International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 12 Issue 6 ǁ June 2024 ǁ PP. 159-179

Risk Assessment on High-tech Projects Considering the Interactive Impact of Risk Factors: a fuzzy BWM-HCI method

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Abstract: *The risk factors of high-tech projects are very diverse and complex. Previous research focuses on project prioritization by evaluating these interacting risk factors. However, the aggregation related to risk interactions has been largely overlooked, which may lead to the selection of inferior alternatives during the investment decision-making process. To address this issue, we propose a systematic approach that combines fuzzy best-worst method (BWM), 2-additive fuzzy measures, and hierarchical Choquet integrals (HCI) for aggregating project risk interactions and prioritizing investment projects. The proposed method utilizes the fuzzy BWM approach to determine the weights of the risk factors, leveraging expert assessments to gauge the intensity of impacts subjectively and linguistically. Then, we apply the maximum entropy principle to determine the 2-additive fuzzy measure. Finally, we integrate the Choquet integral with the 2-additive fuzzy measure. To demonstrate its feasibility and advantages, the proposed method is applied to the risk assessment of high-tech project investment.*

Keywords *Fuzzy BWM, Hierarchical Choquet integral, 2-additive fuzzy measure, High-tech venture capital.*

Date of Submission: 11-06-2024 Date of acceptance: 23-06-2024

I. Introduction

In the realm of project management, high risk is perceived as a substantial obstacle to achieving project success (Ahmadabadi and Heravi, 2019). A project risk is defined as "an uncertain event or condition that, if it occurs, could positively or negatively affect one or more project targets" (Guide, 2008). Typical characteristics of project risk factors include limited predictability, extended risk exposure, substantial financial losses, and the interaction of multiple risk variables (Mohagheghi, 2020). For example, the successful test flight of a large aircraft in China, C919, occurred 16 years after the inception of the project. Given its status as a large passenger airplane, the C919 is significantly influenced by various environmental factors such as weather conditions, equipment reliability, radiation, and more. Therefore, ensuring product dependability and safety is of significant importance. In a multi-objective decision-making context, high-tech project investment around the selection of the optimal project for investment, striking a balance between project risks and potential rewards (Mohagheghi, 2020). When a project is huge and involves high-tech developments, the complexity of PRA (project risk assessment) and investment is further increased (Mousavi, et al., 2015).

In response to the complexity and uncertainties inherent in high-tech projects, an increasing number of scholars have initiated research to explore effective methods for evaluating and investing in such projects (Moradi et al., 2017). Risk assessment demands that decision-makers identify key risk elements and potential hazards, gauge the level of risk along with its consequences, analyze decision variables, and quickly make effective decisions while considering diverse preferences (Ergu et al., 2014). PRA entails the utilization of historical data and expert judgment for risk identification. Employing a suitable decision-making method aims to derive an overall risk value for each project and derive the optimal investment decisions based on the risk value (Fang and Marle, 2012).

However, obtaining enough data sources from the historical risks associated with high-tech initiatives can often be challenging. High-tech project risk assessment often relies on expert judgment and expertise due to the insufficient historical data for conducting probabilistic analyses (Mohagheghi, 2020). The fuzzy theory was developed to cope with ambiguous and uncertain information or data in typical quantitative expressions for project investment appraisal (Zhao, 2016). Some of the most popular techniques in fuzzy theory are interval numbers, triangular fuzzy numbers, and trapezoidal fuzzy numbers (Li et al., 2021; Wang et al., 2021; Büyüközkan, 2021). In contrast, the occurrence of project risks in real-world projects depends on an interaction of several risk factors, including technology, production and development, environment, and marketing. There are overlaps and correlations among these risk indicators, and interdependence could result in the occurrence of one or more risks (Wang et al., 2020). Therefore, it becomes imperative to consider the interdependencies among risk factors to enhance the effectiveness and precision of project risk assessment, particularly for complex high-tech projects (Guan et al., 2021; Tavana et al., 2021).

The best-worst method (BWM) is a multi-criteria decision-making (MCDM) method developed by Rezaei (2015), similar to the analysis hierarchical process (AHP) (Guo and Zhao, 2017; Rezaei, 2015). BWM is a pairwise comparison-based method that uses two evaluation vectors (the best criterion to other criteria and other criteria to the worst criterion) to obtain the decision criterion weights. In MCDM problems with n decision criteria, AHP requires $n*(n-1)/2$ pairwise comparisons, while BWM requires only $2n-3$ comparisons (Rezaei, 2015). Compared with AHP, BWM has three advantages. The first is the fewer times of comparisons; the second is the structured comparing process; the third benefit is better consistency (Mi et al., 2019). Due to the above advantages, the best-worst method (BWM) has been widely adopted for determining criterion weights in decision-making problems across various domains, including management, education, energy, and supply chain management. However, its application in the field of risk assessment has been relatively limited. Subsequently, to address issues related to assessment uncertainty, various uncertainty modeling techniques such as fuzzy sets, triangular fuzzy numbers, interval-valued multiplicative numbers, and probability hesitant fuzzy numbers have been employed to represent uncertainty within the BWM framework (Guo and Zhao, 2017). BWM has also been utilized to combine with other common aggregation operators like TOPSIS and VIKOR (Gupta and Barua, 2017; Gölcük, 2020). Additionally, the combination of BWM with fuzzy logic and group decision-making (GDM) has emerged as two popular areas of research (Mou, Xu and Liao, 2016; Guo and Zhao, 2017; Tavana et al., 2023).

The discrete Choquet integral, a mathematical tool incorporating fuzzy measures and weight assignments, offers a means to address uncertainty in discrete data (Corrente et al., 2016). Its application extends to domains such as MCDM and risk assessment. However, for decision problems involving n criteria, there are $2n-2$ coefficients are required to determine the fuzzy measures. Consequently, determining the fuzzy measures based on fuzzy integrals is often considered a mathematical programming problem, including the maximum entropy principle, the maximum split approach, the minimum variance approach, and a less constrained approach (Chen and Huang, 2019). Many researchers have conducted extensive investigations into how to reduce the computation of fuzzy measures, such as λ-fuzzy measures, Möbius transformation, k-additive fuzzy measures and p-symmetric measures (Murillo et al., 2017). To address criteria with a hierarchical structure, Sugeno (1995) introduced the hierarchical Choquet integral as a means to reduce the computational complexity of fuzzy measures (Sugeno et al., 1995). Recently, some scholars have investigated the combination of hierarchical Choquet integration with genetic algorithms and neural networks for addressing classification problems. The results indicate that machine learning incorporating Choquet integration offers enhanced interpretability (Chen and Huang, 2019).

Therefore, the main two motives of this paper are as follows:

(1) While quantitative risk assessment has improved rapidly and many methods have been introduced, the challenge of acquiring quantitative data has compelled experts to rely on personal experience and intuitive judgment for risk evaluation. MCDM techniques offer the capacity to assess, rank, and prioritize multiple decision criteria and alternatives. Since decision criterion weights usually need to be determined by domain experts, how to deal with the ambiguity, subjectivity, and consistency problems when determining criterion weight is one of the goals of this paper.

(2) Decision-making models based on fuzzy integrals encounter a significant challenge in situations with a high number of criteria, particularly in the identification of fuzzy measures. While experts can provide a fuzzy measure for an individual risk factor based on empirical judgment (Chen and Huang, 2016), practical applications often involve multiple factors contributing to project risk. As the number of risk factors grows, assigning correlation indicators for a subset of factors becomes not only highly subjective but also challenging. While the use of g_λ fuzzy measures can simplify computational costs, it may also compromise the representational effectiveness of the measure (Murillo et al., 2017). How to make a good compromise between the complexity and the expression of interaction information is another motive.

To tackle issues related to the subjectivity and ambiguity in expert judgment, and interactions among evaluation criteria in PRA, this paper suggests a novel approach to address the problem of high-tech project risk assessment by merging fuzzy BWM, 2-additive fuzzy measure and HCI (hierarchical Choquet integral). The following are the main contributions:

Firstly, since the factors that cause the investment risk of a project are mainly qualitative indicators, it is difficult to assess the importance of the criteria with objective data. As an improvement of the AHP method, BWM has more simplicity and better consistency (Guo and Zhao, 2017). With the BWM approach, experts are only required to provide two comparison vectors. Additionally, the incorporation of triangular fuzzy numbers with BWM serves to mitigate the uncertainties associated with expert judgments to some extent.

Secondly, the issue of interactive criteria has been frequently overlooked in existing MCDM evaluation models. To address this, our paper incorporates the hierarchical Choquet integral (HCI) theory into the multi-criterion comprehensive evaluation. We employ the principle of maximum entropy to determine the indicator interaction coefficients, which subsequently lead to the determination of the 2-additive fuzzy measure. This approach not only takes into account indicator interactions but also makes a good compromise between computational complexity and the articulation of interaction information when determining the fuzzy measure.

