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Selection of Suitable Cloud Vendors for Health Centre: A Personalized Decision Framework with Fermatean Fuzzy Set, LOPCOW, and CoCoSo

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Abstract. Cloud computing has emerged as a transformative technology in the healthcare industry, but selecting the most suitable CV ("cloud vendor") remains a complex task. This research presents a decision framework for CV selection in the healthcare industry, addressing the challenges of uncertainty, expert hesitation, and conflicting criteria. The proposed framework incorporates FFS ("Fermatean fuzzy set") to handle uncertainty and data representation effectively. The importance of experts is attained via the variance approach, which considers hesitation and variability. Furthermore, the framework addresses the issue of extreme value hesitancy in criteria through the LOPCOW ("logarithmic percentage change-driven objective weighting") method, which ensures a balanced and accurate assessment of criterion importance. Personalized grading of CVs is done via the ranking algorithm that considers the formulation of CoCoSo ("combined compromise solution") with rank fusion, providing a compromise solution that balances conflicting criteria. By integrating these techniques, the proposed framework aims to enhance the rationale and reduce human intervention in CV selection for the healthcare industry. Also, valuable insights are gained from the framework for making informed decisions when selecting CVs for efficient data management and process implementation. A case example from Tamil Nadu is presented to testify to the applicability, while sensitivity and comparison analyses reveal the pros and cons of the framework.

Key words: cloud vendor selection, Health 4.0, fermatean fuzzy set, variance method, LOPCOW method, CoCoSo method.

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1. Introduction

In the healthcare industry, cloud computing has revolutionized data management and has been efficiently implemented across various healthcare units. It provides an attractive solution to the vast problem of handling massive volumes of data in this sector. Healthcare organizations can improve their work culture and address data management challenges by incorporating cloud computing into their systems. Cloud computing in healthcare includes data analysis, sharing, access, and storage capabilities, which become more effective and scalable as data volumes grow (Satoskar *et al.*, 2023). Furthermore, cloud computing aids in increasing customer engagement and commercial outcomes for large enterprises and healthcare organizations. Given that research has demonstrated a beneficial relationship between cloud computing and data management in the healthcare industry, it is clear that this novel technology has the potential to play a significant role in this industry and others in the future. Despite various issues confronting the healthcare business, the demand for advanced technology is increasing, making cloud computing an increasingly important component in overcoming these obstacles and driving advancement in the field (Agapito and Cannataro, 2023).

The usage of cloud computing by healthcare organizations is subtle in India compared to other countries like the USA and China. As of 2022, it was determined that only 400 out of 62,000 hospitals in India actively utilized cloud computing to collect, organize, and manage data (Krishankumar *et al.*, 2022b). Although India has become well-advanced in using cloud services in the healthcare industry, there must be a gap in how the data are effectively organized, stored, and managed. After surveying the Indian healthcare industry, Dash *et al.* (2019) inferred that implementing cloud computing in healthcare industry sectors is crucial for handling massive amounts of medical data and promoting healthcare quality. Due to the high demand for cloud computing services, there has been a sharp increase in CVs ("cloud vendors") globally. The fast growth of CVs has complicated the selection of the appropriate vendor for the healthcare industry.

From the user's point-of-view, different CVs have different preferences based on different QoS ("quality of service") parameters, making the selection of CVs even more challenging. Mardani *et al.* (2019) reviewed various decision models available in the healthcare industry. They inferred that fuzzy sets are crucial for handling uncertainty, and MCDM ("multi-criteria decision-making") can be adopted for solving decision problems. MCDM is a promising concept that can effectively consider multiple competing/conflicting criteria for rating different alternatives (CVs) based on pre-defined preference scales from a group of experts. Since then, researchers, including Sharma and Sehrawat (2020) and Krishankumar *et al.* (2022b), have developed interesting MCDM solutions for selecting CVs in the healthcare industry. According to this research, it can be inferred that existing CV selection approaches (i) may inadequately handle uncertainty, (ii) may overlook expert hesitation and uncertainty, (iii) struggle with extreme value hesitancy in criteria, and (iv) may neglect the importance of compromise solutions in balancing conflicting criteria. These inferences have motivated the following research points:

- A decision framework must be adopted to handle the uncertainty of the experts' and users' views. This structure has to reduce the uncertainty present in the data.

- The data from the experts must be preprocessed to acquire preference and non-preference degree values, which would greatly help in handling the uncertainty.
- The importance of the experts must be effectively captured in an uncertain environment to handle extreme values.
- The hesitation in the criteria must be effectively captured in an uncertain environment using a model that also considers the experts' importance.
- An effective and compromised ranking model considering the importance of both experts and criteria must be modelled in an uncertain environment.

Driven by these motivations, the key contributions achieved in the presented study include:

- Uncertainty has been handled effectively by adopting FFS ("Fermatean fuzzy sets") since it represents the choices as degree values of preference and non-preference using a broader window than the earlier orthopair versions.
- The importance of the experts has been effectively captured using the variance approach since it captures the hesitation present in the criteria.
- The importance of the criteria has been effectively captured using the LOPCOW ("logarithmic percentage change-driven objective weighting"), which captures the extreme values effectively using a logarithmic operator.
- Finally, a compromise ranking of CVs is obtained using the CoCoSo ("combined compromise solution") algorithm, which provides a ranking index as a cumulative aggregate of three measures: sum, minimum, and maximum compromise solutions.

The contributions presented above are backed by some rationale that is presented here. FFS (Senapati and Yager, 2020) was introduced as an extension of the IFS ("intuitionistic fuzzy sets") (Atanassov, 1986) and PFS ("Pythagorean fuzzy sets") (Yager, 2016). FFS has properties similar to an orthopair fuzzy set with value $q = 3$, offering higher flexibility by preference-sharing for experts. To calculate the expert importance, the variance approach has been used since it captures experts' hesitation and considers all data points before determining the preference distribution. Further, the LOPCOW method (Ecer and Pamucar, 2022) captures the importance of criteria intending to generate more reasonable weights. Finally, to rank the CVs, the CoCoSo method (Yazdani *et al.*, 2019) has been utilized since it provides an overview of all possible compromise solutions by aggregating the weights of the compared sequences of the alternatives using the multiplication rule and weighted power of distances and provides a ranking index as a cumulative aggregate of three measures for every given alternative. The research problem addressed by the authors in this study is to select a suitable cloud vendor for managing data and analytics within healthcare centres by considering FFS as the rating information and an integrated LOPCOW-CoCoSo method as the decision approach. The study aims to reduce human intervention and model uncertainty better by presenting a methodical approach for determining the values for the decision parameters. A group of experts rates different vendors based on quality of service parameters or criteria fed to the system for determining criteria weights and ranks for cloud vendors in the cumulative and personalized fashion. The former way of ranking vendors is the traditional decision-making style where the group opinion is considered holistically to arrive at a decision. At the same time, in a personalized fashion, authors provide a ranking of vendors for each expert's data. This provides a sense of personalization and aids in better tracking the reasons for a specific selection, which is lacking in the earlier models.

