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An Extended EDAS Approach Based on Cumulative Prospect Theory for Multiple Attributes Group Decision Making with Interval-Valued Intuitionistic Fuzzy Information

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Abstract. The interval-valued intuitionistic fuzzy sets (IVIFSs), based on the intuitionistic fuzzy sets (IFSs), combine the classical decision method and its research and application is attracting attention. After a comparative analysis, it becomes clear that multiple classical methods with IVIFSs' information have been applied to many practical issues. In this paper, we extended the classical EDAS method based on the Cumulative Prospect Theory (CPT) considering the decision experts (DEs)' psychological factors under IVIFSs. Taking the fuzzy and uncertain character of the IVIFSs and the psychological preference into consideration, an original EDAS method, based on the CPT under IVIFSs (IVIF-CPT-EDAS) method, is created for multiple-attribute group decision making (MAGDM) issues. Meanwhile, the information entropy method is used to evaluate the attribute weight. Finally, a numerical example for Green Technology Venture Capital (GTVC) project selection is given, some comparisons are used to illustrate the advantages of the IVIF-CPT-EDAS method and a sensitivity analysis is applied to prove the effectiveness and stability of this new method.

Key words: MAGDM, IVIFSs, EDAS, CPT, entropy.

1. Introduction

During the long history of humanity, conflicts between environmental issues and economic growth have always been one of the key issues (Yang *et al.*, 2022) discussed by various researchers. Especially after the Industrial Revolution, while human society greatly improved production efficiency and promoted economic development, the environmental pollution caused by industrial production and manufacturing also constantly threatened human health and survival. Therefore, in order to ensure stable economic development,

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we should seek a more long-term and sustainable development path. Specifically, the GTVC (Dong *et al.*, 2021; Dhayal *et al.*, 2023), created by integrating the concept of green development into the traditional financial system, is in line with the demand. It is an emerging project technology related to protecting and improving the environment. In the processes of GTVC, project screening and evaluation are important. However, project evaluation often involves many qualitative indicators, coupled with the cognitive limitations of DEs and the complexity of actual decision making (DM) scenarios, which may lead to significant ambiguity in input information.

On the other hand, multiple criteria decision-making (MCDM) is usually classified (Hashemi-Tabatabaei *et al.*, 2019; Keshavarz-Ghorabaee, 2021; Keshavarz-Ghorabaee *et al.*, 2018, 2021, 2016) into two categories: multiple attribute decision-making (MADM) (Ning *et al.*, 2022; Zhang *et al.*, 2021) and multiple objective decision-making (MODM), based on whether the DM scheme is finite or infinite. MODM refers to the DM problem that only considers two or more objectives simultaneously. MADM, also known as finite alternative MODM, refers to the decision problem of selecting the optimal alternative solution considering multiple attributes. MAGDM is an important component of modern decision science, as it integrates the advantages of MADM and group DM (GDM). Currently, the relative theories and methods on MAGDM (Y. Li *et al.*, 2021; Ning *et al.*, 2023; Zhang *et al.*, 2023) are widely applied in fields such as investment risk and economic management. Moreover, MAGDM technology can utilize a systematic and logical approach to collect and process multidimensional fuzzy evaluation information to determine the best alternative.

That being the case, it is necessary to design a suitable and advanced MAGDM model in a fuzzy environment to select the optimal GTVC project. To enhance the readability of the proposed research work, we have sorted out some important abbreviations, as shown in Table 1.

1.1. *Motivations and Contributions for Proposed Research*

The motivations of this study are given below:

(1) With the increasing complexity of DM problems and the ambiguity of informative data, DEs find it is difficult to accurately quantify their evaluations using single numerals, but their preferences can be expressed more completely in natural language. Linguistic IVIFS theory is one of the most effective generalizations in FS theory, which can describe the assessment information of DEs in even more detail.

(2) Compared with other evaluation methods, the EDAS method is a highly effective tool to execute classification and decision for contradictory attributes in MAGDM. Classical EDAS algorithms assume that all decision makers are perfectly rational, but people have different views on the same level of risks and benefits in practical environments. They are more conservative when facing equal risks than when facing returns. Therefore, it is necessary to develop a technology that simulates the real DM environment to model IVIF information and evaluate the weights of attributes. From this perspective, it is necessary to integrate the CPT, which takes the DEs' risk preference into consideration, and the IVIF-EDAS method.

Table 1
Description of abbreviations.

Abbreviations	Description
DE	Decision expert
DM	Decision making
FS	Fuzzy set
IFS	Intuitionistic fuzzy set
IVIFS	Interval valued intuitionistic fuzzy set
IVIFN	Interval valued intuitionistic fuzzy number
IVIFWA	Interval valued intuitionistic fuzzy weighted averaging
IVIFWG	Interval valued intuitionistic fuzzy geometric
SF	Score function
AF	Accuracy function
CPT	Cumulative prospect theory
GTVC	Green technology venture capital
PDA(NDA)	Positive (Negative) distance from average
MAGDM	Multiple attribute group decision making
CRITIC	CRiteria importance through intercriteria correlation
EDAS	Evaluation based on distance from average solution
TOPSIS	Technique for order preference by similarity to ideal solution
TODIM	An acronym in Portuguese for interactive and multicriteria decision making
MABAC	Muti-attributive border approximation area comparison

(3) Due to the fact that the entropy method determines attribute weights based on the degree of the indicator confusion, the higher the degree of indicator information confusion, the greater the entropy value, and the smaller the assigned weights. Combined with the advantages of the EDAS method in solving DM problems with conflicting attributes, it is necessary to extend the information entropy method to handle qualitative information in the IVIF environment to guarantee the stability of the entire DM system.
(4) As a key research issue in the MAGDM field, the selection of high-quality GTVC projects has a great significance for environmental protection and sustainable economic development. In this regard, considering the advantages of the EDAS method, the CPT's characteristics and the IVIFSs which may contain more information, the aim of this paper is to extend the EDAS method based on CPT for MAGDM under IVIFSs and apply it to the GTVC project selection.

The contributions of this paper are as follows:

(1) The integration of CPT and the EDAS method in IVIFSs, named as the IVIF-CPT-EDAS method, is discussed to determine which GTVC project is suitable. The attribute weights are determined by using IVIF-entropy method and alternatives are ranked by using CPT-EDAS method in a IVIF context. Therefore, our proposed method combines DEs evaluation values which makes it more profitable to use and the decision results more precise.
(2) The IVIF-CPT-EDAS method, which considers not only the relatively simple and reasonable classical method, but also the psychological state of DEs, which is more realistic, has been constructed.

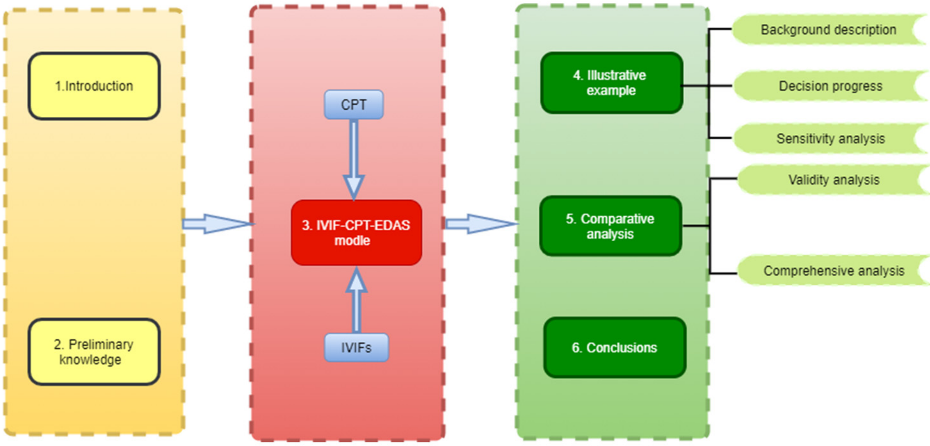

Fig. 1. Full text framework diagram.

(3) We implement the constructed approach to a numerical example for GTVC project selection to demonstrate the applicability of our proposed methodology.
(4) We compare the constructed approach with the existing methods to illustrate the advantages of the IVIF-CPT-EDAS method. Furthermore, comparative analysis and sensitivity analysis are used to illustrate the effectiveness and authenticity of the developed approach.

In order to do so, the overall structure of the article is as follows: the basic knowledge of IVIFSs is briefly introduced in Section 2, then the IVIF-CPT-EDAS method is constructed in Section 3. Section 4 gives a numerical study for GTVC project selection, and the corresponding parameters' sensitivity, and in Section 5, a comparison analysis is made to prove its effectiveness and stability. In Section 6, conclusions are made to summarize this paper. Figure 1 represents the full framework of our study.

1.2. *Literature Review*

In most practical decisions, the DEs' evaluation of an index cannot be simply expressed by real numbers (Ye, 2017; Liu and You, 2019; Gao *et al.*, 2019a, 2019b). Therefore, Zadeh (1965) introduced fuzzy sets (FSs), and later this theory and its extensions have been applied to many fields (Zeng *et al.*, 2018; Chen, 2018). An extension of the FSs, such as the IFSs (Atanassov, 1986), is the classical fuzzy set, and due to the fact that the IFSs are in the range of real numbers, the IVIFSs can extend the IFSs with the interval numbers to fully express different conditions of the DM. Atanassov and Gargov (1989) proposed the IVIFSs, and the corresponding operators (Atanassov, 1994), and with some basic research made, the corresponding innovation of IVIFSs has been proposed. Grzegorzewski (2004) proposed a new distance assessment based on Hausdorff metric which is the well-known Hamming distance. Based on some operational laws of IVIFSs, TOPSIS method (Lin *et al.*, 2019; Yue and Zhang, 2020; Zulqarnain *et al.*, 2021; Chen, 2015), Grey Relational

Analysis method (Fankang *et al.*, 2020; Hongjiu *et al.*, 2019; Wei and Lan, 2008; Zhang and Wang, 2022), VIKOR method (Dammak *et al.*, 2020; Salimian *et al.*, 2022a; Wu *et al.*, 2019), TODIM method (Krohling and Pacheco, 2014; Lin *et al.*, 2020; Zhao *et al.*, 2021; Zindani *et al.*, 2021), MABAC method (Keshavarz-Ghorabaee *et al.*, 2015; Liu *et al.*, 2019; Mahmoudi *et al.*, 2019; Salimian *et al.*, 2022b), and other methods have been applied to the IVIFSs (Kumar and Chen, 2022; Li *et al.*, 2012, 2021; Lee, 2009; Ye *et al.*, 2021).