The remaining sections of the paper are structured as follows: Section 2 presents the related research of existing literature in PRA. In section 3, the fundamental theories of triangular fuzzy numbers, BWM, and the detailed steps of the fuzzy BWM method are introduced. Section 4 introduces the method of MCDM-based 2-additive-HCI. In section 5, the numerical experiment is carried out and compared with the other methods; and the last section gives a summary and some future work of this paper.

II. Related research

The following three aspects have been summarized from a review of the PRA methods and models: (1) traditional project risk assessment models, (2) research of the interrelation among project risks, (3) intelligent risk assessment.

2.1 Traditional project risk assessment models

Early project risk indicators were typically expressed in terms of a risk factor's probability to occur (P), the risk factor's corresponding impact on the project's objectives (I), or by multiplying P and I. The (P-I) risk matrix was also utilized by decision-makers to evaluate and categorize specific project risks (Fang et al., 2016). PRA is mostly dependent on MCDM approaches due to the complexity and variety of elements (Marle et al., 2013). The AHP , a commonly employed (MADM) method, often integrates historical data and expert insights to quantitatively evaluate qualitative information (Aguilar Lasserre et al., 2009). However, when using AHP for decision-making, the elements need to satisfy the assumption of independence, while the actual risk factors have a complex hierarchical structure and the risk factors interact with each other. Additionally, the risk assessment produced by the AHP approach is very subjective, and the outcome is unreliable if the judgment matrix's consistency test is unsuccessful (Ergu et al., 2014). As a result, the AHP technique has some restrictions when it comes to solving such issues.

The MCDM approach was subsequently combined with fuzzy set theory to tackle ambiguity, subjectivity, and uncertainty in the decision-making process. Li et al. (2021) introduced a risk assessment method that employs a triangular fuzzy number to calculate risk values on expert opinions and applied an extended VIKOR method for risk prioritization (Li et al., 2021). Büyüközkan and Göcer (2021) recommended the integration of PFS, SAW, and VIKOR methods to mitigate the challenges related to subjective judgments and imprecision, and it is used to assess software development projects (Büyüközkan and Göcer, 2021). Aydemir and Yilmaz Gunduz (2020) examined how aggregation operators influence the decision-making process and utilized dombi operations to construct fermatean fuzzy aggregation operators (Aydemir and Yilmaz Gunduz, 2020). Pamučar et al. (2018) proposed an uncertainty approach based on interval-valued fuzzy rough numbers. By integrating the rough approach with traditional fuzzy methods, the subjectivity present when defining the boundaries of fuzzy sets is effectively eliminated (Pamučar et al., 2018). Rodríguez et al. (2016) present a hybrid technique based on fuzzy logic, which integrates fuzzy hierarchy analysis and a fuzzy inference system, and they consider this technique to provide better consistency for assessing the risk of complicated and unpredictable projects (Rodríguez et al., 2016).

2.2 The interrelation among project risks

To address the challenge of interdependencies among risks, the analytic network process (ANP) has been proposed as an extended complementary method to the AHP, which does not have the assumption of internal and external independence and is a suitable method for resolving complex decision problems characterized by hierarchical structures (Ergu et al., 2014). Haeri and Rezaei (2019) proposed a hybrid approach integrating grey correlation analysis with BWM, aiming to enhance the consistency of judgment matrices and effectively capture interdependencies among decision criteria (Haeri and Rezaei, 2019). In contrast, the majority of MCDM techniques are grounded in the assumption of distinct decision criteria, exemplified by methods like the weighted arithmetic mean (WAM) and the ordered weighted average (OWA). Nonetheless, given the complexity and interrelationships inherent in the decision criteria, discrete Choquet integral (CI) is predominantly employed for aggregation in the realm of high-tech risk assessment and various other practical applications (Ruan, 2010). The Choquet integral aggregation function describes the relative importance of the decision criteria and their interactions.

The interaction of risks in high technology projects is becoming a growing concern, and more systematic and comprehensive PRA approaches are being proposed to analyze the issue. As an example, bayesian belief networks (BBNs) represent a widely favored approach for managing complex systems and addressing issues of uncertainty (Biswas and Zaman, 2019). The subjective bias is eliminated by using expert judgment to construct models utilizing bayesian belief networks (Ojha et al., 2018). However, this risk analysis approach does not explicitly take into account the uncertainty related to the calculation of probabilistic parameters (Hu et al., 2013). Gölcük (2020) combined the interval type-2 fuzzy best-worst method (IT2F-BWM) and perceptual reasoning to determine the relative importance of risk factors and apply them to the risk assessment of digital transformation projects (Gölcük, 2020). Many researchers also have used hybrid models that incorporate DEMATEL to address the interactions between risk factors, but it's worth noting that these models require a substantial body of expert knowledge to effectively formalize the interdependencies and impacts of the variables (Du and Li, 2021; Si, 2018). An exploration of project risks and their interplay can also be conducted through the application of methods such as structural equation modeling (SEM), social network analysis (SNA), and interpretative structural modeling (ISM) (Ahmadabadi and Heravi, 2019; Ergu et al., 2014; Wang et al., 2020).

2.3 Intelligent risk assessment

Regression analysis, decision trees, cluster analysis, and neural networks are just a few of the statistical and data mining techniques that have been utilized extensively to study the correlations between variables (Chen and Huang, 2020). Each of these approaches offers unique advantages and benefits. Regression analysis can be used to create predictions about future data and to identify connections between variables. Decision tree is a simple method for classifying projects based on the degree of risk. Similar projects can be divided using cluster analysis, and the risk factors that lead to such projects can then be further investigated. Because they are self-organizing and self-learning, neural networks can solve challenging non-linear issues (Guan et al., 2021). However, rather than actual data, the majority of these models are based on simulation-generated data.

Generally, traditional MCDM methods assume that decision criteria are additive and independent. However, given the diversity and interactivity of project risk factors in real-world scenarios, most existing literature primarily emphasizes the consideration of interactions when determining criterion weights, with relatively limited attention paid to the interaction of criterion sets during the aggregation process (Zhang et al., 2021). Additionally, conventional network analysis methods that account for interactions, such as (ANP), encounter more intricate consistency issues when constructing judgment matrices (Ergu et al., 2014). On the other hand, established machine learning approaches can effectively address non-linearity in aggregation, provided that historical data and expert experiences are readily available. Nevertheless, for project risk assessments where historical data and expert opinions are challenging to obtain, these methods may introduce some bias due to the limited sample size for training data.

To tackle these aforementioned challenges, this paper introduces an innovative MCDM fusion method. It harnesses the fuzzy BWM to determine criterion weights, reducing the workload associated with pairwise criterion comparisons and enhancing overall consistency. For multi-criteria decision problems, it integrates hierarchical Choquet integration with 2-additive fuzzy measures. This approach not only considers the interdependencies among criteria but also reduce the complexities involved in fuzzy measure calculations. Consequently, the proposed fuzzy BWM-HCI method presented in this paper offers a more suitable approach for project risk assessment.

III. Fuzzy best and worst method (F-BWM)

To deal with the ambiguity, subjectivity, and consistency problems when determining criterion weight, this paper adopts the fuzzy BWM method. the fundamental theories of triangular fuzzy numbers, BWM, and the detailed steps of the fuzzy BWM method are introduced in this section.

3.1 Triangular fuzzy number (TFN)

The fuzzy set theory was proposed by Zadeh in 1965. As a generalization of classical set theory, fuzzy set theory can solve practical problems in uncertain environments (Zadeh, 1999). The fuzzy set $\breve{a}=(U,m)$, where U is a set of [0,1], m is the membership function given by each element in the terminological domain $u_a(x)$, which can be mapped to the real interval [0,1].

Definition of a fuzzy number. Let $\breve{a}\in F(R)$ be a fuzzy number, then there exists $x_0\in R$, such that $u_a(x_0)=1$.

For any $\alpha\in[0,1]$, $\breve{a}_\alpha=[x,u_{a_\alpha}(x)\geq\alpha]$ is a closed interval, where R is a real number and $F(R)$ is a closed interval.

Definition of the triangular fuzzy number (Guo and Zhao, 2017). The fuzzy number $\tilde{\alpha}$ on R is defined as the triangular fuzzy number (TFN) if its affiliation function $\mu_{\alpha}(x): R \to [0,1]$ is equal to

$$u_a(x)=\begin{cases}0 & ,x<l\\ \dfrac{x-l}{m-l} & ,l\le x<m\\ \dfrac{u-x}{u-m} & ,m\le x\le u\\ 0 & ,x>u\end{cases} \quad . \quad (1)$$

Where $l,m,u \quad (-\infty<l\le m\le u<\infty)$ represents the lower, median, and upper limits of the support degree. they are exact values, and TFN can be expressed as a ternary array $\tilde{a}=(l,m,u)$.