The rest of the article is presented as follows. Section 2 reviews the recent work done on CV selection, FFS, variance method, LOPCOW, and CoCoSo. Section 3 describes the methodology of the proposed framework. Section 4 presents a case study to demonstrate the usefulness of the proposed framework. Section 5 compares the proposed framework with existing frameworks to reveal its strengths and limitations. Section 6 provides the concluding remarks and directs attention to future work.

2. Literature Review

2.1. *Selection of Cloud Vendor Services*

Ranking cloud service providers is essential for optimizing resource utilization and improving the user experience. It enables informed decision-making and addresses the challenges of the rapidly changing cloud environment. Garg *et al.* (2013) proposed the first decision framework for ranking cloud services using the AHP ("analytical hierarchical process") based ranking mechanism to compare different cloud services. Since then, several studies have proposed fuzzy logic-based techniques to enhance cloud computing services. These techniques include an intelligent intermediary that assists inexperienced users in specifying their requirements, a self-learning approach for efficiently allocating resources in online games, and an algorithm for minimizing costs and time in IaaS clouds.

Additionally, a hybrid system is developed for analysing nuanced sentiments in tweets about cloud services. Another method considers QoS attributes and user feedback to rank cloud providers. A fuzzy logic model is suggested for selecting cloud providers, while another measures the uncertainty in survey responses. Finally, a trust model is introduced to aid users in identifying reliable cloud service providers (Mateen *et al.*, 2020; Alharbi and Alhalabi, 2020; Gireesha *et al.*, 2020; Khorsand *et al.*, 2019; Nagarajan and Thirunavukarasu, 2019; Rizvi *et al.*, 2020; Zhou *et al.*, 2019). A comprehensive summary of literature focusing on CV selection using MCDM and fuzzy methodologies is provided in Table 1.

Table 1 provides an overview of various MCDM and fuzzy methodologies for CV selection. From Table 1, the following inferences can be drawn. (i) The existing approaches to CV selection may not robustly handle uncertainty through linguistic and hesitant fuzzy set variations in criteria weights, expert opinions, or alternatives, potentially resulting in unreliable or inconsistent results. (ii) The existing approaches to CV selection may not effectively capture the hesitation or uncertainty of experts where human-centric hesitation and varying degrees of confidence are not adequately accounted for in these approaches. (iii) The existing approaches to CV selection struggle to capture extreme value hesitancy in criteria, where experts have difficulty assigning precise importance to the criteria for

Table 1
Literature summary of MCDM and fuzzy methodologies involved in the selection of CVs.

Source	Fuzzy set used	Criteria considered	Expert weight estimation	Criteria weight estimation	Ranking algorithm	Uncertainty handling	SA/ CA
Dahooie *et al.* (2020)	IVIFS	Performance, Cost, Availability, System reliability and security, System elasticity as consumption peak, System stability, Usability and serviceability, Functional transparency, Throughput and efficiency, Average time required for repair, Average CPU utilization, Scalability, and Open-source	n/a	Delphi method	CODAS	No	n/a
Hussain *et al.* (2020a)	n/a	Reliability, Assurance, Tangibility, Empathy, Responsiveness, Processes of CVs, Administrative support, Security practices, and Technical capabilities and processes	n/a	Best-worst method	MOSS	No	CA
Hussain *et al.* (2020b)	Triangular fuzzy numbers	Response time, Latency, Throughput, Availability, and Price	n/a	Max-normalization	FLBWM	Yes	SA and CA
Krishankumar *et al.* (2020)	IFS	Economics, Technology, Environment, CV profile	n/a	IFSV	Three-way IF-VIKOR	Yes	SA and CA
Krishankumar *et al.* (2021)	Probabilistic hesitant fuzzy set	Assurance, Availability, Security, Agility, Scalability, Total cost, and Response time	Inequality-constrained optimization model using partial information	Inequality-constrained optimization model using partial information	COPRAS	Yes	SA and CA
Radhika and Sadasivam (2021)	Triangular fuzzy numbers	Performance, Cloud availability, Cost optimization, Scalability, and Reliability	n/a	n/a	Fuzzy–AHP	Yes	n/a
Krishankumar *et al.* (2022a)	q-rung Orthopair fuzzy set	Availability, Assurance, Agility, Security, Scalability, Response time, and Total cost	n/a	Constrained optimization model using partial information	Evidence	Yes	CA

(*continued on next page*)

Table 1
(*continued*)

Source	Fuzzy set used	Criteria considered	Expert weight estimation	Criteria weight estimation	Ranking algorithm	Uncertainty handling	SA/CA
Krishankumar *et al.* (2022b)	Hesitant fuzzy linguistic term set	Availability, Security, Accessibility, Speed, Storage capacity, Features, Ease of use, Response time, and Total cost	n/a	Constrained optimization model using partial information	EDAS	Yes	SA and CA
Kumar *et al.* (2022)	Triangular fuzzy numbers	CPU performance, Memory performance, Disk performance, Disk I/O latency, Network latency, and Cost on demand	n/a	AHP	TOPSIS	Yes	SA and CA
Haque *et al.* (2023)	Generalized spherical fuzzy number	Accessibility & performance, Reliability & management skills, Costing & security	n/a	n/a	LGSWA, LGSWG	Yes	SA and CA
Hang Nguyen *et al.* (2023)	PULTS	Agility and innovation, Cost, Time to market, and Risks	n/a	CRITIC	TODIM	Yes	SA and CA
Ghorui *et al.* (2023)	PIFN	Cloud security/privacy, Pricing, Downtime, Support services, Portability, Scalability, Disaster & recovery, Deployment & upgrades, and Service level agreements	n/a	AHP	TOPSIS	Yes	SA and CA
Krishankumar *et al.* (2023)	DHHFLTS	Assurance, Performance, Accountability, Agility, Usability, Scalability, Data/privacy breach, and E-waste generation	CRITIC	Evidence-based Bayesian approach	CRADIS	No	SA and CA

Note: SA – sensitivity analysis; CA – comparative analysis; IVIFS – interval-valued intuitionistic fuzzy set; CODAS – combinative distance-based assessment; CV – cloud vendor; MOSS – methodology for optimal service selection; FLBWM – fuzzy linear best-worst method; IFS – intuitionistic fuzzy set; IFSV – intuitionistic fuzzy statistical variance; IF-VIKOR – intuitionistic fuzzy viekriterijumsko kompromisno rangiranje; COPRAS – complex proportional assessment; AHP – analytical hierarchical process; EDAS – evaluation based on distance from average solution; LGSWA – logarithmic generalized spherical weighted averaging; LGSWG – logarithmic generalized spherical weighted geometric; PULTS – probabilistic uncertainty linguistic fuzzy set; CRITIC – criteria importance through inter-criteria correlation; TODIM – tomada de decisão interativa e multicritério; PIFN – pentagonal intuitionistic fuzzy number; DHHFLTS – double hierarchy hesitant fuzzy linguistic term set; CRADIS – compromise ranking of alternatives from distance to ideal solution.

ranking the CVs. (iv) The existing approaches to CV selection may need to pay more attention to the need for a compromise solution that balances conflicting criteria or objectives in an uncertain, potentially leading to suboptimal or biased CV selections. Motivated by these inferences, the authors formulated an MCDP ("multi-criteria decision problem") for CV selection in an uncertain condition having a precise depiction of data, a human-centric approach for capturing experts' importance, methodology to capture extreme values for criteria importance, a compromised methodology for ranking the CVs.