The EDAS method (Huang and Lin, 2021; Karunanithi *et al.*, 2015; Keshavarz-Ghorabaee *et al.*, 2015) assesses the alternatives by the positive (negative) distance from average (PDA and NDA). In other words, the higher value of the PDA or the lower value of the NDA means a more optimal alternative. Among numerous evaluation methods, EDAS not only has much easier formulas, but also has unique advantages in resolving conflicts between economic development and green technology evaluation elements, making it more efficient and accurate than others. On the one hand, the EDAS method has been applied to many fuzzy sets (Agrawal *et al.*, 2023; Ecer *et al.*, 2022; Zolfani *et al.*, 2021), for instance, IFSs (Kahraman *et al.*, 2017), interval-valued fuzzy soft sets (Peng *et al.*, 2017), hesitant fuzzy linguistic sets (Feng *et al.*, 2018), interval-valued neutronsophic sets (Karasan and Kahraman, 2018), and so on. On the other hand, it can be seen that the EDAS method has good adaptability in the DM fields. Dinghong and Wenhua (2021) applied the EDAS method to the selection of smart zero waste cities, and Mishra *et al.* (2020) applied the EDAS method to the selection of medical waste treatment technologies. Although Li and Wang (2020) extended the EDAS method to IVIFSs, this model cannot take the risk reference of DEs into consideration. Due to the fact that most methods are based on the utility theory which considers that DEs are entirely rational, the combination of CPT (Tversky and Kahneman, 1992) and the classical EDAS method are now applied to some FSs, such as probabilistic hesitant fuzzy sets (Liao *et al.*, 2023) and picture fuzzy sets (Jiang *et al.*, 2022). We discussed some important previously proposed models and methods in Table 2 to highlight the superiority of our study.

1.3. *Research Gaps*

1. According to the literature review, it is evident that while some scholars have successfully utilized the CPT-EDAS method in various fuzzy environments (Zhang *et al.*, 2022), its application under the IVIF environment is inadequate. Additionally, there are still deficiencies in certain existing methods for enhancing EDAS that require further investigation to better meet vague and variable DM environments.
2. In the entire process of GTVC, project screening and evaluation are crucial steps. However, since GTVC primarily focuses on emerging technology projects related to environmental protection and improvement, the evaluation of such projects often involves numerous qualitative indicators and cognitive limitations, which can also cause significant ambiguity. To address this issue, it is important to construct a scientific evaluation index system for green finance risk capital projects and establish an appropriate evaluation model. This will bridge the gap and help venture investors make informed and optimal investment decisions related to these projects.

Table 2
Characteristic table of different approaches.

Year	Approach	Linguistic data	Fuzzy information form	Application
2012	IVIF-TOPSIS (Izadikhah, 2012)	✓	Intuitionistic fuzzy number	Supplier selection
2018	EHFLTS-EDAS (Feng *et al.*, 2018)	✓	Hesitant fuzzy linguistic term set	Company project selection
2019	IVIF-VIKOR (Wu *et al.*, 2019)	×	Interval-valued intuitionistic fuzzy set	Financing risk assessment
2020	IVIF-EDAS (Li and Wang, 2020)	×	Intuitionistic fuzzy number	Computer network system assessment
2022	F-SECA (Keshavarz-Ghorabaee *et al.*, 2022)	✓	Triangular fuzzy numbers	E-waste scenario evaluation
2022	F-SBWM (Amiri *et al.*, 2023)	✓	Triangular fuzzy numbers	Warehouse location and medical selection
2022	PDHFWEPGMSM (Ning *et al.*, 2022)	×	Probabilistic dual hesitant fuzzy set	Sustainable supplier selection
2022	IVIF-GRA (Zhang and Wang, 2022)	×	Interval-valued intuitionistic fuzzy set	The service quality evaluation of agricultural e-commerce
2023	SF-CPT-TODIM (Zhang *et al.*, 2023)	×	Spherical fuzzy set	Commercial insurance selection
2023	PHF-CPT-EDAS (Liao *et al.*, 2023)	×	Probabilistic hesitant fuzzy set	Commercial vehicles and green supplier selection
Current study		✓	Interval-valued intuitionistic fuzzy set	Green technology venture capital selection

3. After reviewing the existing research on GTVC projects, we can state that there is a lack of emphasis on the psychological well-being. However, the psychological state of DM is an inevitable objective presence in influencing their investment decisions. In order to address this gap, the improved EDAS algorithm has been applied to GTVC, offering new methods and tools for venture capitalists to effectively screen green investment projects.

Overall, it is meaningful to use the IVIF-CPT-EDAS method for the GTVC project selection. This study aims to promote the future development of the venture capital field, provide solutions to guide practical cases, and also provide references for research on DM methods and theories.

2. Preliminary Knowledge

In order to better understand the content of this article, in this section, we will review some basic concepts of FSs and aggregation operators of IVIFSs.

Definition 1 (Zadeh, 1965). Set T as a finitely non-empty set, and the FSs on T is described as follows:

$$FS = \left\{ \langle t, \eta_{IFS}(t) \rangle \,\middle|\, t \in T \right\}, \tag{1}$$

where $\eta_{IFS}(t)$ denotes the degree of membership of FSs, and $\eta_{IFS} : T \to [0, 1]$ is a single real value.

Definition 2 (Atanassov, 1986). Set T as a finitely non-empty set, and the IFSs on T is described as follows:

$$IFS = \{\langle t, \eta_{IFS}(t), \nu_{IFS}(t)\rangle \mid t \in T\}, \tag{2}$$

where $\eta_{IFS}(t)$ and $\nu_{IFS}(t)$ respectively represent the degree of membership and non-membership of IFSs which are denoted as follows: $0 \leqslant \eta_{IFS}(t) + \nu_{IFS}(t) \leqslant 1$,

$$\eta_{IFS}(t) : T \to [0, 1], \quad t \in T \to \eta_{IFS}(t) \in [0, 1], \tag{3}$$
$$\nu_{IFS}(t) : T \to [0, 1], \quad t \in T \to \nu_{IFS}(t) \in [0, 1], \tag{4}$$
$$0 \leqslant \eta_{IFS}(t) + \nu_{IFS}(t) \leqslant 1. \tag{5}$$

Moreover, the hesitation degree of IFSs is denoted as follows:

$$\pi_{IFS}(t) = 1 - \eta_{IFS}(t) - \nu_{IFS}(t), \tag{6}$$

where $\forall t \in T, 0 \leqslant \pi_{IFS}(t) \leqslant 1$.

Definition 3 (Atanassov and Gargov, 1989). Set T as a finitely non-empty set, and the IVIFSs on T is described as follows:

$$\widetilde{MN} = \{\langle t, \tilde{\eta}_{\widetilde{MN}}(t), \tilde{\nu}_{\widetilde{MN}}(t)\rangle \mid t \in T\}, \tag{7}$$

where $\tilde{\eta}_{\widetilde{MN}}(t)$ and $\tilde{\nu}_{\widetilde{MN}}(t)$ respectively represent the interval of the degree of membership and non-membership which are shown as follows:

$$\tilde{\eta}_{\widetilde{MN}}(t) : t \in T \to \tilde{\eta}_{\widetilde{MN}}(t) = [ZM(t), UM(t)] \subseteq [0, 1], \tag{8}$$
$$\tilde{\nu}_{\widetilde{MN}}(t) : t \in T \to \tilde{\nu}_{\widetilde{MN}}(t) = [ZN(t), UN(t)] \subseteq [0, 1], \tag{9}$$
$$0 \leqslant UM(t) + UN(t) \leqslant 1. \tag{10}$$

Similarly, the interval of the hesitation degree of IVIFSs is described as follows:

$$\tilde{\pi}_{\widetilde{MN}}(t) = [1 - UM(t) + UN(t), 1 - ZM(t) - ZN(t)], \tag{11}$$

where $\forall t \in T, 0 \leqslant \tilde{\pi}_{\widetilde{MN}}(t) \leqslant 1$.

Usually, the interval-valued intuitionistic fuzzy number (IVIFN) (Xu and Chen, 2007) of IVIFSs in Eq. (7) is shown in Eq. (12):

$$\tilde{N} = (\tilde{\eta}_{\widetilde{MN}}(t), \tilde{\nu}_{\widetilde{MN}}(t)) = ([ZM(t), UM(t)], [ZN(t), UN(t)]). \tag{12}$$

The Eq. (12) can be abbreviated in Eq. (13):

$$\tilde{N} = \big([ZM, UM], [ZN, UN]\big). \tag{13}$$

Especially when $ZM = UM$, $ZN = UN$, IVIFSs can be degenerated into IFSs. The maximum IVIFN is $\tilde{N}_{\max} = ([1, 1], [0, 0])$, and the minimum IVIFN is $\tilde{N}_{\min} = ([0, 0], [1, 1])$.

Definition 4 (Xu, 2007). Suppose any three IVIFNs $\tilde{N}_i = ([ZM_i, UM_i], [ZN_i, UN_i])$, $i = 1, 2, 3$ and the calculation rules of IVIFNs are defined as follows:

(1) $(\tilde{N}_1)^c = \big([ZN_1, UN_1], [ZM_1, UM_1]\big)$;

(2) $\tilde{N}_1 \oplus \tilde{N}_2 = \begin{pmatrix} [ZM_1 + ZM_2 - ZM_1 ZM_2, UM_1 + UM_2 - UM_1 UM_2], \\ [ZN_1 ZN_2, UN_1 UN_2] \end{pmatrix}$;

(3) $\tilde{N}_1 \otimes \tilde{N}_2 = \begin{pmatrix} [ZM_1 ZM_2, UM_1 UM_2], \\ [ZN_1 + ZN_2 - ZN_1 ZN_2, UN_1 + UN_2 - UN_1 UN_2] \end{pmatrix}$;

(4) $\tilde{N}_1 \cup \tilde{N}_2 = \begin{pmatrix} [\max\{ZM_1, ZM_2\}, \max\{UM_1, UM_2\}], \\ [\min\{ZN_1, ZN_2\}, \min\{UN_1, UN_2\}] \end{pmatrix}$;

(5) $\tilde{N}_1 \cap \tilde{N}_2 = \begin{pmatrix} [\min\{ZM_1, ZM_2\}, \min\{UM_1, UM_2\}], \\ [\max\{ZN_1, ZN_2\}, \max\{UN_1, UN_2\}] \end{pmatrix}$;

(6) $\kappa \tilde{N}_1 = \big(\big[1 - (1 - ZM_1)^\kappa, 1 - (1 - UM_1)^\kappa\big], \big[ZN_1^\kappa, UN_1^\kappa\big]\big), \kappa > 0$;

(8) $\tilde{N}_1^\kappa = \big(\big[ZM_1^\kappa, UM_1^\kappa\big], \big[1 - (1 - ZN_1)^\kappa, 1 - (1 - UN_1)^\kappa\big]\big), \kappa > 0$.

