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Unveiling the implementation barriers to the digital transformation in the energy sector using the Fermatean cubic fuzzy method

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HIGHLIGHTS

- This study identifies a structure of barriers to the implication of the digital economy in achieving energy transition.
- A synthetical decision model integrating the weighted Heronian mean aggregation operator is presented.
- The RAFSI model with FCF is proposed to evaluate the barriers of digital transformation implementation in energy transition.

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ABSTRACT

Digital transformation has been regarded as a primary styrategy to promote transitions in diverse fields, but industry pioneers believe that the existing barriers may hamper the speed of digital transformation. Hence, this paper presents a synthetical decision model integrating the weighted Heronian mean aggregation (WHMA) operator, the Level-Based Weight Assessment (LBWA) model, the CRITIC (criteria importance through inter-criteria correlation) method, and the Ranking of Alternatives through Functional mapping of criterion sub-intervals into a Single Interval (RAFSI) model with Fermatean cubic fuzzy sets to evaluate the barriers to digital transformation implementation in energy transitions with unknown weights of experts and criteria. In this framework, an extended WHMA operator with the deviation-based method is established to fuse experts' preference information. The LBWA model and CRITIC method with FCF setting are combined to derive the weights of barriers. Next, these methods are incorporated into the RAFSI model to analyze these barriers. A numerical example of evaluating barriers to digital transformation implementation in the power sector displays the application of the RAFSI model-based decision method. The result reveals that a_3 "Equipment manufacturer" (0.7063) has the highest barrier level, and a_4 "Consumers of smart power electronic" (0.4391) have the lowest barrier level. After that, sensitivity and comparative explorations are applied to examine the feasibility and reliability of the synthetical model. The results show that the proposed model can provide a more practical and stable evaluation result for supporting the decision of stakeholders associated with ET.

1. Introduction

Recent years have witnessed "digital transformation (DT)" rapidly transforming business models, technology, and processes in various industries, including the transportation, manufacturing, service, and energy industries [1,2]. Among these industries, sustainable development of the energy sector is unavoidable for human survival and national economic growth [3]. Scholars and policymakers believe integrating the DT and "energy transition (ET)" is an effective way to reach this goal because implementing DT in the energy industry can

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accelerate ET [4,5]. Energy digital transformation refers to using emerging information technologies to improve resource allocation, security, and intelligent interaction capabilities in energy production, transmission, trading, and consumption. These digital technological advancements have significantly changed energy production, transmission, and consumption. In power plants, for instance, the digital twin has been adopted to enhance the resilience of networked microgrids [6]. In the renewable energy sector, blockchain techniques are designed to tackle trust and security problems in trade [7]. Moreover, various digital techniques have already been explored to integrate the power grid in China, resulting in enhanced smart inspection levels, lessening of fault handling times, and greater network security reliability [8,9].

The cases above prove that implementing DT or digital technologies for energy efficiency can make energy systems more flexible and efficient [10,11]. However, there are still various barriers that may impose restrictions on the implementation of DT. According to Liu and Lu [12], for example, many challenges impact the performance of DT in ET. Ren et al. [5] revealed that the cost and technical support influenced the implementation of DT by associated companies in the renewable energy sector. Kumar and Barua [13] suggested a set of ten barriers to digital technology adoption in the petroleum industry. Almutairi et al. [14] reported the barriers to digital technology implementation in the renewable energy sector from five aspects: efficiency, security, operations, technology, and cooperation. Unfortunately, the existing studies seldom analyze the implementation barriers to DT in ET from the perspective of "multi-attribute decision-making (MCDM)". Consequently, the current work develops an integrated MCDM framework to unveil the barriers to the implementation of DT in ET. To this end, this study raises the following questions: (i) which barriers are the most significant influencing factors for implementing DT in ET? (ii) Which model is more practical to identify the company with the highest barrier level with complex and uncertain information?

In considering the evaluation of qualitative barriers to the implementation of DT in ET, the experts can not utilize crisp data to express their preference on these barriers fully. Given this, the fuzzy set has been widely implemented to model the experts' vague and uncertain preferences [15,16,13,17]. Recently, some extended fuzzy sets consisting of "membership degree (MD)" and "non-membership degree (NMD)" have been extended to process subjective preference for analyzing barriers to DT, such as "intuitionistic fuzzy set (IFS)" [18], "Pythagorean fuzzy set (PFS)" [19], and "Fermatean fuzzy set (FFS)" [20,21]. In FFS, the cube sum of MD and NMD is restricted to 1, which makes it presents a broader perspective of IFS and PFS [22,23,24]. In practice, the single crisp number-based FFS or interval values-based FFS may struggle to fit the various uncertainties because of the cognitive limitations and professional differences of barriers to DT [25]. To this end, the "Fermatean cubic fuzzy set (FCFS)", as an integrated and extended fuzzy set, was defined by Niu et al. [26] to combine the superiorities of the cubic fuzzy set and Fermatean fuzzy set. The FCFS contains more information to represent the data in terms of interval-valued Fermatean fuzzy set and FFS simultaneously. Therefore, the FCFS is an exceptional approach for modeling complex human preferences in the barrier analysis process. Moreover, FCFS has been applied to diverse research areas, such as university ranking [27], the selection of cold chain logistics distribution centers [28], the determination of intercity railway systems [26], and medical diagnosis [29]. Thus, the present work adopts the FCFS to express the experts' uncertain preference information about the implementation barriers.

Moreover, assessing the DT barriers has been treated as an MCDM issue in the current literature ([30,31,32]). Hence, MCDM techniques are valuable in assessing the DT barriers. Currently, some MCDM methods have been introduced to assess the DT barriers, such as "weighted aggregated sum product assessment (WASPAS)" [33], "evaluation based on distance from average solution (EDAS)" [14], and "(COPARS)" [34]. However, these methods have some limitations, such as rank reversal issues and unstable results, which can cause reasonable and incomplete decision outcomes. The "Ranking of Alternatives through Functional Mapping of Criterion Subintervals into a Single Interval (RAFSI)" model, initiated by Žižović et al. [35], is reported as a novel decision-making technique to avoid the rank reversal consequence existing in other MCDM methods. Further, this method has successfully addressed diverse decision-making issues [36,37,38]. In the contemporary literature, this model has been modified in different uncertain settings [39,40,41,42,43,44]; however, no study has developed the RAFSI model from the perspective of FCFS. Further, preference information aggregation is a key issue for the RAFSI model; however, the current aggregation methods in this model seldom consider the interdependencies between the preference information [44]. The "weighted Heronian mean aggregation (WHMA)" operator, as an efficient information aggregation tool, is free from the aggregation issue of inter-dependent preference information [45]. Moreover, the extant studies have not integrated the RASFI model and WHMA operator with the FCFS. Thus, it is beneficial to combine the RAFSI model with the WHMA operator. On the other hand, the current RAFSI models neglect the integration of objective-subjective criteria weights. The "Level-Based Weight Assessment (LBWA)" model and the "criteria importance through intercriteria correlation (CRITIC)" method are notable weighting tools to determine the subjective and objective weights for barriers. Thus, the current work integrates the RAFSI model with the LBWA and CRITIC for analyzing barriers to DT in ET. Consequently, as far as the authors know, this is the first study that presents an integrated FCF-RAFSI model by combining the WHMA operator and the RAFSI method under the FCF environment. This hybrid decision model provides a robust and straightforward algorithm with accurate and rational results for evaluating the implementation barrier of DT on the energy transition-reaching process.

1.1. Motivations

The discussion above indicates that very few studies adopt an integrated decision-making model to unveil the effect of implementation barriers to DT in ET with uncertain information. The key challenges for implementing the current research are listed as.

- Unveiling the barriers to implementing the DT in the ET process is a significant problem for promoting the digital transformation of the energy industry. In recent literature, many MCDM methods [46,47,34,30,48] have been reported to identify and rank barriers to digital transformation. However, the MCDM method for analyzing the implementation barriers to the DT in ET with complex uncertainty is still missing in the current literature.
- The aggregation operator-based decision information fusion method is crucial for barrier evaluation. The now available FCF aggregation operators [49,27,28] cannot model the interrelationships between the evaluation information. The WHMA operator is a valid and widely adopted method to portray this situation in decision-making issues. However, current WHMA operators fail to process FCF information. Hence, it is worth extending the WHMA operator to the FCF setting for collecting the experts' decision information.
- Estimating weights for implementation barriers is a significant procedure for evaluating and prioritizing these barriers, in which the subjective preference, objective features, and the inter-correlations among barriers may be included simultaneously. Thus, a hybrid weights-calculation method is more favorable for generating a reasonable analysis result. In addition, the LBWA model and CRITIC method are notable methods for determining subjective and objective weights. So far, there is no research on combining the LBWA-CRITIC method with FCFS. Therefore, this paper integrates the LBWA-CRITIC method with FCFS to obtain a comprehensive weight.
- The RAFSI model is a stable means to appraise the implementation barriers to DT in ET. However, the extensions of the RAFSI model [40,37,38,42] can not handle decision-making issues in the FCF

environment. Moreover, these extended RAFSI models neglect to integrate the LBWA model and CRITIC method. For this, we present a synthetical decision framework based on the WHMA operator, the LBWA-CRITIC method, and the RAFSI model for analyzing the implementation barriers to DT in ET under the FCF environment.

1.2. Contributions

Inspired by the motivations summarized above, this paper aims to construct a hybrid FCF decision model to resolve the issues existing in estimating the implementation barriers to DT in ET, as shown in Fig. 1. First, the FCFS is introduced to model the experts' subjective judgment of barriers. Then, an extended WHMA operator is established to obtain a collective evaluation matrix with FCF information. Next, an integrated significance degree of each barrier is determined by using the FCF-LBWA-CRITIC method. Finally, a decision framework based on the extended FCF-RAFSI model is suggested to evaluate the barrier levels of alternative options. In what follows, the main contributions of the current study are given below.

- This work identifies and establishes a hierarchical structure of barriers to implementing DT in the energy sector, according to the literature review.
- A collective evaluation matrix construction method based on FCFS and WHMA operator is built to fuse individual experts' judgment data. Moreover, an objective weighting model with the deviation-based method is introduced to calculate the weights of experts.
- A weighting method based on the LBWA model and CRITIC method is generated to determine the relative significance of barriers. The CRITIC method can calculate the weights of barriers considering the inter-correlations between them. This work integrates the CRITIC method with FCFS to determine the objective weights for barriers. The LBWA model combining the FCFS and CRITIC is presented to comprehensively resolve the subjective preference, objective features, and the inter-correlations among barriers.
- An integrated RASFI model based on the FCF-WHMA operator and FCF-LBWA-CRITIC method is proposed to estimate the barrier levels of alternative options. The RAFSI effectively overcomes the rank reversal issue. In view of this advantage and considering the dual interactions existing in input estimation data and barriers, this study presents a hybrid FCF-RAFSI model integrating the WHMA operator and LBWA-CRITIC method.
- A real case study of barriers estimation of DT in the power sector is conducted to illustrate the application and feasibility of the proposed framework. Further, sensitivity and comparative investigations are conducted to confirm the advantages of the proposed framework.

1.3. The core novelties of this work

Based on the contributions, we can summarize the core novelties as follows: (i) Uncertain preference information can be expressed flexibly by expanding the scope of uncertainty representation by incorporating non-membership to complement the membership interval; (ii) Weights of barriers are methodically calculated by considering the interactions between barriers along with the preferences of experts; (iii) A holistic perspective of the significance of barriers is obtained through the subjective and objective weights calculation methods along with the changing parameters; (iv) Barrier levels of alternative options are estimated using an extended ranking model along with eliminating the rank reversal issue; (v) The integrated decision methods aid in the barriers estimation of implementing DT in ET.

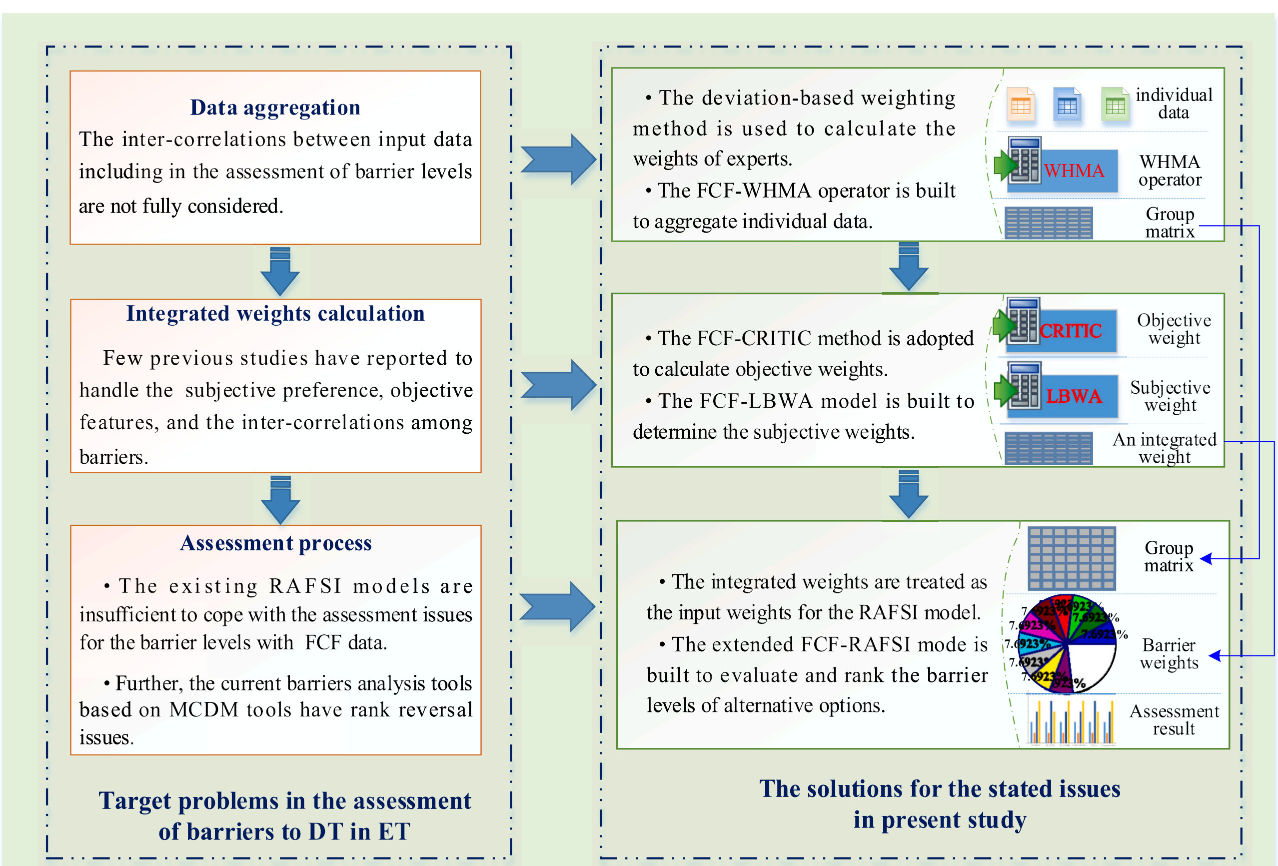

Fig. 1. The solutions for the issues in the assessment of barriers.

1.4. Layout of this study

The contents of the present study are organized as follows: The subsequent section is a list of previous studies associated with this work. Section 3 reports the proposed integrated methodology for unveiling the role of barriers in implementing DT in the energy industry. This integrated methodology includes the FCF-information collection method, the FCF-hybrid weights calculation method, and the FCF-RAFSI method. Section 4 displays a case of implementation barriers evaluation for the DT in the energy sector to illustrate the application of the developed FCF-RAFSI method. After that, the sensitivity and comparative explorations are included in this section to test the merits of the methodology. Lastly, Section 5 highlights the conclusions and future directions.

2. Literature review

This section includes three sub-sections. The first three sub-sections briefly review the latest related studies on the DT implementation barriers analysis and RAFSI model. The last subsection summarizes the previous research and points out the research gaps.