2.2. *Fermatean Fuzzy Sets*

In recent years, fuzzy logic has been successfully used to resolve the challenges of estimating decision-making under uncertain conditions. Atanassov (1986) proposed IFS, which can solve many MCDM problems in uncertain environments. IFS does not cover more data points (u, v), where u is the degree value of preference and v is the degree value of non-preference, such that $u+v \leqslant 1$. As an extension of IFS, Yager (2016) introduced PFS that can accommodate more points (u, v) compared to IFS, such that $u^2 + v^2 \leqslant 1$ in uncertain environments. Further, Senapati and Yager (2020) introduced FFS as an extension of IFS and PFS, focusing on their properties and applications in MCDM problems. FFS supports a more fine-grained representation of uncertainty and more flexible modelling of complex decision-making scenarios since it can cover more data points (u, v), such that $u^3 + v^3 \leqslant 1$. Senapati and Yager (2020) stated that for an MCDM problem under the FF ("Fermatean fuzzy") domain, there are multiple alternatives and criteria with certain weights. The assessment values for each alternative with respect to each criterion are represented as FFN ("Fermatean fuzzy number"). These FFNs form a Fermatean fuzzy decision matrix. Senapati and Yager (2020) also suggested that MCDM issues with FFNs can be approached similarly as other fuzzy frameworks. To show the compatibility of FFS in MCDM, Senapati and Yager (2020) applied the TOPSIS ("technique for order preference by similarity to ideal solution") ranking algorithm on the FF decision matrix, and this proved to be effective in interpreting MCDM problems with FFD ("Fermatean fuzzy data").

Since its introduction, many researchers have utilized FFS and its extensions. For instance, Garg *et al.* (2020) developed new aggregation operators, merging FFS with Yager's t-norm and t-conorm, and applied them in an MCDM scenario of selecting an authentic lab for COVID-19 tests. Keshavarz-Ghorabaee *et al.* (2020) proposed a methodology using WASPAS ("weighted aggregated sum product assessment"), SMART ("simple multi-attribute rating technique"), and FFS for evaluating and selecting green suppliers in the construction industry, demonstrating its stability and congruence with existing methods through sensitivity and comparative analyses. Aydemir and Yilmaz Gunduz (2020) introduced FF aggregation operators based on Dombi operations, analysed their arithmetic and geometric properties, compared them with existing operators, and applied them in the TOPSIS to evaluate their impact on the MCDM process. Gül (2021) extended SAW ("simple additive weighting"), ARAS ("additive ratio assessment"), and VIKOR ("viekriterijumsko kompromisno rangiranje") to handle FFD, with application in selecting the best

COVID-19 testing laboratory, validating the proposed methods against existing FFS-based decision methods. Jeevaraj (2021) introduced IVFFS ("interval-valued Fermatean fuzzy sets") as an extension of FFS, established mathematical operations and score functions for IVFFS, compared ranking methods using the proposed score functions, and applied the TOPSIS method on IVFFS to demonstrate their applicability through numerical examples. Rani and Mishra (2021) proposed an integrated decision-making method based on the MULTIMOORA ("multiplicative form of multi-objective optimization based on ratio analysis and reference point approach"), maximizing deviation method, and Einstein aggregation operators within FFS context. They applied this method for optimal EVCS ("electric vehicle charging station") location selection to effectively handle uncertainty and incorporate quantitative and qualitative factors, providing a robust and consistent approach compared to existing methods.

Mishra *et al.* (2022b) assessed different barriers in the IoT ("internet of things") by considering the CoCoSo method in the FFS context for supporting waste management in smart cities. Akram *et al.* (2022) introduced linguistic FFS as a novel approach to qualitative information processing and decision-making, showcasing its applications in multi-attribute group decision-making and solving practical problems in food company ranking and green supplier selection while comparing its effectiveness with existing methods. Rani *et al.* (2022) proposed a novel MCDM approach by combining the CRITIC ("criteria importance through inter-criteria correlation") and COPRAS ("complex proportional assessment") methods with IVFFS for addressing the imprecise and incomplete information in MCDM under an uncertain environment and demonstrated its effectiveness in evaluating and selecting sustainable community-based tourism locations. Mishra *et al.* (2022a) introduced IVHFFS ("interval-valued hesitant Fermatean fuzzy sets"), presented various operations, distance measures, and aggregation operators for IVHFFS, and demonstrated their application in MCDM using COPRAS, specifically for the selection of desalination technology, providing a robust and stable method to address uncertainties and influencing factors. Ashraf *et al.* (2023) developed innovative FFS-based information measures, including distance, similarity, entropy, and inclusion measures, and demonstrated their applicability in pattern recognition, building materials, and medical diagnosis without encountering counter-intuitive cases. Akram and Bibi (2023) introduced an improved version of the PROMETHEE ("preference ranking organization method for enrichment evaluation") using 2-tuple linguistic FFS for MCDM problems with linguistic variables, demonstrating its effectiveness and reliability in addressing such issues. Zeng *et al.* (2023) presented a novel framework combining FF hybrid weighted distance measure and TOPSIS for comprehensive evaluation of LCC ("low-carbon city") quality, addressing challenges posed by uncertainty and complicated indicators, and providing insights for LCC development assessment and decision-making. Saha *et al.* (2023) introduced two new methods, FF-Delphi for criteria identification and FF-DN MARCOS for criteria weighting, to optimize warehouse location in the automotive industry, emphasizing "energy availability and cost" and "proximity to port and customs" as pivotal factors. Deveci *et al.* (2023) assessed the risks impacting sustainable mining in Greece, employing a new FF score function with SWARA for risk weighting to find the most crucial risks, aligning with SDG12 and identifying "Risk to Environment" as the highest risk category, thereby offering a roadmap for sustainable mining practices. Zaman *et al.* (2023) developed new decision-making techniques based on complex Fermatean fuzzy numbers and introduced various aggregation operators like CFFEWAA (“complex Fermatean fuzzy Einstein weighted average aggregation”), CFFEOWAA (“complex Fermatean fuzzy Einstein ordered weighted average aggregation”), and CFFEHAA (“complex Fermatean fuzzy Einstein hybrid average aggregation”), applying them in an extended TOPSIS method for multi-attribute group decision-making, specifically for selecting an English language instructor.