Furthermore, the above algorithms also satisfy the following operation laws (Atanassov, 1994):

i. Commutative laws:

a) $\tilde{N}_1 \oplus \tilde{N}_2 = \tilde{N}_2 \oplus \tilde{N}_1$;
b) $\tilde{N}_1 \otimes \tilde{N}_2 = \tilde{N}_2 \otimes \tilde{N}_1$.

ii. Associative laws:

a) $(\tilde{N}_1 \oplus \tilde{N}_2) \oplus \tilde{N}_3 = \tilde{N}_1 \oplus (\tilde{N}_2 \oplus \tilde{N}_3)$;
b) $(\tilde{N}_1 \otimes \tilde{N}_2) \otimes \tilde{N}_3 = \tilde{N}_1 \otimes (\tilde{N}_2 \otimes \tilde{N}_3)$.

iii. Distributive laws:

a) $\kappa(\tilde{N}_1 \oplus \tilde{N}_2) = \kappa \tilde{N}_1 \oplus \kappa \tilde{N}_2$;
b) $\kappa_1 \tilde{N}_1 \oplus \kappa_2 \tilde{N}_1 = (\kappa_1 + \kappa_2)\tilde{N}_1$.

iv. Exponential operation laws:

a) $(\tilde{N}_1 \otimes \tilde{N}_2)^\kappa = \tilde{N}_1^\kappa \otimes \tilde{N}_2^\kappa$;
b) $\tilde{N}_1^{\kappa_1} \otimes \tilde{N}_1^{\kappa_2} = \tilde{N}_1^{(\kappa_1 + \kappa_2)}$,

where $\kappa, \kappa_1, \kappa_2 \geqslant 0$.

Definition 5 (Wang and Chen, 2018). Let $\tilde{N} = ([ZM, UM], [ZN, UN])$ be IVIFN, and the score functions $SF(\tilde{N})$ and $AF(\tilde{N})$ of IVIFN are defined as follows:

$$SF(\tilde{N}) = \left(\frac{(ZM + UM)(ZM + UN) - (ZN + UN)(ZM + UN)}{2}\right), \tag{14}$$

where $SF(\tilde{N}) \in [-1, 1]$, if the value of $SF(\tilde{N})$ is greater, the corresponding IVIFN is larger.

$$AF(\tilde{N}) = \frac{(1 - ZM + UM)(1 - ZM - ZN) + (1 - ZN + UN)(1 - UM - UN)}{2}, \tag{15}$$

where $AF(\tilde{N}) \in [0, 1]$, if the value of $AF(\tilde{N})$ is greater, the corresponding IVIFN is larger.

Example 1. If $\tilde{A} = ([0.593, 0.638], [0.126, 0.243])$, $\tilde{B} = ([0.553, 0.658], [0.100, 0.266])$, according to Wang and Chen (2017), the score function cannot compare these two IVIFs, then it can be calculated that $SF_w(\tilde{\text{A}}) = SF_w(\tilde{\text{B}}) = 0.687$. Nevertheless, the two IVIFs can be calculated as $SF(\tilde{\text{A}}) = 0.280$ and $SF(\tilde{\text{B}}) = 0.226$ using the formula in Definition 5, which can overcome the shortcomings of the score function in Wang and Chen (2017) and is of good quality.

Definition 6 (Wang and Chen, 2018). According to Definition 4, suppose any two IVIFNs $\tilde{N}_1 = ([ZM_1, UM_1], [ZN_1, UN_1])$ and $\tilde{N}_2 = ([ZM_2, UM_2], [ZN_2, UN_2])$, and the comparison of these two IVIFNs is described as follows:

If $SF(\tilde{N}_1) > SF(\tilde{N}_2)$, then $\tilde{N}_1 > \tilde{N}_2$;
If $SF(\tilde{N}_1) < SF(\tilde{N}_2)$, then $\tilde{N}_1 < \tilde{N}_2$.
If $SF(\tilde{N}_1) = SF(\tilde{N}_2)$, then it can be divided into the following three cases:

a) If $AF(\tilde{N}_1) < AF(\tilde{N}_2)$, then $\tilde{N}_1 < \tilde{N}_2$;
b) If $AF(\tilde{N}_1) > AF(\tilde{N}_2)$, then $\tilde{N}_1 > \tilde{N}_2$;
c) If $AF(\tilde{N}_1) = AF(\tilde{N}_2)$, then $\tilde{N}_1 = \tilde{N}_2$.

Definition 7 (Xu and Chen, 2007). Let a set of n-dimensional IVIFNs $\tilde{N}_m = ([ZM_m, UM_m], [ZN_m, UN_m])$, $m = 1, 2, \dots, n$. According to Definition 3, the IVIF weighted average operator (IVIFWA) is defined as follows:

$$\begin{aligned} IVIFWA_\vartheta(\tilde{N}_1, \tilde{N}_2, \dots, \tilde{N}_n) &= \sum_{m=1}^{n} \vartheta_m \tilde{N}_m \\ &= \left(\left[1 - \prod_{k=1}^{n}(1 - ZM_m)^{\vartheta_m}, 1 - \prod_{m=1}^{n}(1 - UM_m)^{\vartheta_m}\right], \left[\prod_{m=1}^{n} ZN_m^{\vartheta_m}, \prod_{m=1}^{n} UN_m^{\vartheta_m}\right]\right), \end{aligned} \tag{16}$$

where $\vartheta = (\vartheta_1, \vartheta_2, \dots, \vartheta_n)^T$ is the weighting vector of $\tilde{N}_m$, and $\forall \vartheta_m \in [0, 1]$, $\sum_{m=1}^{n} \vartheta_m = 1$.

Especially when $\vartheta = (1/n, 1/n, \dots, 1/n)^T$, IVIFWA operators degenerate into IVIF average operators (IVIFA).

Definition 7 (Xu, 2007). Let a set of n-dimensional IVIFNs $\tilde{N}_m = ([ZM_m, UM_m], [ZN_m, UN_m])$, $m = 1, 2, \dots, n$. According to Definition 3, IVIF weighted geometric operator (IVIFWG) can be defined as follows:

$$IVIFWG_\vartheta(\tilde{N}_1, \tilde{N}_2, \dots, \tilde{N}_n) = \prod_{m=1}^{n} (\tilde{N}_m)^{\vartheta_m}$$
$$= \left(\left[\prod_{m=1}^{n} ZM_m^{\vartheta_m}, \prod_{m=1}^{n} UM_m^{\vartheta_m} \right], \left[1 - \prod_{m=1}^{n} (1 - ZN_m)^{\vartheta_m}, 1 - \prod_{m=1}^{n} (1 - UN_m)^{\vartheta_m} \right] \right), \tag{17}$$

where $\vartheta = (\vartheta_1, \vartheta_2, \dots, \vartheta_n)^T$ is the weighting vector of $\tilde{N}_m$, and $\forall \vartheta_m \in [0, 1]$, $\sum_{m=1}^{n} \vartheta_m = 1$.

Especially, when $\vartheta = (1/n, 1/n, \dots, 1/n)^T$, IVIFWG operators degenerate into IVIF geometric operators (IVIFG).

Definition 8 (Grzegorzewski, 2004; Xu and Chen, 2007). Suppose two IVIFNs $\tilde{N}_1 = ([ZM_1, UM_1], [ZN_1, UN_1])$ and $\tilde{N}_2 = ([ZM_2, UM_2], [ZN_2, UN_2])$, then the hybrid distance of Hamming distance and Hausdorff distance is defined as follows:

$$D^M(\tilde{N}_1, \tilde{N}_2) = \frac{1}{4} \begin{pmatrix} |ZM_1 - ZM_2| + |UM_1 - UM_2| \\ + |ZN_1 - ZN_2| + |UN_1 - UN_2| \end{pmatrix} + \frac{1}{2} \max \begin{Bmatrix} |ZM_1 - ZM_2|, & |UM_1 - UM_2|, \\ |ZN_1 - ZN_2|, & |UN_1 - UN_2| \end{Bmatrix}. \tag{18}$$

3. The Extended EDAS Method Based on CPT with IVIFSs

Keshavarz-Ghorabaee *et al.* (2015) proposed a new evaluation approach named EDAS method which is based on the average distance between solutions in 2015. In this method, the average scheme of alternative schemes under all attributes is selected as the reference point, and then the positive and negative distances between each scheme and the average scheme are calculated respectively. Finally, the optimal scheme is selected by synthesizing the positive and negative distances. In this section, the influence of the DEs' risk attitude on the decision result is considered in the classical EDAS method, also the IVIFNs are used to represent the evaluation value of the alternative attributes when the attribute weights are completely unknown. Therefore, the following is a description of our proposed method to solve the MAGDM problem in IVIF environment.

We assume that the set of decision-makers is $HD = \{HD_1, HD_2, \dots, HD_e\}$, as well as the weighting vector of these e decision-makers is $\nu = (\nu_1, \nu_2, \dots, \nu_e)^T$ and satisfies the condition that $\forall \nu_l \in [0, 1]$, $\sum_{l=1}^{e} \nu_l = 1$. Simultaneously, the set of alternatives is $HL = \{HL_1, HL_2, \dots, HL_n\}$ and the set of attributes is $HT = \{HT_1, HT_2, \dots, HT_k\}$. Therefore, the assessment value of the $r-th$ alternative under the $s-th$ attribute by $l-th$ expert is denoted by IVIFN: $\tilde{\Re}_{rs}^{(l)} = ([ZM_{rs}^{(l)}, UM_{rs}^{(l)}], [ZN_{rs}^{(l)}, UN_{rs}^{(l)}])$, where $[ZM_{rs}^{(l)}, UM_{rs}^{(l)}] \subset [0, 1]$ and $[ZN_{rs}^{(l)}, UN_{rs}^{(l)}] \subset [0, 1]$, $(r = 1, 2, \dots, n;\ s = 1, 2, \dots, k;\ l = 1, 2, \dots, e)$ denote the membership and non-membership degree interval of the l-th decision-maker.

As previously mentioned, the IVIF-MAGDM matrices (19) are constructed by $n \times k$ IVIF evaluation values:

$$R^{(l)} = [\tilde{\Re}_{rs}^{(l)}]_{n\times k} = \begin{bmatrix} \tilde{\Re}_{11}^{(l)} & \tilde{\Re}_{12}^{(l)} & \cdots & \tilde{\Re}_{1s}^{(l)} & \cdots & \tilde{\Re}_{1k}^{(l)} \\ \tilde{\Re}_{21}^{(l)} & \tilde{\Re}_{22}^{(l)} & \cdots & \tilde{\Re}_{2s}^{(l)} & \cdots & \tilde{\Re}_{2k}^{(l)} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{\Re}_{r1}^{(l)} & \tilde{\Re}_{r2}^{(l)} & \cdots & \tilde{\Re}_{rs}^{(l)} & \cdots & \tilde{\Re}_{rk}^{(l)} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{\Re}_{n1}^{(l)} & \tilde{\Re}_{n2}^{(l)} & \cdots & \tilde{\Re}_{ns}^{(l)} & \cdots & \tilde{\Re}_{nk}^{(l)} \end{bmatrix}, \tag{19}$$

$r = 1, 2, \dots, n;\ s = 1, 2, \dots, k;\ l = 1, 2, \dots e.$

Then, the IVIF-CPT-EDAS detailed steps are as follows (Fig. 2):

Step 1. Obtain the IVIF decision matrix $\aleph$.