Definition of GMIR. Let the graded mean integral of TFN be expressed as (GMIR), $R(\tilde{a}_i)$ denotes the ordering of the triangular fuzzy numbers, then for $\tilde{a}_i=(l_i,m_i,u_i)$, $R(\tilde{a}_i)$ is defined as:

$$R(\tilde{a}_i)=\frac{l_i+4m_i+u_i}{6} \quad . \quad (2)$$

The above formula converts the fuzzy numbers into crisp values, which are easy to calculate and rank the final weights.

3.2 Best and worst method（BWM）

Since risk assessment is mostly a qualitative attribute, to minimize the errors caused by the subjectivity of expert evaluation, fuzzy BWM was introduced based on fuzzy set theory under the guidance of the study by Guo and Zhao (2017). Assuming that there are n criteria for the study object, the linguistic variables of the pairwise comparison results of each decision criterion were first converted into triangular fuzzy numbers, and a fuzzy BWM model was established accordingly to solve for the minimum deviation. The rules of language value variables and trigonometric fuzzy number conversion are listed in Table 1.

Table 1 Language variables and trigonometric fuzzy number conversion rules

Linguistic terms	Membership function
Equally Importance (EI)	(1,1,1)
Weakly Importance (WI)	(2/3,1,3/2)
Fairly Importance (FI)	(3/2,2,5/2)
Very Importance (VI)	(5/2,3,7/2)
Absolutely Importance (AI)	(7/2,4,9/2)

According to the basic principle of BWM, it is known that it is not necessary to make a two-by-two comparison for each criterion but only to find the most and least important criterion in a set (Ruan, 2010; Rezaei, 2015). The fuzzy best-worst method (fuzzy BWM) can be used to determine the fuzzy weights of the criteria, and then the GMIT method is used to calculate the crisp values of the attributes (Guo and Zhao, 2017).

The following will describe the detailed steps of fuzzy BWM to calculate the attribute weights.

Step1: Establishing an evaluation index system. The evaluation index system consists of a set of evaluation criteria, and different index values can reflect the performance of different projects. Suppose there are n evaluation criteria $\{c_1,c_2,\dots c_n\}$.

Step2: Determine the best (most important) and worst (least important) criteria. In this step, the decision maker should determine the best and worst criteria based on the established evaluation index system. The best criterion is denoted as c_B, and the worst criterion is denoted as c_W.

Step3: Determine the fuzzy preferences of other criteria for the best and worst criterion.

Using the linguistic terms of the experts listed in Table 2 to determine the fuzzy preferences of the best criteria for all criteria. Then, the obtained fuzzy preferences are converted to TFN according to the conversion rules shown in Table 2. The obtained fuzzy best-to-other vector is:

$$\tilde{A}_B=(\tilde{a}_{B1},\tilde{a}_{B2},\dots,\tilde{a}_{Bn}).$$

Where $\tilde{A}_B$ denotes the fuzzy best vector, $\tilde{a}_{Bj}$ denotes the fuzzy preference of the best criterion c_B to criterion j, $j=1,2,\dots,n$. It can be known $\tilde{a}_{BB}=(1,1,1)$.

Using the linguistic evaluation of the experts listed in Table 2, the fuzzy preferences of other criteria for the worst criterion can be determined, and then they are converted to TFN according to the conversion rules listed in Table 2. The fuzzy others-to-worst vector is:

$$\tilde{A}_w = \left(\tilde{a}_{1w}, \tilde{a}_{2w}, \dots, \tilde{a}_{nw}\right).$$

Where $\tilde{A}_w$ denotes the fuzzy others-to-worst vector, $\tilde{a}_{iw}$ denotes the fuzzy preference of the criterion i for worst criterion c_W, $i = 1, 2, \dots, n$. It can be known $\tilde{a}_{ww} = (1,1,1)$.

Step4: The linear model proposed by Guo and Zhao (2017) was used to calculate the criterion fuzzy weights $\left(\tilde{w}_1^*, \tilde{w}_2^*, \dots, \tilde{w}_n^*\right)$, $\xi^* = \left(k^*, k^*, k^*\right)$.

$$\min \xi^*$$

$$s.t.\begin{cases} \left| \dfrac{l_B^w, m_B^w, u_B^w}{l_j^w, m_j^w, u_j^w} - \left(l_{Bj}, m_{Bj}, u_{Bj}\right) \right| \le \left(k^*,\ k^* \quad k^*\right) \\ \left| \dfrac{l_j^w, m_j^w, u_j^w}{l_w^w, m_w^w, u_w^w} - \left(l_{jw}, m_{jw}, u_{jw}\right) \right| \le \left(k^*,\ k^* \quad k^*\right) \\ l_j^w \le m_j^w \le u_j^w \\ l_j^w \ge 0 \\ \sum_{j=1}^{n} R\left(\tilde{w}_j\right) = 1 \\ j = 1, 2, \dots n \end{cases} \quad . \quad (3)$$

By solving model (3), the optimal fuzzy weights $\left(\tilde{w}_1^*, \tilde{w}_2^*, \dots, \tilde{w}_n^*\right)$ can be obtained. The fuzzy weights of the criteria represented by TFN need to be converted to crisp values by GMIR.

However, when BWM deals with decision problems involving more than three criteria, more than one optimal solution is often obtained (Rezaei, 2016). To improve the decision-making efficiency while avoiding the subjective bias indirectly caused by multiple solutions, the maximum and minimum values of the weights are determined based on the minimum deviation and the interval of each weight placed respectively.

$$\min w_j$$

$$s.t.\begin{cases} \left| \dfrac{l_B^w, m_B^w, u_B^w}{l_j^w, m_j^w, u_j^w} - \left(l_{Bj}, m_{Bj}, u_{Bj}\right) \right| \le \left(k^*,\ k^* \quad k^*\right) \\ \left| \dfrac{l_j^w, m_j^w, u_j^w}{l_w^w, m_w^w, u_w^w} - \left(l_{jw}, m_{jw}, u_{jw}\right) \right| \le \left(k^*,\ k^* \quad k^*\right) \\ l_j^w \le m_j^w \le u_j^w \\ l_j^w \ge 0 \\ \sum_{j=1}^{n} R\left(\tilde{w}_j\right) = 1 \\ j = 1, 2, \dots n \end{cases} \quad . (4)$$

$$\max w_j$$

$$s.t.\begin{cases}\left|\dfrac{l_B^w,m_B^w,u_B^w}{l_j^w,m_j^w,u_j^w}-\left(l_{Bj},m_{Bj},u_{Bj}\right)\right|\le\left(k^*,\ k^*\quad k^*\right)\\ \left|\dfrac{l_j^w,m_j^w,u_j^w}{l_w^w,m_w^w,u_w^w}-\left(l_{jw},m_{jw},u_{jw}\right)\right|\le\left(k^*,\ k^*\quad k^*\right)\\ l_j^w\le m_j^w\le u_j^w\\ l_j^w\ge 0\\ \sum_{j=1}^{n}R\left(\tilde{w}_j\right)=1\\ j=1,2,\ldots n\end{cases} \quad (5)$$

By solving model (4) and model (5), the interval of the weights within the real numbers can be obtained, denoted as $\omega=\left[\omega_{\min},\omega_{\max}\right]$. Finally, the center of the interval is used to denote the upper, median, and lower limits of the triangular fuzzy number, respectively.

Consistency analysis is performed based on determining the minimum deviation, and consistency is an important indicator to test the merit of the comparison results (Lootsma, 1980; Van Laarhoven and Pedrycz, 1983; Murofushi and Sugeno, 1989). By solving Eq (6) for different u_{Bw}, the maximum possible ξ can be found, which is employed as a consistency index for fuzzy BWM. The obtained consistency index about different linguistic terms of decision-makers for fuzzy BWM is listed in Table 2.

$$\xi^2-\left(1+2u_{Bw}\right)\xi+\left(u^2_{Bw}-u_{Bw}\right)=0 . \quad (6)$$

Table 2 Consistency index

	EI	WI	FI	VI	AI
$\breve{a}_{Bw}$	(1,1,1)	(2/3,1,3/2)	(3/2,2,5/2)	(5/2.3,7/2)	(7/2,4,9/2)
CI	3.00	3.80	5.29	6.69	8.04

By solving model (3) the uniqueness ξ^* can be determined, and the CR of the fuzzy BWM is calculated using equation (7) proposed by Guo and Zhao (2017).

$$CR=\frac{\xi^*}{CI} . \quad (7)$$

For a given CI, the smaller the ξ^*, the smaller the CR. It indicates the better consistency of pairwise comparison results and vice versa.

IV. The method of MCDM-based hierarchical Choquet integral

To make a good compromise between the complexity and the expression of interaction information is another motive. This section introduced the method of MCDM-based 2-additive-HCI. The fundamental theories and the detailed steps of the 2-additive-HCI model are introduced as follows.

4.1 Fuzzy measure and interaction index

In 1974, a Japanese scholar, Sugeno (1989) proposed a fuzzy measure to solve the multi-attribute decision problem where attributes are related but not additive (Murofushi and Sugeno, 1989; Grabisch, 2020; Nguyen, 2016; Pham and Yan, 1997). It can represent the combined importance of one or more attributes and more accurately describes the interaction between multiple attributes. The relevant definitions and concepts are as follows.