On reviewing the literature on FFS, the following points can be inferred. (i) FFS possesses distinctive characteristics that make it highly advantageous in uncertain decision-making scenarios. (ii) The ability of FFS to manage uncertainty effectively and depict detailed uncertainty representations renders it an invaluable tool for experts. (iii) Integrating FFS into decision models and methodologies enhances the resulting decisions’ dependability, resilience, and precision. (iv) Approaches based on FFS provide a comprehensive and precise assessment of various options, empowering experts with a heightened comprehension of the inherent uncertainty within the decision-making environment. Hence, the authors propose using FFS to precisely depict data to solve the MCDP of CV selection for healthcare centres in uncertain conditions.

2.3. *Variance, LOPCOW & CoCoSo Methods*

Kao (2010) claimed that weights must be determined via a method rather than direct assignment as they tend to be inaccurate and driven by bias. Specifically, variance is a method for weight calculation that resembles human behaviour by considering the hesitation of experts during MCDM. Higher variability indicates high hesitation/confusion from the experts regarding that particular criterion, so uncertainty is high. Hence, the uncertainty of the model has to be measured, which is done using the variance. Optimistically, experts tend to pay less attention to or are influenced by those criteria. Still, from a pessimistic perspective, these criteria are considered vital as they influence the ranking, and such behavioural depiction is possible from the variance measure. Hence, the authors propose utilizing the variance method to effectively capture the experts’ importance within the defined MCDP.

Ecer and Pamucar (2022) proposed the LOPCOW method to generate more acceptable outcomes by addressing significant differences in weight values, negative values, criterion limitations, and data size discrepancies in real-life problems. They benchmarked LOPCOW with other objective weighting methods, such as Entropy and MEREC. Subsequently, they showed that the LOPCOW method achieves a relatively smaller ratio between the most crucial and least important criteria, indicating a more balanced weight calculation capability and addressing the drawbacks of the other methods. Since its introduction, many researchers have utilized the LOPCOW method and its extensions. Simic *et al.* (2023) proposed an advanced two-stage model under the T2NN (“type-2 neutrosophic number”) environment, combining T2NN-LOPCOW and T2NN-ARAS methods, to support the transition and upgrading of warehouse management systems with Industry 4.0-based solutions. The latter study includes a case study demonstrating the superiority of AGVs as the most favourable material handling solution. Ecer *et al.* (2023) introduced a practical decision-making framework combining Delphi, LOPCOW, and CoCoSo methods with IVFNN ("interval-valued fuzzy neutrosophic number") information to evaluate the sustainability performance of MMS ("micro-mobility solutions"), providing insights into critical criteria and identifying the most promising MMS options. Ulutaş *et al.* (2023) developed a novel integrated MCDM model utilizing PSI ("preference selection index"), MEREC ("method based on removal effects of criteria"), LOPCOW, and MCRAT ("multiple-criteria ranking by alternative trace") methods to effectively select the most efficient natural fibre insulation material, addressing the complexity of criteria and alternatives in the decision-making process. Nila and Roy (2023) introduced a hybrid multi-criteria decision-making model that combines LOPCOW, FUCOM, and DOBI ("Dombi Bonferroni") methods with triangular fuzzy numbers to objectively evaluate and select third-party logistics providers for food manufacturing companies. Biswas and Joshi (2023) analysed the performance of IPOs in the Indian Stock Market from 2018–2021, using the LOPCOW method to assess market-based indicators and fundamental efficiency, suggesting that post-listing IPO performance is not necessarily tied to fundamentals and is often influenced by investor speculation, with the LOPCOW ranking method proving consistent with the widely-used Entropy model. From this literature review, the following point can be made about the LOPCOW method: (i) LOPCOW addresses significant differences in weight values, negative values, criterion limitations, and data size discrepancies in real-life problems, ensuring a more balanced weight calculation capability and leading to more acceptable outcomes compared to other objective weighting methods. (ii) Since LOPCOW achieves a relatively smaller ratio between the most crucial and least important criteria, it indicates a more reasonable and balanced assessment of criterion importance, helping experts achieve a more comprehensive and accurate evaluation of different criteria in their decision-making processes. Hence, the authors propose utilizing the LOPCOW method to effectively capture the criteria importance within the defined MCDP.

The CoCoSo method, developed by Yazdani *et al.* (2019), aims to provide a compromise solution to rank alternatives based on three levels of compromise space: sum, minimum, and maximum. This method aggregates weights of compared alternatives using the multiplication rule and weighted power of distance methods, calculates a ranking index as an aggregate of these three measures, and provides the final ranking of alternatives. Since the inception of CoCoSo by Yazdani *et al.* (2019), many researchers have utilized this method and its extensions. Wen *et al.* (2019) employed a probabilistic fuzzy linguistic term set and applied SWARA ("step-wise weight assessment ratio analysis") along with CoCoSo for the selection of cold chain logistics management for medicine in clinical decision support systems. Banihashemi *et al.* (2021) utilized triangular fuzzy numbers and the CoCoSo method to investigate the environmental impacts of construction projects. Mishra *et al.* (2021) employed hesitant fuzzy sets and CoCoSo to rank sustainable third-party reverse logistic providers. Rani *et al.* (2021) used single-valued neutrosophic fuzzy sets and applied SWARA and CoCoSo to the renewable energy resource selection problem. Deveci *et al.* (2021) extended the CoCoSo method by incorporating logarithmic and power Heronian functions and applied triangular fuzzy numbers for ranking real-time traffic management systems. Demir *et al.* (2022) used triangular fuzzy numbers as well as both the FUCOM ("fuzzy composite evaluation method") and CoCoSo to evaluate the sump development in urban areas. Qiyas *et al.* (2022) employed logarithmic picture fuzzy sets along with CoCoSo and used this framework for the drug selection for COVID-19. Jafarzadeh Ghoushchi *et al.* (2023) utilized spherical fuzzy sets and applied the Best-Worst method and CoCoSo to assess strategies for managing the COVID-19 infodemic. Zhang and Wei (2023) employed spherical fuzzy sets and combined CoCoSo and D-CRITIC ("distance correlation criteria importance through inter-criteria correlation") for the location selection of electric vehicle charging stations. Su *et al.* (2023) used Pythagorean fuzzy sets along with the CoCoSo method to identify the technical challenges of blockchain technology for a sustainable manufacturing paradigm. Zhu *et al.* (2023) used an Entropy-CoCoSo framework to evaluate China's inter-provincial Doing Business environment, finding significant regional differences and suggesting targeted improvements for optimizing business conditions and promoting economic development. Tripathi *et al.* (2023) introduced an MCDM approach using IFS and CoCoSo, which utilizes a generalized score function and parametric divergence measures for criteria weighting, and it was applied to medical decision-making problems for therapy evaluation. Based on this literature review, the following points about the CoCoSo method can be inferred: (i) CoCoSo is widely used because it provides a comprehensive and compromise-based approach to rank alternatives, considering multiple levels of compromise space and aggregating weights using various methods. (ii) Its ability to handle different types of fuzzy sets and incorporate other decision-making techniques makes it a versatile and effective method for addressing various research problems. Hence, the authors propose utilizing the CoCoSo method to rank the CVs within the defined MCDP.

3. Methodology

This section describes the methodology used in the present study. A pictorial representation of the methodology is shown in Fig. 1.