2.1. The barriers to digital transformation implementation in energy

According to the literature review organized by Maroufkhani et al. [1], evaluating implementation barriers to DT in the energy sector mainly focuses on digital technologies. In the electricity system, for example, Akhavan-Hejazi and Mohsenian-Rad [50] pointed out six barriers to big data analytics adoption. Based on stating references, Andoni et al. [51] discussed the barriers to blockchain adoption in the energy industry from the perspective of technical requirements, costs, and resilience. After summarizing the application status of artificial intelligence, Ahmad et al. [52] analyzed the barriers to its adoption in the sustainable energy sector. In the literature [53], the author explored the integration barriers to blockchain in the renewable energy industry. Chen et al. [54] argued that we can identify the implementation barriers to blockchain in the power sector from technology, legal policy, and application aspects. Gawusu et al. [55] generalized barriers to blockchain application in the renewable energy industry from the aspects of public cognition, uncertainties, laws and regulations, and costs. Nour et al. [56] discussed the barriers to the mass adoption of blockchain in different power sectors. To recognize and prioritize the factors influencing blockchain utilization in supply chain processes, Almutairi et al. [14] proposed twelve barriers to renewable energy. Karumba et al. [57] proposed an influencing factors system for blockchain implementation in the energy trading procedure consisting of four and nine specific barriers. Kumar and Barua [13] developed a set of ten barriers to investigate the application of blockchain in the energy supply chain. Reddy et al. [58] proposed a set of fifteen barriers to adopting the "Internet of things (IoT)" in the clean energy industry. Olabi et al. [59] summarized the implementation barriers to DT in the energy industry from the aspects of technology, finance, environment, society, and organization. Guo et al. [60] suggested the potential barriers to AI implementation in the power industry according to analyzing the current application situation. According to the above research on barriers evaluation, we summarize the barriers to DT implementation in the energy sector, which is given in Table 1.

Table 1
The implementation barriers to DT in the energy sector.

Specific barriers	Description	References
Short-term planning	Companies that do not prioritize long-term returns are more hesitant to embrace digital and sustainable investments, as the potential benefits of such investments may not be realized immediately.	Reddy et al. [58]; Mishra et al. [61]
Information disclosure concerns	Because the energy digitalization process has an open, distributed architecture, energy supply chain partners are hesitant to share sensitive financial data. Moreover, different energy digital platforms may possess heterogeneous privacy needs and sharing policies.	Olabi et al. [59]; Tseng et al. [62]
Deficiency of infrastructure providers	Various digital techniques for the energy sector should adopt plentiful intelligent devices. Thus, it requires sufficient suppliers to provide instruments and services that conform to standards.	Andoni et al. [51]; Mishra et al. [61]
Coordination, communication, and collaboration issues	Energy industries with different operational objectives and priorities may lack collaboration, disrupting supply chain operations and the implementation of digital techniques.	Ahmad et al. [52]; Govindan et al. [63]
Limited technology maturity	The insufficient data storage and processing capability makes the significantly lower transaction of energy digital platforms than the extant systems.	Wu et al. [64]; Guo et al. [60]
The security issues	Security challenges with energy digitalization can hurt a business. One of the most concerning is the possibility of an attack against a company.	Almutairi et al. [14]; Andoni et al. [51]
Shortage of stakeholder awareness	The majority of stakeholders are unacquainted with the digital tools for energy transition. They are also not sure whether to implement DT. This barrier is because of the knowledge shortage about supporting techniques for energy digitalization.	Govindan et al. [63]
Inadequate information on costs, ROI, and losses	Incomplete information about the costs and benefits of energy digitalization-based business models has led small and medium businesses to question the potential losses and returns.	Ahmad and Zhang [65]; Jones et al. [66]
Highest investment cost	DT implementation needs huge investment costs associated with the new systems and facilities related to various energy industries. Moreover, these installations require different energy costs.	Almutairi et al. [14]

(continued on next page)

2.2. Fuzzy MCDM for evaluating implementation barriers to digital transformation in energy

In terms of analysis tools, fuzzy MCDM methods are one of the most popular directions in the evaluation of the barriers to digital technology adoption in the energy sector. In renewable energy systems, for example, Yildizbasi [53] integrated AHP with PFS to calculate the priority of each implementation barrier to the blockchain. Mishra et al. [61] utilized a combined "decision-making trial and evaluation laboratory

Table 1 (*continued*)

Specific barriers	Description	References
Shortage of specialists associated with the DT implementation in the energy industry	Technically skilled professionals must implement emerging technologies in their early stages of development in various energy industries.	Olabi et al. [59]; Kumar and Barua [13]
Shortage of standardization	The DT implementation in the energy sector has started to gain traction among some governments, so there are no clear regulations and rules for it.	Reddy et al. [58]; Kumar and Barua [13]
Interoperability with the current system in the energy industry	The ability to use, operate, and transact on different energy systems is essential for the mainstream implementation of DT.	Guo et al. [60]; Mishra et al. [61]
Unadaptable DT infrastructure of the energy sector	It is challenging to implement the DT effectively due to limited technical infrastructure. Moreover, the various digital infrastructure is still in development; thus, there is no guarantee that DT can be implemented in the energy sector.	Rahimi et al. [30]; Nour et al. [56]
Shortage of government support and legal uncertainties	Because the DT implementation should have settled laws and policies from the government, the energy sector stakeholders can be encouraged to strengthen the investment in energy transition.	Maroufkhani et al. [1]; Almutairi et al. [14]
Limited acceptance in society	Increasing the acceptance of digital technologies is a critical element of digitizing energy systems. Despite numerous studies supporting them, society hesitates to utilize them.	Rahimi et al. [30]; Su et al. [67]; Mishra et al. [61]
Lack of synthetical environment assessment regulation	Digitalization of energy improves efficiency and reduces energy losses, but its implementation requires a lot of computing power, which can negatively impact the environment.	Olabi et al. [59]; Sawhney [68]
Shortage of the market auditing	Over and above presenting new audit challenges, DT provides a new level of complexity to auditors as the technology is developed for privacy. Moreover, DT in energy is irreversible; thus, audits must assess whether automated controls effectively validate the transactions.	Mishra et al. [61]; Kaur et al. [69]; Chen et al. [70]
Market risk	Since its complexity and time-consuming nature, DT in the energy sector might affect the firm's market competitiveness. The energy industries are concerned that their supply chain partners will not implement the DT.	Mishra et al. [61]; Rahimi et al. [30]

(DEMATEL)" model with a "triangular fuzzy set (TrFS)" to identify the significant implementation barriers to IoT in the renewable energy industry. An integrated fuzzy linguistic DEMATEL was constructed by Chen et al. [54] to prioritize the barriers influencing digital technology adoption in the power sector. In reference [14], the authors explored the "stepwise weight assessment ratio analysis (SWARA)" based-integrated decision models for ranking the barriers to blockchain adoption in the renewable energy sector. Reddy et al. [58] explored a developed "weighted aggregated sum product assessment (WASPAS)" model for evaluating the barriers to IOT application in the clean energy sector with FFS.

Table 2
The fuzzy MCDM methods for barriers analysis in energy digitization.

Authors	Fuzzy sets	MCDM method	Digital tools
Yildizbasi [53]	PFS	AHP	Blockchain
Mishra et al. [61]	TrFS	DEMATEL	IOT
Chen et al. [54]	Hybrid fuzzy linguistic set	DEMATEL	Blockchain
Almutairi et al. [14]	–	SWARA	Blockchain
Reddy et al. [58]	FFS	WASPAS	IOT

2.3. RAFSI model

In the current literature, many scholars have built various extensions of the RAFSI model to resolve realistic decision-making issues. For example, Pamučar et al. [43] identified the appropriate guidelines for reorganizing and adjusting healthcare systems using a developed RAFSI model with a comprehensive weight-determination method. Akyurt et al. [39] explored the evaluation and prioritization issues for the pilot training center using an integrated rough-RAFSI model. Reference [40] determined the suitable construction machinery that enables mobility by developing an RAFSI model with the FUCOM method. Deveci et al. [36] integrated the RAFSI model with the fuzzy rough sets to assess the alternative site for floating photovoltaics. In reference [41], the authors extended the RAFSI model based on the "q-rung orthopair fuzzy set (q-ROFS)" for selecting autonomous vehicles. An integrated RAFSI model with the "best-worst method (BWM)" was reported by Kaya et al. [42] to choose the alternative antivirus mask. Gokasar et al. [38] combined the RAFSI model with "Type-2 neutrosophic numbers (T2NNs)" to address the determination issues for the optimal implication schemes of electric vehicles. To choose the optimal charging strategy, Sadrani et al. [44] proposed the RAFSI-BWM framework to rank the options. As mentioned above, the roundup of the application scenarios and extended versions of the RAFSI model are given in Table 3.

2.4. Summary of the research gaps

From the overview of prior work (see Tables 1–3), we can observe that evaluating barriers to DT implementation in the energy sector is still an open topic. For this, there are some gaps in current studies related to the present work, which are presented as.

(i) Most of the studies available now concentrate on analyzing the implementation barriers to a single digital technique in the energy sector, which rarely identifies the specific barriers from the perspective of multiple digital techniques adoption.

(ii) The reported fuzzy MCDM techniques have limited capability to evaluate and rank the implementation barriers to DT in the energy sector with FCF information. Moreover, the current methods just utilize a single weight-determining approach to measure the relative importance of each barrier, which may cause inaccuracies in a subjective or objective weight calculation approach.

(iii) The RAFSI model has been incorporated into different uncertain contexts; however, these extensions cannot tackle the MCDM issue with the FCFS-based decision data. Moreover, although the comprehensive weight calculation method has been introduced to the RAFSI model, it failed to handle the situation in which the intercorrelations between barriers are considered, especially under FCF circumstances.

(iv) To our knowledge, no study has explored the integrated RASFI

Table 3
The summary of the application and extension of the RAFSI model.

Literature	Ambiance	Combined methods	Focus
Pamučar et al. [43]	Triangular fuzzy set	LBWA-MACBETH	Healthcare systems
Alosta et al. [71]	Crisp	AHP	Location of medical service
Akyurt et al. [39]	Rough set	MACBETH	Pilot training center
Božanić et al. [40]	D-numbers	FUCOM	Construction machinery
Deveci et al. [41]	q-ROFS	Ordinal priority approach	Autonomous vehicles
Deveci et al. [36]	Fuzzy rough set	LAAW	Floating photovoltaics
Gokasar et al. [38]	T2NNs	No	Electric vehicles
Sadrani et al. [44]	Triangular fuzzy set	BWM	Charging strategy
Present method	FCFS	LBWA-CRITIC	Energy digitalization

model based on the LBWA model, the CRITIC method, WHMA operator with FCFS for evaluating the implementation barriers to DT in the energy sector.

3. The proposed methodology

This section introduces an FCF-based evaluation model for unveiling the impact of DEDs on the energy transition-reaching process. The first subsection recalls some fundamental conceptions of the FCFSs. The second subsection presents a three-phase decision-making model for evaluating the DEDs in achieving ET based on an integrated FCF-RAFSI method.

3.1. Preliminaries

This subsection discusses the fundamental conceptions of the FCFS. The detailed notions and basic operations are recalled as follows [49,26,28].

Definition 1. Let $\chi = \{x_1, x_2, \cdots, x_n\}$ be a universal set, an FCFS X on χ is represented as.

$$\mathrm{X} = \{\langle x_i, \mathrm{A}(x_i), \mathrm{B}(x_i)\rangle | x_i \in \chi\} \tag{1}$$

where $\mathrm{A} = \{\langle x_i, [\mu_{\mathrm{A}}^{-}(x_i), \mu_{\mathrm{A}}^{+}(x_i)], [\vartheta_{\mathrm{A}}^{-}(x_i), \vartheta_{\mathrm{A}}^{+}(x_i)]\rangle | x_i \in \chi\}$ and $\mathrm{B} = \{\langle x_i, \mu(x_i), \vartheta(x_i)\rangle | x_i \in \chi\}$ are the IV-FFS and FFS on χ. Moreover, all the elements satisfy the following condition: $0 \le \mu_{\mathrm{A}}^{-}(x) \le \mu_{\mathrm{A}}^{+}(x) \le 1$, $0 \le \vartheta_{\mathrm{A}}^{-}(x) \le \vartheta_{\mathrm{A}}^{+}(x) \le 1$ and $0 \le (\mu_{\mathrm{A}}^{+}(x))^3 + (\vartheta_{\mathrm{A}}^{+}(x))^3 \le 1$, $0 \le \mu_{\mathrm{B}}(x)$, $\vartheta_{\mathrm{B}}(x) \le 1$, and $0 \le (\mu_{\mathrm{B}}(x))^3 + (\vartheta_{\mathrm{B}}(x))^3 \le 1$. Then, the element $\langle([\mu_{\mathrm{A}}^{-}(x), \mu_{\mathrm{A}}^{+}(x)], [\vartheta_{\mathrm{A}}^{-}(x), \vartheta_{\mathrm{A}}^{+}(x)]), (\mu_{\mathrm{B}}(x), \vartheta_{\mathrm{B}}(x))\rangle$ is defined as the Fermatean cubic fuzzy number (FCFN).

Definition 2. Let $\mathrm{K}_1 = \langle([\mu_{\mathrm{A}1}^{-}, \mu_{\mathrm{A}1}^{+}], [\vartheta_{\mathrm{A}1}^{-}, \vartheta_{\mathrm{A}1}^{+}]), (\mu_{B1}, \vartheta_{B1})\rangle$ and $\mathrm{K}_2 = \langle([\mu_{\mathrm{A}2}^{-}, \mu_{\mathrm{A}2}^{+}], [\vartheta_{\mathrm{A}2}^{-}, \vartheta_{\mathrm{A}2}^{+}]), (\mu_{B2}, \vartheta_{B2})\rangle$ be any two FCFNs; then, the operations are defined as.

$$K_1 + K_2 = \left(\begin{array}{c} \left(\left[\begin{array}{c} \sqrt[3]{1-(1-(\mu_{A1}^{-})^3)\cdot(1-(\mu_{A2}^{-})^3)}, \\ \sqrt[3]{1-(1-(\mu_{A1}^{+})^3)\cdot(1-(\mu_{A2}^{+})^3)} \end{array} \right], [\vartheta_{A1}^{-}\cdot\vartheta_{A2}^{-}, \vartheta_{A1}^{+}\cdot\vartheta_{A2}^{+}] \right), \\ \left(\mu_{B1}\cdot\mu_{B2}, \sqrt[3]{1-(1-(\vartheta_{B1})^3)\cdot(1-(\vartheta_{B2})^3)} \right) \end{array} \right) \tag{2}$$

$$K_1 \otimes K_2 = \left(\begin{array}{c} \left(\begin{array}{c} [\mu_{A1}^{-}\cdot\mu_{A2}^{-}, \mu_{A1}^{+}\cdot\mu_{A2}^{+}], \\ \left[\begin{array}{c} \sqrt[3]{1-(1-(\vartheta_{A1}^{-})^3)\cdot(1-(\vartheta_{A2}^{-})^3)}, \\ \sqrt[3]{1-(1-(\vartheta_{A1}^{+})^3)\cdot(1-(\vartheta_{A2}^{+})^3)} \end{array} \right] \end{array} \right), \\ \left(\sqrt{31-(1-(\mu_{B1})^3)\cdot(1-(\mu_{B2})^3)}, \vartheta_{B1}\cdot\vartheta_{B2} \right) \end{array} \right) \tag{3}$$

$$\lambda\cdot K_1 = \left(\begin{array}{c} \left(\begin{array}{c} \left[\begin{array}{c} \sqrt[3]{1-(1-(\mu_{A1}^{-})^3)^{\lambda}}, \\ \sqrt[3]{1-(1-(\mu_{A1}^{+})^3)^{\lambda}} \end{array} \right], \\ [(\vartheta_{A1}^{-})^{\lambda}, (\vartheta_{A1}^{+})^{\lambda}] \end{array} \right), \\ \left((\mu_{B1})^{\lambda}, \sqrt[3]{1-(1-(\vartheta_{B1})^3)^{\lambda}} \right) \end{array} \right), \lambda > 0 \tag{4}$$

$$(K_1)^{\lambda} = \left(\begin{array}{c} \left(\begin{array}{c} [(\mu_{A1}^{-})^{\lambda}, (\mu_{A1}^{+})^{\lambda}], \\ \left[\begin{array}{c} \sqrt[3]{1-(1-(\vartheta_{A1}^{-})^3)^{\lambda}}, \\ \sqrt[3]{1-(1-(\vartheta_{A1}^{+})^3)^{\lambda}} \end{array} \right] \end{array} \right), \\ \left(\sqrt{31-(1-(\mu_{B1})^3)^{\lambda}}, (\vartheta_{B1})^{\lambda} \right) \end{array} \right), \lambda > 0 \tag{5}$$

Definition 3. Let $\mathrm{K} = \langle([\mu_{\mathrm{A}}^{-}, \mu_{\mathrm{A}}^{+}], [\vartheta_{\mathrm{A}}^{-}, \vartheta_{\mathrm{A}}^{+}]), (\mu_B, \vartheta_B)\rangle$ be any FCFN; then, the score and accuracy functions are defined as follows:

$$\mathfrak{S}(\mathrm{K}) = 0.5\left(0.25\left[(\mu_{\mathrm{A}}^{-})^3 + (\mu_{\mathrm{A}}^{+})^3 - (\vartheta_{\mathrm{A}}^{-})^3 - (\vartheta_{\mathrm{A}}^{+})^3\right] + 0.5\left((\mu_B)^3 - (\vartheta_B)^3\right) + 1\right) \tag{6}$$

$$\Re(\mathrm{K}) = 0.5\left(0.5\left[(\mu_{\mathrm{A}}^{-})^3 + (\mu_{\mathrm{A}}^{+})^3 + (\vartheta_{\mathrm{A}}^{-})^3 + (\vartheta_{\mathrm{A}}^{+})^3\right] + (\mu_{\mathrm{B}})^3 + (\vartheta_{\mathrm{B}})^3\right) \tag{7}$$

where $\mathfrak{S}(\mathrm{K}) \in [0,1]$ and $\Re(\mathrm{K}) \in [0,1]$.

