4 ([22]). Let $\alpha_i = ([a_i, b_i], [c_i, d_i], [e_i, f_i])$ be an IVPFN. Then the score function $SF(\alpha_i)$ and the accuracy function $AF(\alpha_i)$ can be described as follows:

$$SF(\alpha_i) = \frac{a_1 - b_1 - c_1 + d_1 - e_1 - f_1}{3}, S(\alpha_1) \in [-1, 1] \quad (1)$$

$$AF(\alpha_i) = \frac{a_1 + b_1 + c_1 + d_1 + e_1 + f_1}{3}, H(\alpha_1) \in [0, 1]$$

Definition 5. Let two IVPFNs $\alpha_1 = ([a_1, b_1], [c_1, d_1], [e_1, f_1])$ and $\alpha_2 = ([a_2, b_2], [c_2, d_2], [e_2, f_2])$. The Hamming distance between α_1 and α_2 is defined as follows:

$$D_H(\alpha_1, \alpha_2) = \frac{1}{6} \{|a_1 - a_2| + |b_1 - b_2| + |c_1 - c_2| + |d_1 - d_2| + |e_1 - e_2| + |f_1 - f_2|\} \quad (2)$$

Definition 6. The Euclidean distance of α_1 and α_2 is as follows:

$$D_E(\alpha_1, \alpha_2) = \sqrt{\frac{1}{6}(|a_1 - a_2| + |b_1 - b_2|)^2 + (|c_1 - c_2| + |d_1 - d_2|)^2 + (|e_1 - e_2| + |f_1 - f_2|)^2} \quad (3)$$

Definition 7 ([23]). Let p_j be a collection of IVPFNs: $p_j = ([\mu_j^L, \mu_j^U], [\eta_j^L, \eta_j^U], [\nu_j^L, \nu_j^U])$, $j = 1, 2, \dots, n$ where $[\mu_j^L, \mu_j^U]$, $[\eta_j^L, \eta_j^U]$, and $[\nu_j^L, \nu_j^U]$ denote the membership, neutrality, and non-membership intervals, respectively.

Let the weight vector be $\omega = (\omega_1, \omega_2, \dots, \omega_n)^T$, where $\omega_j \geq 0$, $\sum \omega_j = 1$, $j = 1, 2, \dots, n$. After the IVPFNs are arranged in descending order according to the score function, the ordered sequence is expressed as $p_{\sigma(1)}, p_{\sigma(2)}, \dots, p_{\sigma(n)}$. If two IVPFNs have the same score value, the accuracy function is used as a secondary comparison criterion.

The IVPFOWIA operator is defined as:

$$IVPFOWIA_{\omega}(p_1, p_2, \dots, p_n) = \omega_1 p_{\sigma(1)} \oplus \omega_2 p_{\sigma(2)} \oplus \dots \oplus \omega_n p_{\sigma(n)} \quad (4)$$

where $\oplus$ denotes the algebraic addition operation between IVPFNs. Therefore, the above expression is not ordinary real-number addition. It is a finite weighted aggregation based on IVPFN operational rules, and the aggregation result is still an IVPFN.

The aggregated IVPFN can be written as:

$$IVPFOWIA_{\omega}(p_1, p_2, \dots, p_n) = ([\mu^L, \mu^U], [\eta^L, \eta^U], [\nu^L, \nu^U])$$

where the membership interval is calculated as:

$$\mu^L = 1 - [(1 - \mu_{\sigma(1)}^L)^{\omega_1} \times (1 - \mu_{\sigma(2)}^L)^{\omega_2} \times \dots \times (1 - \mu_{\sigma(n)}^L)^{\omega_n}]$$

$$\mu^U = 1 - [(1 - \mu_{\sigma(1)}^U)^{\omega_1} \times (1 - \mu_{\sigma(2)}^U)^{\omega_2} \times \dots \times (1 - \mu_{\sigma(n)}^U)^{\omega_n}]$$

The neutrality interval is calculated as:

$$\eta^L = (\eta_{(1)}^L)^{\omega} \times (\eta_{(2)}^L)^{\omega} \times \dots \times (\eta_{(n)}^L)^{\omega}$$

$$\eta^U = (\eta_{(1)}^U)^{\omega} \times (\eta_{(2)}^U)^{\omega} \times \dots \times (\eta_{(n)}^U)^{\omega}$$

The non-membership interval is calculated as:

$$v^L = (v_{(1)}^L)^\omega \times (v_{(2)}^L)^\omega \times \dots \times (v_{(n)}^L)^\omega$$

$$v^U = (v_{(1)}^U)^\omega \times (v_{(2)}^U)^\omega \times \dots \times (v_{(n)}^U)^\omega$$

The refusal degree of the aggregated IVPFN is:

$$\pi = [\pi^L, \pi^U]$$

where

$$\pi^L = 1 - \mu^U - \eta^U - v^U$$

$$\pi^U = 1 - \mu^L - \eta^L - v^L$$

Thus,

$$\pi = [1 - \mu^U - \eta^U - v^U, 1 - \mu^L - \eta^L - v^L]$$

2.3. Cumulative Prospect Theory

In practical construction risk assessment, decision-makers do not always follow the assumptions of traditional expected utility theory. Construction managers may overestimate low-probability but high-consequence events, such as hoisting accidents, component connection failures, or severe on-site safety incidents. Meanwhile, they are often more sensitive to potential losses than to equivalent gains, showing typical loss-aversion behavior. Therefore, cumulative prospect theory is introduced in this study to better describe decision-makers' psychological and behavioral responses under uncertain construction risks.

Prospect theory was developed by Tversky and Kahneman in 1979 [24]. In 1992, Tversky and Kahneman further advanced their theory by proposing the CPT. Enhanced by extensive empirical data, CPT extends PT's applicability to decision-making scenarios involving a wide range of potential outcomes and addresses the issue of stochastic dominance. The prospect function $P(z)$ is defined in reference [25] as follows:

$$P(z) = \sum_{\varepsilon=1}^k v(\bar{\Delta}_{i\sigma(j)}) \Delta \pi_j \quad (5)$$

3. Determination of Risk Factor Weights Based on the AHP–Entropy Approach

3.1. AHP-Based Weighting Method

Within the AHP framework, a pairwise comparison matrix is first constructed, and the IVPFOWIA operator is then used to aggregate the judgments in each row to obtain the subjective weights. Suppose there are m risk factors, and the comparison matrix is $A = (a_{ij})_{m \times m}$, where a_{ij} is an IVPFN representing the relative importance of factor i with respect to factor j . Let $\alpha_i = ([a_i, b_i], [c_i, d_i], [e_i, f_i])$, and denote the aggregation weight vector by $\omega = (\omega_1, \omega_2, \dots, \omega_n)^T$, which satisfies $\sum_{i=1}^n \omega_i = 1$. According to Definition 4, the IVPFNs α_i are arranged in descending order on the basis of their score (and, where necessary, accuracy) values, yielding a reordered sequence of α_i . Then, the IVPFOWIA aggregation result can be expressed as:

$$\text{IVPFOWIA}(\alpha_1, \alpha_2, \dots, \alpha_n) = \omega_1 \alpha_{\sigma(1)} \oplus \omega_2 \alpha_{\sigma(2)} \cdots \oplus \omega_n \alpha_{\sigma(n)} \quad (6)$$

where $\oplus$ denotes the algebraic addition operation between IVPFNs and is computed according to the basic IVPFN operational laws defined in Definition 3.

The aggregated IVPFN can then be expressed as $\alpha = ([a, b], [c, d], [e, f])$.

$$\begin{aligned}
 a &= 1 - \prod_{i=1}^n (1 - a_{\sigma(i)})^{\omega_i} \\
 b &= 1 - \prod_{i=1}^n (1 - b_{\sigma(i)})^{\omega_i} \\
 c &= \prod_{i=1}^n (c_{\sigma(i)})^{\omega_i} \\
 d &= \prod_{i=1}^n (d_{\sigma(i)})^{\omega_i} \\
 e &= \prod_{i=1}^n (e_{\sigma(i)})^{\omega_i} \\
 f &= \prod_{i=1}^n (f_{\sigma(i)})^{\omega_i}
 \end{aligned} \tag{7}$$

In summary, the AHP procedure is first applied, the entries of the pairwise comparison matrices are then aggregated using the IVPFOWIA operator, the geometric means and corresponding score values are subsequently computed, and these results are finally normalized to obtain the subjective weight vector.

Step 1: Constructing the pairwise comparison matrix

Suppose there are m risk factors. Each expert k provides a judgment matrix C^k , in which the element C_{ij}^k is an IVPFN representing the relative importance of risk factor i compared with factor j . By aggregating the judgment matrices of all experts, the collective judgment matrix C is obtained:

$$C_{ij} = \text{IVPFOWIA}(C_{ij}^1, C_{ij}^2, \dots, C_{ij}^K) \tag{8}$$

Step 2: Computing the geometric mean IVPFN

For each risk factor i , calculate its geometric mean δ_i as follows:

$$\delta_i = (C_{i1} \otimes C_{i2} \cdots \otimes C_{im})^{\frac{1}{m}} \tag{9}$$

Step 3: Computing the score function and deriving the weights

For each δ_i , compute the score function $SF(\delta_i)$ according to Definition 4. Since $SF(\delta_i) \in [-1, 1]$, it is first converted into a positive value as follows:

$$S_i^{AHP} = \frac{SF(\delta_i) + 1}{2} \tag{10}$$

The AHP-based subjective weights are finally obtained by normalizing these adjusted score values.

$$\omega_i^{AHP} = \frac{S_i^{AHP}}{\sum_{i=1}^m S_i^{AHP}} \tag{11}$$

3.2. Entropy-Weight Method

The entropy-weight method is used to derive objective criterion weights from the discriminatory information contained in the decision matrix. Since the original evaluation information is expressed in the form of IVPFNs, it must first be transformed into comparable scalar input values before entropy calculation.

Suppose there are m alternatives and n risk criteria. Let r_{ij} denote the aggregated IVPFN evaluation of alternative A_i under criterion C_j : $r_{ij} = ([\mu_{ij}^L, \mu_{ij}^U], [\eta_{ij}^L, \eta_{ij}^U], [v_{ij}^L, v_{ij}^U])$ where μ , η , and v represent membership, neutrality, and non-membership degrees, respectively. The corresponding refusal degree is calculated as:

$$\pi_{ij}^L = 1 - \mu_{ij}^U - \eta_{ij}^U - v_{ij}^U$$

$$\pi_{ij}^U = 1 - \mu_{ij}^L - \eta_{ij}^L - v_{ij}^L$$

Then, each IVPFN is converted into a scalar score value:

$$S(r_{ij}) = 1/2(\mu_{ij}^L + \mu_{ij}^U) + 1/4(\eta_{ij}^L + \eta_{ij}^U) - 1/2(v_{ij}^L + v_{ij}^U) - 1/4(\pi_{ij}^L + \pi_{ij}^U)$$

In this score function, membership contributes positively to the evaluation result, non-membership contributes negatively, and neutrality and refusal are incorporated as moderate and uncertainty-related components. Therefore, the transformation does not ignore the semantic information contained in IVPFSs, but compresses membership, neutrality, non-membership, and refusal into a comparable scalar value for entropy calculation.

Because entropy calculation requires non-negative comparable input values, the score values are further normalized. For benefit-type criteria, the normalized entropy input value is calculated as:

$$x_{ij} = \frac{S(r_{ij}) - \min_i S(r_{ij})}{\max_i S(r_{ij}) - \min_i S(r_{ij})} \quad (12)$$

For cost-type criteria, the normalized entropy input value is calculated as:

$$x_{ij} = \frac{\max_i S(r_{ij}) - S(r_{ij})}{\max_i S(r_{ij}) - \min_i S(r_{ij})} \quad (13)$$

where x_{ij} is the normalized entropy input value of alternative A_i under criterion C_j . If $\max_i S(r_{ij}) = \min_i S(r_{ij})$, all alternatives have the same score under criterion C_j , and x_{ij} is assigned the same value for all alternatives.