Fig. 1 depicts the research model and methodology used in this research to solve the MCDP of CV selection for healthcare centres in uncertain environments. The methodology described in Fig. 1 is presented below in the following manner: (i) Section 3.1 presents some basic concepts related to FFS; (ii) Section 3.2 describes the steps involved in calculating the expert's importance vector using the variance method; (iii) Section 3.3 explains the steps involved in calculating the criteria importance vector using the LOPCOW method; and (iv) Section 3.4 discusses the steps involved in calculating the net ranking index of CVs using the CoCoSo method.

3.1. *Preliminaries*

Some basic concepts related to IFS and FFS are presented below:

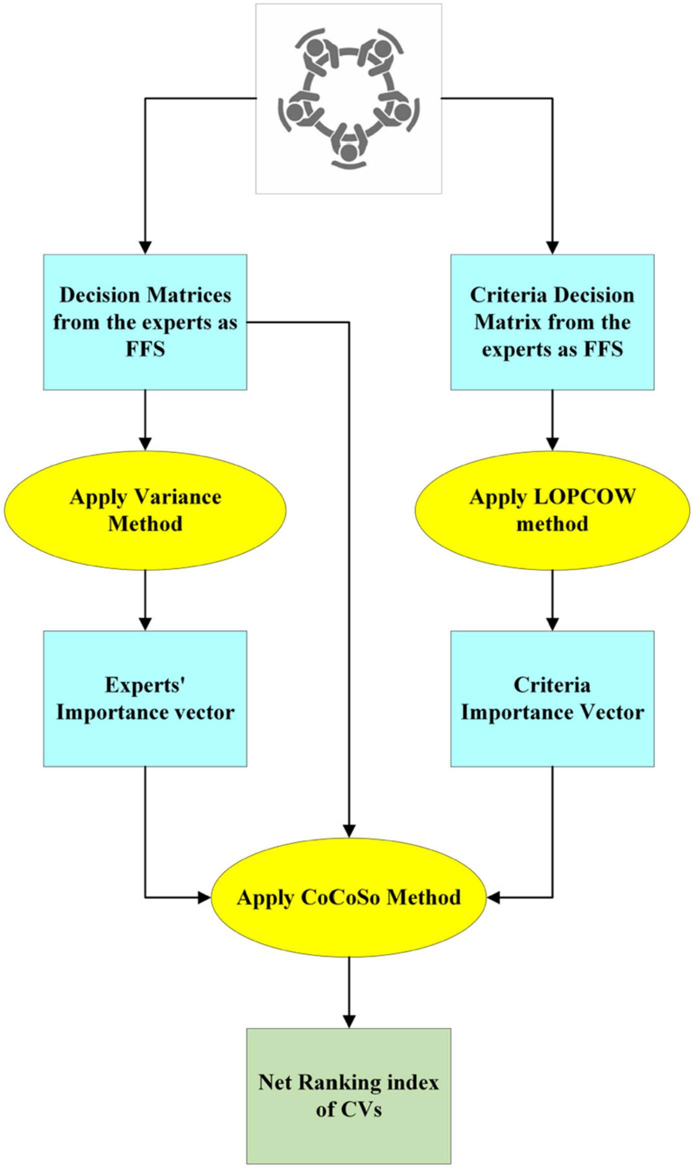

Fig. 1. Methodology of the proposed framework.

Definition 1 (Atanassov, 1986). Let H be a fixed set and let N be another fixed set such that $N \subset H$. $\overline{N}$ is an IFS in H and is defined in Eq. (1):

$$\overline{N} = \{h, \mu_{\overline{N}}(h), v_{\overline{N}}(h) \mid h \in H\}. \tag{1}$$

It is to be noted that in Eq. (1), $\mu_{\overline{N}}(h)$, $v_{\overline{N}}(h)$, and $\pi_{\overline{N}}(h) = 1 - (\mu_{\overline{N}}(h) + v_{\overline{N}}(h))$ are the degrees of truth, false, and hesitancy such that they belong to [0, 1], and $\mu_{\overline{N}}(h) + \upsilon_{\overline{N}}(h) \leqslant 1$.

Definition 2 (Senapati and Yager, 2020). Let H be a fixed set. $\overline{V}$ is an FFS in H and is given by Eq. (2):

$$\overline{V} = \{h, \mu_{\overline{V}}(h), \upsilon_{\overline{V}}(h) \mid h \in H\}. \tag{2}$$

It is to be noted that in Eq. (2), $\mu_{\overline{V}}(h)$ and $\upsilon_{\overline{V}}(h)$ are the degrees of preference and non-preference such that they belong to [0, 1], and $\mu_{\overline{V}}(h)^3 + \upsilon_{\overline{V}}(h)^3 \leqslant 1$.

Definition 3 (Senapati and Yager, 2020). Let V_p be a FFN given by Eq. (3). FFS V is defined as a collection of FFN V_p given by Eq. (4). Eqs. (5)–(8) define the unary operations, i.e. scalar product, power, accuracy, score of V_p, respectively:

$$V_p = (\mu_p, \nu_p), \tag{3}$$

$$V = \{V_p,\ \forall p = 1, 2, \dots, n\}, \tag{4}$$

$$\eta V_p = \big(\big(1 - \big(1 - \mu_p^3\big)^{\eta}\big)^{1/3}, \nu_p^{\eta}\big), \quad \eta > 0, \tag{5}$$

$$V_p^{\eta} = \big(\mu_p^{\eta}, \big(1 - \big(1 - \nu_p^3\big)^{\eta}\big)^{1/3}\big), \tag{6}$$

$$A(V_p) = \mu_p^3 + \nu_p^3, \tag{7}$$

$$S(V_p) = \mu_p^3 - \nu_p^3. \tag{8}$$

Definition 4 (Senapati and Yager, 2020). Let V_1 and V_2 be two FFNs. Eqs. (9)–(10) define the binary operations, i.e. sum and product of V_1 and V_2, respectively:

$$V_1 \oplus V_2 = \big(\big(1 - \big(1 - \mu_1^3\big)\big(1 - \mu_2^3\big)\big)^{1/3}, \nu_1\nu_2\big), \tag{9}$$

$$V_1 \otimes V_2 = \big(\mu_1\mu_2, \big(1 - \big(1 - \nu_1^3\big)\big(1 - \nu_2^3\big)\big)^{1/3}\big). \tag{10}$$

3.2. *Expert Weight Estimation*

This section discusses the calculation of experts' weights, which were calculated using the variance method. The advantage of the variance method inferred from Section 2.3 is as follows: (i) The variance method effectively captures the hesitation and uncertainty exhibited by experts when assigning weights to different criteria. A higher variance in weight values signifies greater uncertainty, allowing the model to reflect real-world complexities that experts may grapple with; and (ii) This method allows for a nuanced understanding of how experts view the importance of various criteria. From a pessimistic perspective, these criteria are vital as they significantly influence the ranking. This behavioural depiction is made possible through the use of variance, providing a more comprehensive understanding of the decision-making process. The steps followed for the calculation of expert weights using the variance method are given below:

Step 1: Let d experts give ratings on x CVs based on c competing criteria. Likert scales are used for converting the ratings into FFNs. The following points are to be noted:

- l refers to the expert number, where $l = 1, 2, \dots, d$.
- i refers to the alternative, i.e. CV number, where $i = 1, 2, \dots, x$.
- j refers to the criteria number, where $j = 1, 2, \dots, c$.