Definition 4. Let $\mathrm{K}_1 = \langle([\mu_{\mathrm{A}1}^{-}, \mu_{\mathrm{A}1}^{+}], [\vartheta_{\mathrm{A}1}^{-}, \vartheta_{\mathrm{A}1}^{+}]), (\mu_{B1}, \vartheta_{B1})\rangle$ and $\mathrm{K}_2 = \langle([\mu_{\mathrm{A}2}^{-}, \mu_{\mathrm{A}2}^{+}], [\vartheta_{\mathrm{A}2}^{-}, \vartheta_{\mathrm{A}2}^{+}]), (\mu_{B2}, \vartheta_{B2})\rangle$ be any two FCFNs; then, the comparison rules are expressed as.

(1) If $\mathfrak{S}(\mathrm{K}_1) > \mathfrak{S}(\mathrm{K}_2)$, then $\mathrm{K}_1 \succ \mathrm{K}_2$;
(2) If $\mathfrak{S}(\mathrm{K}_1) = \mathfrak{S}(\mathrm{K}_2)$, then
① If $\Re(\mathrm{K}_1) > \Re(\mathrm{K}_2)$, then $\mathrm{K}_1 \succ \mathrm{K}_2$;
② If $\Re(\mathrm{K}_1) < \Re(\mathrm{K}_2)$, then $\mathrm{K}_1 \prec \mathrm{K}_2$;
③ If $\Re(\mathrm{K}_1) = \Re(\mathrm{K}_2)$, then $\mathrm{K}_1 = \mathrm{K}_2$.

3.2. The integrated FCFS-based RAFSI model

Here, we present an integrated decision-making model with FCFS-based information by combining the WHMA operator, the LBWA model, the CRITIC method, and the RAFSI model. First, the extended WHMA operator based on deviation-based method and FCFS is utilized to collect the experts' preference information considering the relationships among these input data. Then, the FCF-LBWA model and the FCF-CRITIC method are adopted to compute digital economy drivers' subjective and objective weights, respectively. Finally, the developed FCFS-based RAFSI model is presented to analyze the digital economy drivers because it is easily accessible and forms a stable ranking result [44]. For this, this section introduces the FCF-WHMA-LBWA-CRITIC-RAFSI framework to resolve the evaluation issue of digital economy drivers toward energy transition. This framework consists of three phases: the individual preference information collection stage, the barriers' weights computation stage, and the ranking result determination stage. The flowchart of this framework is given in Fig.2 and expounds on the following procedures.

Stage 1: Collection of FCFS-based decision data

This phase describes an extension of the WHMA operator in which the deviation-based method with FCF information is applied to measure the significance degree of experts. The calculation procedures are listed as.

Step 1.1. Generate the assessment matrix of each expert. First, let the sets $A = \{a_i | i = 1, 2, \cdots, m\}$ and $B = \{b_j | j = 1, 2, \cdots, n\}$ be the collection of alternatives and barriers, which are identified by a group of experts denoted as $\mathrm{E} = \{e_t | t = 1, 2, \cdots, \tau\}$. Then, the experts $e_t (t = 1, 2, \cdots, \tau)$ provide their preference information about the alternatives $a_i (i = 1, 2, \cdots, m)$ under each barrier $b_j (j = 1, 2, \cdots, n)$ using the associated evaluation scale. Subsequently, the assessment matrix $\mathrm{X}^t = \left[x^t_{ij}\right]_{m \times n}$ for the expert e_t is represented as.

$$X^t = \begin{array}{cc} & \begin{array}{cccc} a_1 & \quad a_2 & \quad \cdots & \quad a_m \end{array} \\ \begin{array}{c} b_1 \\ \\ b_2 \\ \vdots \\ b_n \end{array} & \begin{bmatrix} \left\langle \begin{matrix} \left(\left[\mu^{-}_{x^t_{11}}, \mu^{+}_{x^t_{11}}\right], \left[\vartheta^{-}_{x^t_{11}}, \vartheta^{+}_{x^t_{11}}\right]\right), \\ \left(\mu_{x^t_{11}}, \vartheta_{x^t_{11}}\right) \end{matrix} \right\rangle & \left\langle \begin{matrix} \left(\left[\mu^{-}_{x^t_{12}}, \mu^{+}_{x^t_{12}}\right], \left[\vartheta^{-}_{x^t_{12}}, \vartheta^{+}_{x^t_{12}}\right]\right), \\ \left(\mu_{x^t_{12}}, \vartheta_{x^t_{12}}\right) \end{matrix} \right\rangle & \cdots & \left\langle \begin{matrix} \left(\left[\mu^{-}_{x^t_{1n}}, \mu^{+}_{x^t_{1n}}\right], \left[\vartheta^{-}_{x^t_{1n}}, \vartheta^{+}_{x^t_{1n}}\right]\right), \\ \left(\mu_{x^t_{1n}}, \vartheta_{x^t_{1n}}\right) \end{matrix} \right\rangle \\ \left\langle \begin{matrix} \left(\left[\mu^{-}_{x^t_{21}}, \mu^{+}_{x^t_{21}}\right], \left[\vartheta^{-}_{x^t_{21}}, \vartheta^{+}_{x^t_{21}}\right]\right), \\ \left(\mu_{x^t_{21}}, \vartheta_{x^t_{21}}\right) \end{matrix} \right\rangle & \left\langle \begin{matrix} \left(\left[\mu^{-}_{x^t_{22}}, \mu^{+}_{x^t_{22}}\right], \left[\vartheta^{-}_{x^t_{22}}, \vartheta^{+}_{x^t_{22}}\right]\right), \\ \left(\mu_{x^t_{22}}, \vartheta_{x^t_{22}}\right) \end{matrix} \right\rangle & \cdots & \left\langle \begin{matrix} \left(\left[\mu^{-}_{x^t_{2n}}, \mu^{+}_{x^t_{2n}}\right], \left[\vartheta^{-}_{x^t_{2n}}, \vartheta^{+}_{x^t_{2n}}\right]\right), \\ \left(\mu_{x^t_{2n}}, \vartheta_{x^t_{2n}}\right) \end{matrix} \right\rangle \\ \vdots & \vdots & \vdots & \vdots \\ \left\langle \begin{matrix} \left(\left[\mu^{-}_{x^t_{m1}}, \mu^{+}_{x^t_{m1}}\right], \left[\vartheta^{-}_{x^t_{m1}}, \vartheta^{+}_{x^t_{m1}}\right]\right), \\ \left(\mu_{x^t_{m1}}, \vartheta_{x^t_{m1}}\right) \end{matrix} \right\rangle & \left\langle \begin{matrix} \left(\left[\mu^{-}_{x^t_{m2}}, \mu^{+}_{x^t_{m2}}\right], \left[\vartheta^{-}_{x^t_{m2}}, \vartheta^{+}_{x^t_{m2}}\right]\right), \\ \left(\mu_{x^t_{m2}}, \vartheta_{x^t_{m2}}\right) \end{matrix} \right\rangle & \cdots & \left\langle \begin{matrix} \left(\left[\mu^{-}_{x^t_{mn}}, \mu^{+}_{x^t_{mn}}\right], \left[\vartheta^{-}_{x^t_{mn}}, \vartheta^{+}_{x^t_{mn}}\right]\right), \\ \left(\mu_{x^t_{mn}}, \vartheta_{x^t_{mn}}\right) \end{matrix} \right\rangle \end{bmatrix} \end{array} \tag{8}$$

Step 1.2. Calculate the score values of the assessment matrix $\mathrm{X}^t = \left[x^t_{ij}\right]_{m \times n}$ using the following formula.

$$\chi^t_{ij} = \mathfrak{S}\left(x^t_{ij}\right) = 0.5\left(0.25\left[\left(\mu^{-}_{x^t_{ij}}\right)^3 + \left(\mu^{+}_{x^t_{ij}}\right)^3 - \left(\vartheta^{-}_{x^t_{ij}}\right)^3 - \left(\vartheta^{+}_{x^t_{ij}}\right)^3\right] + 0.5\left(\left(\mu_{x^t_{ij}}\right)^3 - \left(\vartheta_{x^t_{ij}}\right)^3\right) + 1\right) \tag{9}$$

where $\chi^t_{ij} (i = 1, 2, \cdots, m; j = 1, 2, \cdots, n; t = 1, 2, \cdots, \tau)$ is the element of the score values-based assessment matrix $\mathrm{Z}^t = \left[\chi^t_{ij}\right]_{m \times n}$.

Step 1.3. Compute the average values of all the matrices $\mathrm{Z}^t = \left[\chi^t_{ij}\right]_{m \times n} (t = 1, 2, \cdots, \tau)$ as follows.

$$\overline{\chi}_{ij} = \frac{1}{\tau}\sum_{t=1}^{\tau}\chi^t_{ij} \tag{10}$$

where $\overline{\chi}_{ij}$ is the element of the matrix $\overline{\mathrm{Z}} = \left[\overline{\chi}_{ij}\right]_{m \times n}$.

Step 1.4. Calculate the standard deviation values $\psi = [\varpi_t]_{1 \times \tau}$ where

$$\varpi_t = \sqrt{\frac{1}{m \times n}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(\chi^t_{ij} - \overline{\chi}_{ij}\right)^2} \tag{11}$$

Step 1.5. Determine the weights $\omega_t (t = 1, 2, \cdots, \tau)$ of experts using the following form.

$$\omega_t = \frac{\varpi_t}{\sum_{t=1}^{\tau}\varpi_t} \tag{12}$$

where $\omega_t \in [0, 1]$ and $\sum_{t=1}^{\tau}\omega_t = 1$.

Step 1.6. Collect the experts' assessment matrices. According to the WHMA operator and the experts' weights, the WHMA operator-based aggregation method for FCF information is defined as.

$$y_{ij} = FCF - WHMA^{\alpha,\beta}_{\omega}\left(x^1_{ij}, x^2_{ij}, \cdots, x^{\tau}_{ij}\right) = \left[\sum_{t=1}^{\tau}\sum_{t'=t}^{\tau}\left(\omega_t\omega_{t'}\left(x^t_{ij}\right)^{\alpha} \otimes \left(x^{t'}_{ij}\right)^{\beta}\right)\right]^{\frac{1}{\alpha+\beta}} \tag{13}$$

in which, $y_{ij} (i = 1, 2, \cdots, m; j = 1, 2, \cdots, n)$ is an element of the group assessment matrix $Y = \left[y_{ij}\right]_{m \times n}$, $\omega_{t'} (t' = 1, 2, \cdots, \tau)$ is the weight vector of the experts $e_{t'} (t' = 1, 2, \cdots, \tau)$ with $\omega_{t'} \in [0, 1]$ and $\sum_{t'=1}^{\tau}\omega_{t'} = 1$, and α, $\beta \geq 0$.

Stage 2: Calculation of the integrated weights for barriers

This phase presents a hybrid weighting method to measure the significant degrees of the implementation barriers. The FCF-LBWA model is utilized to calculate the subjective weights of these barriers, considering the experts' preference for each barrier. Then, the FCF-CRITIC method is introduced to determine each barrier's objective weight, which can consider the interaction among barriers. Finally, the integrated weights of barriers are obtained based on the subjective and objective weights. The detailed calculation steps are listed as follows.

Step 2.1. The FCF-LBWA model for subjective weight calculation

This sub-step describes the FCF-LBWA model to form the subjective weight of each barrier, and the calculation procedures are organized as follows.

Step 2.1.1. Identify the most critical barrier

First, the experts $e_t (t = 1, 2, \cdots, \tau)$ prefer the barriers according to their significance using FCFS. Then, the preference information of experts is expressed as.

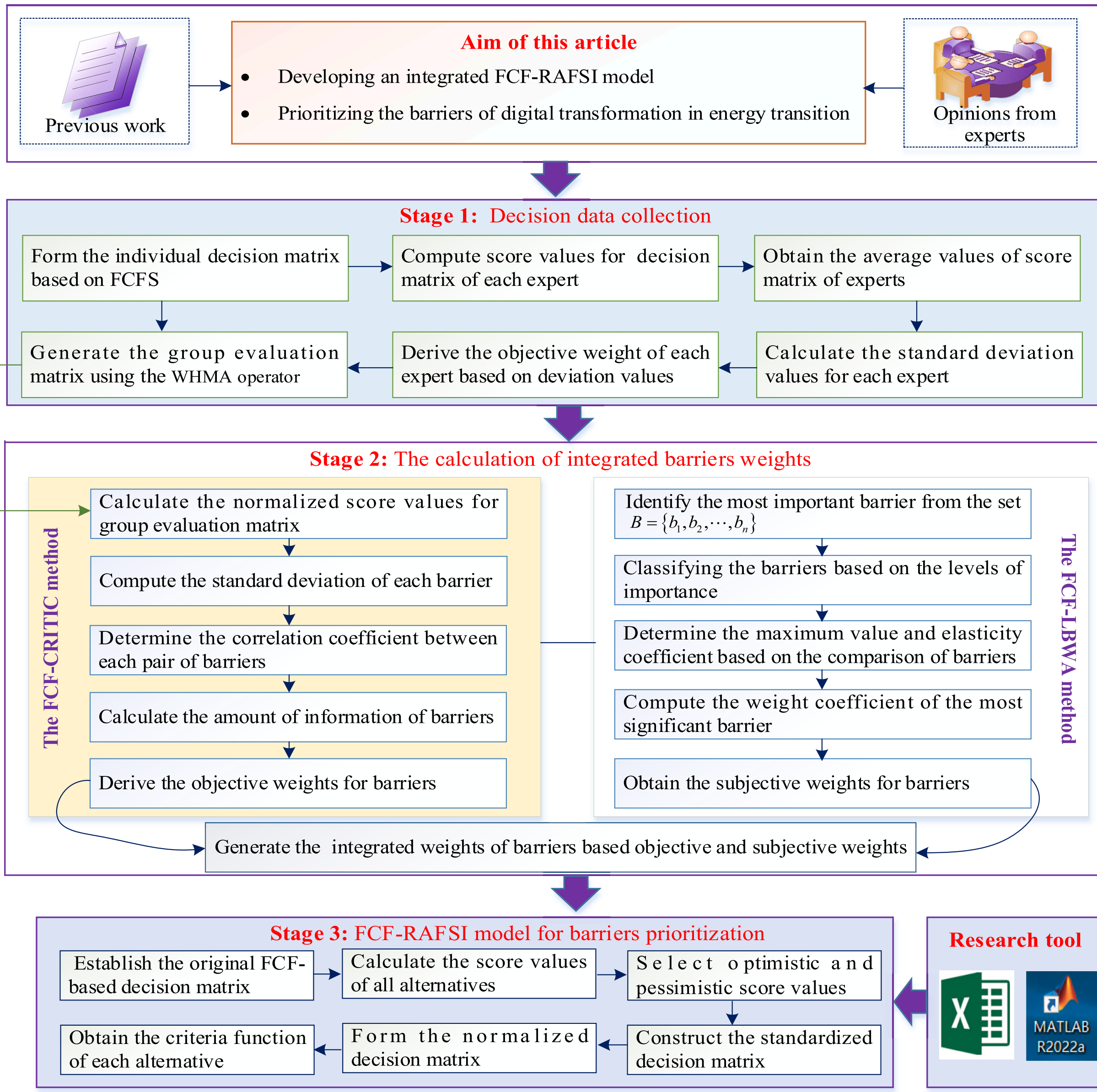

Fig. 2. The flowchart of the evaluation framework.

$$\Omega = \begin{array}{c} b_1 \\ b_2 \\ \cdots \\ b_n \end{array} \begin{bmatrix} \varsigma_{b_1} \\ \varsigma_{b_2} \\ \cdots \\ \varsigma_{b_n} \end{bmatrix} \tag{14}$$

where the element ς_{b_j} is an FCFN, denoted as $\varsigma_{b_j} = \left\langle \left(\left[\mu_{b_j}^-, \mu_{b_j}^+ \right], \left[\vartheta_{b_j}^-, \vartheta_{b_j}^+ \right] \right), \left(\mu_{b_j}, \vartheta_{b_j} \right) \right\rangle$.