The normalized proportion used for entropy calculation is obtained as:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}} \quad (14)$$

Then, the entropy value of criterion C_j is calculated as:

$$E_j = -\frac{1}{\ln m} \sum_{i=1}^m p_{ij} \ln p_{ij} \quad (15)$$

where m is the number of alternatives. If $p_{ij} = 0$, $p_{ij} \ln p_{ij}$ is defined as 0.

The information utility value of criterion C_j is $d_j = 1 - E_j$.

Finally, the entropy-based objective weight is calculated as:

$$\omega_j^{Entropy} = d_j / \sum_{j=1}^n d_j$$

It should be noted that this score-based scalar transformation is used only to generate entropy input values for objective weighting. The original IVPFN structure is still retained in the subsequent IVPFS–CPT–TOPSIS evaluation process.

3.3. Comprehensive Weight Calculation

After obtaining the AHP-based subjective weights and entropy-based objective weights, a coordination coefficient θ is introduced to integrate the two types of weighting information. The comprehensive weight of criterion C_j is calculated as:

$$\omega_j = \theta \omega_j^{AHP} + (1 - \theta) \omega_j^{Entropy} \quad (16)$$

where ω_j^{AHP} is the subjective weight obtained from AHP, $\omega_j^{Entropy}$ is the objective weight obtained from the entropy method, and θ represents the relative importance assigned to subjective expert judgment. When θ is closer to 1, greater emphasis is placed on AHP weights. When θ is closer to 0, greater emphasis is placed on entropy weights.

In the baseline model, θ is set to 0.5, indicating that subjective expert judgment and objective information are treated with equal importance. The influence of θ on the final ranking is further examined in the sensitivity analysis.

4. Risk Assessment Based on the IVPFS–CPT–TOPSIS Method

4.1. Establishment of a Risk Indicator System

To ensure that the risk indicator system for prefabricated construction was established with sufficient rigor, a carefully structured procedure was adopted. Specifically, relevant topics were first searched in the Web of Science database to construct an initial set of evaluation indicators. On this basis, a two-round Delphi process was employed to solicit and consolidate expert opinions, thereby refining and finalizing the risk assessment indicator system.

In the first round, the initial indicator list was submitted to the expert panel for review. The experts evaluated the relevance, clarity, and completeness of each indicator according to the characteristics of construction-stage risk management in prefabricated building projects. Based on their feedback, several indicator descriptions were revised to avoid ambiguity, and overlapping expressions were merged.

In the second round, the revised indicator system was returned to the experts for confirmation. The experts were asked to judge whether each indicator should be retained and whether the five-dimensional structure could adequately reflect construction-stage risks in prefabricated building projects. Consensus was considered to be reached when no expert raised further objections to the inclusion, wording, or classification of the indicators. After the second round, all experts agreed that the revised indicator system was suitable for the subsequent IVPFS–CPT–TOPSIS evaluation. Therefore, the final indicator system was validated through both literature-based construction and expert consensus, as presented in Table 3 and Figure 2.

Table 3. Risk Assessment Indicator System.

Indicators	Number	Influence Factors	Reference
Personnel	C ₁₁	Technical level of construction personnel	[26–29]
	C ₁₂	Security personnel configuration	[26,27,29]
	C ₁₃	Health status of construction personnel	[28,29]
	C ₁₄	Safety awareness of construction personnel	[26,27]
	C ₁₅	Degree of coordination between jobs	[27]
Management	C ₂₁	Site safety management system	[27,28,30,31]
	C ₂₂	Emergency management program	[26,27,30,31]
	C ₂₃	Safety measures for component hoisting	[26,28,29]
	C ₂₄	Implementation of security measures	[30]
	C ₂₅	Storage of finished goods	[28,29]
Technology	C ₃₁	Deep design of embedded parts	[26,29]
	C ₃₂	Component connection node design	[28,29,31,32]
	C ₃₃	Construction scheme	[26,27,30,31]
	C ₃₄	Hoisting plan and supervision	[27,33,34]
	C ₃₅	Hoisting technology	[32,35]
Environment	C ₄₁	Temporary hole protection	[29]

	C ₄₂	State of the natural environment	[31,34]
	C ₄₃	Construction site environmental status	[31,34,35]
	C ₄₄	Surrounding environment of hoisting process	[30,32,33]
	C ₄₅	Safety standards policy environment	[26,35]
Materials	C ₅₁	Reliability of mechanical equipment	[30,31]
	C ₅₂	Hoisting machine selection	[26,29]
	C ₅₃	Precast component quality	[33,34]
	C ₅₄	Equipment maintenance	[27,35]
	C ₅₅	Site stacking of components	[31,33]

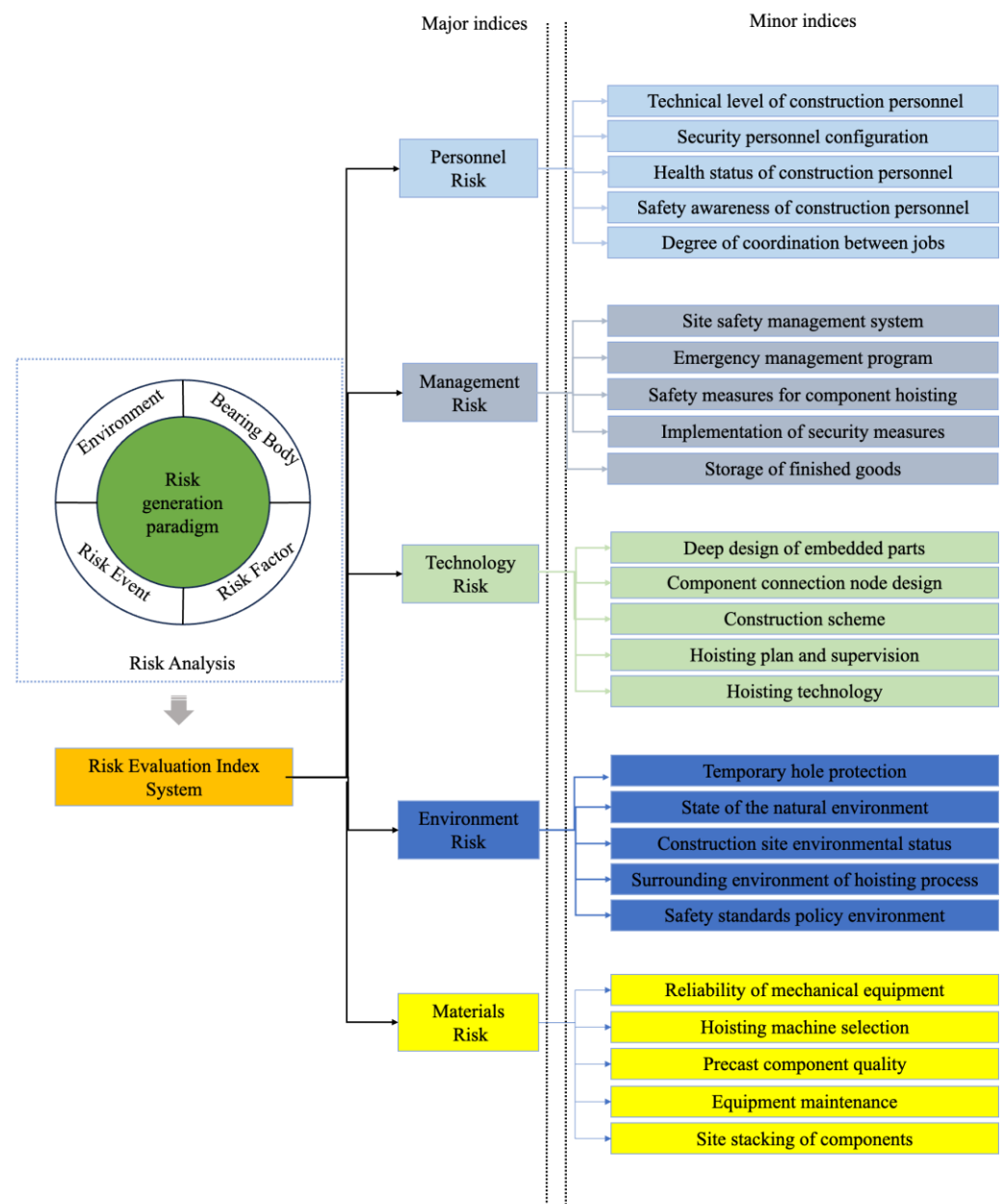


Figure 2. Risk assessment indicator system.

4.2. Determination of Expert Weights

Let the evaluation provided by expert E_k for alternative A_j under criterion C_l be denoted by:

$$\alpha_{jkl} = ([a_{jkl}, b_{jkl}], [c_{jkl}, d_{jkl}], [e_{jkl}, f_{jkl}])$$

Step 1: The group mean of each indicator is calculated as follows:

$$\bar{\alpha}_{jl} = \left(\left[\frac{1}{h} \sum_k a_{jkl}, \frac{1}{h} \sum_k b_{jkl} \right], \left[\frac{1}{h} \sum_k c_{jkl}, \frac{1}{h} \sum_k d_{jkl} \right], \left[\frac{1}{h} \sum_k e_{jkl}, \frac{1}{h} \sum_k f_{jkl} \right] \right)$$

where h denotes the number of experts.

Step 2: Given two IVPFS evaluations $\alpha = ([a, b], [c, d], [e, f])$ $\beta = ([a', b'], [c', d'], [e', f'])$, the endpoint Hamming distance is defined as follows:

$$d_{end}(\alpha, \beta) = \frac{1}{6} (|a - a'| + |b - b'| + |c - c'| + |d - d'| + |e - e'| + |f - f'|) \quad (17)$$

Information sufficiency is measured as:

$$H^*(\alpha) = \frac{(a + c + e) + (b + d + f)}{2} \quad (18)$$

$$s(\alpha, \beta) = (1 - d_{end}(\alpha, \beta)) \sqrt{\frac{H^*(\alpha) + H^*(\beta)}{2}} \quad (19)$$

The within-attribute average similarity S_{kl} , that is, the mean similarity of expert E_k on criterion C_l , is defined as follows:

$$S_{kl} = \frac{1}{m} \sum_{j=1}^m s(\alpha_{jkl}, \bar{\alpha}_{jl}) \quad (20)$$

Step 3: Determination of expert weights:

$$S_k = \sum_{l=1}^n \omega_l S_{kl} \quad (21)$$

$$w_k = \frac{S_k}{\sum_{k=1}^h S_k}, k = 1, \dots, h \quad (22)$$

4.3. Evaluation of the IVPFS–CPT–TOPSIS Model

The parameter settings of CPT are adopted from the commonly used empirical values in cumulative prospect theory. Specifically, α and β describe the curvature of the value function in the gain and loss domains, respectively; λ represents the degree of loss aversion; and γ^+ and γ^- reflect the nonlinear weighting of gains and losses. In the baseline model, $\alpha = \beta = 0.88$, $\lambda = 2.25$, $\gamma^+ = 0.61$, and $\gamma^- = 0.69$ are used as the reference parameter values. These values are widely adopted in CPT-based decision-making studies and provide a general representation of risk attitude, loss aversion, and probability distortion. Since decision-makers in construction projects may have heterogeneous behavioral preferences, the influence of these parameters on the final ranking is further examined through sensitivity analysis. For clarity, the parameters involved in the formulas in this section are summarized in Table 4.

Table 4. Attributes of Parameters Used in the Formulas.

Parameter	Symbol	Recommended Value	Meaning
Risk attitude for gains	α	0.88	Degree of risk aversion in the gain domain
Risk attitude for losses	β	0.88	Degree of risk seeking in the loss domain
Loss aversion	λ	2.25	Sensitivity of losses relative to gains

Curvature of gain weight function	γ^+	0.61	Shape of the probability weighting function for gains
Curvature of loss weight function	γ^-	0.69	Shape of the probability weighting function for losses

Step 1: Determining the positive and negative ideal solutions.