Definition of a fuzzy measure. Given a set S, and any subset X of S, the function $\mu:\rightarrow[0,1]$ is called a fuzzy measure on X if the following properties are satisfied.

(1) $\mu(\varnothing)=0$ and $\mu(S)=1$,

(2) $\forall M\subseteq N\subseteq S$, $\mu(M)\le\mu(N)$.

Definition of a Möbius transform of a fuzzy measure. Given a non-empty set S, and any subset X of S, for any set function $\mu:X\rightarrow R$, its Möbius transform is defined by:

$$m(T)=\sum_{K\subset T}(-1)^{|T|-|K|}\mu(K),\forall T\subset S \quad (8)$$

The Möbius transform provides an alternative representation of a fuzzy measure. This is a one-to-one correspondence between μ and m. The fuzzy measure coefficients are computed from the Möbius representation using the Zeta-transform:

$$\mu(T)=\sum_{M\subset T}m(M),\forall T\subset S \quad (9)$$

Definition of a 2-additive fuzzy measure. A fuzzy measure μ is called a 2-additive fuzzy measure, if for all T satisfying $|T|\geq 2$, $m(T)=0$, there exists at least one subset T of S with 2 elements such that $m(T)\neq 0$.

Therefore, according to Möbius transform coefficients, $K\subseteq S$, $|K|\geq 2$, the 2-additive fuzzy measure is measure is defined by

$$\mu(K)=\sum_{i\in K}m_i+\sum_{\{i,j\}\subset K}m_{ij} \quad (10)$$

Definition of the Shapley value. let μ be a fuzzy measure on set S with n elements. Then the Shapley value of the element $i\in S$ is defined by:

$$I_i=\sum_{k=0}^{n-1}\frac{(n-k-1)!(k)!}{n!}\sum_{\substack{T\subset S\backslash i\\ |T|=k}}(\mu_{iT}-\mu_T) \quad (11)$$

The interaction of any two elements is defined as follows.

Definition of the interaction of any two criteria. The interaction of any two elements with respect to fuzzy measure μ is defined by:

$$I_{ij}=\sum_{k=0}^{n-2}\frac{(n-k-2)!k!}{(n-1)!}\sum_{\substack{T\in S\backslash\{i,j\},\\ |T|=k}}(\mu_{ijT}-\mu_{iT}-\mu_{jT}+\mu_T) \quad (12)$$

The above index can be interpreted as positive or negative synergy among various elements. For example, if $I_{ij}>I_i+I_j$, we call the elements $\{i,j\}$ complementary; if $I_{ij}<I_i+I_j$, we say they are redundant; otherwise, they are independent.

In the 2-additive fuzzy measure, the interaction between three or more decision criteria is zero and the interaction coefficients are not given arbitrarily.

For any $T\subset S$, any $i\in T$, any $j\in T\backslash i$, the I_{ij} should be satisfied:

$$|I(ij)|\leq 2I(i)/(n-1) \;\&\; |I(ij)|\leq 2I(j)/(n-1). \quad (13)$$

Let $t_{ij}\leq\min\{2I(i)/(n-1),2I(j)/(n-1)\}$, Then the value of the interaction be restricted to the interval $[-t_{ij},t_{ij}]$.

4.2 The maximum entropy principle determined the 2-addition fuzzy measure

Discussing the importance of risk factors and interaction indicators based on fuzzy measures not only takes into account dependencies but also provides better interpretability. In this paper, we adopt the maximum entropy principle of 2-additive fuzzy measures, which is a compromise between the complexity and expressiveness of fuzzy measures. The specific steps are as follows.

Step1: The determination of importance weights for each criterion is carried out using the best and worst methods, as elaborated in detail in section3.2.

Step2: Estimate the degree of the interaction corresponding to a particular interval.

In practice, to present the risk assessors' uncertainty about the interaction of the factors, we allow the interaction to be estimated within a subinterval. In order to determine the interaction between the criteria $\{i,j\}$, the interval can be divided into seven subintervals. In this paper, we used "HR", "MR", "LR", "NI", "LC", "MC" and "HC" to represent the seven categories. Denote the range of values of interaction $I(ij)$ as the interval $\overline{t_{ij}}=[t_{ij}^d,t_{ij}^u]$ ($i,j=1,2,\quad,n$, and $i\neq j$)

An interaction is explained as the complementarity or redundancy of any two factors by the assessor. As Fig.1 shows, the seven subintervals are explained as the two factors i and j have different degrees of interaction. The risk assessor needs to estimate the degree of the interaction.

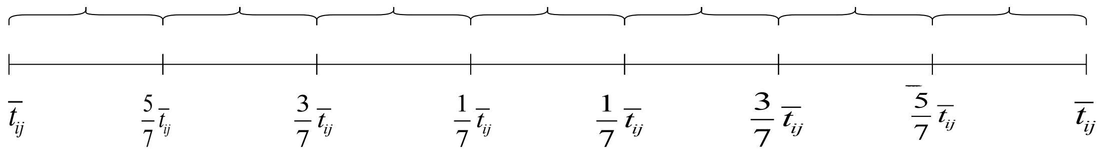

Fig. 1 The degree of interaction in different intervals

Step3: Determination of interaction values using the principle of maximum entropy.

The higher the entropy value of a fuzzy measure means that the fuzzy measure contains more uncertainty or information. The maximum entropy principle can be used to determine the unknown variables given some constraints (Bao, Wu and Li, 2018).

Definition of Marichal entropy. The entropy of a fuzzy measure μ is defined as:

$$H(\mu)=\sum_{i=1}^{n}\sum_{T\subset S\backslash i}\frac{(n-|T|-1)!|T|!}{n!}h(\mu(iT)-\mu(T)) \quad . \quad (14)$$

Where $h(x_i)=-x_i\ln(x_i)$, is called the Shannon entropy.

For the 2-additive fuzzy measure, we have

$$H(\mu)=\sum_{i=1}^{n}\sum_{T\subset S\backslash i}\frac{(n-|T|-1)!|T|!}{n!}h\left(m(i)+\sum_{j\in T}m(ij)\right) . \quad (15)$$

After we obtain the weight of a criterion (determined by experts) and the boundaries of the interaction of any two criteria, the interaction values can be obtained by the following optimization problem.

$$\max H(\mu)=\sum_{i=1}^{n}\sum_{T\subset S\backslash i}\frac{(n-|T|-1)!|T|!}{n!}h\left(I(i)-\frac{1}{2}\sum_{j\in S\backslash i}I(ij)+\sum_{j\in T}I(ij)\right)$$

$$\text{s.t.}\begin{cases} w_i=I(i), \\ I(ij)\in \overline{t}_{ij}, \\ \sum_{i=1}^{n}w_i=1 \\ i,j=1,2,\quad ,\text{且}\, i\neq j \end{cases} \quad . \quad (16)$$

Step4: Determine the corresponding Möbius transform coefficients.

For the 2-additive fuzzy measure, the interaction of any order can be written as (Bao, Wu and Li, 2018):

$$\begin{cases} I(\varnothing)=m(\varnothing)+\frac{1}{2}\sum_{i\in S}a(i)+\frac{1}{3}\sum_{\{i,j\}\in S}m(ij) \\ I(i)=m(i)+\frac{1}{2}\sum_{j\in S\backslash i}m(ij) \\ I(ij)=m(ij) \\ I(A)=0,\forall |A|>2. \end{cases} \quad .(17)$$

which in turn gives

$$\begin{cases} m(\varnothing)=I(\varnothing)+\frac{1}{2}\sum_{i\in S} I(i)+\frac{1}{6}\sum_{\{i,j\}\in S} I(ij) \\ m(i)=I(i)-\frac{1}{2}\sum_{j\in S\backslash i} I(ij) \\ m(ij)=I(ij) \\ m(A)=0, \forall |A|>2. \end{cases} \quad (18)$$

Therefore, we can obtain the Möbius coefficients of any subset of the criteria according to Eq (18).

Step5: Determined the 2-additive fuzzy measure values for any subsets

Thus far, we have obtained the weight of a criterion and the interaction of any two criteria. According to Eq (10), the transformation relationship between the fuzzy measures and the Möbius transform coefficients, then, the 2-additive fuzzy measure of any subset of the criterion can be obtained.

4.3 Hierarchical Choquet integral

For a project risk assessment question, Let $A=\{A_1, A_2, \quad , A_m\}$ be a set of alternatives, $C=\{C_1, C_2, \quad , C_n\}$ be a set of criteria, and $w_j=\{w_1, w_2, \quad , w_n\}$ be the weights of criteria, satisfying $0 \le w_j \le 1$ and $\sum_{j=1}^{n} w_j = 1$. Experts give his payoff judgments A_i to C_j. The hierarchical Choquet integral plays an important role in reducing the number of fuzzy measures in multi-attribute index problems.