Integrate the IVIF decision matrix $R^{(l)}$ $(l = 1, 2, \dots, e)$ by IVIFWA operator, and obtain the IVIF decision matrix $\aleph = [\tilde{\Re}_{rs}]_{n\times k}$ using Eq. (20).

$$\begin{aligned} \tilde{\Re}_{rs} &= \big([ZM_{rs}, UM_{rs}], [ZN_{rs}, UN_{rs}]\big) = IVIFWA_{\vartheta}\big(\tilde{\Re}_{rs}^{(1)}, \tilde{\Re}_{rs}^{(2)}, \dots, \tilde{\Re}_{rs}^{(l)}\big) \\ &= \Bigg(\Bigg[1 - \prod_{l=1}^{e}\big(1 - ZM_{rs}^{(l)}\big)^{\nu_l}, 1 - \prod_{l=1}^{e}\big(1 - UM_{rs}^{(l)}\big)^{\nu_l}\Bigg], \\ &\quad \Bigg[\prod_{l=1}^{e}\big(ZN_{rs}^{(l)}\big)^{\nu_l}, \prod_{l=1}^{e}\big(UN_{rs}^{(l)}\big)^{\nu_l}\Bigg]\Bigg). \end{aligned} \tag{20}$$

Step 2. Calculate the normalized IVIF decision matrix $\aleph^*$.

Transform the IVIF decision matrix $\aleph = [\tilde{\Re}_{rs}]_{n\times k}$ into normalized IVIF decision matrix $\aleph^* = [\tilde{\Re}_{rs}^*]_{n\times k} = ([ZM_{rs}^*, UM_{rs}^*], [ZN_{rs}^*, UN_{rs}^*])_{n\times k}$ using Eq. (21):

$$\tilde{\Re}_{rs}^* = \begin{cases} \big([ZM_{rs}, UM_{rs}], [ZN_{rs}, UN_{rs}]\big), & \text{attribute } HT_s \text{ is positive;} \\ \big([ZN_{rs}, UN_{rs}], [ZM_{rs}, UM_{rs}]\big), & \text{attribute } HT_s \text{ is negative;} \end{cases} \tag{21}$$

$r = 1, 2, \dots, n;\ s = 1, 2, \dots, k.$

Step 3. Determine the original attribute weight ϖ_s $(s = 1, 2, \dots, k)$ using the extended entropy method.

The specific steps of IVIF-entropy method are shown as follows:

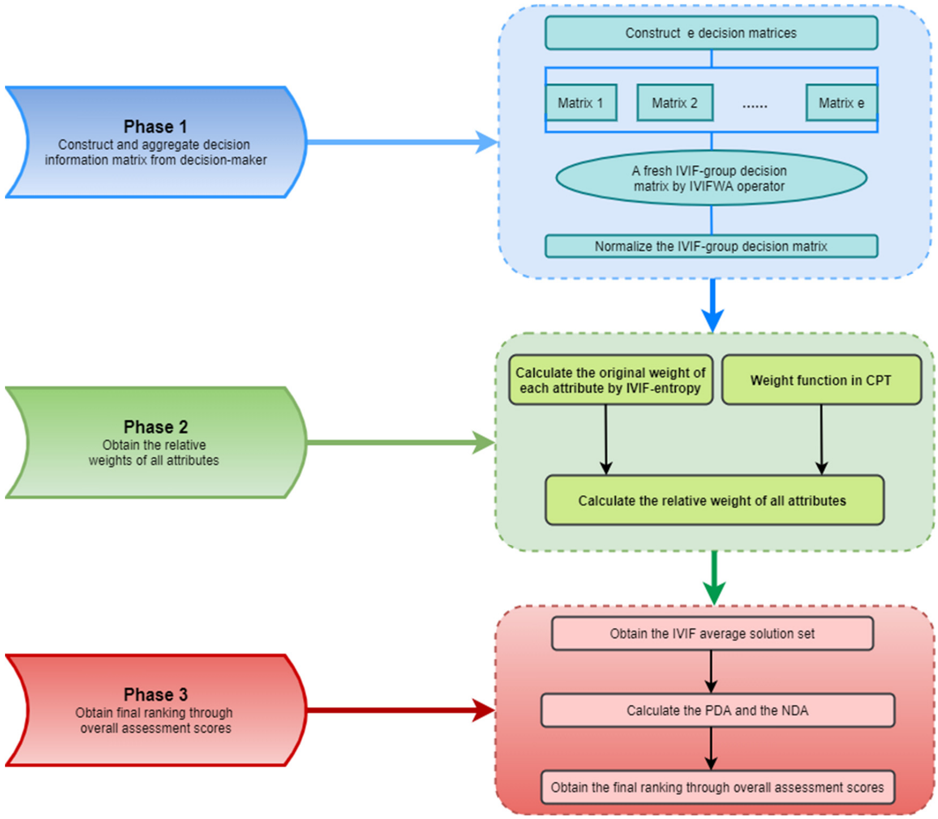

Fig. 2. The flowchart of IVIF-CPT-EDAS.

(1) Determine the IVIF negative ideal point (IVIF-NIP): $\tilde{\Re}_s^{*-}$ $(s = 1, 2, \dots, k)$, by satisfying the below condition:

$$\begin{aligned}\tilde{\Re}_s^{*-} &= \left(\left[\min_r ZM_{rs}^*, \min_r UM_{rs}^*\right], \left[\max_r ZN_{rs}^*, \max_r UN_{rs}^*\right]\right)\\ &= \left(\left[ZM_{rs}^{*-}, UM_{rs}^{*-}\right], \left[ZN_{rs}^{*-}, UN_{rs}^{*-}\right]\right).\end{aligned} \tag{22}$$

(2) Calculate the hybrid distance matrix $\Lambda = [DM_{rs}(\tilde{\Re}_{rs}^*, \tilde{\Re}_s^{*-})]_{n\times k}$ between the IVIF-NIP and all alternatives HL_r under each attribute HT_s by employing Eq. (23):

$$\begin{aligned}D_{rs}^M(\tilde{\Re}_{rs}^*, \tilde{\Re}_s^{*-}) = {} & \frac{1}{4}\left(\begin{array}{c}|ZM_{rs}^* - ZM_{rs}^{*-}| + |UM_{rs}^* - UM_{rs}^{*-}|\\ + |ZN_{rs}^* - ZN_{rs}^{*-}| + |UN_{rs}^* - UN_{rs}^{*-}|\end{array}\right)\\ & + \frac{1}{2}\max\left\{\begin{array}{cc}|ZM_{rs}^* - ZM_{rs}^{*-}|, & |UM_{rs}^* - UM_{rs}^{*-}|,\\ |ZN_{rs}^* - ZN_{rs}^{*-}|, & |UN_{rs}^* - UN_{rs}^{*-}|\end{array}\right\},\end{aligned} \tag{23}$$

$r = 1, 2, \dots n;\ s = 1, 2, \dots, k.$

(3) The normalized distance matrix $\Lambda' = [DM'_{rs}(\tilde{\Re}^*_{rs}, \tilde{\Re}^{*-}_s)]_{n\times k}$ can be normalized by Eq. (24):

$$D^{M'}_{rs}(\tilde{\Re}^*_{rs}, \tilde{\Re}^{*-}_s) = \frac{DM_{rs}(\tilde{\Re}^*_{rs}, \tilde{\Re}^{*-}_s)}{\sum_{r=1}^n DM_{rs}(\tilde{\Re}^*_{rs}, \tilde{\Re}^{*-}_s)}, \quad r = 1, 2, \dots, n;\ s = 1, 2, \dots, k. \tag{24}$$

(4) Calculate the entropy degree E_s of the s-th attribute HT_s using Eq. (25):

$$E_s = -\frac{1}{\ln n}\sum_{r=1}^{n} D^{M'}_{rs}(\tilde{\Re}^*_{rs}, \tilde{\Re}^{*-}_s) \ln D^{M'}_{rs}(\tilde{\Re}^*_{rs}, \tilde{\Re}^{*-}_s), \quad s = 1, 2, \dots, k,\ 0 \leqslant E_s \leqslant 1. \tag{25}$$

(5) Figure out the original attribute weight ϖ_s using Eq. (26):

$$\varpi_s = \frac{1 - E_s}{\sum_{s=1}^k 1 - E_s}, \quad s = 1, 2, \dots, k. \tag{26}$$

Step 4. Determine the average solution $\widetilde{AV}_s$ $(s = 1, 2, \dots, k)$ using Eq. (27) with the information of IVIFWA operator and normalized IVIF decision matrix $\aleph^*$.

$$\widetilde{AV}_s = \begin{pmatrix} \left[1 - \left(\prod_{r=1}^n (1 - ZM^*_{rs})\right)^{\frac{1}{n}}, 1 - \left(\prod_{r=1}^n (1 - UM^*_{rs})\right)^{\frac{1}{n}}\right], \\ \left[\left(\prod_{r=1}^n ZN^*_{rs}\right)^{\frac{1}{n}}, \left(\prod_{r=1}^n UN^*_{rs}\right)^{\frac{1}{n}}\right] \end{pmatrix}. \tag{27}$$

Step 5. Calculate the relative attribute weight $g'_{rs}(\varpi_s)$ of all attributes using Eq. (28) $(\alpha = 0.61, \beta = 0.69)$.

$$g'_{rs}(\varpi_s) = \begin{cases} \dfrac{\varpi_s^\alpha}{(\varpi_s^\alpha + (1 - \varpi_s)^\alpha)^{\frac{1}{\alpha}}}, & \tilde{\Re}^*_{rs} \geqslant \widetilde{AV}_s; \\ \dfrac{\varpi_s^\beta}{(\varpi_s^\beta + (1 - \varpi_s)^\beta)^{\frac{1}{\beta}}}, & \tilde{\Re}^*_{rs} < \widetilde{AV}_s; \end{cases} \quad r = 1, 2, \dots, n;\ s = 1, 2, \dots, k. \tag{28}$$

Step 6. Calculate the PDA'_{rs} and NDA'_{rs} according to normalized decision matrix $(\aleph^*)$ and average solution ($\widetilde{AV}$), ($\rho = 0.88$).