According to Equation (22), the expert evaluations are first aggregated as follows:

$$\alpha_{ij} = \bigoplus_{k=1}^h \omega_k \alpha_{ijk} \quad (23)$$

where $[a_{ijk}, b_{ijk}]$, $[c_{ijk}, d_{ijk}]$, and $[e_{ijk}, f_{ijk}]$ represent the membership, neutrality, and non-membership intervals, respectively. Then the aggregated group evaluation α_{ij} can be obtained as:

$$\alpha_{ij} = ([a_{ij}, b_{ij}], [c_{ij}, d_{ij}], [e_{ij}, f_{ij}])$$

where

$$a_{ij} = 1 - \prod_{k=1}^h (1 - a_{ijk})^{\omega_k}$$

$$b_{ij} = 1 - \prod_{k=1}^h (1 - b_{ijk})^{\omega_k}$$

$$c_{ij} = \prod_{k=1}^h (c_{ijk})^{\omega_k}$$

$$d_{ij} = \prod_{k=1}^h (d_{ijk})^{\omega_k}$$

$$e_{ij} = \prod_{k=1}^h (e_{ijk})^{\omega_k}$$

$$f_{ij} = \prod_{k=1}^h (f_{ijk})^{\omega_k}$$

The aggregated group evaluation is finally obtained as:

$$\alpha_{ij} = ([a_{ij}, b_{ij}], [c_{ij}, d_{ij}], [e_{ij}, f_{ij}]) \quad (24)$$

Before determining the positive and negative ideal solutions, each IVPFN is first transformed into a comparable scalar value using the score function. When two IVPFNs have the same score value, the accuracy function is further used as a secondary comparison criterion. Therefore, the max/min operators in Equations (25) and (26) are not directly applied to the interval endpoints of IVPFNs, but to their score values and, where necessary, accuracy values.

For benefit-type criteria:

$$\begin{aligned} r_j^+ &= r_{ij}, \text{ where } S(r_{ij}) = \max_i S(r_{ij}) \\ r_j^- &= r_{ij}, \text{ where } S(r_{ij}) = \min_i S(r_{ij}) \end{aligned} \quad (25)$$

For cost-type criteria:

$$\begin{aligned} r_j^+ &= r_{ij}, \text{ where } S(r_{ij}) = \min_i S(r_{ij}) \\ r_j^- &= r_{ij}, \text{ where } S(r_{ij}) = \max_i S(r_{ij}) \end{aligned} \quad (26)$$

When two or more IVPFNs have the same score value, the accuracy function $H(r_{ij})$ is used as the secondary criterion to determine the final positive or negative ideal solution.

Step 2: CPT-based prospect distance calculation

An improved Euclidean distance is adopted to measure the CPT-based prospect distance. Specifically, the distances to the positive and negative ideal solutions are given by:

$$D_{ij}^+ = \sqrt{\frac{1}{6} \left[(a_{ij} - a_j^+)^2 + (b_{ij} - b_j^+)^2 + (c_{ij} - c_j^+)^2 + (d_{ij} - d_j^+)^2 + (e_{ij} - e_j^+)^2 + (f_{ij} - f_j^+)^2 \right]} \quad (27)$$

$$D_{ij}^- = \sqrt{\frac{1}{6} \left[(a_{ij} - a_j^-)^2 + (b_{ij} - b_j^-)^2 + (c_{ij} - c_j^-)^2 + (d_{ij} - d_j^-)^2 + (e_{ij} - e_j^-)^2 + (f_{ij} - f_j^-)^2 \right]} \quad (28)$$

Step 3: Calculating gains and losses

Taking the positive ideal solution (PIS) as the reference point, the gains and losses are defined as follows:

Gain (relative to the PIS):

$$\Delta_{ij}^+ = D_{ij}^- - D_{ij}^+ \quad (29)$$

Loss (relative to the PIS):

$$\Delta_{ij}^- = D_{ij}^+ - D_{ij}^- \quad (30)$$

For $\Delta_{ij}^+ > 0$ and $\Delta_{ij}^- < 0$, these terms represent gains and losses, respectively.

Step 4: IVPFS–CPT value function

A normalization procedure is then applied as follows:

$$\bar{\Delta}_{ij}^+ = \frac{\Delta_{ij}^+}{\max_{ij} |\Delta_{ij}^+|} \quad (31)$$

$$\bar{\Delta}_{ij}^- = \frac{\Delta_{ij}^-}{\max_{ij} |\Delta_{ij}^-|} \quad (32)$$

The value function is defined as:

$$V(\bar{\Delta}_{ij}) = \begin{cases} (\bar{\Delta}_{ij}^+)^{\alpha}, & \text{if } \bar{\Delta}_{ij}^+ > 0 \\ -\lambda(-\bar{\Delta}_{ij}^-)^{\beta}, & \text{if } \bar{\Delta}_{ij}^- < 0 \end{cases} \quad (33)$$

where α and β (both set to 0.88) are the risk-attitude parameters, and $\lambda = 2.25$ denotes the degree of loss aversion.

(1) IVPFS–CPT weighting function

In IVPFS, the refusal degree represents the part of expert judgment that cannot be clearly assigned to membership, neutrality, or non-membership. A higher refusal degree indicates that the evaluation information is more incomplete, more hesitant, or less certain. In construction risk assessment, such incomplete information may arise from insufficient project data, divergent expert cognition, or the limited predictability of uncertain construction events.

In CPT, the weighting function reflects decision-makers' subjective perception of uncertain outcomes rather than objective probability alone. Therefore, the refusal degree can be introduced as an uncertainty adjustment factor in the weighting function. When the refusal degree increases, the perceived uncertainty of the corresponding evaluation infor-

mation also increases. This changes the subjective decision weight assigned to the criterion or alternative, thereby affecting the cumulative prospect value. In this way, the proposed model links the informational incompleteness captured by IVPFS with the behavioral weighting mechanism of CPT.

Taking the refusal degree as an indicator of information incompleteness, the probability weighting function is further adjusted to account for uncertainty as follows:

$$\Omega_j = [\Omega_j^-, \Omega_j^+] = [1 - (b_j + d_j + f_j), 1 - (a_j + c_j + e_j)] \quad (34)$$

$$\rho_j = 1 - \frac{\Omega_j^- + \Omega_j^+}{2} \quad (35)$$

(2) Prospect weighting function:

Substituting the above into the CPT probability weighting function yields:

$$\pi_j^+(\omega_j) = \frac{(\omega_j \cdot \rho_j)^{\gamma^+}}{[(\omega_j \cdot \rho_j)^{\gamma^+} + (1 - \omega_j \cdot \rho_j)^{\gamma^+}]^{\frac{1}{\gamma^+}}} \quad (36)$$

$$\pi_j^-(\omega_j) = \frac{(\omega_j \cdot \rho_j)^{\gamma^-}}{[(\omega_j \cdot \rho_j)^{\gamma^-} + (1 - \omega_j \cdot \rho_j)^{\gamma^-}]^{\frac{1}{\gamma^-}}} \quad (37)$$

The meanings of the parameters are as follows: $\gamma^+, \gamma^- \in (0, 1]$ control the curvature of the weighting functions in the gain and loss domains, respectively, and are typically set to 0.61 and 0.69. ρ_j denotes the uncertainty adjustment factor based on the refusal degree.

Step 5: Detailed procedure for computing cumulative prospect values

(1) Ordering of criteria. For each alternative A_j , the criteria are ranked in descending order according to the value $V(\bar{\Delta}_{ij})$.

$$v(\bar{\Delta}_{i\sigma(1)}) \geq v(\bar{\Delta}_{i\sigma(2)}) \geq \dots \geq v(\bar{\Delta}_{i\sigma(n)})$$

(2) Cumulative weight calculation

For the gain part with $v(\bar{\Delta}_{ij}) \geq 0$, $\omega_{\sigma(l)}$ is the comprehensive weight of various influencing factors. Assume that the first k criteria are gain-type criteria; the corresponding cumulative weights are then computed as:

$$P_j^+ = \sum_{l=j}^k \rho_{\sigma(l)} \omega_{\sigma(l)}$$

$$\pi_j^+ = \frac{(P_j^+)^{\gamma^+}}{[(P_j^+)^{\gamma^+} + (1 - P_j^+)^{\gamma^+}]^{\frac{1}{\gamma^+}}} \quad (38)$$

$$\Delta\pi_j^+ = \pi^+(P_j^+) - \pi^+(P_{j+1}^+) \quad (39)$$

For the loss part with $V(\bar{\Delta}_{ij}) < 0$, If the remaining $n - k$ criteria are treated as loss-type criteria, their cumulative weights are then given by:

$$P_j^- = \sum_{l=k+1}^j \rho_{\sigma(l)} \omega_{\sigma(l)} \quad (40)$$

$$\pi_j^- = \frac{(P_j^-)^{\gamma^-}}{[P_j^{-\gamma^-} + (1 - P_j^-)^{\gamma^-}]^{\frac{1}{\gamma^-}}}$$

$$\Delta\pi_j^- = \pi^-(P_j^-) - \pi^-(P_{j+1}^-) \quad (41)$$

(3) Comprehensive prospect value:

$$V_i^+ = \sum_{j=1}^k v(\bar{\Delta}_{i\sigma(j)}) \cdot \Delta\pi_j^+ \quad (42)$$

$$V_i^- = \sum_{j=k+1}^n v(\bar{\Delta}_{i\sigma(j)}) \cdot \Delta\pi_j^- \quad (43)$$

$$V_i = V_i^+ + V_i^- \quad (44)$$

Step 6: Detailed computation of the final ranking

(1) Prospect values of the positive and negative ideal solutions

$$V^+ = \max_i V_i \quad (45)$$

$$V^- = \min_i V_i \quad (46)$$

(2) Distance calculation:

$$d_i^+ = |V_i - V^+| \quad (47)$$

$$d_i^- = |V_i - V^-| \quad (48)$$

(3) Relative closeness:

$$RC_i = \frac{d_i^-}{d_i^- + d_i^+} \quad (49)$$

The alternatives are then ranked in descending order of RC_i , with a larger RC_i indicating a more favorable option. The overall evaluation framework is illustrated in Figure 3.

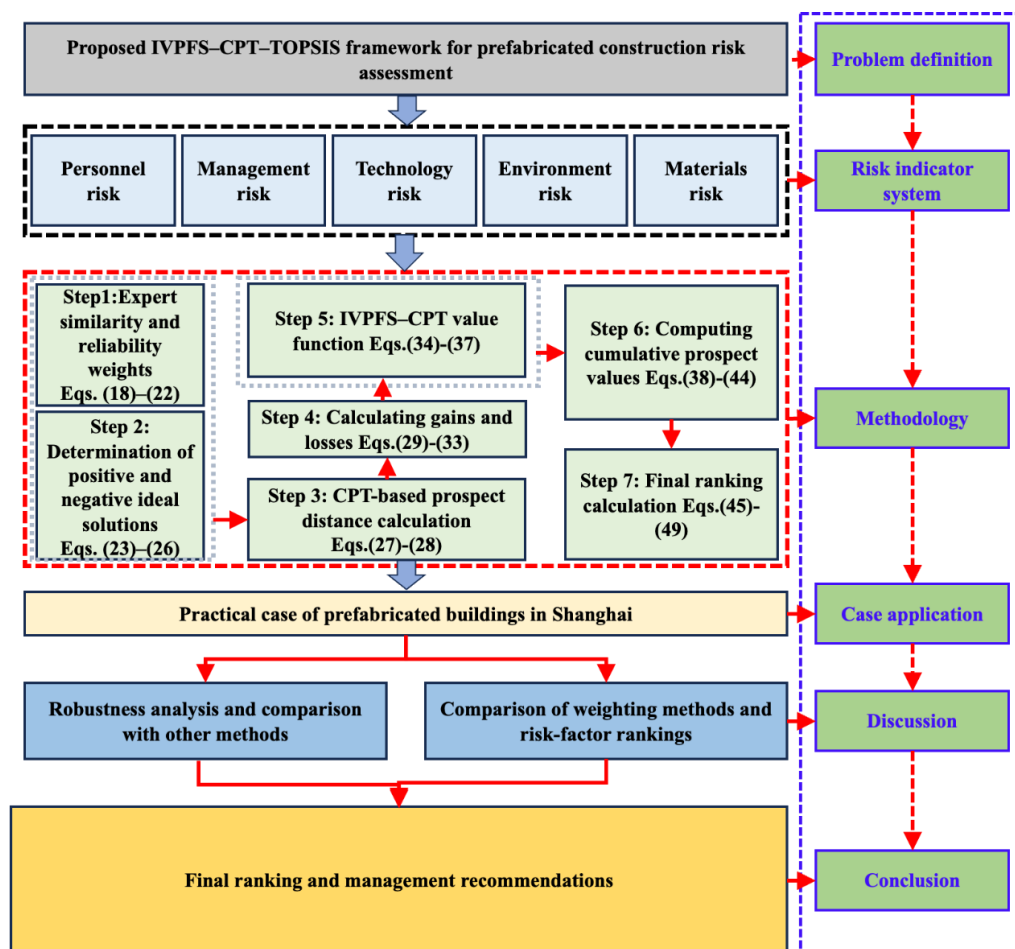


Figure 3. Flowchart of the proposed IVPFS-CPT-TOPSIS framework with expert similarity analysis.