After that, the score value φ_j of ς_{b_j} is calculated as.

$$\varphi_j = \Im\left(\varsigma_{b_j}\right) = 0.5\left(0.25\left[\left(\mu_{b_j}^-\right)^3 + \left(\mu_{b_j}^+\right)^3 - \left(\vartheta_{b_j}^-\right)^3 - \left(\vartheta_{b_j}^+\right)^3\right] + 0.5\left(\left(\mu_{b_j}\right)^3 - \left(\vartheta_{b_j}\right)^3\right) + 1\right) \tag{15}$$

in which, $\varphi_j \in [0,1]$.

Step 2.1.2. Clasifly the barriers

The significance levels of barriers are classified with the following rules based on the value of φ_j.

Level T_1: This level contains all of the barriers that have a score value up to twice less than that of the most critical barrier.

Level T_2: This level contains all of the barriers with a score value between two and three times less than the most critical barrier.

Level T_l: This level contains all of the barriers with a score value between l and $l+1$ times less than the most critical barrier.

By doing so, all of the barriers are classified into each significance level $T_\varepsilon(\varepsilon = 1, 2, \cdots, l)$.

Step 2.1.3. Defining the elasticity coefficient

First, based on the generated significance levels, the experts compare the barriers by their significance. Each barrier $b_j \in T_\varepsilon$ is assigned a value $\phi_{b_j} \in [0, \hbar]$. If the barrier b_j has greater importance than the barrier b_{j+1}, then $\phi_{b_j} < \phi_{b_{j+1}}$. The value of the parameter $\hbar$ is determined by:

$$\hbar = max\{|T_1|, |T_2|, \cdots, |T_l|\} \tag{16}$$

Then, according to the maximum value $\hbar$, the elasticity coefficient $\Delta\hbar$ is defined as.

$$\Delta\hbar > \hbar, \Delta\hbar = max\{|T_1|, |T_2|, \cdots, |T_l|\} \tag{17}$$

Step 2.1.4. Calculate the optimal values of weight coefficients of barriers

The weight coefficient of the most influential barrier is computed as.

$$w_{Bf} = \frac{1}{1 + \sum_{\substack{j=1 \\ j \neq Bf}}^{n} F(b_j)} \tag{18}$$

where the function $F(b_j)$ is structured as follows:

$$F(b_j) = \frac{\Delta\hbar}{\Delta\hbar \cdot \ell + \phi_{b_j}}, 1 \le \ell \le l \tag{19}$$

in which, the parameter ℓ indicates the number of levels of significance.

Step 2.1.5. Obtain the subjective weights of barriers

The final weight of each barrier is determined as.

$$w_j^s = F(b_j) w_{Bf}, j \neq Bf \tag{20}$$

where $w_j^s \in [0,1]$ and $\sum_{j=1}^{n} w_j^s = 1$.

Step 2.2. The FCF-CRITIC method for objective weight calculation

This sub-step introduces the FCF-CRITIC method to determine the objective weights of barriers and the computation process is expressed as follows.

Step 2.2.1. Standardize the group assessment matrix

The normalized group assessment matrix $\mathrm{K} = [k_{ij}]_{m\times n}$ is structured as follows.

$$k_{ij} = \begin{cases} \dfrac{\left|\left(\mu^-_{y_{ij}}\right)^3 - \left(\mu^-_{y_{i-}}\right)^3\right| + \left|\left(\mu^+_{y_{ij}}\right)^3 - \left(\mu^+_{y_{i-}}\right)^3\right| + \left|\left(\vartheta^-_{y_{ij}}\right)^3 - \left(\vartheta^-_{y_{i-}}\right)^3\right| + \left|\left(\vartheta^+_{y_{ij}}\right)^3 - \left(\vartheta^+_{y_{i-}}\right)^3\right| + \left|\left(\mu_{y_{ij}}\right)^3 - \left(\mu_{y_{i-}}\right)^3\right| + \left|\left(\vartheta_{y_{ij}}\right)^3 - \left(\vartheta_{y_{i-}}\right)^3\right|}{\left|\left(\mu^-_{y_{i+}}\right)^3 - \left(\mu^-_{y_{i-}}\right)^3\right| + \left|\left(\mu^+_{y_{i+}}\right)^3 - \left(\mu^+_{y_{i-}}\right)^3\right| + \left|\left(\vartheta^-_{y_{i+}}\right)^3 - \left(\vartheta^-_{y_{i-}}\right)^3\right| + \left|\left(\vartheta^+_{y_{i+}}\right)^3 - \left(\vartheta^+_{y_{i-}}\right)^3\right| + \left|\left(\mu_{y_{i+}}\right)^3 - \left(\mu_{y_{i-}}\right)^3\right| + \left|\left(\vartheta_{y_{i+}}\right)^3 - \left(\vartheta_{y_{i-}}\right)^3\right|}, & if\ j \in B \\ \dfrac{\left|\left(\mu^-_{y_{ij}}\right)^3 - \left(\mu^-_{y_{i+}}\right)^3\right| + \left|\left(\mu^+_{y_{ij}}\right)^3 - \left(\mu^+_{y_{i-}}\right)^3\right| + \left|\left(\vartheta^-_{y_{ij}}\right)^3 - \left(\vartheta^-_{y_{i-}}\right)^3\right| + \left|\left(\vartheta^+_{y_{ij}}\right)^3 - \left(\vartheta^+_{y_{i-}}\right)^3\right| + \left|\left(\mu_{y_{ij}}\right)^3 - \left(\mu_{y_{i-}}\right)^3\right| + \left|\left(\vartheta_{y_{ij}}\right)^3 - \left(\vartheta_{y_{i-}}\right)^3\right|}{\left|\left(\mu^-_{y_{i+}}\right)^3 - \left(\mu^-_{y_{i-}}\right)^3\right| + \left|\left(\mu^+_{y_{i+}}\right)^3 - \left(\mu^+_{y_{i-}}\right)^3\right| + \left|\left(\vartheta^-_{y_{i+}}\right)^3 - \left(\vartheta^-_{y_{i-}}\right)^3\right| + \left|\left(\vartheta^+_{y_{i+}}\right)^3 - \left(\vartheta^+_{y_{i-}}\right)^3\right| + \left|\left(\mu_{y_{i+}}\right)^3 - \left(\mu_{y_{i-}}\right)^3\right| + \left|\left(\vartheta_{y_{i+}}\right)^3 - \left(\vartheta_{y_{i-}}\right)^3\right|}, & if\ j \in NB \end{cases} \tag{21}$$

where k_{ij} is the standardized value of the element y_{ij}; $y_{i+} = max(y_1, y_2, \cdots, y_m)$, and $y_{i-} = min(y_1, y_2, \cdots, y_m)$.

Remark 1. The elements y_{i+} and y_{i-} are identified by comparing the actual values of the barriers, which are conducted using Eqs. (6) and (7).

Step 2.2.2. Compute the standard deviation of each barrier

The standard deviation δ_j of each barrier is gained as.

$$\delta_j = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}\left(k_{ij} - \overline{k}_j\right)^2} \tag{22}$$

where $\overline{k}_j$ is the mean value of the barrier b_j, which is computed as follows.

$$\overline{k}_j = \frac{1}{n}\sum_{i=1}^{m} k_{ij}, i = 1, 2, \cdots, m \tag{23}$$

Step 2.2.3. Calculate the correlation coefficient between each pair of barriers

The correlation coefficient ρ_{jj} between barriers b_j and b_j is defined as.

$$\rho_{jj} = \frac{\sum_{i=1}^{m}\left(k_{ij} - \overline{k}_j\right)\left(k_{ij} - \overline{k}_j\right)}{\sqrt{\sum_{i=1}^{m}\left(k_{ij} - \overline{k}_j\right)^2 \sum_{i=1}^{m}\left(k_{ij} - \overline{k}_j\right)^2}} \tag{24}$$

where $\overline{k}_j$ is the mean value of the barrier b_j whose calculation process is the same as the parameter $\overline{k}_j$.

Step 2.2.4. Compute the amount of information for each barrier

The amount of information $w_j^{'}$ for the barrier b_j is determined as follows.

$$w_j^{'} = \delta_j \sum_{j=1}^{n}\left(1 - \rho_{jj}\right) \tag{25}$$

Step 2.2.5. Obtain the objective weight of each barrier

The final objective weight w_j for the barrier b_j is computed as.

$$w_j^o = \frac{w_j^{'}}{\sum_{j=1}^{n} w_j^{'}} \tag{26}$$

where $w_j \in [0,1]$ and $\sum_{j=1}^{n} w_j = 1$.

Step 2.3. Obtain the integrated weights of barriers

The integrated weights of barriers are derived by combining the objective and subjective weights as follows:

$$w_j = \lambda \cdot w_j^o + (1-\lambda) \cdot w_j^s \tag{27}$$

in which, $w_j \in [0,1]$ and $0 \le \lambda \le 1$.

Stage 3: Evaluate and prioritize the implementation barriers using the FCF-RAFSI model

This phase describes the FCF-RAFSI model for evaluating and prioritizing the implementation barriers to DT in ET. The group assessment matrix $Y = [y_{ij}]_{m\times n}$ emanating from the FCF-WHMA operator (Stage 1) with the weight vector $w_j (j = 1, 2, \cdots, n)$ emanating from FCF-LBWA and FCF-CRITIC serves as the input information for the FCF-RAFSI model. The specific modeling procedures are expressed as follows.

Step 3.1. Form the original FCF-based decision matrix

Based on the calculation result obtained using Eq. (13), the original FCF-based decision matrix for barriers prioritization is expressed as $Y = [y_{ij}]_{m\times n}$.

Step 3.2: Calculate the score values of the decision matrix

The score matrix $\aleph = [r_{ij}]_{m\times n}$ of the decision matrix $Y = [y_{ij}]_{m\times n}$ is gained as follows.

$$\begin{aligned} r_{ij} = \mathfrak{I}(y_{ij}) = 0.5\Bigg(&0.25\left[\left(\mu^-_{y_{ij}}\right)^3 + \left(\mu^+_{y_{ij}}\right)^3 - \left(\vartheta^-_{y_{ij}}\right)^3 - \left(\vartheta^+_{y_{ij}}\right)^3\right] \\ &+ 0.5\left(\left(\mu_{y_{ij}}\right)^3 - \left(\vartheta_{y_{ij}}\right)^3\right) + 1\Bigg) \end{aligned} \tag{28}$$

where $r_{ij} \in [0,1]$ and $i = 1,2,\cdots,m; j = 1,2,\cdots,n$.

Step 3.3: Identity the optimistic and pessimistic values for barriers

The optimistic and pessimistic values for any barrier are determined using r_{ij} and the following equation.

$$b_j \in \begin{cases} \left(r_{Nj}, r_{Ij}\right), & \text{if } j \in B \\ \left(r_{Ij}, r_{Nj}\right), & \text{if } j \in NB \end{cases} \tag{29}$$

where the parameters r_{Nj} and r_{Ij} indicate the anti-ideal and ideal values of the barrier b_j.

Step 3.4: Establish the standardized decision matrix

The standardized decision matrix $\Gamma = \left(f_{ij}\right)_{m\times n}$ is formed through the following formulas. First, to transfer barriers of the original decision matrix to the criteria range $[\xi_1, \xi_{2\theta}]$, this paper sets a series of numbers from the interval θ.

$$\xi_1 \le \xi_2 \le \zeta_3 \le \xi_4 \cdots \le \xi_{2\theta-1} \le \xi_{2\theta} \tag{30}$$

Then the matrix $\Gamma = \left(f_{ij}\right)_{m\times n}$ is generated as follows.

$$\Gamma = \begin{array}{c} \\ b_1 \\ b_2 \\ \vdots \\ b_n \end{array} \begin{array}{c} \begin{array}{cccc} a_1 & a_2 & \cdots & a_m \end{array} \\ \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ f_{m1} & f_{m2} & \cdots & f_{mn} \end{bmatrix}_{m\times n} \end{array} \tag{31}$$

in which $f_{ij}(i = 1,2,\cdots,m; j = 1,2,\cdots,n)$ is calculated as.

$$f_{ij} = \frac{\xi_{2\theta} - \xi_1}{r_{Ij} - r_{Nj}} r_{ij} + \frac{r_{Ij}\cdot\xi_1 - r_{Nj}\cdot\xi_{2\theta}}{r_{Ij} - r_{Nj}} \tag{32}$$

where the parameters ξ_1 and $\xi_{2\theta}$ are suggested to be set as $\xi_1 = 1$ and $\xi_{2\theta}$ [41].

Step 3.5: Form the normalized decision matrix

We construct the normalized decision matrix $Z = [z_{ij}]_{m\times n}$ using the following formulas. First, the element z_{ij} is computed as.

$$z_{ij} = \begin{cases} \dfrac{f_{ij}}{2\sigma}, & \text{if } j \in B \\ \dfrac{\nu}{2f_{ij}}, & \text{if } j \in NB \end{cases} \tag{33}$$

where the parameters σ and ν denote the arithmetic and harmonic means, which are determined as follows.

$$\sigma = \frac{\xi_1 + \xi_{2\theta}}{2} \tag{34}$$

$$\nu = \frac{2}{\frac{1}{\xi_1} + \frac{1}{\xi_{2\theta}}} \tag{35}$$

Finally, the normalized decision matrix Z is denoted as.

$$Z = \begin{array}{c} \\ b_1 \\ b_2 \\ \vdots \\ b_n \end{array} \begin{array}{c} \begin{array}{cccc} a_1 & a_2 & \cdots & a_m \end{array} \\ \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1n} \\ z_{21} & z_{22} & \cdots & z_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ z_{m1} & z_{m2} & \cdots & z_{mn} \end{bmatrix}_{m\times n} \end{array} \tag{36}$$

where $z_{ij} \in [0,1]$, $i = 1,2,\cdots,m; j = 1,2,\cdots,n$.

Step 3.6: Gain the criteria function of alternatives

The priorities are determined based on the criteria function $\pi(a_i)$, which is defined as.

$$\pi(a_i) = w_1 z_{i1} + w_2 z_{i2} + \cdots + w_n z_{in} = \sum_{j=1}^{n} w_j z_{ij} \tag{37}$$

4. Empirical illustration

This section presents an empirical example to illustrate the application of the hybrid FCF-RAFSI model in assessing the barrier levels of DT in the energy sector.