Definition of the discrete Choquet integral. Given a set S with elements $(x_1, x_2, \quad , x_n)$, the discrete Choquet integral of function $f: s \to R^+$ with respect to fuzzy measure μ is defined as:

$$\int f d\mu = \sum_{i=1}^{n}\left(f\left(x_{(i)}\right)-f\left(x_{(i-1)}\right)\right)\mu\left(A_{(i)}\right) \quad . \quad (19)$$

Where the subscript (i) indicates that the indices have been permuted so that $f\left(x_{(1)}\right) \le f\left(x_{(2)}\right) \le \quad \le f\left(x_{(n)}\right)$, and $A_{(i)}=\{x_{(i)}, \quad , x_{(n)}\}$.

Decision-making systems can be modeled by fuzzy integral-based hierarchical MCDM. The concept of the hierarchical Choquet integral was proposed by Sugeno et al. (1995) to decompose a Choquet integral model into several sub-Choquet integral models (Sugeno et al., 1995). The three-level MCDM model based on hierarchical Choquet integration is given in Fig.2.

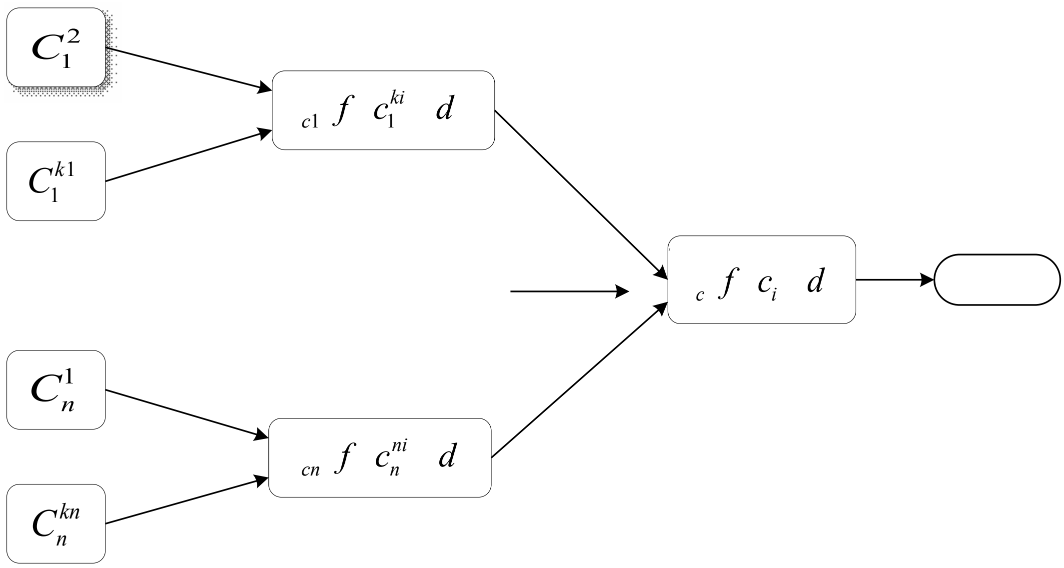

Fig.2 The three-level MCDM model based on hierarchical Choquet integration

The evaluated value of the parent attribute in hierarchical MCDM is calculated from the Choquet integral of the sub-attributes. As shown in Fig.2, the evaluation value of the attribute C_1 is obtained by calculating the Choquet integral of the attribute C_1^1 C_1^{k1}; the evaluation value of the attribute C_n is obtained by calculating the Choquet integral of the attribute C_n^1 C_n^{kn}; and the comprehensive evaluation value of the whole alternatives is obtained by calculating the Choquet integral of the attribute C_1 C_n. Based on the comprehensive evaluation value of the alternatives, we rank the alternatives and select the optimal one.

V. Numerical experiments

It becomes difficult for venture capital firms to select suitable investment targets from projects. PRA usually employs the method of expert identification. On the one hand, it can fully leverage experts' rich theoretical knowledge and valuable practical experience; on the other hand, it makes the identification and interrelationship between the indexes highly subjective.

In this section, to demonstrate the practicability and effectiveness of the HCI methods, a high-tech project risk assessment question is taken as an example. The identical example is also employed in the literature (Zhang, 2001; Xu and Peng, 2005). The literature (Zhang, 2001) uses classical BP neural networks to evaluate the risk of high-tech venture capital projects. The literature (Xu and Peng, 2005) uses a variable structure classical BP neural network for evaluation. While the neural network is good at addressing the non-linear interrelationships of risk factors, the utilization of neural network methods for risk assessment in this question may introduce some bias due to the small sample size. This paper uses the traditional multi-attribute decision-making method to assess the project risks. combining the subjective weights calculated by fuzzy BWM with the 2-additive fuzzy measure determined by maximum entropy. Then, the overall risk value is aggregated using HCI.

5.1 Calculate the attribute weights by fuzzy BWM

According to section 3.2 to calculate the subjective weights, the detailed processes of the proposed method are following.

Step1: Construct a risk indicator system for projects.

As the main reference, the investment risks of high-tech projects are subjected to a comprehensive evaluation of risk factors, taking into account the key elements as illustrated in Fig.3.

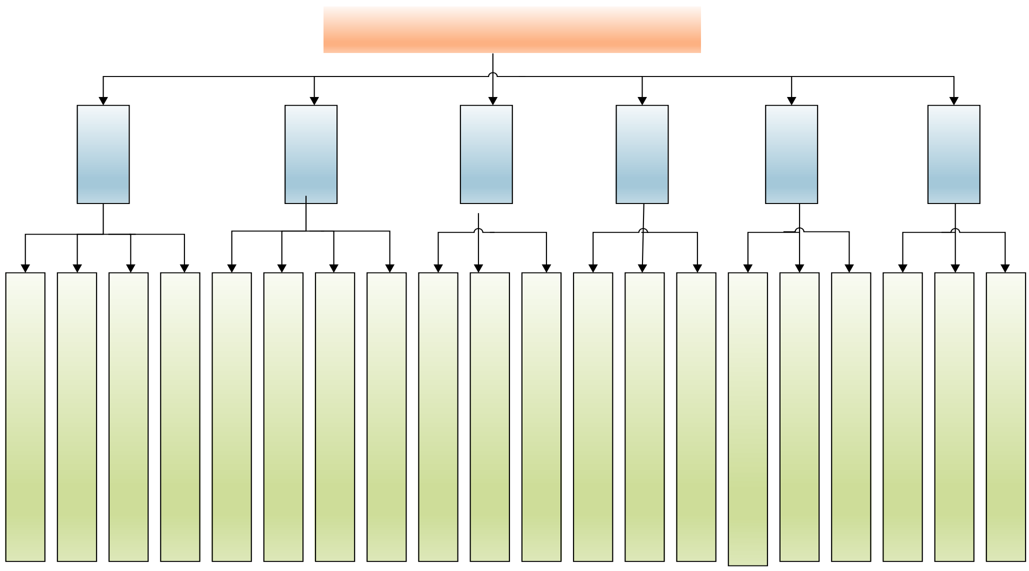

Fig.3 High-tech projects risk assessment index system

In a comprehensive multilayer index system, interdependencies tend to arise among the subsystems. For example, the criteria $U2$ (human resources) and $U4$ (R&D conditions) in C_1(R&D risk) are interdependent; the criteria $U5$ (technological maturity) and $U7$ (technical compatibility) in C_2 (technology risk) are also interdependent. Therefore, this is not an internally independent hierarchy structure. The AHP method cannot be used to determine the weight of each criterion. So, the fuzzy BWM method is introduced to solve the indicator weighting problem in this paper.

Step2: Use expert scoring to give an evaluation matrix and best-worst criteria

16 high-tech projects in Fujian province were selected for investment evaluation in China (Zhang, 2001). Since there are more qualitative factors in the index to measure the investment risk of high-tech projects, the expert scoring method is used for each risk index with five levels, 0.1, 0.3, 0.5, 0.7, and 1, respectively. When scoring, the experts fully review and analyze the business plan to give the scoring value of each risk indicator. The degree of relevant risk is judged by the evaluated project's performance on this indicator. Thus, the expert evaluates the 16 projects according to the risk index system and their performance. A higher value indicates better performance in a specific aspect of the project, corresponding to a lower level of risk. The expert evaluation matrix is shown in Table 3.

Next, we use the 0-1 matrix to determine the best and worst criteria. Suppose there exist n criteria, members of the set $\{c_1, c_2, \ldots c_n\}$. compare the importance between c_i and c_j, and use f_{ij} to show the degree of importance. If c_i is more important than that c_j, then we can let $f_{ij} = 1$, and $f_{ji} = 0$. If c_i and c_j are equally important, then $f_{ij} = f_{ji} = 1$. The importance ranking matrix of the criterion values is:

$$F = f_{n\times n} = \begin{bmatrix} f_{11} & & f_{1n} \\ & & \\ f_{n1} & & f_{nn} \end{bmatrix} \quad i, j = 1, 2, \quad , n$$
,

In this paper, the 0-1 matrix will be determined by multiple decision-makers. Calculate the average of the rows of the matrix F and arrange them from largest to smallest, then determine the best and worst criteria.