5. Analysis Example

5.1. Case Application

The case project is a prefabricated building project located in Shanghai, China. Due to confidentiality requirements, the project name is anonymized. The project adopts prefabricated construction techniques during the construction stage, involving the transportation, storage, hoisting, installation, and connection of precast components. Compared with conventional cast-in-place construction, the construction process of prefabricated buildings relies more heavily on component accuracy, hoisting operations, on-site coordination, and the technical competence of construction personnel. Therefore, risk control during the construction stage is particularly important.

In this case, the main risk-control task is to select the most suitable construction-stage risk-control scheme from five alternatives. These alternatives are not general construction plans, but risk-control schemes with different management priorities. They were developed according to the five dimensions of the risk indicator system; namely, personnel, management, technology, environment, and materials/equipment. The purpose of the case study is to evaluate these schemes under the proposed IVPFS–CPT–TOPSIS framework and identify the scheme that provides the most favorable overall risk-control performance.

The five alternative schemes are described as follows and are summarized in Table 5. Scheme A_1 is a personnel-oriented risk-control scheme. It emphasizes the allocation and management of engineering and technical personnel, including worker training, technical competence, safety awareness, health status, and job coordination. Scheme A_2 is a management-oriented risk-control scheme. It focuses on on-site safety management, emergency planning, implementation of safety measures, and storage management of finished components. Scheme A_3 is a technology-oriented risk-control scheme. It gives priority to embedded-part design, component connection-node design, hoisting technology, construction scheme optimization, and hoisting supervision. Scheme A_4 is an environment-oriented risk-control scheme. It focuses on temporary opening protection, natural environmental conditions, construction-site environmental conditions, the surrounding hoisting environment, and the policy environment of safety standards. Scheme A_5 is a materials/equipment-oriented risk-control scheme. It emphasizes mechanical equipment reliability, hoisting-machine selection, precast component quality, equipment maintenance, and on-site stacking of components.

Table 5. Practical interpretation of the five-alternative risk-control schemes.

Scheme	Risk-Control Orientation	Practical Focus
A_1	Personnel-oriented scheme	Technical training, safety awareness, health monitoring, personnel allocation, job coordination
A_2	Management-oriented scheme	Site safety management, emergency response, implementation of safety measures, component storage
A_3	Technology-oriented scheme	Embedded-part design, connection-node control, hoisting plan, hoisting technology, technical supervision
A_4	Environment-oriented scheme	Temporary opening protection, natural environment, site conditions, surrounding hoisting environment, safety-policy environment
A_5	Materials/equipment-oriented scheme	Mechanical equipment reliability, crane selection, precast component quality, equipment maintenance, component stacking

Based on the above practical definitions, the expert panel evaluated the performance of each scheme under the 25 risk indicators. The linguistic evaluations were then transformed into IVPFNs and processed using the proposed IVPFS–CPT–TOPSIS framework.

5.2. Determination of Parameters

An evaluation panel consisting of ten senior experts was invited to participate in this study. To improve the credibility of the expert-based assessment, the experts were selected according to three criteria: professional experience in prefabricated construction, direct participation in prefabricated building projects, and complementary expertise related to construction-phase risk control. The ten experts represent different professional roles, including project management, construction technology, on-site safety supervision, quality inspection, hoisting operation, BIM-based digital construction, component production, and construction management consulting. Their profiles are summarized in Table 6.

Table 6. Profiles of the expert panel.

Expert	Professional Role	Experience	Participation in Prefabricated Projects	Main Expertise
E ₁	Project manager	More than 10 years	7 prefabricated building projects	Project organization, schedule coordination, and risk management
E ₂	Construction technical engineer	More than 10 years	8 prefabricated building projects	Hoisting technology, component installation, and connection-node control
E ₃	Safety supervisor	More than 10 years	12 prefabricated building projects	Site safety management, emergency response, and safety inspection
E ₄	Prefabricated construction project manager	More than 12 years	10 prefabricated building projects	Construction organization, resource coordination, and construction-stage risk control
E ₅	Hoisting operation engineer	More than 10 years	9 prefabricated building projects	Hoisting operation, crane selection, lifting-plan implementation, and hoisting safety
E ₆	Quality inspection engineer	More than 9 years	8 prefabricated building projects	Precast component quality inspection, installation quality control, and acceptance management
E ₇	BIM/digital construction engineer	More than 8 years	6 prefabricated building projects	BIM-based construction coordination, digital simulation, and information management
E ₈	Site safety manager	More than 11 years	10 prefabricated building projects	Construction-site safety control, hazard identification, and safety training
E ₉	Component production and supply chain engineer	More than 10 years	9 prefabricated building projects	Component production, transportation, storage, and supply chain coordination
E ₁₀	Senior construction management consultant	More than 12 years	11 prefabricated building projects	Prefabricated construction management, risk assessment, and expert decision-making

The interval-valued linguistic mapping in Table 7 was established through an approximately equidistant semantic division from “Very Low” to “Very High” and was further reviewed by the expert panel. The experts examined whether the assigned IVPFNs reflected the relative intensity of each linguistic term and satisfied the basic constraints of IVPFS. Therefore, the mapping was not directly assigned by the authors but was determined based on equidistant linguistic scaling and expert calibration.

The ten experts conducted pairwise comparisons of the risk factors associated with the construction phase of prefabricated buildings and expressed their judgments using IVPFN linguistic terms. Based on the ten individual pairwise comparison matrices, a collective pairwise comparison matrix was obtained through the IVPFOWIA aggregation

procedure. The aggregated first-level comparison matrix and the corresponding AHP weights are reported in Table 8.

Table 7. Equidistant and expert-calibrated linguistic scale with IVPFNs.

Linguistic Terms	IVPFNs $\alpha_i = ([a_i, b_i], [c_i, d_i], [e_i, f_i])$
Very Low (VL)	[(0.00,0.05), (0.10,0.15), (0.70,0.75)]
Low (L)	[(0.05,0.10), (0.10,0.15), (0.60,0.65)]
Medium Low (ML)	[(0.10,0.15), (0.10,0.15), (0.50,0.55)]
Equal (E)	[(0.15,0.20), (0.10,0.15), (0.40,0.45)]
Medium High (MH)	[(0.20,0.25), (0.10,0.15), (0.30,0.35)]
High (H)	[(0.25,0.30), (0.10,0.15), (0.20,0.25)]
Very High (VH)	[(0.30,0.35), (0.10,0.15), (0.10,0.15)]

Table 8. Aggregated AHP linguistic comparison matrix and first-level weights of risk indicators.

Risk Factor	Personnel	Management	Technology	Environment	Materials	Weights
Personnel	<i>E</i>	<i>H</i>	<i>VH</i>	<i>VH</i>	<i>VH</i>	0.3659
Management	<i>L</i>	<i>E</i>	<i>MH</i>	<i>H</i>	<i>VH</i>	0.2334
Technology	<i>VL</i>	<i>ML</i>	<i>E</i>	<i>MH</i>	<i>H</i>	0.1631
Environment	<i>VL</i>	<i>L</i>	<i>ML</i>	<i>E</i>	<i>MH</i>	0.1392
Materials	<i>VL</i>	<i>VL</i>	<i>L</i>	<i>ML</i>	<i>E</i>	0.0984
CR	0.057					

Based on the evaluation results of the ten experts, the IVPFN evaluations were first transformed into entropy input values using the score-based procedure described above. The entropy weights were then calculated from the normalized score values, while the AHP weights were obtained from the aggregated expert pairwise comparisons. Finally, the AHP weights and entropy weights were integrated through the coordination coefficient (θ). The final weighting results are reported in Table 9.

The AHP method reflects expert knowledge and practical experience, while the entropy method captures the objective discriminatory information contained in the evaluation data. To balance subjective and objective information, the final criterion weight is calculated using a coordination coefficient (θ):

$$w_j = \theta w_j^{AHP} + (1 - \theta) w_j^{ENT}$$

where w_j^{AHP} is the AHP weight, w_j^{ENT} is the entropy weight, and θ represents the relative importance assigned to subjective expert judgment. In the baseline model, θ is set to 0.5, indicating that AHP and entropy weights are treated with equal importance. The influence of θ on the final ranking is further examined in the sensitivity analysis.

Table 9. The Weights of Each Influential Factor in the Risk Evaluation Index System of Prefabricated Building Construction Stage.

Serial Number	Indicators	AHP Weighting	Entropy Method Weighting	AHP—Entropy Method Weighting
C ₁₁	Technical level of construction personnel	0.1607	0.1244	0.1426
C ₁₂	Security personnel configuration	0.0326	0.0281	0.0304
C ₁₃	Health status of construction personnel	0.0851	0.1093	0.0972
C ₁₄	Safety awareness of construction personnel	0.0557	0.0368	0.0463
C ₁₅	Degree of coordination between jobs	0.0318	0.0258	0.0288
C ₂₁	Site safety management system	0.0705	0.0804	0.0755
C ₂₂	Emergency management program	0.0323	0.0305	0.0314

C ₂₃	Safety measures for component hoisting	0.0625	0.0641	0.0633
C ₂₄	Implementation of security measures	0.0132	0.0344	0.0238
C ₂₅	Storage of finished goods	0.0549	0.0303	0.0426
C ₃₁	Deep design of embedded parts	0.0351	0.0349	0.0350
C ₃₂	Component connection node design	0.0553	0.0671	0.0612
C ₃₃	Construction scheme	0.0204	0.0314	0.0259
C ₃₄	Hoisting plan and supervision	0.0313	0.0473	0.0393
C ₃₅	Hoisting technology	0.0210	0.0347	0.0279
C ₄₁	Temporary hole protection	0.0349	0.0389	0.0369
C ₄₂	State of the natural environment	0.0203	0.0459	0.0331
C ₄₃	Construction site environmental status	0.0381	0.0267	0.0324
C ₄₄	Surrounding environment of hoisting process	0.0103	0.0179	0.0141
C ₄₅	Safety standards policy environment	0.0356	0.0135	0.0246
C ₅₁	Reliability of mechanical equipment	0.0345	0.0341	0.0343
C ₅₂	Hoisting machine selection	0.0168	0.0105	0.0137
C ₅₃	Precast component quality	0.0211	0.0177	0.0194
C ₅₄	Equipment maintenance	0.0163	0.0094	0.0129
C ₅₅	Site stacking of components	0.0097	0.0059	0.0078

According to the fuzzy linguistic scale in Table 7, the ten experts evaluated the five-alternative risk-control schemes under the 25 risk indicators. To improve the readability of the main text, the complete ten-expert linguistic evaluation matrix is provided in Supplementary Table S1.