4.1. Background of case study

Due to climate change, China has set an unambiguous target for a carbon peak by 2030 and carbon neutrality by 2060. Plenty of countries, such as the United States, Germany, and Switzerland, have introduced relevant policies and measures to promote the implementation of related digital technology in the energy revolution and transition. In addition, several studies provide evidence that digital technologies will benefit the resource and energy sectors in the future. In such cases, the Chinese government has unveiled a trio of proposals to accelerate the digitalization of the energy sector. Currently, the National Energy Administration of China published "several opinions on accelerating the development of energy digitalization and intelligence", in which the priority development of electric power industry digitization has been

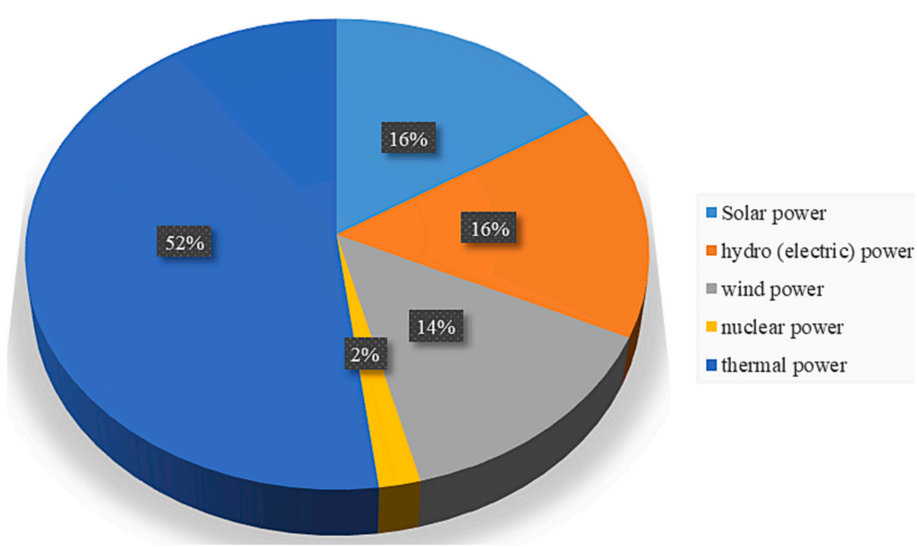

Fig. 3. Proportion of installed power sources in 2022.

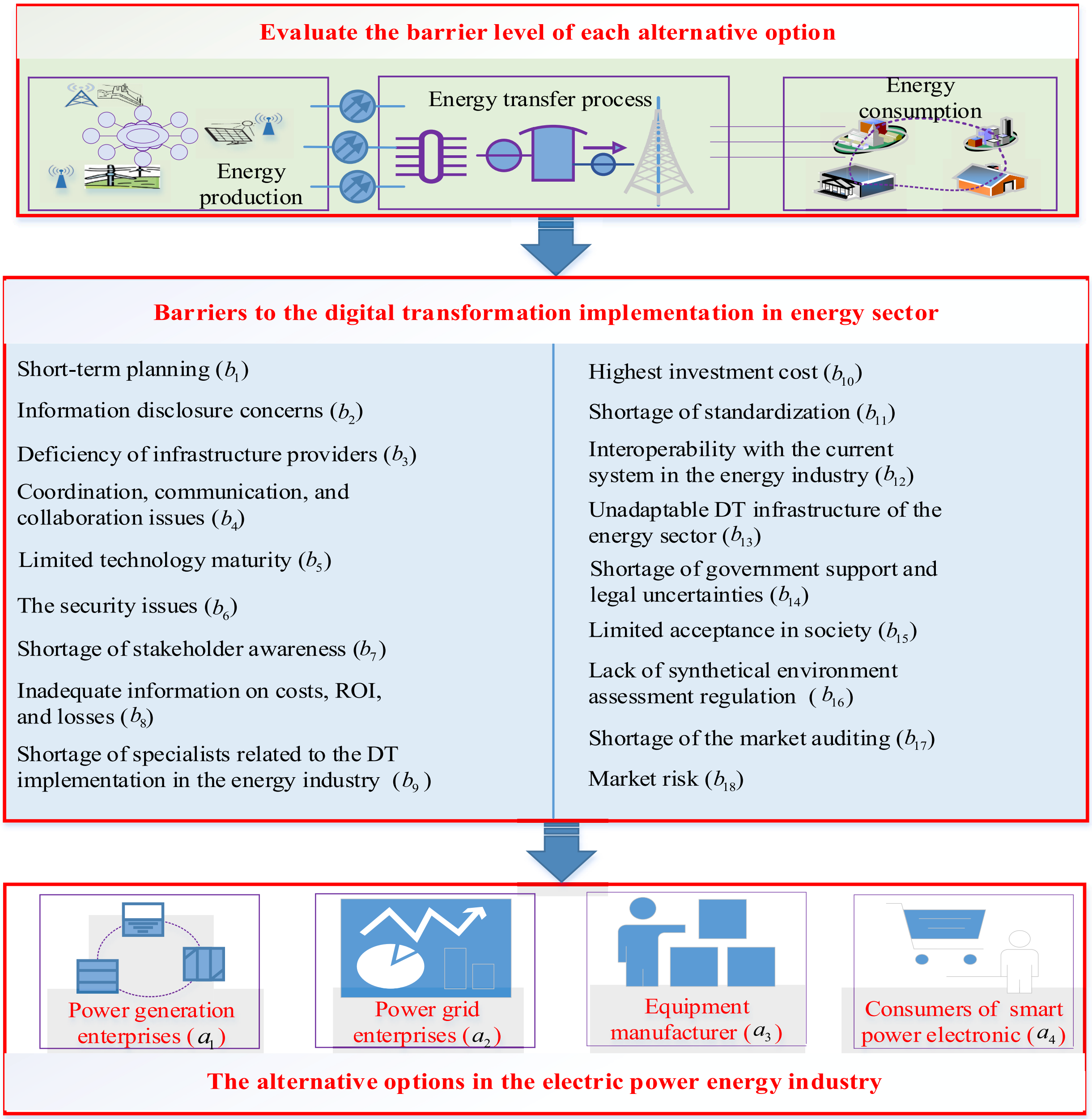

Fig. 4. Hierarchical structure of evaluating barriers to DT implementation in the energy industry.

suggested. On the other hand, with the continuous structural adjustment of China's electric power system (see Fig. 3), the digitalization of the power industry chain should overcome various challenges and barriers [72]. Identifying, analyzing, and evaluating barrier levels of enterprises involved in the electric power industry chain is the foundation of its digitization. To analyze and assess the barrier levels of different electric power industry chain enterprises, this paper selects four enterprises (a_1, a_2, a_3, a_4) as the alternative options and the barriers listed in Section 2 as the criteria. So, the evaluation of barriers to implementing DT in the electric power industry chain is presented in Fig. 4. Fig.4 illustrates the hierarchical structure of evaluating barriers to DT implementation in the energy industry, which consists of three levels: the goal, the barriers, and the alternative options.

4.2. Data collection

In the current work, evaluation data is collected by conducting an interviewing method. The questionnaire was developed in two sections, one for basic information of experts and the second for a rating of alternatives with respect to barriers using the linguistic scale defined in Ref. [73]. The questionnaire is provided in Appendix A. In such cases, to evaluate the implementation barriers to DT in the electric power energy industry and appraise the barrier levels of the alternative options, we generate a panel of three experts (e_1, e_2, e_3) who are in charge of conducting the two procedures. These experts are chosen from different positions associated with DT and the power industry. All the experts have more than five years of experience in digital technology, and detailed information about these experts is given in Table 4. Three experts and evaluation data that evaluate the barrier level of each option are reported in Table 5.

4.3. Experimental results

This subsection describes the detailed application procedures for the

Table 4
The information of experts.

Experts	Degree	Field	Positions	Experiential overall	Experience in DT
e_1	M.S	Power industry	Senior executive	15	7
e_2	Ph.D.	Academia	Researcher	9	6
e_3	Ph.D.	Academia	Researcher	16	5

presented framework according to the input evaluation data of the alternative electric power companies.

Steps 1.1–1.3: First, based on Table 5, the FCFN-based assessment matrixes are created through the transformation rules introduced by Rong et al. [28], given in Appendix B. Then, the mean value matrix is calculated using Eqs. (9) and (10), and the elements are given in Table 6.

Steps 1.4–1.6: First, the experts' weights are determined using Eqs. (11)–(12) and MS Excel, and the result is expressed as $\omega_t = \{0.333, 0.350, 0.317\}$. Finally, the group assessment matrix is generated using Eq. (13) and MS Excel, provided in Table 7.

To generate the weights of barriers, we should conduct three steps: Step 2.1, Step 2.2, and Step 2.3, which include eleven substeps. These substeps are organized as follows. Steps 2.1.1–2.1.2: First, three experts provide their preference for the significance of each barrier. Later, we determine the level of each implementation barrier based on Eq. (15) with the help of rules presented in Step 2.1.2, which is reported in Table 8.

Steps 2.1.3–2.1.5: First, the value of the parameter $\hbar$ is determined using Eq. (16), and the result is expressed as $\hbar = max\{|T_1|, |T_2|, |T_3|, |T_4|\} = 9$. Next, the elasticity coefficient is determined using Eq. (17), denoted as $\Delta\hbar = 10$. Finally, from Eqs. (18)–(20), we can calculate the subjective weights of barriers, and the results are given in Table 9.

Next, we conduct Step 2.2 to obtain the objective weights of barriers, which include 5 substeps. Step 2.2.1: the normalized group assessment matrix is created using Eq. (21) and MS Excel, are presented in Table 10.

Steps 2.2.2–2.2.5: the correlation coefficient and standard deviation are calculated using Eqs. (22)–(24). After that, the amount of information and objective weight of each barrier is gained using Eqs. (25)–(26). The calculation process is finished through MATLAB R2022a and MS Excel, which is presented in Table 11.

Step 2.3: According to the weights from Step 2.1 and Step 2.2, the integrated weight of each barrier is derived using Eq. (27) with the parameter $\lambda = 0.5$, and the results are given in Table 12.

Steps 3.1–3.2: First, the score values of the decision matrix are gained using Eq.(28) with the help of Table 7. Then, the optimistic and pessimistic values for barriers are identified using Eq. (29), is given in Table 13.

Steps 3.4–3.6: First, the standardized and normalized decision matrixes are created using Eqs. (30)–(36) and MS Excel. Then, the criteria function of each option is determined using Eq. (37) and MATLAB R2022a, and the results are reported in Table 14.

From Table 14, the barrier levels of options are prioritized concerning the criteria function $\pi(a_i)$, and the final ranking $a_3 \succ a_2 \succ a_1 \succ a_4$. The option a_3 has the highest barrier level while a_4 has the lowest barrier level.

Table 6
The mean value matrix.

	a_1	a_2	a_3	a_4
b_1	0.283	0.317	0.450	0.717
b_2	0.250	0.283	0.350	0.650
b_3	0.317	0.350	0.350	0.717
b_4	0.350	0.250	0.217	0.317
b_5	0.283	0.350	0.250	0.517
b_6	0.317	0.317	0.317	0.350
b_7	0.450	0.383	0.317	0.317
b_8	0.450	0.317	0.317	0.250
b_9	0.383	0.317	0.283	0.250
b_{10}	0.383	0.317	0.250	0.250
b_{11}	0.383	0.317	0.283	0.317
b_{12}	0.283	0.350	0.417	0.283
b_{13}	0.450	0.317	0.317	0.650
b_{14}	0.683	0.717	0.517	0.450
b_{15}	0.350	0.283	0.217	0.783
b_{16}	0.250	0.317	0.417	0.750
b_{17}	0.383	0.350	0.383	0.683
b_{18}	0.317	0.250	0.217	0.517

4.4. Sensitivity study

This section presents a three-part sensitivity analysis. The first two parts explore the impact of parameters λ, α, and β on the final barrier levels of the four alternative options in the power sector. Since the values of the parameter λ are assigned by experts, this may cause inconsistent results under different conditions. Further, the parameters α and β impact on the group assessment matrix formed via the WHMA operator. Consequently, a sensitivity study should be involved to analyze the influence of these parameters on the final evaluation result for barriers to the implementation of DT in the energy sector. To do that, we describe two simulations of the variation of these parameters and

Table 5
The linguistic decision matrix from experts.

	e_1				e_2				e_3			
Barriers	a_1	a_2	a_3	a_4	a_1	a_2	a_3	a_4	a_1	a_2	a_3	a_4
b_1	VH	H	M	VL	H	H	M	L	VH	VH	M	VL
b_2	H	VH	H	L	EH	H	H	L	VH	VH	H	L
b_3	VH	H	VH	L	H	H	H	VL	H	H	M	VL
b_4	H	VH	EH	H	H	VH	VH	H	H	VH	VH	VH
b_5	VH	H	VH	M	H	H	VH	L	VH	H	VH	M
b_6	H	H	VH	H	VH	VH	H	H	H	H	H	H
b_7	M	H	VH	H	M	M	H	H	M	H	H	VH
b_8	M	H	VH	VH	M	VH	H	VH	M	H	H	VH
b_9	H	VH	VH	VH	H	H	VH	H	M	H	VH	EH
b_{10}	H	VH	VH	VH	H	H	VH	VH	M	H	H	VH
b_{11}	H	H	VH	VH	M	H	H	H	H	VH	VH	H
b_{12}	VH	H	H	VH	VH	H	M	H	H	H	M	VH
b_{13}	M	H	VH	L	M	VH	H	L	M	H	H	L
b_{14}	L	VL	L	M	VL	VL	M	M	L	L	M	M
b_{15}	H	VH	EH	VL	H	VH	VH	EL	H	H	VH	VL
b_{16}	H	H	M	VL	VH	VH	M	EL	EH	H	H	L
b_{17}	H	M	M	L	H	VH	H	VL	M	H	H	L
b_{18}	VH	VH	VH	M	H	VH	EH	L	H	VH	VH	M

Table 7
The group assessment matrix.