Then, the importance of the parent attribute and sub-attribute are judged in two by two, respectively. The 0-1 matrix of indicators is obtained from three experts. The average value of the 0-1 matrix gives:

$$f_2 = 4.67 > f_6 = 4.33 > f_5 = 3.33 > f_4 = 3 > f_1 = 2.67 > f_3 = 2$$

The best and worst criteria are C_2 and C_3. Similarly, the sub-criteria under each risk indicator are treated.

Step3: Determine the fuzzy preferences of other criteria for the best and worst criterion.

After gaining the best and worst criteria, the expert compares the other criteria with the best and worst criteria by using the linguistic terms listed in Table 2. Then, according to the conversion rules, the obtained fuzzy preferences are converted to TFN. The result of the best-to-other vector and other-to-worst vector is shown in Table 4 and Table 5.

Step4: Calculate the fuzzy criterion weights.

Since the parent attributes involve more than three criteria, there often is more than one optimal solution. We adopt the maximum and minimum values of the weights to determine the weight interval based on the minimum deviation (Guo and Zhao, 2017). By solving model (4) and model (5), the median value of the interval is used to represent the triangular fuzzy weight of the criteria. By solving model (3), we can obtain the unique optimal fuzzy weight values for the sub-indicators. After solving the fuzzy weights of all indicators, they are converted into crisp values. The subjective weights of the criteria are shown in Table 6.

5.2 Determined the 2-addition fuzzy measure and calculated the risk evaluation value

The second step is to obtain the interaction of any two criteria and a fuzzy measure of sub-attributes. According to the steps of section3.2, based on the importance of each sub-criteria and the degree of interaction estimated by the risk assessor, we obtain the boundaries of the interactions of any two criteria. The interaction of sub-attributes is reported in Table 7. To obtain the interaction between sub-attributes, the optimization problem (16) is solved. According to Eq (18), the result of interaction value and Möbius coefficients of any two sub-attributes could be derived, as shown in Table 7. And then, based on Eq (10), the 2-addictive fuzzy measures are reported, as shown in Table 8.

In the following, we can calculate the risk evaluation value of sub-criteria by Choquet integral operator. Based on the fuzzy measure values calculated in Table 8 and the evaluation matrix in Table 3, according to Eq (19), each parent attribute's risk value is calculated by Lingo18. The specific results are shown in Table 9.

Table 9 The value of the parent attribute's risk value

project	C1	C2	C3	C4	C5	C6
1	0.865	0.727	0.957	0.805	0.765	1.000
2	0.569	0.620	0.654	0.553	0.700	0.639
3	0.480	0.382	0.411	0.309	0.300	0.239
4	0.500	0.451	0.654	0.434	0.700	0.560
5	0.551	0.687	0.805	0.941	0.765	0.518
6	0.853	0.870	0.957	0.941	0.808	0.389

7	0.853	0.870	0.957	0.941	0.765	0.679
8	0.680	0.559	0.672	0.586	0.700	0.677
9	0.742	0.559	0.700	0.586	0.660	0.639
10	0.825	0.687	0.957	0.941	0.765	0.677
11	0.566	0.652	0.654	0.586	0.572	0.757
12	0.742	0.687	0.805	0.941	0.765	0.518
13	0.598	0.405	0.521	0.434	0.572	0.338
14	0.959	0.768	0.957	0.805	0.700	0.677
15	0.757	0.768	0.957	0.941	0.700	0.639
16	0.680	0.559	0.654	0.586	0.700	0.575

The risk assessor considered the parent criteria to be largely independent of each other, and therefore the interaction between the criteria was evaluated as "NI". Based on the importance of the criteria obtained in Table 6, the fuzzy measures of the parent criteria were calculated using the same method as for the sub-criterion and the result is shown in Table 10. Then based on Table 9 and Table 10, the overall risk value of the project was obtained by Choquet integral, as shown in Table 11.

5.3 Comparative analysis

A comparison analysis is conducted in this sub-section to demonstrate the effectiveness of our proposed combined method. When the risk factors in this MCDM problem are assumed to be independent, the Shapley value of each attribute represents its degree of importance. We employ both objective methods (entropy) and subjective methods (FUZZY BWM) to determine attribute weights. By comparing the weighted average operator (WOA) with the Choquet integral operator [15], we can integrate different weights and operators to calculate the overall risk value, as illustrated in Table 11.

Table 11 The value of risk value of the sub-criterion

Project	FBWM- OWA	Entropy- OWA	FBWM- g_λ CI	Entropy - g_λ CI	FBWM- HCI
1	0.846	0.861	0.878	0.853	0.817
2	0.645	0.604	0.662	0.626	0.629
3	0.347	0.34	0.368	0.356	0.337
4	0.561	0.488	0.595	0.530	0.539
5	0.727	0.713	0.770	0.694	0.696
6	0.828	0.913	0.871	0.846	0.776
7	0.848	0.81	0.887	0.842	0.822
8	0.647	0.641	0.668	0.646	0.632
9	0.641	0.683	0.660	0.650	0.624
10	0.790	0.827	0.850	0.794	0.764
11	0.645	0.647	0.646	0.654	0.632
12	0.745	0.727	0.784	0.733	0.715
13	0.477	0.46	0.507	0.478	0.458
14	0.794	0.817	0.826	0.813	0.769
15	0.777	0.766	0.809	0.778	0.759
16	0.626	0.63	0.661	0.639	0.614

To further observe the impact of subjective and objective weights, as well as the aggregate operator considering interactions, on project investment decisions, a line graph was plotted. Fig. 4 reveals that the optimal and suboptimal investment projects determined by the proposed approach align closely with the outcomes of the other five methods. Moreover, the overall trend analysis suggests that the results from these methods exhibit a similar pattern. Furthermore, when disregarding relevance, the assessed project risk value generally surpasses the risk value based on the correlation scenario. Such as project 6 and project 1 are heavily influenced by the ranking of risk values. Project 6 exhibits a lower risk value compared to project 1 when accounting for subjective weights or criterion relevance. In contrast, when utilizing objective weights and disregarding relevance, project 6 displays a significantly higher risk value than project 1.

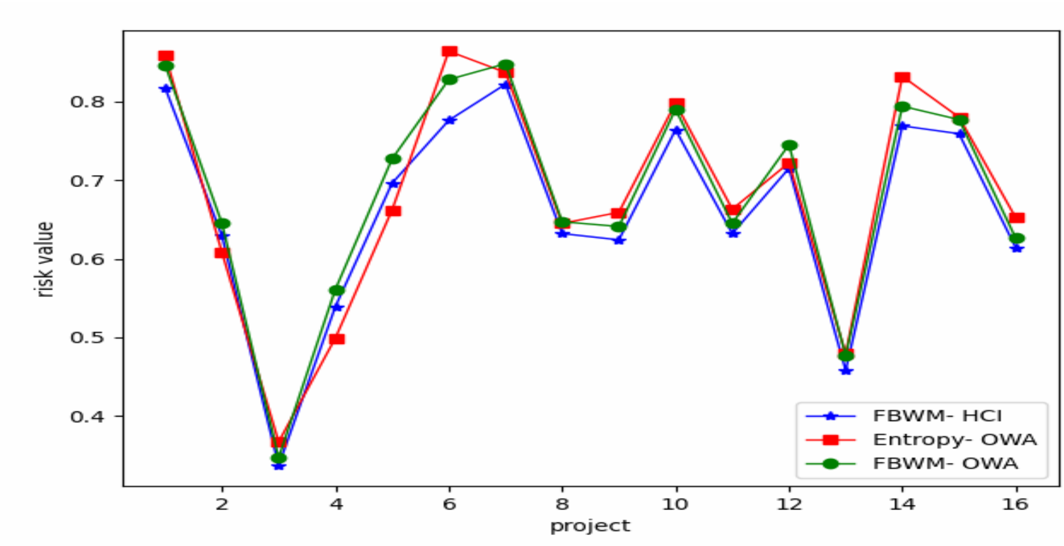

Fig. 4 The line graph of comparative methods

In other aspects, the HCI model proposed in this paper is more interpretable compared to other models. To illustrate this, a radar chart depicting the sub-Choquet integral is generated for selected projects. As depicted in Fig. 5, project 1, despite exhibiting a lower risk in the environmental dimension, has higher risks in technology and marketing dimensions compared to project 7. Consequently, project 7 is considered a more favorable choice than project 1. Similarly, project 13 carries lower R&D risk than project 4, yet its risks in environmental production and management dimensions outweigh those of project 4, resulting in a higher overall risk for project 13 compared to project 4.