Using Equations (18)–(22), the expert reliability weights under each risk indicator were calculated based on expert similarity and information sufficiency. Because the complete expert-weight matrix contains ten experts and 25 indicators, the detailed results are provided in Supplementary Table S2. These expert reliability weights were then used to aggregate the ten experts' IVPFN evaluations into a collective decision matrix.

The ten-expert linguistic evaluations were first converted into IVPFNs and then aggregated using the expert reliability weights derived from similarity and information sufficiency. Based on the aggregated collective decision matrix, the positive and negative ideal solutions were determined according to the score and accuracy functions. The prospect values with respect to the positive and negative ideal solutions are reported in Table 10 and Table 11, respectively.

Table 10. Prospect values with respect to the positive ideal solution.

V_i^+	C ₁₁	C ₁₂	C ₁₃	C ₁₄	C ₁₅	C ₂₁	C ₂₂	C ₂₃	C ₂₄
A ₁	0.256	0.194	0.269	0.269	0.295	0.212	0.269	0.194	0.287
A ₂	0.212	0.275	0.237	0.269	0.333	0.256	0.237	0.269	0.265
A ₃	0.276	0.333	0.269	0.333	0.375	0.295	0.233	0.194	0.333
A ₄	0.169	0.367	0.273	0.373	0.333	0.193	0.367	0.269	0.375
A ₅	0.294	0.333	0.294	0.333	0.295	0.256	0.333	0.333	0.333
V_i^+	C ₂₅	C ₃₁	C ₃₂	C ₃₃	C ₃₄	C ₃₅	C ₄₁	C ₄₂	C ₄₃
A ₁	0.256	0.256	0.194	0.269	0.212	0.269	0.212	0.212	0.276
A ₂	0.276	0.265	0.265	0.295	0.267	0.275	0.294	0.173	0.279
A ₃	0.287	0.196	0.194	0.333	0.267	0.333	0.365	0.296	0.384
A ₄	0.235	0.265	0.256	0.375	0.265	0.376	0.333	0.314	0.384
A ₅	0.326	0.295	0.333	0.333	0.287	0.169	0.375	0.277	0.333
V_i^+	C ₄₄	C ₄₅	C ₅₁	C ₅₂	C ₅₃	C ₅₄	C ₅₅		
A ₁	0.212	0.197	0.256	0.273	0.194	0.212	0.278		
A ₂	0.257	0.276	0.234	0.349	0.277	0.389	0.329		
A ₃	0.333	0.378	0.345	0.394	0.229	0.276	0.345		

A_4	0.333	0.356	0.382	0.373	0.368	0.368	0.327
A_5	0.394	0.333	0.348	0.351	0.394	0.327	0.346

Table 11. Prospect values with respect to the negative ideal solution.

V_i^-	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{21}	C_{22}	C_{23}	C_{24}
A_1	0.000	0.573	0.189	0.573	0.291	0.376	0.482	0.222	0.392
A_2	0.374	0.000	0.000	0.000	0.147	0.186	0.396	0.000	0.395
A_3	0.175	0.184	0.184	0.191	0.284	0.222	0.396	0.386	0.000
A_4	0.287	0.136	0.184	0.147	0.000	0.385	0.291	0.361	0.197
A_5	0.172	0.000	0.184	0.147	0.291	0.000	0.000	0.291	0.212
V_i^-	C_{25}	C_{31}	C_{32}	C_{33}	C_{34}	C_{35}	C_{41}	C_{42}	C_{43}
A_1	0.294	0.277	0.245	0.296	0.275	0.396	0.222	0.281	0.392
A_2	0.000	0.284	0.386	0.000	0.185	0.271	0.573	0.392	0.392
A_3	0.281	0.000	0.212	0.238	0.173	0.274	0.374	0.212	0.259
A_4	0.194	0.364	0.000	0.275	0.269	0.294	0.000	0.238	0.000
A_5	0.355	0.212	0.000	0.248	0.000	0.000	0.222	0.000	0.000
V_i^-	C_{44}	C_{45}	C_{51}	C_{52}	C_{53}	C_{54}	C_{55}		
A_1	0.553	0.000	0.364	0.256	0.482	0.000	0.392		
A_2	0.376	0.461	0.317	0.377	0.392	0.291	0.000		
A_3	0.216	0.189	0.189	0.293	0.189	0.000	0.392		
A_4	0.000	0.174	0.141	0.000	0.216	0.147	0.271		
A_5	0.185	0.222	0.000	0.000	0.000	0.175	0.000		

On the basis of Tables 10 and 11, the comprehensive prospect values are derived and summarized in Table 12.

Table 12. Comprehensive Prospect Value.

V_i	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{21}	C_{22}	C_{23}	C_{24}
A_1	0.256	0.767	0.458	0.842	0.586	0.588	0.751	0.416	0.679
A_2	0.586	0.275	0.237	0.269	0.480	0.442	0.633	0.269	0.66
A_3	0.451	0.517	0.453	0.524	0.659	0.517	0.629	0.580	0.333
A_4	0.456	0.503	0.457	0.520	0.333	0.578	0.658	0.630	0.572
A_5	0.466	0.333	0.478	0.480	0.586	0.256	0.333	0.624	0.545
V_i	C_{25}	C_{31}	C_{32}	C_{33}	C_{34}	C_{35}	C_{41}	C_{42}	C_{43}
A_1	0.550	0.533	0.439	0.565	0.487	0.665	0.434	0.493	0.668
A_2	0.276	0.549	0.651	0.295	0.452	0.546	0.867	0.565	0.671
A_3	0.568	0.196	0.406	0.571	0.44	0.607	0.739	0.508	0.643
A_4	0.429	0.629	0.256	0.650	0.534	0.67	0.333	0.552	0.384
A_5	0.681	0.507	0.333	0.581	0.287	0.169	0.597	0.277	0.333
V_i	C_{44}	C_{45}	C_{51}	C_{52}	C_{53}	C_{54}	C_{55}		
A_1	0.765	0.197	0.62	0.529	0.676	0.212	0.670		
A_2	0.633	0.737	0.551	0.726	0.669	0.680	0.329		
A_3	0.549	0.567	0.534	0.687	0.418	0.276	0.737		
A_4	0.333	0.530	0.523	0.373	0.584	0.515	0.598		
A_5	0.579	0.555	0.348	0.350	0.394	0.502	0.346		

Following Step 6, the final scores of the five alternatives are obtained as follows: $A_1 = 0.857$, $A_2 = 0.604$, $A_3 = 0.772$, $A_4 = 0.685$, and $A_5 = 0.546$. Using the comprehensive weights in Table 9 and the comprehensive prospect values in Table 12, the relative closeness coefficients of the five alternatives were calculated according to Step 6. Therefore, the

final ranking is $A_1 > A_3 > A_4 > A_2 > A_5$, indicating that the personnel-oriented risk-control scheme is the most favorable alternative in the examined case.

5.3. Sensitivity Analysis of the Proposed Model

The proposed model incorporates the coordination coefficient and CPT parameters to describe the weighting structure and decision-makers' behavioral preferences under risk. The baseline parameter values are adopted from commonly used empirical settings in cumulative prospect theory, as summarized in Table 4. However, these values may vary across decision-makers and project contexts. Therefore, to examine whether the final ranking depends strongly on a specific parameter setting, a ceteris paribus sensitivity analysis is conducted. In each test, one parameter is varied within a broad range, while the remaining parameters are kept unchanged. The tested parameters include the coordination coefficient θ , as well as the CPT parameters γ^+ , γ^- , α , β , and λ .

a. Sensitivity analysis of the coordination coefficient θ

The combined AHP–entropy weight depends on the coordination coefficient θ , which reflects the relative importance assigned to subjective expert judgment and objective information. In the baseline model, θ is set to 0.5, indicating that AHP weights and entropy weights are treated with equal importance. To examine whether this setting affects the final ranking, three scenarios are considered: $\theta = 0.3$, $\theta = 0.5$, and $\theta = 0.7$. When $\theta = 0.3$, greater emphasis is placed on the entropy weight. When $\theta = 0.7$, greater emphasis is placed on the AHP weight. The calculation results are shown in Table 13.

Table 13. Sensitivity analysis results of the coordination coefficient θ .

θ	Weighting Scheme	Score of A_1	Score of A_2	Score of A_3	Score of A_4	Score of A_5	Best Alternative
0.3	Entropy-dominant weighting	0.794	0.670	0.755	0.703	0.658	A_1
0.5	Balanced AHP–entropy weighting	0.857	0.604	0.772	0.685	0.546	A_1
0.7	AHP-dominant weighting	0.893	0.703	0.819	0.772	0.688	A_1

As shown in Table 13, the optimal alternative remains A_1 under the three settings of θ . The overall ranking also remains unchanged; namely, $A_1 > A_3 > A_4 > A_2 > A_5$. This result indicates that the final ranking is not highly sensitive to the relative proportion assigned to AHP and entropy weights. Therefore, the baseline setting ($\theta = 0.5$) is acceptable because it provides a balanced integration of subjective expert judgment and objective information contained in the evaluation data.

b. Sensitivity analysis of parameter γ^+ under different values

To ensure the accuracy of the sensitivity analysis, we adopt a ceteris paribus (control-variable) approach to evaluate the impact of different values of the parameter γ^+ . The corresponding results are reported in Table 14 and Figure 4.

Table 14. Sensitivity Analysis for Parameter γ^+ .

γ^+	Alternative Solutions Calculation Results				
	A_1	A_2	A_3	A_4	A_5
0.61	0.857	0.604	0.772	0.685	0.546
0.05	0.966	0.760	0.887	0.782	0.376
0.15	0.942	0.747	0.855	0.764	0.399
0.25	0.938	0.733	0.823	0.749	0.421
0.35	0.923	0.705	0.818	0.725	0.476

0.45	0.915	0.659	0.804	0.707	0.495
0.55	0.909	0.638	0.783	0.692	0.513
0.65	0.847	0.603	0.734	0.662	0.553
0.75	0.811	0.593	0.711	0.648	0.560
0.85	0.793	0.581	0.686	0.621	0.563
0.95	0.777	0.578	0.655	0.612	0.571

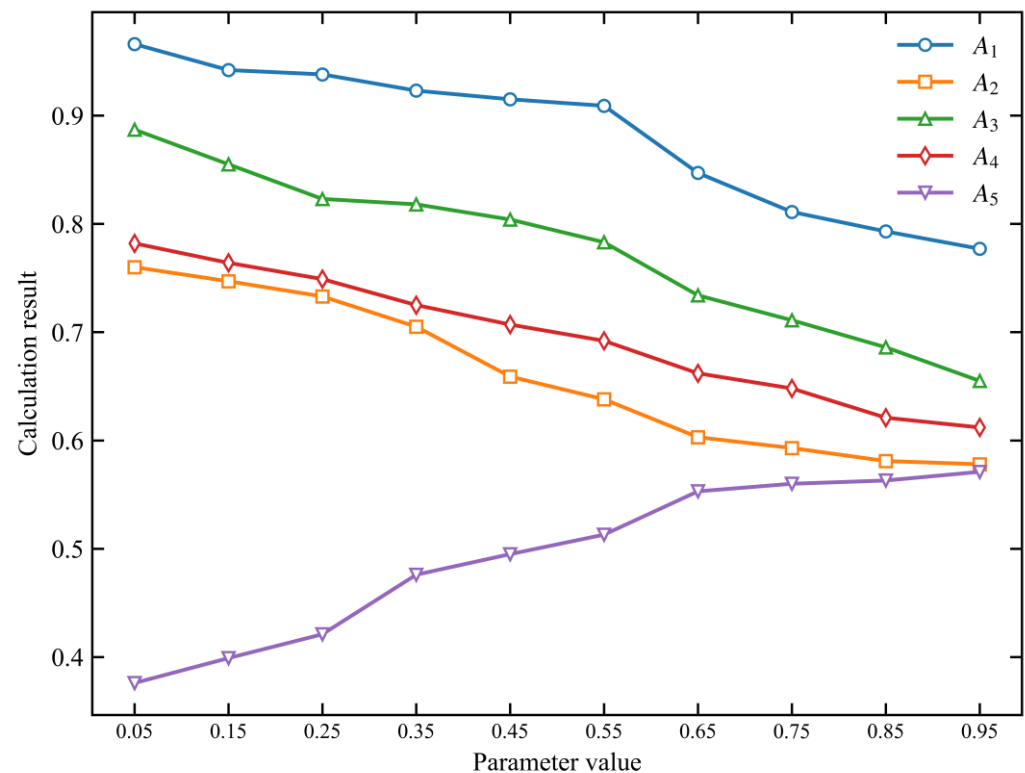


Figure 4. Sensitivity Analysis for Parameter γ^+ .