	a_1	a_2	a_3	a_4
b_1	<([0.719,0.769], [0.701,0.709]), (0.905,0.265)>	<([0.686,0.735], [0.721,0.736]), (0.903,0.298)>	<([0.466,0.512], [0.773,0.82]), (0.848,0.419)>	<([0.218,0.265], [0.841,0.973]), (0.753,0.671)>
b_2	<([0.755,0.807], [0.688,0.691]), (0.91,0.238)>	<([0.719,0.769], [0.701,0.709]), (0.905,0.265)>	<([0.654,0.702], [0.743,0.756]), (0.891,0.326)>	<([0.279,0.326], [0.84,0.953]), (0.794,0.607)>
b_3	<([0.688,0.736], [0.731,0.734]), (0.894,0.296)>	<([0.654,0.702], [0.743,0.756]), (0.891,0.326)>	<([0.635,0.684], [0.763,0.762]), (0.881,0.329)>	<([0.218,0.265], [0.841,0.973]), (0.753,0.671)>
b_4	<([0.654,0.702], [0.743,0.756]), (0.891,0.326)>	<([0.751,0.802], [0.676,0.675]), (0.901,0.232)>	<([0.787,0.839], [0.66,0.65]), (0.9,0.205)>	<([0.686,0.735], [0.721,0.736]), (0.903,0.298)>
b_5	<([0.719,0.769], [0.701,0.709]), (0.905,0.265)>	<([0.654,0.702], [0.743,0.756]), (0.891,0.326)>	<([0.751,0.802], [0.676,0.675]), (0.901,0.232)>	<([0.41,0.456], [0.801,0.886]), (0.848,0.484)>
b_6	<([0.688,0.736], [0.731,0.734]), (0.894,0.296)>	<([0.688,0.736], [0.731,0.734]), (0.894,0.296)>	<([0.688,0.736], [0.731,0.734]), (0.894,0.296)>	<([0.654,0.702], [0.743,0.756]), (0.891,0.326)>
b_7	<([0.466,0.512], [0.773,0.82]), (0.848,0.419)>	<([0.596,0.643], [0.75,0.782]), (0.886,0.358)>	<([0.688,0.736], [0.731,0.734]), (0.894,0.296)>	<([0.686,0.735], [0.721,0.736]), (0.903,0.298)>
b_8	<([0.466,0.512], [0.773,0.82]), (0.848,0.419)>	<([0.688,0.736], [0.731,0.734]), (0.894,0.296)>	<([0.688,0.736], [0.731,0.734]), (0.894,0.296)>	<([0.751,0.802], [0.676,0.675]), (0.901,0.232)>
b_9	<([0.599,0.647], [0.77,0.779]), (0.875,0.357)>	<([0.688,0.736], [0.731,0.734]), (0.894,0.296)>	<([0.721,0.771], [0.714,0.705]), (0.892,0.264)>	<([0.751,0.802], [0.676,0.675]), (0.901,0.232)>
b_{10}	<([0.599,0.647], [0.77,0.779]), (0.875,0.357)>	<([0.688,0.736], [0.731,0.734]), (0.894,0.296)>	<([0.751,0.802], [0.676,0.675]), (0.901,0.232)>	<([0.754,0.806], [0.681,0.691]), (0.917,0.241)>
b_{11}	<([0.596,0.643], [0.75,0.782]), (0.886,0.358)>	<([0.686,0.735], [0.721,0.736]), (0.903,0.298)>	<([0.719,0.769], [0.701,0.709]), (0.905,0.265)>	<([0.688,0.736], [0.731,0.734]), (0.894,0.296)>
b_{12}	<([0.721,0.771], [0.714,0.705]), (0.892,0.264)>	<([0.654,0.702], [0.743,0.756]), (0.891,0.326)>	<([0.531,0.578], [0.773,0.802]), (0.864,0.389)>	<([0.719,0.769], [0.701,0.709]), (0.905,0.265)>
b_{13}	<([0.466,0.512],[0.773,0.82]), (0.848,0.419)>	<([0.688,0.736], [0.731,0.734]), (0.894,0.296)>	<([0.688,0.736],[0.731,0.734]), (0.894,0.296)>	<([0.279,0.326], [0.84,0.953]), (0.794,0.607)>
b_{14}	<([0.25,0.296],[0.832,0.965]), (0.78,0.64)>	<([0.217,0.264],[0.823,0.974]), (0.762,0.673)>	<([0.41,0.456], [0.801,0.886]), (0.848,0.484)>	<([0.466,0.512], [0.773,0.82]), (0.848,0.419)>
b_{15}	<([0.654,0.702], [0.743,0.756]), (0.891,0.326)>	<([0.721,0.771], [0.714,0.705]), (0.892,0.264)>	<([0.787,0.839], [0.66,0.65]), (0.9,0.205)>	<([0.16,0.205], [0.811,0.988]), (0.711,0.736)>
b_{16}	<([0.754,0.806], [0.681,0.691]), (0.917,0.241)>	<([0.688,0.736], [0.731,0.734]), (0.894,0.296)>	<([0.529,0.576], [0.755,0.804]), (0.875,0.391)>	<([0.193,0.238], [0.806,0.984]), (0.75,0.708)>
b_{17}	<([0.599,0.647], [0.77,0.779]), (0.875,0.357)>	<([0.631,0.679], [0.741,0.765]), (0.894,0.33)>	<([0.596,0.643], [0.75,0.782]), (0.886,0.358)>	<([0.25,0.296], [0.832,0.965]), (0.78,0.64)>
b_{18}	<([0.688,0.736], [0.731,0.734]), (0.894,0.296)>	<([0.751,0.802], [0.676,0.675]), (0.901,0.232)>	<([0.787,0.839], [0.66,0.65]), (0.9,0.205)>	<([0.41,0.456],[0.801,0.886]), (0.848,0.484)>

their effects on the final barriers level evaluation result in the subsequent subsections.

4.4.1. Exploration of the variation of parameter λ

In the presented framework, the weights calculation model is set that the variation range of the parameter λ should be $\lambda \in [0,1]$; namely, the value $\lambda = 0.5$ is utilized to generate the integrated weight. Then, this portion explores the change rule of the criteria function $\pi(a_i)$ in which we simulate the variation of the parameter λ in the interval $[0,1]$. We first set the initial value of the parameter λ as $\lambda = 0.0$, while the value keeps the increase of 10% in the follow-up scenarios. The impact of the parameter's variation values on the criteria function of each option $\pi(a_i)$ is shown in Fig.5.

Fig.5 indicates the variation tendency in the values of the function $\pi(a_i)$ for each option. The results show that the values of the parameter λ do have an impact on $\pi(a_i)$. More precisely, the values of the function $\pi(a_i)$ of options a_1 and a_2 decrease along with the values of the parameter λ increasing, while the values in the function $\pi(a_i)$ of options a_3 and a_4 increase. At the meantime, these variation tendencies on the function $\pi(a_i)$ remain within a small interval and do not affect the ranking result of the options. Consequently, according to the results described in Fig.5, we can conclude that the ranking $a_3 \succ a_2 \succ a_1 \succ a_4$ is stable through the simulation process. This result means that the established framework in the current study is robust to analyze the barriers to DT implementation in the energy sector.

4.4.2. Exploration of the variation of parameters α and β

In the individual decision data collection procedure, the elements are related to the parameters α and β involved in the WHMA operator. In the presented construction model for the group assessment matrix, a scene is set that the values of the parameters α and β should be $\alpha > 0, \beta > 0$; that is, the values $\alpha = 1$ and $\beta = 1$ are applied to calculate the elements of the group assessment matrix. This subsection describes a simulation for exploring the impact of the variation of the parameters α and β where the change of α and β is set in the interval $[1,10]$. In the first condition, we analyze the ranking orders of alternative options with different combinations of the values of the parameters α and β, and the result is presented in Table 15.

Table 15 shows the change in ranking orders of the alternative options $a_i (i = 1,2,3,4)$. The results indicate that the values of criteria function of options a_1 and a_2 remain within a small interval, while the values of options a_3 and a_4 vary significantly. These results reveal that the combinations of the parameters α and β have an indeed influence on the final calculation result of the barrier levels. Moreover, in the first scenario, the parameter α is set as $\alpha = 1$, different values are assigned to the parameter β, and the ranking orders are listed in the last column in Table 15. The result shows that the option a_4 has the lowest barrier level, irrespective of the values of the parameter β. In contrast, the other options have inconsistent ranking orders with different values of the parameter β. In particular, the ranking orders of the options remain stable when the value of the parameter β is set as $\beta > 6$. In Scenario II and Scenario III, the parameter α is set as $\alpha = 2$ and $\alpha = 3$; then, we investigate the variation tendency of ranking orders for each option with the change of the value of the parameter β. The result shows that the ranking orders are determined as $a_3 \succ a_2 \succ a_1 \succ a_4$ when the parameters α and β have smaller values. Conversely, the ranking orders are derived as $a_2 \succ a_1 \succ a_3 \succ a_4$ when the value of the parameter β is set to a number higher than six. In Scenario IV, we can reach a similar conclusion.

Furthermore, we also simulate the variation tendency of the criteria function $\pi(a_i)$ when the values of the parameters α and β synchronously change. To give a more visualized simulation result, the variation ten-

Table 8
Comparisons of importance degrees for barriers from experts.

Barriers	e_1	e_2	e_3	Level T_ε
b_1	<([0.30,0.35], [0.70,0.75]), (0.35,0.65)>	<([0.28,0.33], [0.68,0.78]), (0.31,0.64)>	<([0.26,0.35], [0.65,0.79]), (0.33,0.62)>	T_2
b_2	<([0.27,0.32], [0.73,0.75]), (0.28,0.63)>	<([0.26,0.33], [0.65,0.70]), (0.31,0.64)>	<([0.23,0.29], [0.67,0.70]), (0.30,0.67)>	T_2
b_3	<([0.27,0.32], [0.73,0.75]), (0.28,0.63)>	<([0.26,0.33], [0.65,0.70]), (0.31,0.64)>	<([0.23,0.29], [0.67,0.70]), (0.30,0.67)>	T_2
b_4	<([0.27,0.32], [0.73,0.75]), (0.28,0.63)>	<([0.26,0.33], [0.65,0.70]), (0.31,0.64)>	<([0.23,0.29], [0.67,0.70]), (0.30,0.67)>	T_2
b_5	<([0.87,0.91], [0.12,0.14]), (0.83,0.12)>	<([0.87,0.93], [0.13,0.16]), (0.81,0.17)>	<([0.85,0.89], [0.13,0.16]), (0.73,0.11)>	T_1
b_6	<([0.70,0.73], [0.33,0.37]), (0.63,0.39)>	<([0.69,0.75], [0.30,0.38]), (0.64,0.37)>	<([0.71,0.75], [0.35,0.36]), (0.65,0.36)>	T_1
b_7	<([0.85,0.89], [0.13,0.17]), (0.81,0.17)>	<([0.87,0.93], [0.13,0.16]), (0.79,0.18)>	<([0.85,0.89], [0.13,0.16]), (0.73,0.11)>	T_1
b_8	<([0.29,0.34], [0.72,0.73]), (0.28,0.62>	<([0.23,0.29], [0.67,0.70]), (0.30,0.67)>	<([0.28,0.34], [0.62,0.68]), (0.30,0.62)>	T_2
b_9	<([0.28,0.33], [0.73,0.74]), (0.28,0.63)>	<([0.27,0.33], [0.63,0.69]), (0.31,0.64)>	<([0.23,0.29], [0.67,0.70]), (0.30,0.67)>	T_2
b_{10}	<([0.9,0.95], [0.1,0.15]), (0.85,0.15)>	<([0.89,0.92], [0.15,0.17]), (0.78,0.17)>	<([0.88,0.94], [0.13,0.18]), (0.82,0.19)>	T_1
b_{11}	<([0.85,0.89], [0.13,0.17]), (0.81,0.17)>	<([0.87,0.93], [0.13,0.16]), (0.79,0.18)>	<([0.85,0.89], [0.13,0.16]), (0.73,0.11)>	T_1
b_{12}	<([0.20,0.25], [0.80,0.85]), (0.25,0.75)>	<([0.19,0.24], [0.79,0.86]), (0.23,0.75)>	<([0.20,0.23], [0.81,0.86]), (0.25,0.75)>	T_2
b_{13}	<([0.27,0.32], [0.73,0.75]), (0.28,0.63)>	<([0.26,0.33], [0.65,0.70]), (0.31,0.64)>	<([0.23,0.29], [0.67,0.70]), (0.30,0.67)>	T_2
b_{14}	<([0.30,0.35], [0.70,0.75]), (0.35,0.65)>	<([0.30,0.34], [0.69,0.74]), (0.31,0.64)>	<([0.27,0.35], [0.65,0.73]), (0.33,0.62)>	T_2
b_{15}	<([0.50,0.55], [0.40,0.45]), (0.50,0.45)>	<([0.65,0.73], [0.35,0.38]), (0.57,0.40)>	<([0.67,0.73], [0.36,0.37]), (0.62,0.43)>	T_1
b_{16}	<([0.08,0.13], [0.93,0.95]), (0.14,0.89)>	<([0.09,0.14], [0.93,0.97]), (0.12,0.88)>	<([0.1,0.15], [0.90,0.95]), (0.15,0.85)>	T_3
b_{17}	<([0.1,0.15], [0.90,0.95]), (0.15,0.85)>	<([0.1,0.14], [0.90,0.93]), (0.15,0.83)>	<([0.1,0.15], [0.90,0.95]), (0.14,0.85)>	T_3
b_{18}	<([0.09,0.14], [0.91,0.96]), (0.12,0.88)>	<([0.09,0.14], [0.91,0.96]), (0.13,0.86)>	<([0.08,0.13], [0.93,0.95]), (0.14,0.89)>	T_3

dency is presented geometrically in Fig. 6(a)–(d). The results in Fig. 6(a) and (b) show that the options a_1 and a_2 have the most prominent criteria functions when the parameters α and β have smaller values. Further, the criteria functions of all four options have relatively large values when only one parameter has a more considerable crisp number. These results reveal that the values of parameters α and β have an impact on the criteria function $\pi(a_i)$. Then, according to the results reported in Table 15 and Fig. 6(a)–(d), we can conclude that it is needful and significant to incorporate the interrelationships between decision information into constructing a group assessment matrix.

4.4.3. *Exploration of changing numbers of experts*

Further, to reflect the influence of different sets of experts on the ranking orders, this subsection conducts the sensitivity investigation of

Table 9
Comparisons of importance degrees for barriers from experts.

Barriers	ϕ_{b_j}	ℓ	$F(b_j)$	$w_{Bf} = \dfrac{1}{1+\sum_{j=1, j\neq Bf}^{18} F(b_j)}$	$w_j^s = F(b_j)w_{Bf}$
b_1	2	2	0.4545	N	0.0484
b_2	8	2	0.3571	N	0.0380
b_3	8	2	0.3571	N	0.0380
b_4	8	2	0.3571	N	0.0380
b_5	1	1	0.9091	N	0.0969
b_6	4	1	0.7143	N	0.0761
b_7	2	1	0.8333	N	0.0888
b_8	3	2	0.4348	N	0.0463
b_9	4	2	0.4167	N	0.0444
b_{10}	0	1	1.0000	0.1065	0.1065
b_{11}	3	1	0.7692	N	0.0820
b_{12}	9	2	0.3448	N	0.0367
b_{13}	8	2	0.3571	N	0.0380
b_{14}	1	2	0.4762	N	0.0507
b_{15}	5	1	0.6667	N	0.0710
b_{16}	3	3	0.3030	N	0.0323
b_{17}	1	3	0.3226	N	0.0344
b_{18}	2	3	0.3125	N	0.0333

Table 10
The normalized group assessment matrix.

	a_1	a_2	a_3	a_4
b_1	0.669	0.651	0.541	0.388
b_2	0.689	0.669	0.622	0.432
b_3	0.638	0.622	0.596	0.388
b_4	0.622	0.684	0.701	0.651
b_5	0.669	0.622	0.684	0.518
b_6	0.638	0.638	0.638	0.622
b_7	0.541	0.601	0.638	0.651
b_8	0.541	0.638	0.638	0.684
b_9	0.582	0.638	0.651	0.684
b_{10}	0.582	0.638	0.684	0.700
b_{11}	0.601	0.651	0.669	0.638
b_{12}	0.651	0.622	0.560	0.669
b_{13}	0.541	0.638	0.638	0.432
b_{14}	0.418	0.403	0.518	0.541
b_{15}	0.622	0.651	0.701	0.357
b_{16}	0.700	0.638	0.579	0.391
b_{17}	0.582	0.618	0.601	0.418
b_{18}	0.638	0.684	0.701	0.518

changing numbers of experts. To this end, we first change the number of experts from four to seven, then calculate the criteria functions and ranking orders of all four alternative options by using Eqs. (8)–(37), MS Excel, and MATLAB R2022a. The results are given in Table 16.

Table 16 shows that the number of experts has an impact on the values of the criteria function $\pi(a_i)$; however, they do not influence the ranking orders of the alternative options. This result indicates that the proposed framework is a robust tool to evaluate the barriers to implementing DT in the ET.

4.5. *Comparison analysis*

This section compares the existing MCDM methods-based barrier analysis frameworks [14] and the proposed model. Therefore, to demonstrate the preponderance and unique character of the FCF-RAFSI model, we choose the FCF-WASPAS method, the FCF-TOPSIS method, the FCF-COPRAS model, and the FCF-EDAS method to fulfill the aforesaid empirical example. Note the individual decision matrixes for all the methods are the same as the presented FCF-RAFSI model. Consequently, the calculation results and ranking orders of alternative options are reported in Table 17.

Based on Table 17, to give a more visualized comparison result, the ranking orders calculated by different frameworks are presented

Table 11
The correlation coefficient and standard deviation.