$$PDA'_{rs} = \begin{cases} \dfrac{(D^M(\tilde{\Re}^*_{rs}, \widetilde{AV}_s))^\gamma}{AF(\widetilde{AV}_s)}, & \tilde{\Re}^*_{rs} \geqslant \widetilde{AV}_s; \\ 0, & \tilde{\Re}^*_{rs} < \widetilde{AV}_s; \end{cases} \tag{29}$$

$$r = 1, 2, \dots, n;\ s = 1, 2, \dots, k.$$

$$NDA'_{rs} = \begin{cases} 0, & \tilde{\Re}^*_{rs} \geqslant \widetilde{AV}_s; \\ \dfrac{\rho \cdot (D^M(\widetilde{AV}_s, \tilde{\Re}^*_{rs}))^\delta}{AF(\widetilde{AV}_s)}, & \tilde{\Re}^*_{rs} < \widetilde{AV}_s; \end{cases} \tag{30}$$

$$r = 1, 2, \dots, n;\ s = 1, 2, \dots, k.$$

Step 7. Calculate the weighted positive and negative distance (SP'_r and SN'_r) using Eqs. (31) and (32).

$$SP'_r = \sum_{s=1}^{k} g'_{rs}(\varpi_s) PDA'_{rs}, \quad r = 1, 2, \dots, n, \tag{31}$$

$$SN'_r = \sum_{s=1}^{k} g'_{rs}(\varpi_s) NDA'_{rs}, \quad r = 1, 2, \dots, n. \tag{32}$$

Step 8. The normalized weighted positive and negative distance (NSP'_r and NSN'_r) can be calculated by Eqs. (33) and (34).

$$NSP'_r = \frac{SP'_r}{\max_r(SP'_r)}, \quad r = 1, 2, \dots, n, \tag{33}$$

$$NSN'_r = 1 - \frac{SN'_r}{\max_r(SN'_r)}, \quad r = 1, 2, \dots, n. \tag{34}$$

Step 9. The overall assessment score S'_r of each alternative HL_r using Eq. (35).

$$S'_r(HL_r) = \frac{1}{2}\big(NSP'_r + NSN'_r\big), \quad r = 1, 2, \dots, n. \tag{35}$$

Step 10. Rank the alternatives by descending order of the overall assessment scores S'_r ($r = 1, 2, \dots, n$) in Step 9, and if the value of overall assessment score S'_r is larger, the alternative is better.

4. An Illustrative Example and Parameter Analysis

4.1. *Background Description*

Development is a timeless topic. However, due to the limitations and irreversibility of resources, it has become a new demand to reduce pollution, save resources, and take the path of sustainable development by developing a green economy. From an investment perspective, GTVC, as one of the five key green investment areas, has a broad space to promote the development of the circular economy, such as comprehensive utilization of resource technology, environmental protection technology, ecological agriculture technology, comprehensive utilization of resource technology, new energy technology, etc. At the same time, evaluating investment projects that can yield significant benefits scientifically and quickly is particularly important for a decision-maker. Therefore, this paper takes the GTVC project selection as an example to verify the effectiveness and applicability of the enhanced EDAS method.

4.2. *Decision Process*

We invite five experts HD_c $(c = 1, 2, \dots, 5)$ to select the best solution from five GTVC projects HL_r $(r = 1, 2, \dots, 5)$ with six attributes HT_s $(s = 1, 2, \dots, 6)$. The specific description of attributes is as follows: HT_1: return on investment; HT_2: amount of waste produced; HT_3: renewable resources; HT_4: difficulty of capital exit; HT_5: degree of market demand; HT_6: the R&D capability of the technical research team, where HT_2 and HT_4 are the cost attributes, and others are the benefit attributes. Meanwhile, the weighting vector $\nu = (\nu_1, \nu_2, \dots, \nu_5) = (0.29, 0.17, 0.19, 0.15, 0.20)$ of five experts is given.

Here, we will refer to the IVIF linguistic evaluation scale proposed by Peng and Luo (2021) to collect expert evaluation information. The IVIF linguistic evaluation scale table used in this article has a total of 10 evaluation scales, and corresponding IVIFNs are used to quantify the evaluation values of the proposed investment project, in order to achieve accurate DM results. Then the linguistic assessment matrices which are provided in Tables 4 reveal the five DEs' evaluation results about six attributes.

Next, the IVIF-CPT-EDAS technique is developed for selecting the best GTVC project.

Step 1. Experts utilize IVIF to provide their own evaluation information, and convert the aforementioned five semantic evaluation matrices into their respective fuzzy decision matrices, refer to Table 3, then aggregate the IVIF decision matrices into a single IVIF group decision matrix using Eq. (20).

Table 3
IVIF linguistic evaluation scale.

Linguistic scale	IVIFN
Extremely terrible (ET)	$\langle[0.00, 0.10], [0.85, 0.90]\rangle$
Very terrible (VT)	$\langle[0.00, 0.10], [0.70, 0.75]\rangle$
Terrible (T)	$\langle[0.15, 0.25], [0.55, 0.60]\rangle$
Medium terrible (MT)	$\langle[0.30, 0.40], [0.45, 0.50]\rangle$
Medium (M)	$\langle[0.40, 0.50], [0.35, 0.40]\rangle$
Medium good (MG)	$\langle[0.50, 0.60], [0.25, 0.30]\rangle$
Good (G)	$\langle[0.60, 0.70], [0.15, 0.20]\rangle$
Very good (VG)	$\langle[0.70, 0.80], [0.05, 0.10]\rangle$
Extremely good (EG)	$\langle[0.80, 0.90], [0.05, 0.10]\rangle$
Perfectly good (PG)	$\langle[1.00, 1.00], [0.00, 0.00]\rangle$

Table 4
The linguistic assessment matrices by five experts.

DEs	Alternatives	Attributes					
		HT_1	HT_2	HT_3	HT_4	HT_5	HT_6
D_1	HL_1	MG	G	M	G	MG	MG
	HL_2	VG	M	EG	M	EG	G
	HL_3	MG	VG	M	MG	G	M
	HL_4	M	G	MT	M	MG	T
	HL_5	G	VT	M	M	G	MG
D_2	HL_1	G	MG	MG	G	M	MG
	HL_2	EG	MT	EG	M	EG	G
	HL_3	G	VG	M	M	MG	MT
	HL_4	MT	G	M	M	G	T
	HL_5	MG	MT	MT	MT	MG	M
D_3	HL_1	MG	G	G	MG	G	M
	HL_2	EG	M	VG	G	EG	G
	HL_3	MG	G	MG	MG	M	MT
	HL_4	M	G	M	MG	G	MT
	HL_5	G	M	VT	M	MG	MG
D_4	HL_1	G	G	M	G	G	MG
	HL_2	EG	M	EG	M	VG	VG
	HL_3	M	EG	MG	MG	MG	M
	HL_4	MT	G	MG	M	G	MT
	HL_5	G	MT	MT	M	MG	M
D_5	HL_1	VG	MG	G	G	MG	G
	HL_2	EG	MT	EG	MG	VG	VG
	HL_3	MG	VG	G	MG	G	M
	HL_4	M	G	MG	M	VG	MT
	HL_5	VG	M	MT	M	M	MG

Table 5
The normalized IVIF decision matrix $\aleph^*$.

	HT_1	HT_2	HT_3
HL_1	$\langle[0.580, 0.682], [0.154, 0.212]\rangle$	$\langle[0.181, 0.232], [0.566, 0.666]\rangle$	$\langle[0.503, 0.606], [0.238, 0.291]\rangle$
HL_2	$\langle[0.775, 0.878], [0.050, 0.100]\rangle$	$\langle[0.338, 0.392], [0.402, 0.505]\rangle$	$\langle[0.784, 0.886], [0.050, 0.100]\rangle$
HL_3	$\langle[0.505, 0.606], [0.241, 0.292]\rangle$	$\langle[0.062, 0.114], [0.702, 0.805]\rangle$	$\langle[0.480, 0.582], [0.264, 0.316]\rangle$
HL_4	$\langle[0.370, 0.470], [0.379, 0.430]\rangle$	$\langle[0.165, 0.216], [0.583, 0.683]\rangle$	$\langle[0.411, 0.512], [0.335, 0.386]\rangle$
HL_5	$\langle[0.682, 0.788], [0.081, 0.136]\rangle$	$\langle[0.464, 0.516], [0.270, 0.404]\rangle$	$\langle[0.284, 0.385], [0.455, 0.506]\rangle$
	HT_4	HT_5	HT_6
HL_1	$\langle[0.165, 0.216], [0.583, 0.683]\rangle$	$\langle[0.522, 0.623], [0.223, 0.274]\rangle$	$\langle[0.505, 0.606], [0.241, 0.292]\rangle$
HL_2	$\langle[0.265, 0.317], [0.479, 0.580]\rangle$	$\langle[0.770, 0.873], [0.050, 0.100]\rangle$	$\langle[0.638, 0.740], [0.102, 0.157]\rangle$
HL_3	$\langle[0.265, 0.315], [0.484, 0.585]\rangle$	$\langle[0.570, 0.671], [0.177, 0.228]\rangle$	$\langle[0.366, 0.466], [0.383, 0.433]\rangle$
HL_4	$\langle[0.328, 0.379], [0.420, 0.521]\rangle$	$\langle[0.597, 0.699], [0.140, 0.196]\rangle$	$\langle[0.235, 0.335], [0.494, 0.544]\rangle$
HL_5	$\langle[0.365, 0.415], [0.384, 0.484]\rangle$	$\langle[0.514, 0.615], [0.231, 0.283]\rangle$	$\langle[0.470, 0.570], [0.278, 0.329]\rangle$

Step 2. Since there are mainly two types of attributes, namely benefit and cost, the Eq. (21) can be used to obtain the normalized IVIF decision matrix $\aleph^*$ (see Table 5).

Step 3. Determine the original relative attribute weight ϖ_s $(s = 1, 2, \ldots, k)$ using the extended entropy method.

Table 6
IVIF-NIS $\tilde{\Re}_s^{*-}$.

IVIF-NIP	HT_1	HT_2	HT_3
$\tilde{\Re}_s^{*-}$	$\langle[0.370, 0.470], [0.379, 0.430]\rangle$	$\langle[0.062, 0.114], [0.702, 0.805]\rangle$	$\langle[0.284, 0.385], [0.455, 0.506]\rangle$
IVIF-NIP	HT_4	HT_5	HT_6
$\tilde{\Re}_s^{*-}$	$\langle[0.165, 0.216], [0.583, 0.683]\rangle$	$\langle[0.514, 0.615], [0.231, 0.283]\rangle$	$\langle[0.235, 0.335], [0.494, 0.544]\rangle$

Table 7
The normalized hybrid distance matrix Λ'.