Although changes in the parameter γ^+ affect the absolute scores of the alternatives, the preference order $A_1 > A_3 > A_4 > A_2 > A_5$ remains unchanged under all tested values. This indicates that the gain-domain probability-weighting parameter (γ^+) influences the attractiveness scores of the alternatives but does not alter the model's core recommendation in terms of ranking.

c. Sensitivity analysis of parameter γ^- under different values

To ensure the accuracy of the sensitivity analysis, we adopt a ceteris paribus (control-variable) approach to evaluate the impact of different values of the parameter γ^- . The corresponding results are reported in Table 15 and Figure 5.

Table 15. Sensitivity Analysis for Parameter γ^- .

γ^-	Alternative Solutions Calculation Results				
	A_1	A_2	A_3	A_4	A_5
0.69	0.857	0.604	0.772	0.685	0.546
0.05	0.922	0.782	0.895	0.800	0.453
0.15	0.917	0.761	0.872	0.789	0.471
0.25	0.894	0.752	0.854	0.763	0.486
0.35	0.888	0.728	0.809	0.744	0.509
0.45	0.874	0.701	0.793	0.720	0.517
0.55	0.860	0.683	0.784	0.701	0.533

0.65	0.822	0.599	0.760	0.666	0.550
0.75	0.804	0.583	0.748	0.648	0.557
0.85	0.787	0.575	0.731	0.622	0.560
0.95	0.761	0.570	0.746	0.608	0.568

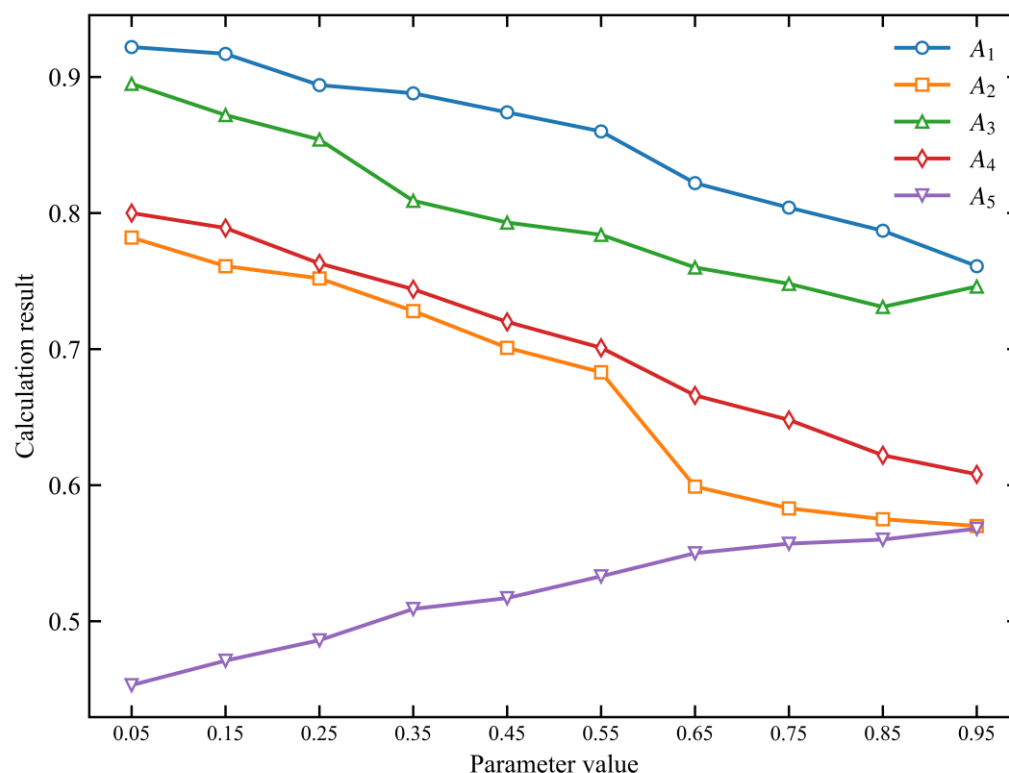


Figure 5. Sensitivity Analysis for Parameter γ^- .

Variations in the parameter γ^- change the absolute scores of the alternatives, but the overall ranking remains unchanged. Under all tested values, the personnel-oriented scheme A_1 remains the best alternative. The ranking is consistently $A_1 > A_3 > A_4 > A_2 > A_5$, which is consistent with the baseline result. This suggests that the primary decision result is relatively stable with respect to changes in the loss-domain probability-weighting parameter.

d. Sensitivity analysis of parameter α under different values

To ensure the accuracy of the sensitivity analysis, we adopt a ceteris paribus (control-variable) approach to evaluate the impact of different values of the parameter α . The corresponding results are reported in Table 16 and Figure 6.

Table 16. Sensitivity Analysis for Parameter α .

α	Alternative Solutions Calculation Results				
	A_1	A_2	A_3	A_4	A_5
0.88	0.857	0.604	0.772	0.685	0.546
0.05	0.716	0.513	0.644	0.579	0.418
0.15	0.733	0.520	0.656	0.582	0.434
0.25	0.746	0.527	0.670	0.602	0.459
0.35	0.757	0.538	0.689	0.611	0.471
0.45	0.777	0.547	0.707	0.625	0.485
0.55	0.782	0.559	0.714	0.633	0.499
0.65	0.804	0.575	0.732	0.641	0.506

0.75	0.824	0.581	0.749	0.666	0.517
0.85	0.842	0.593	0.761	0.690	0.538
0.95	0.947	0.619	0.787	0.703	0.559

As the gain-domain risk-attitude parameter α increases, the scores of the alternatives generally increase, while the final ranking remains unchanged. Under all tested values, A_1 remains the optimal alternative, and the ranking is consistently $A_1 > A_3 > A_4 > A_2 > A_5$. This indicates that the model's recommendation is relatively robust to variations in the decision-maker's risk attitude on the gain side.

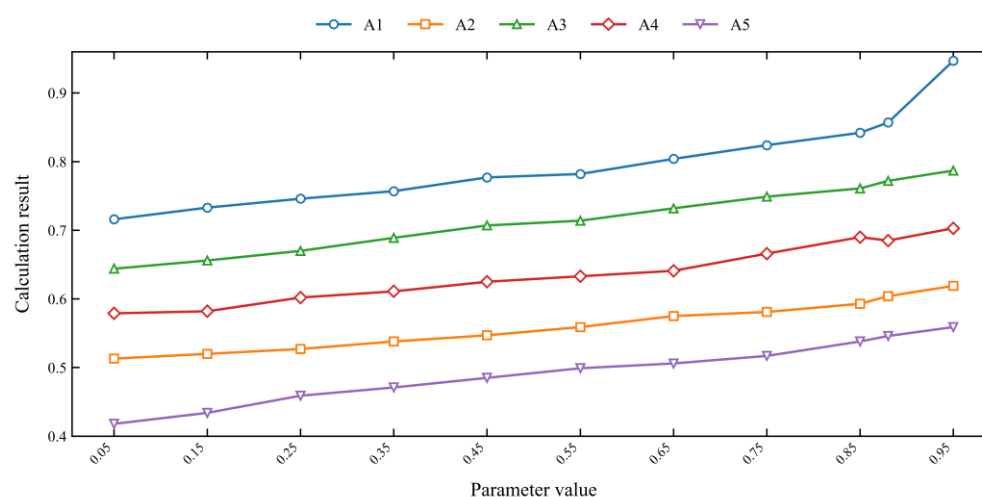


Figure 6. Sensitivity Analysis for Parameter α .

e. Sensitivity analysis of parameter β under different values

To ensure the accuracy of the sensitivity analysis, we adopt a ceteris paribus (control-variable) approach to evaluate the impact of different values of the parameter β . The corresponding results are reported in Table 17 and Figure 7.

Table 17. Sensitivity analysis for parameter β .

β	Alternative Solutions Calculation Results				
	A_1	A_2	A_3	A_4	A_5
0.88	0.857	0.604	0.772	0.685	0.546
0.05	0.730	0.499	0.653	0.562	0.428
0.15	0.754	0.503	0.669	0.578	0.444
0.25	0.763	0.516	0.687	0.593	0.462
0.35	0.782	0.532	0.696	0.606	0.476
0.45	0.801	0.547	0.702	0.617	0.484
0.55	0.815	0.558	0.715	0.631	0.492
0.65	0.824	0.571	0.731	0.646	0.507
0.75	0.831	0.584	0.745	0.658	0.519
0.85	0.844	0.595	0.760	0.669	0.537
0.95	0.868	0.612	0.799	0.692	0.558

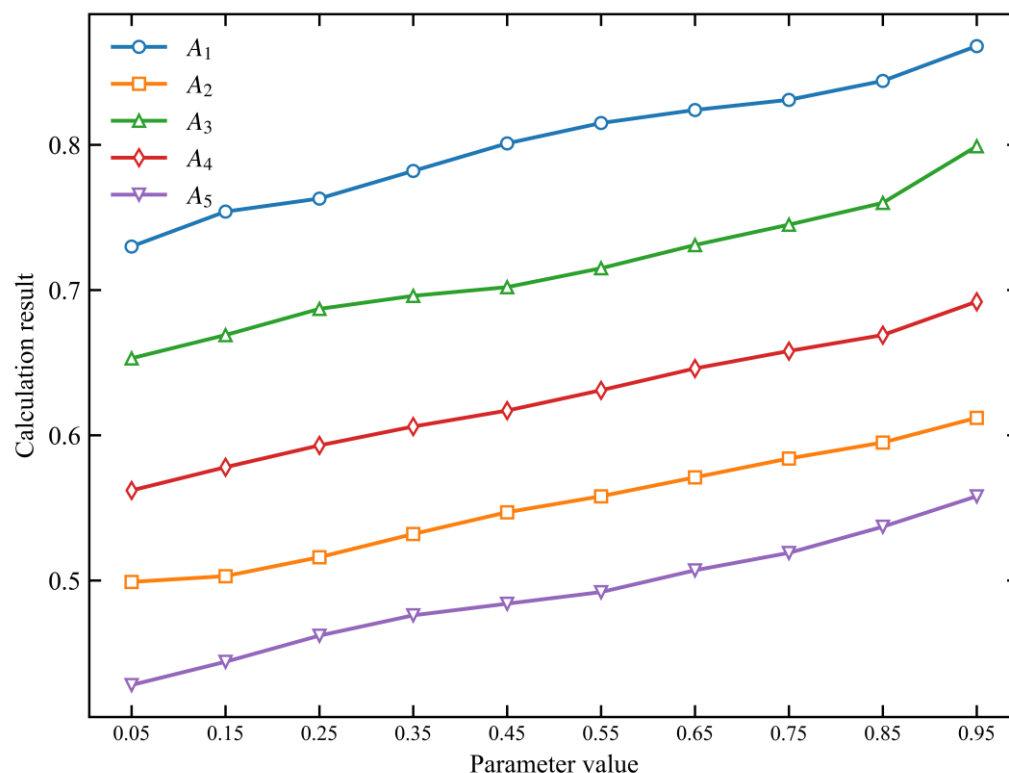


Figure 7. Sensitivity Analysis for Parameter β .