	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}	b_{11}	b_{12}	b_{13}	b_{14}	b_{15}	b_{16}	b_{17}	b_{18}	δ_j
b_1	1.000	0.952	0.873	0.601	0.998	0.804	0.998	0.991	0.919	0.998	1.000	0.998	0.996	0.496	0.933	0.997	0.864	0.990	0.901
b_2	0.906	1.000	0.958	0.264	0.937	0.893	0.940	0.824	0.632	0.868	0.908	0.940	0.947	0.179	0.997	0.944	0.951	0.969	0.937
b_3	0.870	0.981	1.000	0.043	0.900	0.993	0.903	0.790	0.574	0.834	0.872	0.903	0.910	−0.09	0.990	0.907	1.000	0.933	0.970
b_4	0.948	0.368	−0.68	1.000	0.923	−0.87	0.920	0.976	0.994	0.965	0.947	0.920	0.910	1.000	0.013	0.915	−0.73	0.865	0.814
b_5	0.992	0.835	0.552	0.532	1.000	0.380	1.000	0.938	0.781	0.970	0.993	1.000	0.999	0.482	0.762	0.999	0.526	0.985	0.908
b_6	−0.95	0.979	0.999	−0.99	−0.90	1.000	−0.89	−0.98	−0.99	−0.97	−0.94	−0.89	−0.86	−0.99	0.992	−0.87	1.000	−0.53	1.000
b_7	0.978	0.813	0.614	0.121	1.000	0.515	1.000	0.832	0.478	0.920	0.981	1.000	0.999	0.068	0.754	1.000	0.599	0.978	0.908
b_8	0.965	0.430	0.021	0.809	0.914	−0.16	0.907	1.000	0.947	0.992	0.962	0.907	0.889	0.778	0.303	0.897	−0.01	0.807	0.889
b_9	0.898	−0.05	−0.58	0.982	0.820	−0.72	0.809	0.974	1.000	0.946	0.894	0.809	0.780	0.975	−0.25	0.793	−0.61	0.646	0.865
b_{10}	0.996	0.545	−0.13	0.898	0.980	−0.38	0.977	0.997	0.964	1.000	0.995	0.977	0.969	0.883	0.346	0.973	−0.17	0.928	0.895
b_{11}	1.000	0.054	−0.49	0.867	0.989	−0.61	0.986	0.978	0.926	0.992	1.000	0.986	0.975	0.856	−0.18	0.980	−0.51	0.896	0.902
b_{12}	0.979	0.668	0.305	0.463	1.000	0.153	1.000	0.875	0.676	0.933	0.981	1.000	0.999	0.426	0.554	1.000	0.280	0.970	0.908
b_{13}	0.995	0.971	0.909	0.306	1.000	0.858	1.000	0.966	0.818	0.985	0.996	1.000	1.000	0.174	0.956	1.000	0.902	0.998	0.910
b_{14}	0.492	0.404	0.350	0.950	0.474	0.314	0.472	0.534	0.635	0.512	0.490	0.472	0.467	1.000	0.389	0.469	0.345	0.452	0.797
b_{15}	0.928	0.998	0.986	0.410	0.949	0.949	0.951	0.876	0.741	0.904	0.930	0.951	0.955	0.316	1.000	0.953	0.982	0.970	0.945
b_{16}	0.997	0.967	0.886	0.573	1.000	0.810	1.000	0.976	0.883	0.989	0.997	1.000	1.000	0.479	0.949	1.000	0.876	0.998	0.909
b_{17}	0.878	0.983	1.000	−0.15	0.908	0.996	0.911	0.792	0.526	0.840	0.880	0.911	0.918	−0.30	0.991	0.915	1.000	0.939	0.974
b_{18}	0.967	0.920	0.650	0.535	0.988	0.455	0.990	0.901	0.756	0.936	0.969	0.990	0.994	0.488	0.860	0.992	0.622	1.000	0.916
w_j^o	0.015	0.029	0.038	0.067	0.032	0.266	0.042	0.054	0.083	0.051	0.071	0.046	0.021	0.075	0.023	0.016	0.042	0.029	_

Table 12
The weight calculation result for each barrier.

	$w_j^{'}$	w_j^o	w_j
b_1	1.4352	0.0154	0.0319
b_2	2.7570	0.0296	0.0338
b_3	3.5738	0.0383	0.0382
b_4	6.1974	0.0665	0.0523
b_5	2.9712	0.0319	0.0644
b_6	24.7791	0.2658	0.1710
b_7	3.9517	0.0424	0.0656
b_8	5.0119	0.0538	0.0500
b_9	7.6890	0.0825	0.0634
b_{10}	4.7051	0.0505	0.0785
b_{11}	6.5853	0.0706	0.0763
b_{12}	4.3042	0.0462	0.0415
b_{13}	1.9707	0.0211	0.0296
b_{14}	6.9986	0.0751	0.0629
b_{15}	2.1256	0.0228	0.0469
b_{16}	1.4750	0.0158	0.0241
b_{17}	3.9548	0.0424	0.0384
b_{18}	2.7347	0.0293	0.0313

Table 13
The score values and optimistic and pessimistic values for barriers.

	a_1	a_2	a_3	a_4	r_{Nj}	r_{Ij}
b_1	0.6694	0.6515	0.5405	0.3885	0.3800	0.6700
b_2	0.6895	0.6694	0.6220	0.4319	0.4300	0.7000
b_3	0.6375	0.6220	0.5964	0.3885	0.3800	0.6400
b_4	0.6220	0.6838	0.7011	0.6515	0.6200	0.7100
b_5	0.6694	0.6220	0.6838	0.5176	0.5100	0.6900
b_6	0.6375	0.6375	0.6375	0.6220	0.6200	0.6400
b_7	0.5405	0.6013	0.6375	0.6515	0.5300	0.6700
b_8	0.5405	0.6375	0.6375	0.6838	0.5300	0.6900
b_9	0.5818	0.6375	0.6512	0.6838	0.5800	0.7000
b_{10}	0.5818	0.6375	0.6838	0.6997	0.5800	0.7100
b_{11}	0.6013	0.6515	0.6694	0.6375	0.5900	0.6800
b_{12}	0.6512	0.6220	0.5600	0.6694	0.5500	0.6800
b_{13}	0.5405	0.6375	0.6375	0.4319	0.4300	0.6500
b_{14}	0.4184	0.4033	0.5176	0.5405	0.3900	0.5500
b_{15}	0.6220	0.6512	0.7011	0.3568	0.3500	0.7100
b_{16}	0.6997	0.6375	0.5791	0.3908	0.3800	0.7100
b_{17}	0.5818	0.6180	0.6013	0.4184	0.4100	0.6300
b_{18}	0.6375	0.6838	0.7011	0.5176	0.5100	0.7100

geometrically in Fig.7.

Table 17 and Fig.7 present the ranking orders of alternative options with different barriers analysis and evaluation models. We can find that a_3 "Equipment manufacturer" has the highest barrier level, and a_4 "Consumers of smart power electronic" has the lowest barrier level in all frameworks but the IVFF-TOPSIS method. This consistent result shows that the proposed FCF-RAFSI model is practical in addressing the analysis and evaluation issues for implementation barriers to DT in the electric power industry chain within an uncertain context. On the other side, the Pearson correlation coefficient among these models is introduced to implement the comparison study, and the result is shown in Fig.8. From Fig.8, we can conclude that the proposed model has significant correlation coefficients with other models except the TOPSIS method.

According to the comparison exploration, the advantages and outcomes of the presented barriers analysis model are listed as follows.

- As stated by Rani et al. [74], the WASPAS method should conduct a complex process of fusing the preference values of alternative options. Compared with the WASPAS method, the proposed FCF-RAFSI model is free from this difficulty. Thus, our developed framework can provide a more practical means for evaluating the barriers to implementing DT in the power sector.
- The TOPSIS method determines the barrier levels using positive and negative distance measures. As pointed out by Stević et al. [75], this

Table 14
The calculation results of the criteria function.

	f_{ij}				z_{ij}			
	a_1	a_2	a_3	a_4	a_1	a_2	a_3	a_4
b_1	5.9897	5.6810	3.7672	1.1466	0.8557	0.8116	0.5382	0.1638
b_2	5.8056	5.4333	4.5556	1.0352	0.8294	0.7762	0.6508	0.1479
b_3	5.9519	5.6538	5.1615	1.1635	0.8503	0.8077	0.7374	0.1662
b_4	1.1111	4.5444	5.5056	2.7500	0.1587	0.6492	0.7865	0.3929
b_5	5.4278	4.1111	5.8278	1.2111	0.7754	0.5873	0.8325	0.1730
b_6	5.3750	5.3750	5.3750	1.5000	0.7679	0.7679	0.7679	0.2143
b_7	1.3750	3.5464	4.8393	5.3393	0.1964	0.5066	0.6913	0.7628
b_8	1.3281	4.3594	4.3594	5.8063	0.1897	0.6228	0.6228	0.8295
b_9	1.0750	3.3958	3.9667	5.3250	0.1536	0.4851	0.5667	0.7607
b_{10}	1.0692	3.2115	4.9923	5.6038	0.1527	0.4588	0.7132	0.8005
b_{11}	1.6278	4.4167	5.4111	3.6389	0.2325	0.6310	0.7730	0.5198
b_{12}	4.8923	3.7692	1.3846	5.5923	0.6989	0.5385	0.1978	0.7989
b_{13}	3.5114	5.7159	5.7159	1.0432	0.5016	0.8166	0.8166	0.1490
b_{14}	1.8875	1.4156	4.9875	5.7031	0.2696	0.2022	0.7125	0.8147
b_{15}	4.7778	5.1833	5.8764	1.0944	0.6825	0.7405	0.8395	0.1563
b_{16}	5.8439	4.9015	4.0167	1.1636	0.8348	0.7002	0.5738	0.1662
b_{17}	4.9045	5.7273	5.3477	1.1909	0.7006	0.8182	0.7640	0.1701
b_{18}	4.1875	5.3450	5.7775	1.1900	0.5982	0.7636	0.8254	0.1700
$\pi(a_i)$		N			0.4977	0.6314	0.7063	0.4391

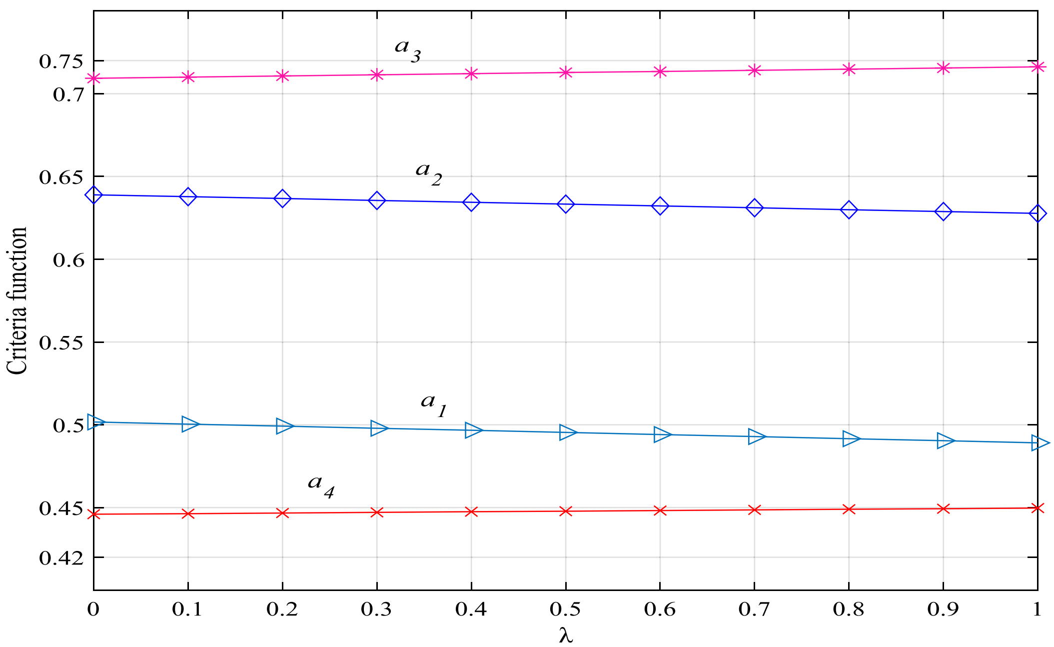

Fig. 5. Impact of the parameter λ on $\pi(a_i)$.

Table 15
Ranking orders with the change values of the parameters.

Different combinations of parameters		Values of the criteria function				Ranking order
		$\pi(a_1)$	$\pi(a_2)$	$\pi(a_3)$	$\pi(a_4)$	
Scenario I	$\alpha = 1, \beta = 3$	0.6426	0.7147	0.6898	0.5290	$a_2 \succ a_3 \succ a_1 \succ a_4$
	$\alpha = 1, \beta = 6$	0.5376	0.6465	0.4136	0.2711	$a_2 \succ a_1 \succ a_3 \succ a_4$
	$\alpha = 1, \beta = 10$	0.5592	0.6280	0.2937	0.1773	$a_2 \succ a_1 \succ a_3 \succ a_4$
Scenario II	$\alpha = 2, \beta = 3$	0.5104	0.6069	0.6200	0.4412	$a_3 \succ a_2 \succ a_1 \succ a_4$
	$\alpha = 2, \beta = 6$	0.5524	0.6259	0.5161	0.4015	$a_2 \succ a_1 \succ a_3 \succ a_4$
	$\alpha = 2, \beta = 10$	0.5860	0.6502	0.3200	0.2139	$a_2 \succ a_1 \succ a_3 \succ a_4$
Scenario III	$\alpha = 3, \beta = 3$	0.5546	0.6339	0.6633	0.5360	$a_3 \succ a_2 \succ a_1 \succ a_4$
	$\alpha = 3, \beta = 6$	0.5097	0.6095	0.4905	0.3225	$a_2 \succ a_1 \succ a_3 \succ a_4$
	$\alpha = 3, \beta = 10$	0.5552	0.6384	0.3733	0.2705	$a_2 \succ a_1 \succ a_3 \succ a_4$
Scenario IV	$\alpha = 10, \beta = 3$	0.5536	0.6344	0.4221	0.3227	$a_2 \succ a_1 \succ a_3 \succ a_4$
	$\alpha = 10, \beta = 6$	0.5251	0.6010	0.5729	0.3831	$a_2 \succ a_3 \succ a_1 \succ a_4$
	$\alpha = 10, \beta = 10$	0.5649	0.6274	0.5822	0.4807	$a_2 \succ a_3 \succ a_1 \succ a_4$

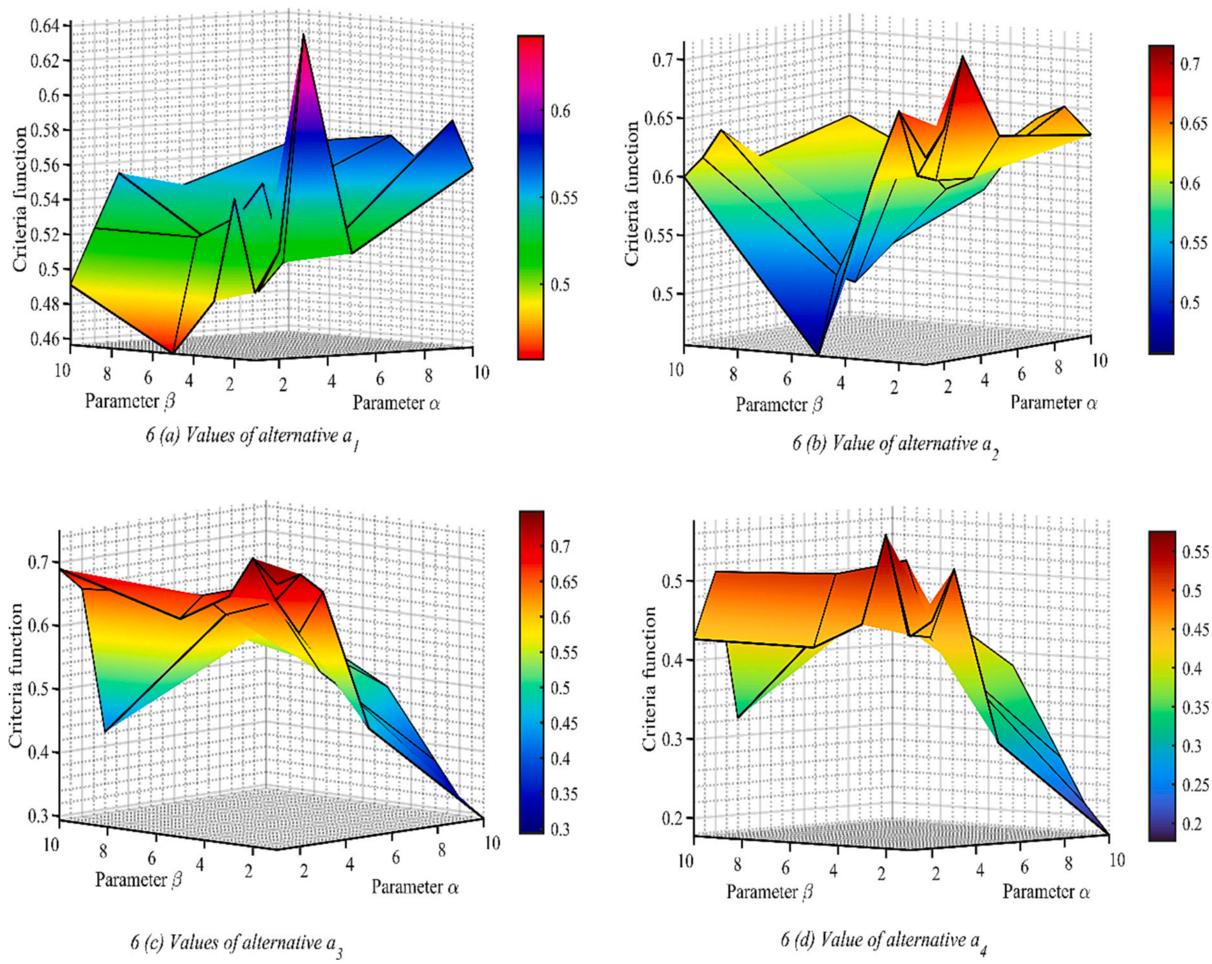

Fig. 6. Values of the criteria function for the alternatives.