Hybris distance	HT_1	HT_2	HT_3	HT_4	HT_5	HT_6
$DM'_{1s}(\tilde{\Re}^*_{1s}, \tilde{\Re}_s^{*-})$	0.209	0.138	0.217	0.000	0.022	0.260
$DM'_{2s}(\tilde{\Re}^*_{2s}, \tilde{\Re}_s^{*-})$	0.364	0.306	0.466	0.182	0.605	0.393
$DM'_{3s}(\tilde{\Re}^*_{3s}, \tilde{\Re}_s^{*-})$	0.131	0.000	0.193	0.176	0.144	0.122
$DM'_{4s}(\tilde{\Re}^*_{4s}, \tilde{\Re}_s^{*-})$	0.000	0.120	0.124	0.337	0.229	0.000
$DM'_{5s}(\tilde{\Re}^*_{5s}, \tilde{\Re}_s^{*-})$	0.296	0.436	0.000	0.354	0.000	0.225

Table 8
The entropy E_s of each attribute.

	HT_1	HT_2	HT_3	HT_4	HT_5	HT_6
E_s	0.821	0.778	0.785	0.839	0.625	0.814
$1 - E_s$	0.179	0.222	0.215	0.161	0.375	0.186

Table 9
The original attribute weight ϖ_s.

Original attribute weight	HT_1	HT_2	HT_3	HT_4	HT_5	HT_6
ϖ_s	0.134	0.166	0.160	0.121	0.280	0.139

(1) Using the decision information in $\aleph^*$, determine the IVIF-NIS: $\tilde{\Re}_s^{*-}$ by Eq. (22) (see Table 6).
(2) Calculate the distance between each alternative solution and IVIF-NIS by employing Eq. (23), then retrieve the hybrid distance matrix $\Lambda = [D^M_{rs}(\tilde{\Re}^*_{rs}, \tilde{\Re}_s^{*-})]_{n\times k}$ and normalize it (see Table 7).
(3) Figure out the entropy degree E_s of each attribute HT_s using the normalized hybrid distance matrix Λ' and Eq. (25) (see Table 8).
(4) Compute the original weight ϖ_s ($s = 1, 2, \dots, 6$) using Eq. (26); the results are shown as Table 9.

Step 4. Determine the average solution $\widetilde{AV}_s$ ($s = 1, 2, \dots, k$) of each attribute HT_s ($s = 1, 2, \dots, k$) by using Eq. (27) (see Table 10).

Step 5. Adjusting attribute weights can be achieved by CPT, which involves calculating the relative attribute weights matrix G' using Eq. (28) ($\alpha = 0.61$, $\beta = 0.69$), and the results are listed in Table 11.

Table 10
The average solution $\widetilde{AV}_s$.

Average solution	HT_1	HT_2	HT_3
$\widetilde{AV}_s$	⟨[0.607, 0.720], [0.142, 0.205]⟩	⟨[0.256, 0.309], [0.479, 0.595]⟩	⟨[0.528, 0.645], [0.217, 0.282]⟩
Average solution	HT_4	HT_5	HT_6
$\widetilde{AV}_s$	⟨[0.281, 0.332], [0.465, 0.567]⟩	⟨[0.608, 0.717], [0.145, 0.203]⟩	⟨[0.460, 0.565], [0.264, 0.324]⟩

Table 11
The relative attribute matrix G'.

	HT_1	HT_2	HT_3	HT_4	HT_5	HT_6
HL_1	0.202	0.230	0.226	0.190	0.314	0.219
HL_2	0.215	0.238	0.234	0.190	0.308	0.219
HL_3	0.202	0.230	0.226	0.190	0.314	0.207
HL_4	0.202	0.230	0.226	0.204	0.314	0.207
HL_5	0.215	0.238	0.226	0.204	0.314	0.219

Table 12
The positive distance PDA'.

	HT_1	HT_2	HT_3	HT_4	HT_5	HT_6
HL_1	0.000	0.000	0.000	0.000	0.000	0.387
HL_2	1.436	0.849	2.131	0.000	1.412	1.444
HL_3	0.000	0.000	0.000	0.000	0.000	0.000
HL_4	0.000	0.000	0.000	0.508	0.000	0.000
HL_5	0.770	1.840	0.000	0.847	0.000	0.120

Table 13
The negative distance NDA'.

	HT_1	HT_2	HT_3	HT_4	HT_5	HT_6
HL_1	0.740	1.824	0.775	2.566	2.068	0.000
HL_2	0.000	0.000	0.000	0.418	0.000	0.000
HL_3	2.464	4.251	1.333	0.491	1.023	2.170
HL_4	5.126	2.151	2.799	0.000	0.384	4.124
HL_5	0.000	0.000	5.184	0.000	2.240	0.000

Step 6. Calculate the distance between each evaluation and $\widetilde{AV}_s$, then obtain the PDA'_{rs} and NDA'_{rs} using Eq. (29)–(30) ($\gamma = 0.88$, $\delta = 0.88$, $\rho = 2.25$), which are listed in Tables 12 and 13.

Steps 7–8. Calculate the weighted positive and negative distance (SP'_r and SN'_r) using Eqs. (31)–(32), and then normalized them based on Eqs. (33)–(34) (see Table 14).

Step 9. Calculate the overall assessment score S' of each alternative HL_r utilizing Eq. (35) (see Table 15).

It follows from the above: $S'_1(HL_1) = 0.224$, $S'_2(HL_2) = 0.987$, $S'_3(HL_3) = 0.079$, $S'_4(HL_4) = 0.029$, $S'_5(HL_5) = 0.429$.

Table 14
The normalized weighted distance.

The normalized weighted distance	HL_1	HL_2	HL_3	HL_4	HL_5
NSP'_r	0.048	1.000	0.000	0.059	0.456
NSN'_r	0.400	0.975	0.158	0.000	0.403

Table 15
The overall assessment score S'.

Overall assessment score	HL_1	HL_2	HL_3	HL_4	HL_5
S'_r	0.224	0.987	0.079	0.029	0.429

Step 10. Based on the final assessment score S'_r $(r = 1, 2, \dots, 5)$ of each alternative, the relationship of five alternatives is listed as follows:

$$HL_2 > HL_5 > HL_1 > HL_3 > HL_4.$$

So, HL_2 will be the best choice.

4.3. *Sensitivity Analysis*

In this section, we incorporate the effects of CPT on the model and refer to the parameter values given by Tversky and Kahneman (1992): the parameters in weight function $\alpha = 0.61$, $\beta = 0.69$ and value function $\gamma = 0.88$, $\delta = 0.88$, $\rho = 2.25$. At this time, it is observed that five parameters are involved in Eqs. (28), (29) and (30), so we consider naturally whether the change of parameter values will affect the DM result, i.e. checking the robustness and effectiveness of the IVIF-CPT-EDAS model. Finally, we discuss the influence of single parameter changes on our decision results in this section.

4.3.1. *The Sensitivity of Parameter α in the Weight Function*

We assign the parameter $0 < \alpha < 1$ and produce data in steps of 0.1 for simulation, specifically taking in this paper $\alpha = 0.61$. All the outcomes are shown in Table 16.

According to Table 16, different parameters have little influence on the score results of the IVIF-CPT-EDAS model. With the value of parameter α increase, the overall scores of HL_2 and HL_3 remain unchanged, while the overall scores of others alternative gradually decrease. The ranking results remain unchanged, the best option alternative is HL_2.

4.3.2. *The Sensitivity Analysis of Parameter β in the Weight Function*

We assign the parameter $0 < \beta < 1$ and produce data in steps of 0.1 for simulation, specifically taking in this paper $\beta = 0.69$. All the outcomes are shown in Table 17.

According to Table 17, different value of parameter β will cause certain fluctuations to the score results of the IVIF-CPT-EDAS model. With the value increase of parameter β,

Table 16
The calculation results with different value of α.

α	HL_1	HL_2	HL_3	HL_4	HL_5	Ranking results	The optimal solution
0.61	0.224	0.987	0.079	0.029	0.429	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.05	0.228	0.987	0.079	0.039	0.458	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.15	0.227	0.987	0.079	0.037	0.453	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.25	0.227	0.987	0.079	0.035	0.448	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.35	0.226	0.987	0.079	0.034	0.443	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.45	0.225	0.987	0.079	0.032	0.438	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.55	0.224	0.987	0.079	0.030	0.433	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.65	0.224	0.987	0.079	0.029	0.427	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.75	0.223	0.987	0.079	0.027	0.422	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.85	0.222	0.987	0.079	0.026	0.417	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.95	0.222	0.987	0.079	0.025	0.411	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2

Table 17
The calculation results of different value of parameter β.

β	HL_1	HL_2	HL_3	HL_4	HL_5	Ranking results	The optimal solution
0.69	0.224	0.987	0.079	0.029	0.429	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.05	0.259	0.985	0.106	0.029	0.492	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.15	0.254	0.985	0.102	0.029	0.484	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.25	0.251	0.986	0.098	0.029	0.475	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.35	0.246	0.986	0.094	0.029	0.465	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.45	0.240	0.986	0.090	0.029	0.455	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.55	0.238	0.987	0.086	0.029	0.445	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.65	0.227	0.987	0.081	0.029	0.434	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.75	0.219	0.988	0.076	0.029	0.423	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.85	0.211	0.988	0.071	0.029	0.411	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.95	0.202	0.988	0.066	0.029	0.398	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2

the overall score of HL_4 remains unchanged, the overall score of HL_2 gradually increases, and the overall scores of other alternatives gradually decrease, but the ranking results remain unchanged, and the optimal alternative is HL_2.

4.3.3. *The Sensitivity Analysis of Parameter γ in the Value Function*

We assign the parameter $0 < \gamma < 1$ and produce data in steps of 0.1 for simulation, specifically taking in this paper $\gamma = 0.88$. All the outcomes are shown in Table 18.

According to Table 18, different values of parameter γ have little influence on the score results of IVIF-CPT-EDAS model. With the value increase of parameter γ, the overall scores of HL_2 and HL_3 remain unchanged, while the overall scores of other alternatives gradually decrease. The ranking results almost remains the same, the optimal alternative is always HL_2.

4.3.4. *The Sensitivity Analysis with Different Value of Parameter δ in the Value Function*

We assign the parameter $0 < \delta < 1$ and produce data in steps of 0.1 for simulation, specifically taking in this paper $\delta = 0.88$. All the outcomes are shown in Table 19.

Table 18
The calculation results with different value of parameter γ.

γ	HL_1	HL_2	HL_3	HL_4	HL_5	Ranking results	The optimal solution
0.88	0.224	0.987	0.079	0.029	0.429	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.05	0.275	0.987	0. 079	0. 079	0.539	$HL_2 > HL_5 > HL_1 > HL_3 = HL_4$	HL_2
0.15	0.265	0.987	0. 079	0. 070	0.515	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.25	0.257	0.987	0. 079	0.062	0.495	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.35	0.250	0.987	0. 079	0.056	0.479	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.45	0.244	0.987	0. 079	0.049	0.466	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.55	0.238	0.987	0. 079	0.044	0.455	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.65	0.233	0.987	0. 079	0.039	0.446	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.75	0.229	0.987	0. 079	0.035	0.437	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.85	0.225	0.987	0. 079	0.031	0.431	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.95	0.222	0.987	0. 079	0.027	0.426	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2

Table 19
The calculation result with different value of parameter δ.