Variations in the parameter β lead to monotonic changes in the scheme scores, but they do not affect the relative ranking of the alternatives. Under all tested values, A_1 remains the optimal alternative, and the ranking is consistently $A_1 > A_3 > A_4 > A_2 > A_5$. This result is consistent with the sensitivity analysis of the gain-domain risk-attitude parameter α , indicating that the proposed model produces a stable ordering of the alternatives under changes in risk-attitude parameters in the examined case.

f. Sensitivity analysis of parameter λ under different values

To ensure the accuracy of the sensitivity analysis, we adopt a *ceteris paribus* (control-variable) approach to evaluate the impact of different values of the parameter λ . The corresponding results are reported in Table 18 and Figure 8.

Table 18. Sensitivity Analysis for Parameter λ .

λ	Alternative Solutions Calculation Results				
	A_1	A_2	A_3	A_4	A_5
2.25	0.857	0.604	0.772	0.685	0.546
1.55	0.857	0.604	0.772	0.685	0.546
3.55	0.857	0.604	0.772	0.685	0.546
4.55	0.857	0.604	0.772	0.685	0.546
5.55	0.857	0.604	0.772	0.685	0.546
6.55	0.857	0.604	0.772	0.685	0.546
7.55	0.857	0.604	0.772	0.685	0.546
8.55	0.857	0.604	0.772	0.685	0.546
9.55	0.857	0.604	0.772	0.685	0.546
10.55	0.857	0.604	0.772	0.685	0.546
11.55	0.857	0.604	0.772	0.685	0.546

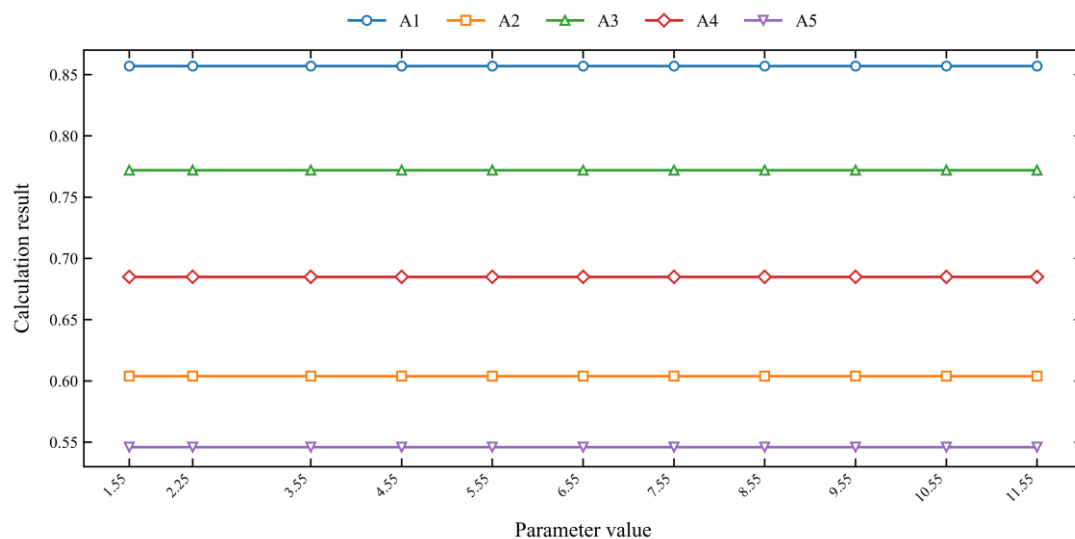


Figure 8. Sensitivity Analysis for Parameter λ .

As shown in Table 18, even when the loss-aversion coefficient λ is increased from 1.55 to 11.55, the scores and rankings remain unchanged under the numerical setting of this case. This may be related to the structure of the normalized gain–loss values, suggesting that the final evaluation results are not highly sensitive to λ in the examined case.

Taken together, the above sensitivity analyses show that when the coordination coefficient and key CPT parameters vary over a relatively wide range, the best alternative remains A_1 in all tested scenarios. Although the absolute scores of some alternatives vary across different parameter settings, the ranking result remains unchanged; namely, $A_1 > A_3 > A_4 > A_2 > A_5$. This suggests that the proposed IVPFS–CPT–TOPSIS framework has acceptable robustness with respect to weighting and behavioral-preference parameters in the examined case. From a managerial perspective, the result indicates that the personnel-oriented risk-control scheme remains the preferred option under different parameter settings.

5.4. Robustness Analysis of Expert Weights

Because the evaluation results are based on expert-judgment data, an additional robustness analysis of expert weights was conducted to examine whether the final ranking is dominated by the expert-weight setting. In the baseline model, the expert reliability weights are calculated using Equations (18)–(22), and the weights vary slightly across different risk indicators. To test the stability of the results, five expert-weight scenarios were designed. Scenario S0 represents the original expert reliability weights. Scenario S1 assigns equal weights to the ten experts. Scenarios S2–S4 represent representative perturbation scenarios in which the weight of one expert is increased by 10%, while the weights of the remaining experts are adjusted proportionally to ensure that the total expert weight remains equal to 1.

The perturbation rule is defined as follows. When the weight of expert E_k is increased by 10%, the adjusted weight is calculated as:

$$\omega'_k = 1.10 \times \omega_k$$

The weights of the remaining experts are adjusted proportionally:

$$\omega'_i = (1 - \omega'_k) \times \omega_i / (1 - \omega_k), i \neq k$$

where ω_k is the original weight of the perturbed expert, ω_i is the original weight of a non-perturbed expert, and ω'_i is the adjusted expert weight. This procedure ensures that

the relative proportions of the non-perturbed experts are retained and that the sum of all expert weights remains equal to 1. Table 19 reports the ranking results under different expert-weight scenarios.

Table 19. Robustness analysis results under different expert-weight scenarios.

Scenario	Expert-Weight Setting	Score of A_1	Score of A_2	Score of A_3	Score of A_4	Score of A_5	Best Alternative
S_0	Original expert weights	0.857	0.604	0.772	0.685	0.546	A_1
S_1	Equal expert weights	0.880	0.722	0.854	0.744	0.699	A_1
S_2	$E_1+10\%$	0.862	0.738	0.799	0.753	0.655	A_1
S_3	$E_2+10\%$	0.845	0.716	0.788	0.747	0.647	A_1
S_4	$E_3+10\%$	0.799	0.693	0.740	0.719	0.582	A_1

The results show that the optimal alternative remains A_1 under all scenarios. In addition, the ranking result remains $A_1 > A_3 > A_4 > A_2 > A_5$, indicating that the final decision result is not dominated by a specific expert-weight setting. Therefore, the proposed model shows acceptable stability with respect to expert-weight variations in the examined case.

5.5. Additional Robustness Checks for Distance Measures and Linguistic Scales

To further examine the robustness of the proposed framework, two additional robustness checks were conducted. The first test examines whether the final ranking is affected by the choice of IVPFN distance measure. The original distance measure was compared with two alternative distance settings; namely, the normalized Hamming distance and the normalized Euclidean distance. All other model settings, including criterion weights, expert weights, CPT parameters, and linguistic scale definitions, were kept unchanged.

The second test examines whether the final ranking is affected by the definition of linguistic scales. The original IVPFN linguistic scale was compared with two alternative scale settings. The conservative scale slightly reduces the differences between adjacent linguistic terms, while the expanded scale slightly increases the differences between adjacent linguistic terms. In all cases, the basic IVPFS constraint was maintained. The results are summarized in Tables 20 and 21. To keep the analysis concise, only the final ranking results are reported, while the intermediate calculation matrices are omitted.

Table 20. Robustness analysis under different distance measures.

Scenario	Distance Measure	Ranking Result	Best Alternative
D0	Original distance measure	$A_1 > A_3 > A_4 > A_2 > A_5$	A_1
D1	Normalized Hamming distance	$A_1 > A_3 > A_4 > A_2 > A_5$	A_1
D2	Normalized Euclidean distance	$A_1 > A_3 > A_4 > A_2 > A_5$	A_1

As shown in Table 20, the optimal alternative remains A_1 under different distance-measure settings. The overall ranking also remains unchanged, indicating that the final decision result is not highly sensitive to the choice of distance measure in the examined case.

Table 21. Robustness analysis under different linguistic scale definitions.

Scenario	Linguistic Scale Definition	Ranking Result	Best Alternative
L0	Original IVPFN linguistic scale	$A_1 > A_3 > A_4 > A_2 > A_5$	A_1
L1	Conservative scale	$A_1 > A_3 > A_4 > A_2 > A_5$	A_1
L2	Expanded scale	$A_1 > A_3 > A_4 > A_2 > A_5$	A_1

As shown in Table 21, the optimal alternative remains A_1 under different linguistic scale definitions. The ranking result also remains $A_1 > A_3 > A_4 > A_2 > A_5$, suggesting that moderate changes in the linguistic scale definition do not alter the main decision result.

Overall, the additional robustness checks show that the best alternative remains A_1 under different distance measures and linguistic scale definitions. Together with the CPT parameter sensitivity analysis, the coordination-coefficient sensitivity analysis, and the expert-weight robustness analysis, these results suggest that the proposed IVPFS–CPT–TOPSIS framework has acceptable stability in the examined case. However, the robustness conclusion should still be interpreted within the scope of this single case study.

5.6. Comparison with Other Methods

In this section, the proposed IVPFS–CPT–TOPSIS method is compared with several existing methods to further examine its applicability and interpretability. The comparative methods include PFN–PT–MAIRCA [36], AHP–TOPSIS [37], CPT [38], and SFT–CPT [39]. The comparison is conducted using the same case data and the same set of alternatives. The purpose of the comparison is not only to examine whether the ranking result is stable, but also to discuss how different methods represent uncertainty, behavioral preference, and alternative differences. The comparative results are shown in Table 22 and Figure 9.

Table 22. Results from Different Methods.

Method	Score Value					Ranking Results
	A_1	A_2	A_3	A_4	A_5	
PFN-PT-MAIRCA [36]	0.652	0.557	0.612	0.595	0.466	$A_1 > A_3 > A_4 > A_2 > A_5$
AHP-TOPSIS [37]	0.688	0.610	0.669	0.644	0.589	
CPT [38]	0.494	0.421	0.469	0.455	0.369	
SFT-CPT [39]	0.575	0.496	0.552	0.517	0.383	
Proposed method	0.857	0.604	0.772	0.685	0.546	

As shown in Table 22, all comparative methods identify A_1 as the best alternative. This indicates that the personnel-oriented risk-control scheme shows a relatively stable advantage in the examined case. In addition, A_3 and A_4 are ranked in the second and third positions, respectively, while A_2 and A_5 are ranked in the fourth and fifth positions. This ranking consistency suggests that the main decision result is relatively stable across different methodological settings.

Although the ranking order remains unchanged across the comparative methods, differences can still be observed in the score gaps among the alternatives. These differences indicate that each method has a different way of handling fuzzy information, behavioral preference, and distance-based closeness. Therefore, the comparison should not be understood only from the perspective of final ranking consistency, but also from the perspective of methodological interpretability.

Compared with AHP–TOPSIS and CPT alone, the proposed IVPFS–CPT–TOPSIS framework integrates several types of information within a unified evaluation process.

IVPFSs are used to represent support, neutrality, opposition, and refusal information in expert judgments. CPT is used to reflect decision-makers' behavioral preferences under risk. The AHP–entropy procedure combines subjective expert judgment with objective discriminatory information, while expert reliability weights are used to reduce the influence of individual judgment differences. Therefore, the value of the proposed method lies not only in producing a stable ranking, but also in providing a more interpretable decision-support process under fuzzy and behaviorally influenced risk conditions.