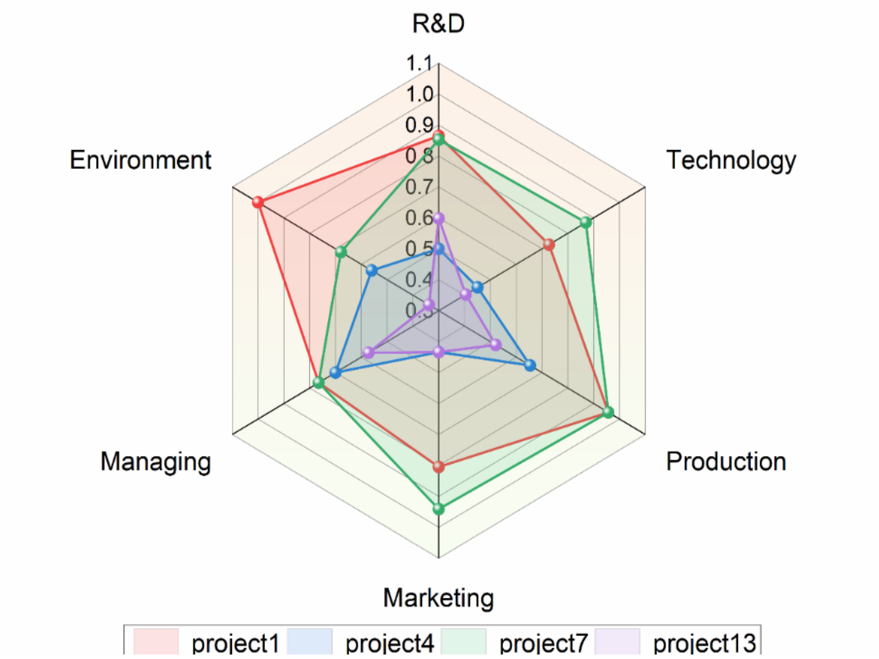

Fig. 5 The radar chart of the parent criterion for some projects

VI. Conclusions

Given the intricate and diverse factors associated with high-tech projects, project risk evaluation is becoming a challenging task. In this paper, the approach based on the fuzzy best-worst method (BWM), 2-additive fuzzy measures, and hierarchical Choquet integrals is proposed. This method relies on the fusion of subjective judgment and empirical insights from risk assessors. It utilized fuzzy BWM to ascertain the significance of individual criteria and derives interaction coefficients for any pair of criteria based on the principle of maximum entropy. Subsequently, by establishing the connections between 2-additive fuzzy measures, Möbius transform coefficients, and interaction coefficients, we obtained the fuzzy measure of the attribute set. Finally, we employed the hierarchical Choquet integral (HCI) to consolidate decision-making information, determined the overall investment risk value for each project, and identified the most suitable investment project.

The HCI decision-making model is successfully applied to the project risk assessment of venture capital. The results shown that the comprehensive evaluation value of project risk was low compared to other traditional methods when attribute correlation was taken into account, but the overall trend was consistent. In addition, the proposed method is more appropriate and more interpretative than other traditional methods.

In forthcoming research, it will be imperative to ensure that the assessment of investment projects reflects the balance between risk and returns. The approach introduced in this paper would be effectively employed for similar assessments of project returns. Additionally, as we encounter more high-dimensional data and contend with the scarcity of expert information, the identification of fuzzy measures would pose greater challenges for the Choquet integral (CI) in addressing real-world issues. Therefore, future endeavors would learn data-driven methodologies to objectively and autonomously identify fuzzy measures.

Acknowledgments

This research has been partially supported by grants from the National Natural Science Foundation of China (#72274132 #71874023 #72002020).

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Appendix

Table 3 Expert evaluation matrix

order	u1	u2	u3	u4	u5	u6	u7	u8	u9	u10	u11	u12	u13	u14	u15	u16	u17	u18	u19	u20
1	0.7	1	1	0.7	0.7	1	0.7	0.7	1	1	0.7	1	0.7	0.7	0.7	0.7	1	1	1	1
2	0.5	0.7	0.5	0.7	0.7	0.5	0.5	0.7	0.5	0.7	0.7	0.5	0.7	0.5	0.7	0.7	0.7	0.7	0.7	0.5
3	0.5	0.5	0.3	0.5	0.3	0.3	0.3	0.5	0.3	0.5	0.3	0.3	0.3	0.5	0.3	0.3	0.3	0.3	0.3	0.1
4	0.5	0.5	0.5	0.5	0.7	0.3	0.3	0.5	0.5	0.7	0.7	0.5	0.3	0.5	0.7	0.7	0.7	0.7	0.3	0.5
5	0.5	0.5	0.5	0.7	0.7	0.5	1	0.7	1	0.7	0.7	1	1	0.7	0.7	0.7	1	0.7	0.7	0.1
6	1	0.7	1	1	1	1	1	0.7	1	1	0.7	1	1	0.7	1	0.7	1	0.3	0.7	1
7	1	0.7	1	1	1	1	1	0.7	1	1	0.7	1	1	0.7	0.7	0.7	1	1	0.7	0.1
8	0.7	0.7	0.5	0.7	0.7	0.5	0.7	0.5	0.7	0.7	0.5	0.5	0.7	0.7	0.7	0.7	0.7	0.7	1	0.5
9	0.7	0.7	1	0.7	0.7	0.5	0.7	0.5	0.7	0.7	0.7	0.5	0.7	0.7	0.5	0.7	0.7	0.7	0.7	0.5
10	0.7	0.7	1	1	0.7	0.5	1	0.7	1	1	0.7	1	1	0.7	0.7	0.7	1	0.7	1	0.5
11	0.7	0.5	0.5	0.7	0.7	0.5	0.7	0.7	0.5	0.7	0.7	0.5	0.7	0.7	0.7	0.5	0.7	0.7	0.7	1
12	0.7	0.7	1	0.7	0.7	0.5	1	0.7	1	0.7	0.7	1	1	0.7	0.7	0.7	1	0.7	0.7	0.1
13	0.7	0.7	0.3	0.5	0.3	0.5	0.3	0.5	0.5	0.5	0.7	0.5	0.3	0.5	0.7	0.5	0.7	0.3	0.3	0.5
14	0.7	1	1	1	0.7	1	1	0.7	1	1	0.7	1	0.7	0.7	0.7	0.7	0.7	0.7	1	0.5
15	0.7	0.7	0.5	1	0.7	1	1	0.7	1	1	0.7	1	1	0.7	0.7	0.7	0.7	0.7	0.7	0.5
16	0.7	0.7	0.5	0.7	0.7	0.5	0.7	0.5	0.5	0.7	0.7	0.5	0.7	0.7	0.7	0.7	0.7	0.3	1	1

Table 4 best-to others vectors

Index	I	Best-to-other vector	Sub-index	I	Best-to-other vector
R&D riskC1	AI	(7/2,4,9/2)	U1	VI	(5/2,3,7/2)
			U2	EI	(1,1,1)
			U3	VI	(5/2,3,7/2)
			4	FI	(3/2,2,5/2)
Technical riskC2	EI	(1,1,1)	U5	FI	(3/2,2,5/2)
			U6	VI	(5/2,3,7/2)
			U7	FI	(3/2,2,5/2)
			U8	EI	(1,1,1)
Production riskC3	AI	(7/2,4,9/2)	U9	FI	(3/2,2,5/2)
			U10	EI	(1,1,1)
			U11	AI	(7/2,4,9/2)
Marketing riskC4	VI	(5/2,3,7/2)	U12	EI	(1,1,1)
			U13	FI	(3/2,2,5/2)
			U14	VI	(5/2,3,7/2)
Managing RiskC5	FI	(3/2,2,5/2)	U15	AI	(7/2,4,9/2)
			U16	EI	(1,1,1)
			U17	FI	(3/2,2,5/2)
Environmental RisksC6	WI	(2/3,1,3/2)	U18	EI	(1,1,1)
			U19	VI	(5/2,3,7/2)
			U20	FI	(3/2,2,5/2)

Table5. others-to-worst vectors

Index	I	other-to-worst vector	Sub-index	I	Best-to-other vector
R&D riskC1	WI	(2/3,1,3/2)	U1	WI	(2/3,1,3/2)
			U2	VI	(3/2,2,5/2)
			U3	EI	(1,1,1)
			4	FI	(3/2,2,5/2)
Technical riskC2	AI	(7/2,4,9/2)	U5	FI	(3/2,2,5/2)
			U6	WI	(2/3,1,3/2)
			U7	EI	(1,1,1)
			U8	FI	(3/2,2,5/2)
Production riskC3	EI	(1,1,1)	U9	FI	(3/2,2,5/2)
			U10	VI	(5/2,3,7/2)
			U11	EI	(1,1,1)
Marketing riskC4	FI	(3/2,2,5/2)	U12	VI	(5/2,3,7/2)
			U13	FI	(3/2,2,5/2)
			U14	EI	(1,1,1)
Managing RiskC5	VI	(5/2,3,7/2)	U15	EI	(1,1,1)
			U16	AI	(7/2,4,9/2)
			U17	VI	(5/2,3,7/2)
Environmental RisksC6	WI	(2/3,1,3/2)	U18	VI	(5/2,3,7/2)
			U19	EI	(1,1,1)
			U20	FI	(3/2,2,5/2)