Table 16
The calculation result with different numbers of experts.

	Four experts		Five experts		Six experts		Seven experts		This paper	
	$\pi(a_i)$	Order	$\pi(a_i)$	Order	$\pi(a_i)$	Order	$\pi(a_i)$	Order	$\pi(a_i)$	Order
a_1	0.4788	3	0.4777	3	0.4879	3	0.4781	3	0.4977	3
a_2	0.5735	2	0.6003	2	0.6697	2	0.6576	2	0.6314	2
a_3	0.6599	1	0.7184	1	0.7517	1	0.7522	1	0.7063	1
a_4	0.4205	4	0.3524	4	0.2763	4	0.2603	4	0.4391	4

Table 17
The result of the comparison study.

	FCF-WASPAS		FCF-TOPSIS		FCF-COPRAS		FCF-EDAS		This paper
	Utility degree	Order	C_i	Order	Utility degree	Order	Appraisal score	Order	Order
a_1	0.503	2	0.283	4	91.14%	3	0.385	3	3
a_2	0.515	3	0.394	2	93.56%	2	0.428	2	2
a_3	0.616	1	0.369	3	100.00%	1	0.676	1	1
a_4	0.499	4	0.547	1	77.62%	4	0.253	4	4

method can not consider the relative significance of these distance measures. However, the extended RAFSI model can deal with this issue through the weighted aggregation procedure in the criteria function.

- Although the result obtained by the proposed method is consistent with that calculated by the COPRAS and EDAS methods, the latter two methods may show some degree of inconsistency or unreasonable results. As pointed out by Žižović et al. [35], the COPRAS method may cause misjudgment of the barrier level since it does not consider the transformation of the values of the cost and benefit criteria in the standardized matrix. According to Ref. Pramanik et al. [76], the EDAS method determines barrier levels based on the average point, which may lead to an impractical result. However, the proposed framework is not only free from the rank reversal issue but also defines referential criteria points. Hence, the proposed framework is more suitable to analyze the barriers.

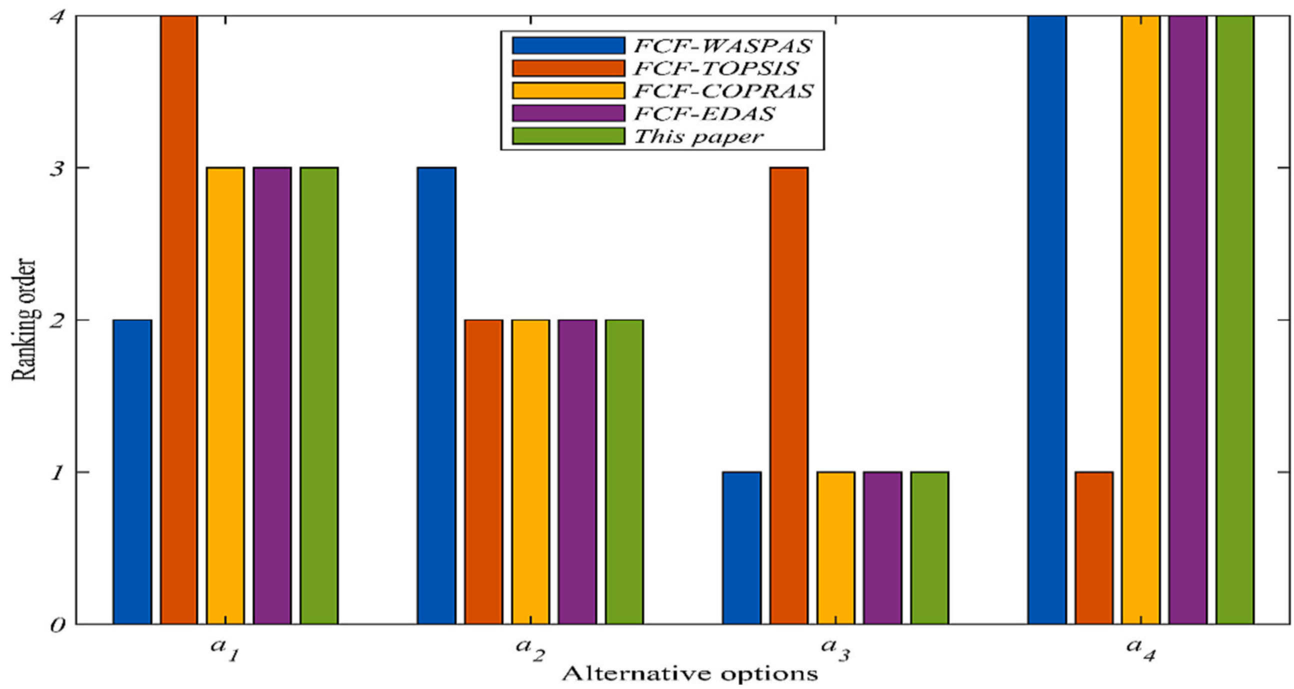

Fig. 7. The result of the comparison study.

Fig. 8. The Pearson correlation coefficient.

- In practice, the barrier estimation of DT should consider subjective preference and intercorrelations among criteria [77]. However, the methods above [78,79,80] can not resolve both of the two aspects. The proposed framework uses the FCF-LBWA-CRITIC-based weighting method to determine barrier weights, which can tackle the two issues. Thus, the proposed framework can provide a more reasonable result.

5. Implications

5.1. Managerial implications

The outcomes of the proposed framework have valuable managerial implications, which are outlined as follows.

(i) The present study reveals that some barriers are the most influential factors in estimating the barrier levels of alternative options in the power sector. Thus, the policymakers and stakeholders can consider these barriers as a guide for working out measures to promote DT in the power sector.

(ii) The barriers to implementing DT in the current study are identified based on previous literature and experienced experts. Thus, the set of barriers can be updated and transformed into practical decision-making issues with diverse participants from the DT.

(iii) The outcomes may provide the stakeholders, policymakers, and participants of DT in the power sector with an expanded understanding of the implementing barriers. Indeed, this work provides a comprehensive guide for individuals seeking to implement DT for the power industry, thereby assisting participants in formulating effective strategies. It also reveals that different participants have diverse barrier levels for implementing DT in the power industry, which can help generate heterogeneous implementation path planning to mitigate the potential barriers and promote DT activity.

(iv) Further, different participants of the DT in the power industry can take the findings and outcomes of this work as guides for determining the suitable measures to overcome the barriers to DT. The implementation of DI in the power industry should consider the investment, cost, and resource constraints. Hence, the outputs of the barriers analysis can help managers prioritize the influential barriers to make precise and reasonable investment programs.

5.2. Theoretical implications

As a result, the current work proposes a synthetical FCF decision framework for estimating the barrier levels of DT in the energy sector. The framework uses the FCFS to model subjective preference information, which can be extended to other complex and uncertain decision issues. Next, the proposed framework introduces the LBWA-CRITIC method for computing barrier weights. Other research works can adopt this weighting method individually and/or integrate it with other decision mathodologies to resolve such barriers analysis issues for practical application. Another theoretical implication is developing the RAFSI model within other well-known extended fuzzy settings, such as T-spherical fuzzy set, picture fuzzy set, and interval-valued spherical fuzzy set.

6. Concluding remarks

6.1. Conclusions

Implementing digital techniques in the energy transition process of different types can improve its performance; however, various potential factors still exist that affect the popularization and implementation of energy digitalization. Ranking and evaluating these barriers are attracting substantial attention from researchers and practitioners. As such, the present work identifies the barriers to DT implementation in the energy sector based on previous studies. The relative importance of eighteen barriers is measured using the FCF-LBWA-CRITIC method. Then, these barriers are adopted to evaluate the barrier levels of participants in the electric power industry chain assisted by the FCF-RAFSI model. The results reveal that the consumers have the lowest barrier levels.

This study contributes to the evaluation and analysis of issues for barriers to DT implementation in the energy sector under an uncertain environment. First, the FCFSs are integrated with a decision model to develop an evaluation framework for analyzing barriers. Then, the WHMA operator is extended to the FCF environment with the deviation-based method for collecting decision data provided by experts. Next, an integrated weight-determining method is utilized to rank barriers with FCF information. Subsequently, the FCF-RAFSI model is presented to appraise the barrier levels of industries involved in the energy industry chain. Finally, a case analysis with sensitivity and comparative explorations is organized to demonstrate the FCF-RAFSI framework. The result reveals that the framework presented here can provide a practical, logical, and flexible tool for analyzing implementation barriers to DT in the energy sector with incomplete information.

6.2. Limitations and future directions

Collectively, the presented evaluation framework still has some limitations. First, the proposed FCF-WHMA operator fails to consider the deviation between experts' judgments, although it can model the interrelationships between this information. Second, the characteristics of the decision behavior of stakeholders, like bounded rationality, are not discussed in the current model. Third, a limited set of experts are interviewed to provide the estimation data, which may lead to an inadequate analysis result. Finally, the example just focuses on the power domain, which may affect the generalizability of the conclusions.

Future research work will try to tackle the limitations of the current work. First, combining the WHMA operator with the power-averaging operator is a promising direction for future study. Then, incorporating the behavioral decision models into the presented framework is also a recommendable study direction. Next, the large-group decision methods can be employed to generate a new estimation framework. Finally, we can employ the presented evaluation framework to handle the barriers analysis problems for DT implementation in other sectors, such as natural gas, the mining industry, and nuclear energy.

CRediT authorship contribution statement

Weizhong Wang: Visualization, Validation, Software, Methodology, Conceptualization. **Yu Chen:** Writing – review & editing, Writing – original draft, Visualization, Data curation, Methodology. **Yi Wang:** Writing – original draft, Visualization, Validation. **Muhammet Deveci:** Writing – review & editing, Visualization, Validation, Methodology. **Sarbast Moslem:** Writing – review & editing. **D'Maris Coffman:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Appendix A. Questionnaire on modeling the implementation barriers to the digital transformation in the energy sector

This questionnaire intends to collect data for modeling the implementation barriers to digital transformation in the energy sector. Please spare a few minutes to respond to the questions. Your time and assistance is highly appreciated.

Part I

Section A: Details of the respondent's

Name (optional)	Gender: Age:	
Work experience:	Area expertise:	
Education:	Company/Institute Name:	
Role in the company/institute		
Mobile No. (optional):	Email (optional):	Address (optional):

Part II

Section B: Judgment by the experts: As per the scale, please fill in the measure for the elimination of the implementation barriers to digital transformation in the electric power industry

Scale: Extremely high (EH), Very high (VH), High (H), Medium (M), Low (L), Very low (VL), Extremely low (EL)

Barriers	a_1	a_2	a_3	a_4
Short-term planning				
Information disclosure concerns				
Deficiency of infrastructure providers				
Coordination, communication, and collaboration issues				
Limited technology maturity				
The security issues				
Shortage of stakeholder awareness				
Inadequate information on costs, ROI, and losses				
Highest investment cost				
Shortage of specialists associated with the DT implementation in the energy industry				
Shortage of standardization				
Interoperability with the current system in the energy industry				
Unadaptable DT infrastructure of the energy sector				
Shortage of government support and legal uncertainties				
Limited acceptance in society				
Lack of synthetical environment assessment regulation				
Shortage of the market auditing				
Market risk				

B1. The FCFNs-based decision matrix from expert e_1

Barriers	a_1	a_2	a_3	a_4
b_1	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.2,0.25],[0.8,0.85]),(0.25,0.75)>
b_2	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.3,0.35],[0.7,0.75]),(0.35,0.65)>
b_3	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.3,0.35],[0.7,0.75]),(0.35,0.65)>
b_4	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.9,0.95],[0.1,0.15]),(0.85,0.15)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>
b_5	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>
b_6	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>
b_7	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>
b_8	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>
b_9	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>
b_{10}	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>
b_{11}	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>
b_{12}	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>
b_{13}	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.3,0.35],[0.7,0.75]),(0.35,0.65)>
b_{14}	<([0.3,0.35],[0.7,0.75]),(0.35,0.65)>	<([0.2,0.25],[0.8,0.85]),(0.25,0.75)>	<([0.3,0.35],[0.7,0.75]),(0.35,0.65)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>
b_{15}	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.9,0.95],[0.1,0.15]),(0.85,0.15)>	<([0.2,0.25],[0.8,0.85]),(0.25,0.75)>
b_{16}	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.2,0.25],[0.8,0.85]),(0.25,0.75)>
b_{17}	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.3,0.35],[0.7,0.75]),(0.35,0.65)>
b_{18}	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>

B2. The FCFNs-based decision matrix from expert e_2.

Barriers	a_1	a_2	a_3	a_4
b_1	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.3,0.35],[0.7,0.75]),(0.35,0.65)>
b_2	<([0.9,0.95],[0.1,0.15]),(0.85,0.15)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.3,0.35],[0.7,0.75]),(0.35,0.65)>
b_3	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.2,0.25],[0.8,0.85]),(0.25,0.75)>
b_4	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>
b_5	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.3,0.35],[0.7,0.75]),(0.35,0.65)>
b_6	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>
b_7	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>
b_8	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>
b_9	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>
b_{10}	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>

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(*continued*)

Barriers	a_1	a_2	a_3	a_4
b_{11}	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>
b_{12}	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>
b_{13}	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.3,0.35],[0.7,0.75]),(0.35,0.65)>
b_{14}	<([0.2,0.25],[0.8,0.85]),(0.25,0.75)>	<([0.2,0.25],[0.8,0.85]),(0.25,0.75)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>
b_{15}	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.1,0.15],[0.9,0.95]),(0.15,0.85)>
b_{16}	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.1,0.15],[0.9,0.95]),(0.15,0.85)>
b_{17}	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.2,0.25],[0.8,0.85]),(0.25,0.75)>
b_{18}	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.9,0.95],[0.1,0.15]),(0.85,0.15)>	<([0.3,0.35],[0.7,0.75]),(0.35,0.65)>

B3. The FCFNs-based decision matrix from expert e_3.

Barriers	a_1	a_2	a_3	a_4
b_1	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.2,0.25],[0.8,0.85]),(0.25,0.75)>
b_2	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.3,0.35],[0.7,0.75]),(0.35,0.65)>
b_3	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.2,0.25],[0.8,0.85]),(0.25,0.75)>
b_4	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>
b_5	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>
b_6	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>
b_7	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>
b_8	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>
b_9	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.9,0.95],[0.1,0.15]),(0.85,0.15)>
b_{10}	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>
b_{11}	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>
b_{12}	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>
b_{13}	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.3,0.35],[0.7,0.75]),(0.35,0.65)>
b_{14}	<([0.3,0.35],[0.7,0.75]),(0.35,0.65)>	<([0.3,0.35],[0.7,0.75]),(0.35,0.65)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>
b_{15}	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.2,0.25],[0.8,0.85]),(0.25,0.75)>
b_{16}	<([0.9,0.95],[0.1,0.15]),(0.85,0.15)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.3,0.35],[0.7,0.75]),(0.35,0.65)>
b_{17}	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.3,0.35],[0.7,0.75]),(0.35,0.65)>
b_{18}	<([0.7,0.75],[0.3,0.35]),(0.65,0.35)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.8,0.85],[0.2,0.25]),(0.75,0.25)>	<([0.5,0.55],[0.4,0.45]),(0.5,0.45)>

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