δ	HL_1	HL_2	HL_3	HL_4	HL_5	Ranking results	The optimal solution
0.88	0.224	0.987	0.079	0.029	0.429	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.05	0.094	0.936	0. 000	0. 094	0.515	$HL_2 > HL_5 > HL_1 = HL_4 > HL_3$	HL_2
0.15	0.099	0.945	0. 000	0. 083	0.498	$HL_2 > HL_5 > HL_1 > HL_4 > HL_3$	HL_2
0.25	0.106	0.953	0. 000	0.069	0.482	$HL_2 > HL_5 > HL_1 > HL_4 > HL_3$	HL_2
0.35	0.114	0.960	0. 000	0.053	0.465	$HL_2 > HL_5 > HL_1 > HL_4 > HL_3$	HL_2
0.45	0.122	0.967	0. 000	0.034	0.448	$HL_2 > HL_5 > HL_1 > HL_4 > HL_3$	HL_2
0.55	0.144	0.973	0. 016	0.029	0.440	$HL_2 > HL_5 > HL_1 > HL_4 > HL_3$	HL_2
0.65	0.169	0.978	0. 036	0.029	0.436	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.75	0.194	0.983	0. 055	0.029	0.433	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.85	0.217	0.986	0. 074	0.029	0.430	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
0.95	0.240	0.989	0. 091	0.029	0.428	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2

According to Table 19, different value of parameter δ will cause certain fluctuations of the score results of IVIF-CPT-EDAS model. With the value increase of the parameter δ, the overall score of the alternative HL_4 decreases gradually and then remains unchanged, and the overall scores of the other alternatives decrease gradually. Despite some changes in the ranking of alternative before and after setting $\delta = 0.55$, the optimal alternative is still HL_2.

4.3.5. *The Sensitivity Analysis of Parameter ρ in the Value Function*

We assign the parameter $1 < \rho \leqslant 10$ and produce data in steps of 0.1 for simulation, specifically taking in this paper $\rho = 2.25$. All the outcomes are shown in Table 20.

According to Table 20, the overall scores and ranking results remain changed with different ρ.

From the simulation analysis of the above five parameters, it can be seen that despite the slight fluctuations in the model calculation and ranking results caused by changing the parameters in the weight and value functions, the optimal and sub-optimal schemes remain unchanged, demonstrating the IVIF-CPT-EDAS model's robustness and effectiveness.

Table 20
The calculation results with different value of parameter ρ.

ρ	HL_1	HL_2	HL_3	HL_4	HL_5	Ranking results	The optimal solution
2.25	0.224	0.987	0.079	0.029	0.429	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
1.55	0.224	0.987	0.079	0.029	0.429	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
2.55	0.224	0.987	0.079	0.029	0.429	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
3.55	0.224	0.987	0.079	0.029	0.429	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
4.55	0.224	0.987	0.079	0.029	0.429	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
5.55	0.224	0.987	0.079	0.029	0.429	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
6.55	0.224	0.987	0.079	0.029	0.429	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
7.55	0.224	0.987	0.079	0.029	0.429	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
8.55	0.224	0.987	0.079	0.029	0.429	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
9.55	0.224	0.987	0.079	0.029	0.429	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2
10.00	0.224	0.987	0.079	0.029	0.429	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2

5. Comparative Analysis

5.1. *Validity Analysis*

In this subsection, we continue to explore the effectiveness of the enhanced EDAS approach based on the same original matrices, the expert weighting vector $\nu = (\nu_1, \nu_2, \dots, \nu_5) = (0.29, 0.17, 0.19, 0.15, 0.20)$ and initial attribute weighting vector $\varpi = (\varpi_1, \varpi_2, \dots, \varpi_6) = (0.134, 0.166, 0.160, 0.121, 0.280, 0.139)$, thus designing the validity analysis between the method proposed by us with IVIFWA operator (Xu and Chen, 2007), IVIF-TOPSIS method (Izadikhah, 2012), IVIF-TAXONOMY method (Xiao *et al.*, 2021), along with IVIF-TODIM method (Krohling and Pacheco, 2014) as follows.

5.1.1. *Comparison with IVIFWA Operator (Xu and Chen, 2007)*

The original matrices of this article are substituted by Eq. (16), Eq. (36) and Eq. (37) (Hashemi-Tabatabaei *et al.*, 2019). The calculation results are shown in Table 21, and the optimal alternative is HL_2.

$$SF(\tilde{N}) = \frac{ZM - ZN + UM - UN}{2}, \tag{36}$$

$$AF(\tilde{N}) = \frac{ZM + ZN + UM + UN}{2}. \tag{37}$$

5.1.2. *Comparison with the IVIF-TOPSIS Method (Izadikhah, 2012)*

We substitute the initial data of this article by the IVIF-TOPSIS method (Izadikhah, 2012), which sorts each alternative by determining the relative closeness degree between it and the positive ideal solution. All the outcomes are shown in Table 22, and the optimal alternative is HL_2.

The DM process is as follows:

Step 1. Calculate the weighted decision matrix Ω using the decision matrix $\aleph$, IVIFN and original attribute weight ϖ.

Table 21
The calculation results of IVIFWA operator.

Alternative	IVIFWA operator	$SF(HL_r)$	$AF(HL_r)$	Ranking results
HL_1	$\langle[0.444, 0.541], [0.284, 0.349]\rangle$	0.176	0.809	3
HL_2	$\langle[0.668, 0.782], [0.103, 0.172]\rangle$	0.588	0.863	1
HL_3	$\langle[0.421, 0.517], [0.311, 0.375]\rangle$	0.126	0.812	4
HL_4	$\langle[0.403, 0.499], [0.317, 0.387]\rangle$	0.099	0.803	5
HL_5	$\langle[0.481, 0.575], [0.251, 0.325]\rangle$	0.240	0.816	2

Table 22
The calculation results of IVIF-TOPSIS.

Alternative	D_r^+	D_r^-	C_r	Ranking results
HL_1	0.129	0.061	0.320	3
HL_2	0.013	0.177	0.932	1
HL_3	0.150	0.040	0.212	5
HL_4	0.145	0.045	0.238	4
HL_5	0.104	0.085	0.449	2

Step 2. Determine the IVIF-PIS $\tilde{\Re}_s^+ = ([ZM_s^+, UM_s^+], [ZN_s^+, UN_s^+])$ and IVIF-NIS $\tilde{\Re}_s^- = ([ZM_s^-, UM_s^-], [ZN_s^-, UN_s^-])$.

$$\tilde{\Re}_s^+ = \begin{cases} \big([\max_r ZM_{rs}, \max_r UM_{rs}], [\min_r ZN_{rs}, \min_r UN_{rs}]\big), \\ \quad \text{attribute } HT_s \text{ is positive;} \\ \big([\min_r ZM_{rs}, \min_r UM_{rs}], [\max_r ZN_{rs}, \max_r UN_{rs}]\big), \\ \quad \text{attribute } HT_s \text{ is negative;} \end{cases} \tag{38}$$

$$r = 1, 2, \dots, n; \ \ s = 1, 2, \dots, k,$$

$$\tilde{\Re}_s^- = \begin{cases} \big([\min_r ZM_{rs}, \min_r UM_{rs}], [\max_r ZN_{rs}, \max_r UN_{rs}]\big), \\ \quad \text{attribute } HT_s \text{ is positive;} \\ \big([\max_r ZM_{rs}, \max_r UM_{rs}], [\min_r ZN_{rs}, \min_r UN_{rs}]\big), \\ \quad \text{attribute } HT_s \text{ is negative;} \end{cases} \tag{39}$$

$$r = 1, 2, \dots, n; \ \ s = 1, 2, \dots, k.$$

Step 2. Calculate the distance between each possible solution and IVIF-PIS (IVIF-NIS).

$$D_r^+ = \frac{1}{4n}\sum_{s=1}^{k} \varpi_s \left\{ \begin{array}{l} |ZM_{rs} - ZM_s^+| + |UM_{rs} - UM_s^+| \\ \quad + |ZN_{rs} - ZN_s^+| + |UN_{rs} - UN_s^+| \end{array} \right\}, \tag{40}$$

$$D_r^- = \frac{1}{4n}\sum_{s=1}^{k} \varpi_s \left\{ \begin{array}{l} |ZM_{rs} - ZM_s^-| + |UM_{rs} - UM_s^-| \\ \quad + |ZN_{rs} - ZN_s^-| + |UN_{rs} - UN_s^-| \end{array} \right\}. \tag{41}$$

Step 3. Calculate the relative proximity degree $C_r(HL_r)$ between IVIF-PIS and each alternative.

Table 23
The calculation results of IVIF-Taxonomy.

Alternative	$F_r(HL_r)$	Ranking results
HL_1	0.617	3
HL_2	0.095	1
HL_3	0.708	4
HL_4	0.741	5
HL_5	0.496	2

$$C_r = \frac{d_r^-}{d_r^+ + d_r^-}, \quad 0 \leqslant C_r \leqslant 1. \tag{42}$$

5.1.3. *Comparison with IVIF-Taxonomy (Xiao* et al., *2021)*
We substitute the initial data of this article by the IVIF-Taxonomy method (Xiao *et al.*, 2021). All the calculation results are shown in Table 23, and the optimal alternative is HL_2.

Step 1. Obtain the hybrid distance matrix $M = [m_{pq}]_{k\times k}$ using Table 14 and Eq. (43).

$$m_{pq} = \frac{1}{4}\sum_{s=1}^{k} \varpi_s \left(\begin{array}{c} \left|\mu_{ZM}(\tilde{\Re}^*_{ps}) - \mu_{ZM}(\tilde{\Re}^*_{ps})\right| + \left|\mu_{UM}(\tilde{\Re}^*_{ps}) - \mu_{UM}(\tilde{\Re}^*_{ps})\right| \\ + \left|\upsilon_{ZN}(\tilde{\Re}^*_{ps}) - \upsilon_{ZN}(\tilde{\Re}^*_{ps})\right| + \left|\upsilon_{UN}(\tilde{\Re}^*_{ps}) - \upsilon_{UN}(\tilde{\Re}^*_{ps})\right| \end{array} \right), \tag{43}$$

$$p, q = 1, 2, \ldots k.$$

Step 2. The alternatives are homogenized using Eq. (44).

$$G = \bar{g} \pm 2H_g, \tag{44}$$

where $\bar{g} = \frac{1}{n}\sum_{r=1}^{n} g_r$, $H_g = \sqrt{\frac{1}{n}\sum_{r=1}^{n}(g_r - \bar{g})}$.