It should also be noted that different methods use different scoring mechanisms. Therefore, the absolute scores in Table 22 should not be interpreted as directly equivalent across methods. The comparison mainly focuses on ranking consistency, score differences, and methodological interpretability. Overall, the comparative results suggest that the proposed framework provides a useful and structured approach for construction-stage risk assessment in the examined prefabricated building project.

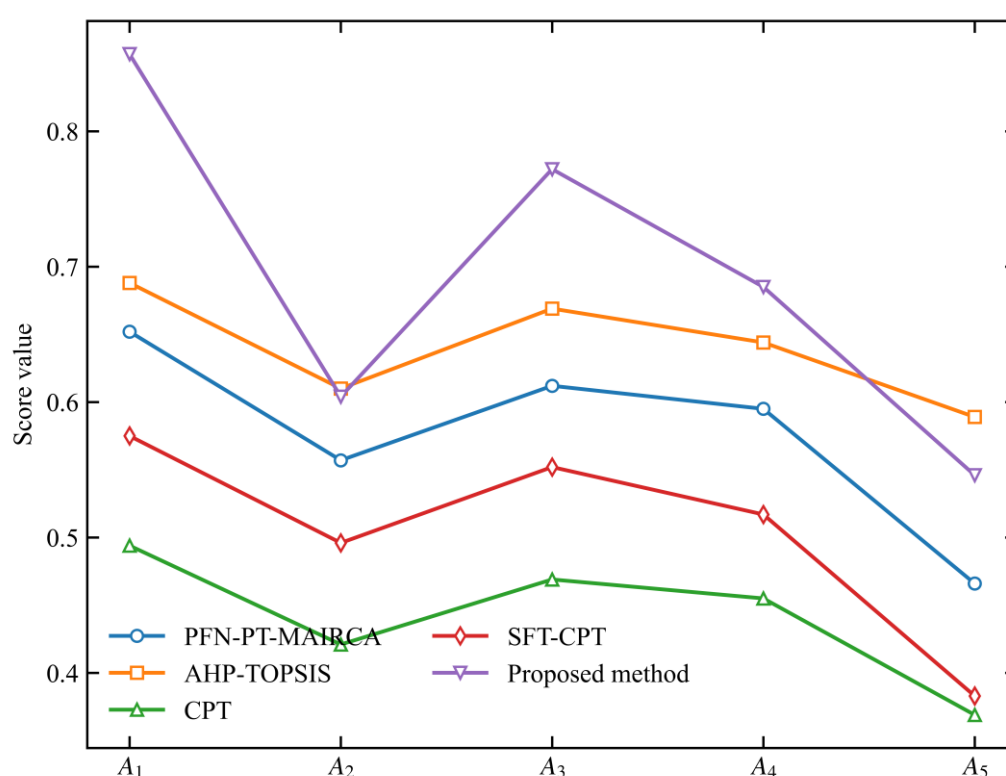


Figure 9. Results from Different Methods.

5.7. Discussion

This study employs a coordinated AHP–entropy weighting scheme to identify the relative priorities of construction-stage risk factors in prefabricated construction. The results cover both first-level risk dimensions and second-level indicators. As reported in Table 8, at the macro level of the first-level criteria, personnel risk obtains the highest weight (0.3659), followed by management risk and technology risk. This result suggests that personnel-related issues play an important role in construction-stage risk control for the examined prefabricated building project. In particular, construction workers' technical competence, safety awareness, health status, and job coordination should receive sufficient managerial attention during on-site implementation.

A closer examination of Table 9 shows that the differences among AHP weights, entropy weights, and combined weights reflect the complementary roles of subjective expert judgment and objective discriminatory information. The AHP weights mainly reflect ex-

pert experience and practical knowledge, whereas the entropy weights capture the degree of variation contained in the evaluation data. For example, the “component connection node design” indicator (C_{32}) receives a relatively high weight under both the entropy-based and combined weighting schemes. This indicates that C_{32} is not only regarded as important by experts, but also shows noticeable discriminatory information across the alternatives.

The combined weighting results therefore should not be understood as a simple mechanical average. Rather, the coordinated AHP–entropy procedure serves as a calibration mechanism for integrating subjective judgment and objective information. It retains the general priority structure reflected by expert knowledge while incorporating the differences revealed by the evaluation data. As a result, the final weighting results provide a more balanced and case-sensitive reference for identifying key construction-stage risk factors in the examined project, as shown in Figure 10.

From a managerial perspective, the results suggest that personnel-related risks should be treated as a priority in prefabricated construction risk control. At the same time, technical and management-related factors, such as component connection design, hoisting safety measures, site safety management, and hoisting supervision, should also be incorporated into routine inspection and preventive management procedures. These findings provide a practical reference for allocating risk-control resources according to the relative importance of different risk factors. This is also consistent with the final ranking result, in which the personnel-oriented risk-control scheme A_1 is identified as the most favorable alternative.

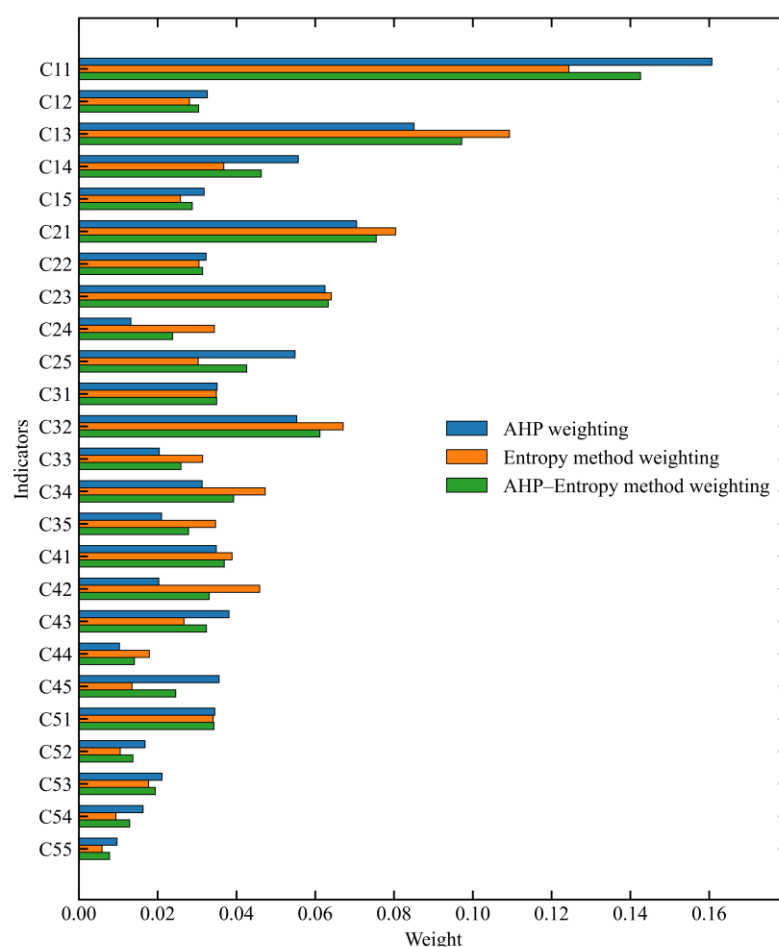


Figure 10. Ranking of risk factors.

6. Conclusions

This study developed an integrated IVPFS–CPT–TOPSIS evaluation framework for assessing construction-stage risks in prefabricated building projects. The framework combines interval-valued picture fuzzy sets, cumulative prospect theory, TOPSIS, an AHP–entropy weighting procedure, and expert reliability weights. By applying the proposed framework to a prefabricated construction project in Shanghai, the following conclusions can be drawn.

First, a construction-stage risk evaluation indicator system for prefabricated buildings was established. The final system includes five dimensions: personnel, management, technology, environment, and materials/equipment. The coordinated AHP–entropy weighting results show that personnel-related risks obtain the highest first-level weight in the examined case. At the second-level indicator level, factors such as the technical level of construction personnel, health status of construction personnel, site safety management, hoisting safety measures, and component connection control receive relatively high weights. These results suggest that construction-stage risk control in prefabricated building projects should pay particular attention to personnel competence, safety management, and key technical operations.

Second, the case results show that the personnel-oriented risk-control scheme is ranked as the most favorable alternative among the five candidate schemes. The final ranking is $A_1 > A_3 > A_4 > A_2 > A_5$, indicating that personnel-oriented risk control performs better than the other schemes under the proposed evaluation framework. This result suggests that strengthening worker training, technical competence, safety awareness, health monitoring, and job coordination can provide an important basis for improving construction-stage risk-control performance in prefabricated building projects.

Third, the sensitivity and robustness analyses indicate that the main ranking result is relatively stable under different parameter and model settings. The optimal alternative remains A_1 when the coordination coefficient, CPT parameters, expert weights, distance measures, and linguistic scale definitions are changed. Although minor variations occur in some alternative scores, the primary decision result remains unchanged. This suggests that the proposed framework has acceptable robustness in the examined case. However, this conclusion should be interpreted within the scope of a single case study and expert-judgment-based data.

From a managerial perspective, the findings suggest three practical implications. First, personnel-related risks should be treated as a priority in construction-stage risk control. Project managers should strengthen skill training, safety education, health monitoring, and job coordination for construction personnel. Second, key technical and management links should be controlled according to their risk priorities. Particular attention should be paid to component hoisting, connection-node control, site safety management, emergency response, and hoisting supervision. Third, a tiered risk-control strategy should be adopted. High-priority risks should be subject to stricter monitoring and preventive control, medium-priority risks can be managed through standardized procedures and regular inspections, and low-priority risks can be tracked through routine management. This strategy can help managers allocate limited risk-control resources more efficiently.

Overall, the proposed IVPFS–CPT–TOPSIS framework provides a structured decision-support approach for construction-stage risk assessment in prefabricated building projects. It helps integrate fuzzy expert judgments, behavioral risk preferences, subjective and objective weighting information, and expert reliability into a unified evaluation process. Future studies can further validate the framework using larger expert panels, multiple projects, and more objective construction safety data.

7. Future Directions and Perspectives

Despite the contributions of this study, several limitations should be acknowledged. First, the empirical application is based on a single prefabricated construction project in Shanghai and expert-judgment-based evaluation data. Although the ten experts have complementary professional backgrounds and direct experience in prefabricated construction projects, the case-based setting may still restrict the generalizability of the findings. Therefore, the results should be interpreted as exploratory case-based evidence rather than broad statistical conclusions. Future studies should involve more projects and more diverse expert groups to further examine the stability and external applicability of the proposed framework.

Second, the proposed IVPFS–CPT–TOPSIS framework is implemented in a static setting, where risk factors and their interrelations are assumed to remain relatively stable during the evaluation process. In practice, however, construction risks may evolve over time and may be affected by feedback mechanisms among personnel, management, technology, environment, and materials/equipment factors. Future research could therefore incorporate time-series data, dynamic Bayesian networks, system dynamics, or other dynamic modeling tools to better capture the temporal evolution and interaction mechanisms of construction-stage risks.

Third, the parameters of cumulative prospect theory are adopted from classical benchmark values in the behavioral decision-making literature rather than being estimated from construction-specific managerial data. Although sensitivity analysis is conducted to examine the influence of these parameters, future studies could further estimate CPT parameters for construction managers through controlled experiments, structured questionnaires, or large-scale surveys. This would help make the CPT parameters more consistent with construction-management contexts.

Overall, future research can extend this study by applying the framework to multiple projects, involving more diverse expert groups, incorporating dynamic risk-evolution mechanisms, and calibrating behavioral parameters using construction-specific empirical data. These extensions could help improve the robustness, external validity, and practical relevance of the proposed approach.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/buildings16142853/s1>, Table S1. Linguistic evaluation matrix provided by the ten experts. Table S2. Normalized numerical decision matrix transformed from the ten-expert linguistic evaluations.

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