The dimension of the decision matrices for every expert l is $x \times c$.

Step 2: Calculate the accuracy $A(V_{ij}^l)$ of each FFN using Eq. (7). Please note that the dimensions of the matrices remain intact for every expert l after calculating the accuracy.

Step 3: Determine the normalized accuracy $AN(V_{ij}^l)$ using Eq. (11). Please note that the dimensions of the matrices remain intact for every expert l after calculating the normalized accuracy.

$$AN\big(V_{ij}^l\big) = \begin{cases} 1 - A(V_{ij}^l), & \text{for cost criterion,} \\ A(V_{ij}^l), & \text{for benefit criterion.} \end{cases} \tag{11}$$

Step 4: Determine the variance vector for every expert d by applying Eq. (12). Please note that Eq. (12) yields a $1 \times c$ vector.

$$v_j^l = \frac{\sum_{i=1}^{x} \big(AN(V_{ij}^l) - \overline{AN(V_j^l)}\big)^2}{x - 1}. \tag{12}$$

It is to be noted that $\overline{AN(V_j^l)}$ is the mean of the normalized accuracy for every criteria c calculated in Step 3.

Step 5: Determine the experts' net confidence using Eq. (13), which is considered the importance of the experts. Please note that Eq. (13) yields a $1 \times c$ vector.

$$w_l = \frac{\sum_{j=1}^{c} v_j^l}{\sum_{l=1}^{d} \big(\sum_{j=1}^{c} v_j^l\big)}. \tag{13}$$

It is to be noted that in Eq. (13), w_l represents the net confidence value of every expert l, where $w_l \in [0, 1]$ and

$$\sum_{l=1}^{d} w_l = 1.$$

3.3. *Criteria Weight Estimation*

This section gives an overview of the steps involved in calculating the weight of the criteria, which was calculated via the LOPCOW method. A few advantages of the LOPCOW method can be inferred from Section 2.3 as follows: (i) LOPCOW method is designed to handle significant differences in the criteria weights, making it more adaptable for real-time problems; (ii) This method can also handle negative values present in the criteria, making it more versatile to different decision-making scenarios; (iii) This method also provides a more balanced and reasonable criteria importance, since it achieves relatively smaller ration between most important and least important criteria; (iv) LOPCOW can also manage data size discrepancies, make it more adaptable to varying size of datasets; and (v) LOPCOW provides a more acceptable and a comprehensive criteria importance in decision-making processes. The steps involved in the calculation of criteria weights using the LOPCOW method are presented below:

Step 1: Let d experts give ratings on c competing criteria. Likert scales are used for converting the ratings into FFNs. The following points are to be noted:

- l refers to the expert number, where $l = 1, 2, \ldots, d$.
- j refers to the criteria number, where $j = 1, 2, \ldots, c$.

The dimension of the criteria decision matrix is $d \times c$.

Step 2: Calculate the accuracy $A(V_{lj})$ of each FFN using Eq. (7). Please note that the dimension of the matrix remains intact after calculating the accuracy.

Step 3: Determine the normalized accuracy $AN(V_{lj})$ using Eq. (14). The *linear min-max* normalization is used in this step. Please note that the dimension of the matrix remains intact after calculating the normalized accuracy.

$$AN(V_{lj}) = \begin{cases} \dfrac{\max_j(A(V_{lj})) - A(V_{lj})}{\max_j(A(V_{lj})) - \min_j(A(V_{lj}))}, & \text{for cost criterion,} \\ \dfrac{A(V_{lj}) - \min_j(A(V_{lj}))}{\max_j(A(V_{lj})) - \min_j(A(V_{lj}))}, & \text{for benefit criterion.} \end{cases} \tag{14}$$

Step 4: Calculate the percentage values pv_j using Eq. (15). Please note that Eq. (15) yields a $1 \times c$ vector.

$$pv_j = \left| \ln\left(\sqrt{\frac{\left(\frac{\sum_{l=1}^{d} AN(V_{lj})^2}{d}\right)}{\sigma_j}} \right) \times 100 \right|. \tag{15}$$

It is to be noted that in Eq. (15), σ_j represents the standard deviation of the criterion j.

Step 5: Compute the criteria weights using Eq. (16). Please note that Eq. (16) yields a $1 \times c$ vector.

$$w_j = \frac{pv_j}{\sum_{j=1}^{c} pv_j}. \tag{16}$$

It is to be noted that in Eq. (16), w_j represents the net confidence value of every criterion j, where $w_j \in [0, 1]$ and

$$\sum_{j=1}^{w} w_j = 1.$$

3.4. *Ranking Algorithm*

This section elucidates the steps involved in ranking the CVs, which were performed using the CoCoSo method. The advantages of the CoCoSo method can be inferred from Section 2.3 as follows: (i) CoCoSo method provides a comprehensive approach to ranking alternatives by considering three levels of compromise space: sum, minimum, and maximum allowing for a more nuanced and balanced decision-making process; (ii) This method employs multiple techniques for aggregating weights, such as the multiplication rule and weighted power of distance methods enhancing the flexibility of its applicability in various scenarios; (iii) This method captures the behavioural aspects of decision-making, allowing for a more human-centric evaluation that can be more aligned with real-world decision-making processes; (iv) The method's ability to aggregate weights using various methods makes it well-suited for scenarios where simple weighting schemes may not capture the complexity of the decision-making environment; and (v) The method's flexibility in aggregating weights allows it to adapt to problems with different scales or units, making it easier to combine disparate types of information into a unified decision-making framework. The steps involved in ranking the CVs using the CoCoSo method are presented below:

Step 1: Let d experts give ratings on x CVs based on c competing criteria. Likert scales are used for converting the ratings into FFNs. The following points are to be noted:

- l refers to the expert number, where $l = 1, 2, \dots, d$.
- i refers to the alternative, i.e. CV number, where $i = 1, 2, \dots, x$.
- j refers to the criteria number, where $j = 1, 2, \dots, c$.

The dimension of the decision matrices for every expert l is $x \times c$.

Step 2: Calculate the accuracy $A(V_{ij}^l)$ of each FFN using Eq. (7). Please note that the dimensions of the matrices remain intact for every expert l after calculating the accuracy.

Step 3: Determine the normalized accuracy $AN(V_{ij}^l)$ using Eq. (11). Please note that the dimensions of the matrices remain intact for every expert l after calculating the normalized accuracy.

Step 4: Determine the weighted normalized accuracy $WAN(V_{ij}^l)$ using Eq. (17). Please note that the dimensions of the matrices remain intact for every expert l after calculating the weighted normalized accuracy.

$$WAN(V_{ij}^l) = w_j \times AN(V_{ij}^l). \tag{17}$$

It is to be noted that in Eq. (17), w_j refers to the weight of the criteria j.