Step 3. Eq. (45) is used to determine the development mode of alternative schemes, and the optimal alternative is selected according to formulas (46) and (47), as shown in Table 23.

$$K_{ro} = \frac{1}{4}\sum_{s=1}^{k} \varpi_s \left(\begin{array}{c} \left|\mu_{ZM}(\tilde{\Re}^*_{rs}) - \mu_{ZM}(\tilde{\Re}^{*+}_{s})\right| + \left|\mu_{UM}(\tilde{\Re}^*_{rs}) - \mu_{UM}(\tilde{\Re}^{*+}_{s})\right| \\ + \left|\upsilon_{ZN}(\tilde{\Re}^*_{rs}) - \upsilon_{ZN}(\tilde{\Re}^{*+}_{s})\right| + \left|\upsilon_{UN}(\tilde{\Re}^*_{rs}) - \upsilon_{UN}(\tilde{\Re}^{*+}_{s})\right| \end{array} \right), \tag{45}$$

where $\tilde{\Re}^{*+}_s = ([\max_r ZN_s, \max_r UN_s].[\min_r ZM_s, \min_r UM_s])$ is the positive ideal point.

$$K = \bar{K}_{ro} + 2S_{K_{ro}}, \quad r = 1, 2, \ldots, n, \tag{46}$$

$$F_r = \frac{K_{ro}}{K}, \quad r = 1, 2, \ldots, n, \tag{47}$$

where $\bar{K}_{ro}$ and $S_{K_{ro}}$ is the average value and variance of K_{ro}.

Table 24
The calculation results of IVIF-TODIM.

Alternative	$\xi_r(HL_r)$	Ranking results
HL_1	0.180	3
HL_2	1.000	1
HL_3	0.018	4
HL_4	0.000	5
HL_5	0.623	2

5.1.4. *Comparison with IVIF-TODIM Method (Krohling and Pacheco, 2014)*

The initial data of this article are substituted by the IVIF-TODIM method (Krohling and Pacheco, 2014). All the outcomes are shown in Table 24, and the optimal alternative is HL_2.

Step 1. Obtain the normalized IVIF decision matrix $\aleph^{*\prime} = [\tilde{\Re}^*_{rs}]_{n\times k}$ using Eq. (48):

$$\tilde{\Re}^*_{rs} = \left(\left[ZM^{*\prime}_{rs}, UM^{*\prime}_{rs}\right], \left[ZN^{*\prime}_{rs}, UN^{*\prime}_{rs}\right]\right) = \left(\begin{array}{l}\left[\frac{ZM^*_{rs}}{\sum_{p=1}^{n}((ZM^*_{ps})^2+(UM^*_{ps})^2)^{\frac{1}{2}}}, \frac{UM^*_{rs}}{\sum_{r=1}^{n}((ZM^*_{ps})^2+(UM^*_{ps})^2)^{\frac{1}{2}}}\right], \\ \left[\frac{ZN^*_{rs}}{\sum_{p=1}^{n}((ZN^*_{ps})^2+(UN^*_{ps})^2)^{\frac{1}{2}}}, \frac{UN^*_{rs}}{\sum_{r=1}^{n}((ZN^*_{ps})^2+(UN^*_{ps})^2)^{\frac{1}{2}}}\right]\end{array}\right). \tag{48}$$

Step 2. Obtain the normalized attribute weight $\varpi' = (\varpi'_1, \varpi'_2, \dots, \varpi'_s)$ using Eq. (49).

$$\varpi'_{qs} = \frac{\varpi_s}{\varpi_q}, \tag{49}$$

where $\varpi_q = \max_s\{\varpi_1, \varpi_2, \dots, \varpi_s\}$.

Step 3. The dominance degree between each alternative HL_p $(p = 1, 2, \dots, n)$ and each alternative HL_r $(r = 1, 2, \dots, n)$ can be calculated by Eqs. (50), (51) and Eq. (52), where the parameter $\theta = 1$.

$$\delta_{pr}(HL_p, HL_r) = \sum_{s=1}^{k} \phi_s(HL_p, HL_r), \quad p, r = 1, 2, \dots, n, \tag{50}$$

$$\phi_s(HL_p, HL_r) = \begin{cases} \sqrt{\dfrac{\varpi_{qs}}{\sum_{s=1}^{k}\varpi_{qs}}} \cdot d_{prs}(\tilde{\Re}^*_{ps}, \tilde{\Re}^*_{rs}), & \tilde{\Re}^*_{ps} > \tilde{\Re}^*_{rs}; \\ 0, & \tilde{\Re}^*_{ps} = \tilde{\Re}^*_{rs}; \\ -\dfrac{1}{\theta}\sqrt{\dfrac{\sum_{s=1}^{k}\varpi_{qs}}{\varpi_{qs}}} \cdot d_{prs}(\tilde{\Re}^*_{ps}, \tilde{\Re}^*_{rs}), & \tilde{\Re}^*_{ps} < \tilde{\Re}^*_{rs}, \end{cases} \tag{51}$$

$$d_{prs} = \frac{1}{4}\left[\left|ZM^{*\prime}_{ps} - ZM^{*\prime}_{rs}\right| + \left|UM^{*\prime}_{ps} - UM^{*\prime}_{rs}\right| + \left|ZN^{*\prime}_{ps} - ZN^{*\prime}_{rs}\right| + \left|UN^{*\prime}_{ps} - UN^{*\prime}_{rs}\right|\right]^{\frac{1}{2}}. \tag{52}$$

Table 25
The ranking results of different DM methods.

Methods	Order	The best choice	The worst choice
IVIFWA (Xu and Chen, 2007)	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2	HL_4
IVIF-TOPSIS (Izadikhah, 2012)	$HL_2 > HL_5 > HL_1 > HL_4 > HL_3$	HL_2	HL_4
IVIF-TOXONOMY (Xiao *et al.*, 2021)	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2	HL_4
IVIF-TODIM (Krohling and Pacheco, 2014)	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2	HL_4
IVIF-CPT-EDAS	$HL_2 > HL_5 > HL_1 > HL_3 > HL_4$	HL_2	HL_4

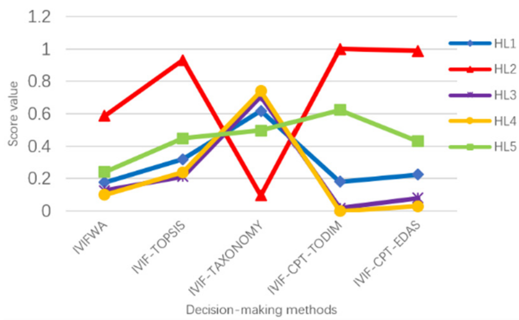

Fig. 3. The score value of different DM methods.

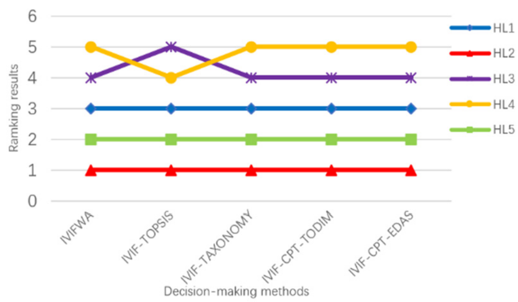

Fig. 4. The ranking results of different DM methods.

Step 4. Calculate the overall dominance degree ξ_r $(r = 1, 2, \dots, n)$ of each alternative HL_r using Eq. (53):

$$\xi_r = \frac{\sum_{p=1}^{n} \delta_{pr}(HL_p, HL_r) - \min_p \delta_{pr}(HL_p, HL_r)}{\max_p \delta_{pr}(HL_p, HL_r) - \min_p \delta_{pr}(HL_p, HL_r)}. \tag{53}$$

5.2. *Comprehensive Analysis*

After conducting the validity analysis above and analysing the research results presented in this article, we can conclude that HL_2 is consistently the superior alternative. For more intuitive comparison results, see Table 25, Figs. 3 and 4. We all know that each of five

MAGDM methods in the same fuzzy environment will have its own merits. IVIFWA operator pays more attention to the overall balance, but cannot avoid the impact of extreme values on the decision results. The IVIF-TOPSIS method, IVIF-TOXONOMY method and IVIF-CPT-TODIM method all utilize the same distance matrix for DM purposes. However, according to the research of other scholars, it is generally believed that these methods are only applicable to conservative investors and may be distorted in the process of information aggregation. In comparison to the aforementioned DM methods, the IVIF-CPT-EDAS method designed in this paper takes fully into account the impact of decision-makers' psychological factors, and enhances the DM process through the utilization of the cumulative prospect function. Consequently, the algorithm logic presented in this paper is more closely aligned with the real-world DM environment. Moreover, the improved method is better equipped to handle MAGDM problems with extreme data and conflicts among all decision attributes during the DM process, and it possesses more distinctive characteristics.

6. Conclusions

In this article, we modified the traditional EDAS method for settling the MAGDM issues better by combining IVIFs. First of all, we briefly review the fundamental definition of IVIFSs, aggregation operator and distance formula. We are aware that the EDAS method is highly effective in resolving DM issues involving contradictory attributes. Therefore, the prominent advantage of introducing the enhanced EDAS technology to IVIFSs in order to address MAGDM problems due to the influence of the actual environment is that it not only lets the average scheme reduce the impact of extreme data, but also takes into account the proximity of the distance between each attribute and the average scheme. Simultaneously, the implementation of the entropy weight method also guarantees the stability of the DM system. Finally, we verified the feasibility of the developed technique by applying the IVIF-CPT-EDAS method to a numerical example of GTVC. Furthermore, sensitivity analysis and several contrast analyses are conducted to validate the rationality and feasibility of MAGDM problems in the practical application process, respectively. Therefore, the main advantages of this paper can be shown as follows: (1) The attribute weights via exploiting information entropy method in IVIFS are constructed. (2) The IVIF-CPT-EDAS approach is designed for addressing MAGDM issues. (3) The presented method of this study not only provides DEs with a broader space for information expression, but also fully considers the psychological characteristics of DEs when facing gains and losses, providing inspiration for subsequent research on DM methods under the framework of bounded rationality.

Nonetheless, the proposed method also has some shortages. On the one hand, the technology developed in this paper solely takes into account the scenario where evaluation information is provided in IVIFs, and real-world evaluation might encounter diverse DM environments. On the other hand, we should thoroughly take into account the genuine psychological alteration trend of decision-makers. Therefore, in future research, we will concentrate on creating novel models and functions for determining attribute weights, enabling them to vary dynamically based on the data. Simultaneously, with the advancement of network technology, numerous DM methods in network form have arisen, including microblog, WeChat, and other online voting forms. In theory, when confronted with such complex DM, we can also extend the findings of this paper to the realm of complex DM that evolves with time.

Compliance with Ethical Standards

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Conflict of interest

The authors declare that they have no conflicts of interest.

Data Availability

The data used to support the findings of this study are included within the article.

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