Table 6 Parent criteria and sub-criteria weights

Index	Fuzzy density (k=0.0797)	Crisp value	Sub-index	Fuzzy weight	Crisp value
R&D riskC1 (k=0.2087)	(0.1320,0.1545,0.2620)	0.0932	U1	(0.1294,0.1466,0.1638)	0.1466
			U2	(0.3753,0.4705,0.4705)	0.4546
			U3	(0.1268,0.1466,0.1472)	0.1434
			U4	(0.1901,0.2626,0.2906)	0.2552
Technical riskC2 (k=0.4384)	(0.2165,0.2560,0.3425)	0.3009	U5	(0.2068,0.2686,0.3133)	0.2658
			U6	(0.1494,0.1720,0.1831)	0.1701
			U7	(0.1434,0.1522,0.1634)	0.1256
			U8	(0.3495,0.4194,0.4390)	0.4110
Production riskC3 (k=0.3542)	(0.1299,0.1455,0.2305)	0.0797	U9	(0.2783,0.3254,0.4362)	0.3361
			U10	(0.4998,0.5355,0.5970)	0.5398
			U11	(0.1230,0.1230,0.1297)	0.1241
Marketing riskC4 (k=0.2087)	(0.1690,0.2030,0.3445)	0.1256	U12	(0.5210,0.5210,0.6022)	0.5345
			U13	(0.2484,0.2909,0.3766)	0.2981
			U14	(0.1624,0.1624,0.1924)	0.1674
Managing RiskC5 (k=0.3542)	(0.2275,0.2875,0.4080)	0.2327	U15	(0.1280,0.1274,0.1274)	0.1263
			U16	(0.4355,0.5547,0.5865)	0.5401
			U17	(0.2733,0.3370,0.3800)	0.3336
Environmental RisksC6 (k=0.2087)	(0.2125,0.2280,0.3035)	0.1697	U18	(0.4393,0.5505,0.5507)	0.5321
			U19	(0.1485,0.1716,0.1757)	0.1684
			U20	(0.2269,0.3074,0.3402)	0.2295

Table 7 The value of the interaction and Möbius capacity in sub-attributes

Attribute Set	interaction	Möbius capacity	Attribute Set	interaction	Möbius capacity
{U1}	0.1467	0.0527	{U11}	0.1241	0.1064
{U2}	0.4546	0.3893	{U9, U10} (NI)	-0.0480	-0.0480
{U3}	0.1435	0.1413	{U9, U11} (NI)	0.0177	0.0177
{U4}	0.2552	0.2552	{U10, U11} (NI)	0.0177	0.0177
{U1, U2} (NI)	0.1466	0.1466	{U12}	0.5345	0.5012
{U1, U3} (NI)	0.0205	0.0205	{U13}	0.2981	0.2648
{U1, U4} (NI)	0.0209	0.0209	{U14}	0.1674	0.1435
{U2, U3} (NI)	0.0205	0.0205	{U12, U13} (NI)	0.0426	0.0426
{U2, U4} (NI)	0.0365	0.0365	{U12, U14} (NI)	0.0239	0.0239
{U3, U4} (NI)	0.0205	0.0205	{U13, U14} (NI)	0.0239	0.0239
{U5}	0.2658	0.1528	{U15}	0.1263	0.0543
{U6}	0.1701	0.0882	{U16}	0.5401	0.4416
{U7}	0.1256	0.1198	{U17}	0.3336	0.2171
{U8}	0.4110	0.4110	{U15, U16} (LC)	0.0540	0.0540
{U5, U6} (NI)	0.1701	0.1701	(MC)	0.0900	0.0900
{U5, U7} (NI)	0.0179	0.0179	(MC)	0.1430	0.1430
{U5, U8} (NI)	0.0380	0.0380	{U18}	0.5321	0.5374
{U6, U7} (NI)	0.0180	0.0180	{U19}	0.1684	0.1249
{U6, U8} (NI)	0.0243	0.0243	{U20}	0.2295	0.1904
{U7, U8} (NI)	0.0180	0.0180	{U18, U19} (LC)	0.0342	0.0342
{U9}	0.3361	0.3512	{U18, U20} (LC)	0.0352	0.0352
{U10}	0.5398	0.0547	{U19, U20} (NI)	0.0766	0.0766

Table 8 The 2-addictive fuzzy measure of sub-attributes set

Attribute Set	2-additive FM	Attribute Set	2-additive FM
{U1}	0.0527	{U5}	0.1528
{U2}	0.3893	{U6}	0.0882
{U3}	0.1413	{U7}	0.1198
{U4}	0.2552	{U8}	0.4110
{U1, U2}	0.5886	{U5, U6}	0.4111

{U1, U3}	0.2145	{U5, U7}	0.2923
{U1, U4}	0.3288	{U5, U8}	0.6018
{U2, U3}	0.5511	{U6, U7}	0.2260
{U2, U4}	0.3444	{U6, U8}	0.5235
{U3, U4}	0.4170	{U7, U8}	0.5488
{U1, U2, U3}	0.7709	{U5, U6, U7}	0.5668
{U1, U2, U4}	0.9012	{U5, U6, U8}	0.8844
{U1, U3, U4}	0.5111	{U5, U7, U8}	0.7575
{U2, U3, U4}	0.8633	{U6, U7, U8}	0.6613
{U1, U2, U3, U4}	1	{U5, U6, U7, U8}	1
{U9}	0.3512	{U12}	0.5012
{U10}	0.5447	{U13}	0.2648
{U11}	0.1064	{U14}	0.1435
{U9,1U0}	0.8579	{U12, U13}	0.8086
{U9, U11}	0.4753	{U12, U14}	0.6686
{U10, U11}	0.7688	{U13, U14}	0.4322
{U9, U10, U11}	1	{U12, U13, U14}	1
{U15}	0.0543	{U18}	0.5374
{U16}	0.4416	{U19}	0.1249
{U17}	0.2171	{U20}	0.1904
{U15, U16}	0.5499	{U18, U19}	0.6965
{U15, U17}	0.3614	{U18, U20}	0.7630
{U16, U17}	0.8017	{U19, U20}	0.3929
{U15, U16, U17}	1	{U18, U19, U20}	1

Table 9 The 2-addictive fuzzy measure of parent attributes

attribute set	2-addictive FM	attribute set	2-addictive FM
	0	{C2, C3, C4}	0.4755
C1	0.0856	{C2, C3, C5}	0.5844
C2	0.2809	{C2, C3, C6}	0.5249
C3	0.0683	{C2, C4, C5}	0.6312
C4	0.1099	{C2, C4, C6}	0.5717
C5	0.2127	{C2, C5, C6}	0.6831
C6	0.1568	{C3, C4, C5}	0.4073
{C1, C2}	0.3718	{C3, C4, C6}	0.3514
{C1, C3}	0.1585	{C3, C5, C6}	0.4567
{C1, C4}	0.2008	{C4, C5, C6}	0.5035
{C1, C5}	0.3036	{C1, C2, C3, C4}	0.5763
{C1, C6}	0.2371	{C1, C2, C3, C5}	0.6852
{C2, C3}	0.3538	{C1, C2, C3, C6}	0.6151
{C2, C4}	0.398	{C1, C2, C4, C5}	0.7327
{C2, C5}	0.5069	{C1, C2, C4, C6}	0.6626
{C2, C6}	0.4474	{C1, C2, C5, C6}	0.774
{C3, C4}	0.1828	{C1, C3, C4, C5}	0.5018
{C3, C5}	0.2856	{C1, C3, C4, C6}	0.4416
{C3, C6}	0.2297	{C1, C3, C5, C6}	0.5469
{C4, C5}	0.3298	{C1, C4, C5, C6}	0.5944
{C4, C6}	0.2739	{C2, C3, C4, C5}	0.7133
{C5, C6}	0.3793	{C2, C3, C4, C6}	0.6538

{C1, C2, C3}	0.4493	{C2, C3, C5, C6}	0.7652
{C1, C2, C4}	0.4942	{C2, C4, C5, C6}	0.8146
{C1, C2, C5}	0.6031	{C3, C4, C5, C6}	0.5856
{C1, C2, C6}	0.533	{C1, C2, C3, C4, C5}	0.8088
{C1, C3, C4}	0.2783	{C1, C2, C3, C4, C6}	0.7493
{C1, C3, C5}	0.382	{C1, C2, C3, C5, C6}	0.8067
{C1, C3, C6}	0.3155	{C1, C2, C4, C5, C6}	0.9108
{C1, C4, C5}	0.426	{C1, C3, C4, C5, C6}	0.6811
{C1, C4, C6}	0.3595	{C2, C3, C4, C5, C6}	0.9013
{C1, C5, C6}	0.4648	{C1, C2, C3, C4, C5, C6}	1