Step 5: Determine the multi-stage compromise solutions X_1^l, X_2^l, and X_3^l using Eqs. (18)–(20). Please note that Eqs. (20)–(22) yield a $1 \times x$ vector for every expert l.

$$X_{i1}^l = \sum_{j=1}^{c} \frac{WAN(V_{ij}^l)}{\sum_{i=1}^{x} WAN(V_{ij}^l)}, \tag{18}$$

$$X_{i2}^l = \sum_{j=1}^{c} \frac{WAN(V_{ij}^l)}{\min_i(WAN(V_{ij}^l))}, \tag{19}$$

$$X_{i3}^l = \sum_{j=1}^{c} \frac{WAN(V_{ij}^l)}{\max_i(WAN(V_{ij}^l))}. \tag{20}$$

It is to be noted that in Eq. (19) and Eq. (20), min(.) and max(.) are the minimum and maximum operators, respectively.

Step 6: Combine the compromise solutions using Eq. (21) to obtain the net ranking vector for every expert l. Please note that Eq. (21) yields a $1 \times x$ vector for every expert l.

$$X_i^l = \sqrt[3]{X_{i1}^l \times X_{i2}^l \times X_{i3}^l} + \frac{X_{i1}^l + X_{i2}^l + X_{i3}^l}{3}. \tag{21}$$

Step 7: Aggregate the rank values for every expert l using Eq. (22). Please note that Eq. (22) yields a $1 \times x$ vector.

$$X_i = \prod_{l=1}^{d} (X_i^l)^{w_l}. \tag{22}$$

It is to be noted that in Eq. (22), w_l is the weight of the expert l, and X_i is the net ranking index of the ith CV. Ordering of the net ranking index of the CVs is done by arranging them in the descending order of values based on the vector obtained from Eq. (22), i.e. if the net ranking index of a CV is high, it is more preferred compared to the other CVs.

The flowchart of the proposed model has been presented in Fig. 2.

In Fig. 2, the flowchart delineates a systematic process for evaluating and ranking CVs. The process commences by converting the linguistic data of both alternative ratings and criteria ratings from various experts into FFS. Subsequently, the evaluation splits into two parallel paths: the left focuses on the calculation of expert weights by first obtaining alternative ratings as FS from different experts and then applying the Variance Method, culminating in a derived set of expert weights. The right path is dedicated to calculating criteria weights, which involves obtaining criteria ratings as FS from different experts and employing the LOPCOW Method. Once both weights are ascertained, the CoCoSo method ranks the CVs, resulting in a net-ranking index. The procedure concludes once the final rankings of the CVs are established.

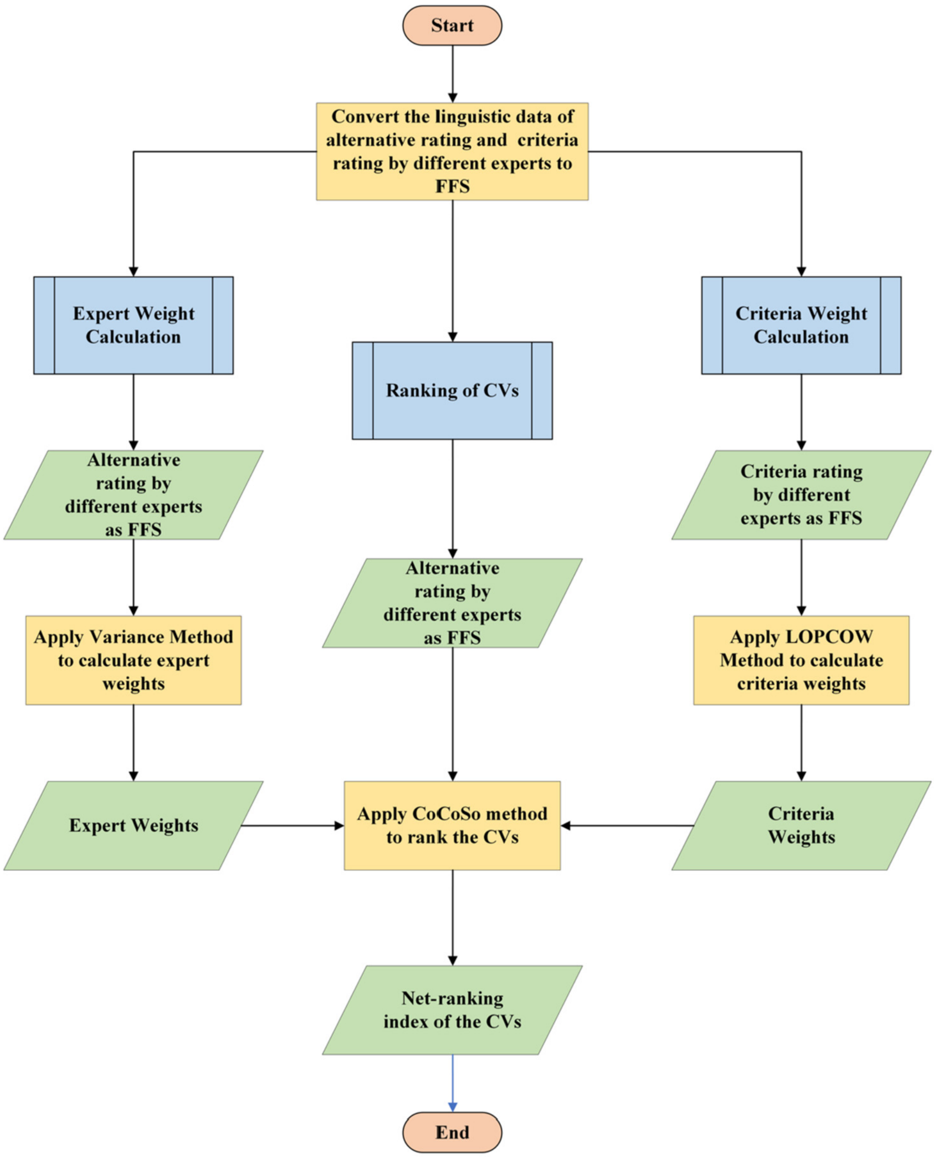

Fig. 2. Flowchart of the proposed model.

4. Case Study

This section presents a case example of CV selection for a health centre, concentrating effectively on the centre's core activities without compromising utility activities. Such utility activities include data storage for patients' data, employee data, inventory data, and official records, appointment maintenance, and analytics operations for planning the next five-year target and focusing on the mechanism for improving profitability. As a result, there was an urge for rational selection of CVs to support the health centre.

Table 2
Likert scale to convert data to FFN.

CV rating		Criteria rating	
Linguistic term	FFN	Linguistic term	FFN
Extremely Low (EL)	(0.6, 0.9)	Extremely Less Preferred (ELP)	(0.6, 0.9)
Very Low (VL)	(0.7, 0.8)	Very Less Preferred (VLP)	(0.7, 0.8)
Moderately Low (ML)	(0.6, 0.8)	Moderately Less Preferred (MLP)	(0.6, 0.8)
Low (L)	(0.6, 0.7)	Less Preferred (LP)	(0.6, 0.7)
Moderate (M)	(0.5, 0.5)	Neutral (N)	(0.5, 0.5)
High (H)	(0.7, 0.6)	Highly Preferred (HP)	(0.7, 0.6)
Moderately High (MH)	(0.8, 0.6)	Moderately Highly Preferred (MHP)	(0.8, 0.6)
Very High (VH)	(0.8, 0.7)	Very Highly Preferred (VHP)	(0.8, 0.7)
Extremely High (EH)	(0.9, 0.6)	Extremely Highly Preferred (EHP)	(0.9, 0.6)

During the annual audit meeting, the centre's officials decided to invest in cloud technology to stay competitive and balance core and utility activities. The advent of the pandemic emphasized the urgent need for effective data storage and maintenance to serve patients and employees better. Learning from the pandemic, the officials framed a panel of three experts with six to eight years of experience in their respective fields, such as technology, finance and audit, and legal/ethical aspects. The experts include a senior professor from the cloud computing division, legal/audit personnel, and a senior cloud admin from a company. These experts selected ten CVs from a cloud armor repository. Based on a peer discussion through emails and phone calls, seven CVs were chosen for the study and were rated by experts based on ten QoS attributes, considered from CSMIC (Siegel and Perdue, 2012) that offers benchmarking factors for cloud services. The ten QoS criteria are agility, assurance, scalability, availability, security, user-friendliness, customer relationship, privacy breach, total cost, and integrity risk. For ease of representation, $C_1, C_2, \dots, C_{10}$ denotes the criteria considered, $A_1, A_2, \dots, A_7$ represents the CVs considered, and D_1, D_2, D_3 represents the experts. Criteria $C_1, C_2, \dots, C_7$ are the benefit criteria, and C_8, C_9, and C_{10} are the cost criteria.

The steps involved in ranking the seven CVs against the ten criteria with the collected data by three experts using the proposed framework are presented below:

Step 1: Construct a 7×10 matrix for every expert by considering their ratings from Table 3. Convert the data into an FFN defined in Section 3.1 with Eq. (7) using the Likert scale in Table 2.

Table 2 presents the Likert scale for converting linguistic data to FFN. Values from Table 2 were used in Table 3 and Table 4 for performing the decision-making process.

Table 3 presents the dataset containing ratings for seven CVs based on the ten criteria by three experts. This data was converted into an FFN by finding the accuracy using Eq. (7) after converting it to (u, v) structure using the Likert scale presented in Table 2.

Step 2: Calculate the experts' importance with the matrices from Step 1 using the variance method presented in Section 3.2 using Eqs. (11)–(13).

The accuracy computed using Eq. (7) was normalized based on cost and benefit criteria using Eq. (11). Variance values were then determined by considering Eq. (12), and later,

Table 3
Dataset consisting of ratings of seven CVs by three experts using ten criteria.

CVs	Experts	Criteria									
		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	D_1	ML	VH	EH	VL	H	VH	L	M	L	H
	D_2	L	VL	MH	ML	VL	H	EH	L	EH	M
	D_3	EH	VH	L	EH	ML	VL	L	M	ML	ML
A_2	D_1	VH	H	MH	MH	M	L	MH	L	M	M
	D_2	VH	VH	ML	MH	H	ML	VH	VH	M	VH
	D_3	L	H	VH	M	ML	L	MH	VH	ML	MH
A_3	D_1	MH	H	VH	ML	VL	ML	M	L	L	MH
	D_2	H	M	H	ML	ML	EH	VL	M	VH	L
	D_3	M	H	ML	M	M	EH	ML	M	M	L
A_4	D_1	VH	ML	ML	VL	H	M	H	EH	MH	MH
	D_2	EH	EH	VL	VH	H	M	L	ML	MH	M
	D_3	VH	H	VL	ML	L	M	VL	VL	VH	VH
A_5	D_1	M	H	H	M	MH	L	VH	M	EH	M
	D_2	M	VH	ML	L	M	MH	ML	VL	ML	H
	D_3	M	ML	L	VL	ML	M	MH	M	L	L
A_6	D_1	VH	VL	M	ML	EH	MH	VL	VH	VH	L
	D_2	H	M	H	MH	VH	L	ML	ML	M	ML
	D_3	H	ML	H	L	ML	VL	M	H	MH	VH
A_7	D_1	M	MH	M	MH	L	L	VH	VL	H	EH
	D_2	EH	VH	VL	L	M	ML	EH	ML	M	L
	D_3	H	M	M	H	EH	MH	ML	ML	EH	M

Note: CV – cloud vendor; Please refer to Table 2 for the expansions of the abbreviations used in this table.

Table 4
Dataset consisting of ratings of ten criteria by three experts.

Experts	Criteria									
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
D_1	N	MHP	LP	VHP	MHP	N	EHP	VLP	N	HP
D_2	VHP	VHP	LP	N	MLP	EHP	VHP	MHP	HP	HP
D_3	MLP	LP	MHP	MLP	N	N	EHP	HP	HP	VHP

Note: Please refer to Table 2 for the expansions of the abbreviations used in this table.

the experts' importance was computed using Eq. (13). The importance of experts D_1, D_2, and D_3 was computed to be 0.339, 0.310, and 0.351, respectively, which were further used for rational decision-making.

Step 3: Construct a 3×10 matrix by considering the criteria ratings by the experts from Table 4. Convert the data into an FFN defined in Section 3.1 using the Likert scale in Table 2.

Table 4 contains the ratings of the ten criteria by the three experts. This data was converted into an FFN by finding the accuracy using Eq. (7) after converting it to (u, v) structure using the Likert scale presented in Table 2.

Step 4: Calculate the criteria importance with the matrices from Step 3 using the LOPCOW method presented in Section 3.3 using Eqs. (14)–(16).

Table 5
Net ranking index of CVs.

Cloud vendors	Net ranking index			
	Experts			Cumulative
	D_1	D_2	D_3	
A_1	17.876	16.966	19.901	18.263
A_2	14.675	17.874	18.302	16.856
A_3	17.652	15.343	13.318	15.312
A_4	18.543	16.238	20.202	18.338
A_5	13.903	15.299	15.232	14.787
A_6	19.973	14.568	17.776	17.387
A_7	16.769	16.104	16.510	16.470

The accuracy computed using Eq. (7) was normalized based on cost and benefit criteria using Eq. (14). The criteria importance was computed to be 0.068, 0.102, 0.153, 0.068, 0.057, 0.153, 0.057, 0.131, 0.153, and 0.057 for criteria $C_1, C_2, \dots, C_{10}$, respectively, by applying Eq. (15) to determine the log vector of the estimates that were further normalized with Eq. (16) to determine weights of criteria shown above.

Step 5: Calculate the net ranking index of CVs with the matrices from Step 1, experts' importance from Step 2, and criteria importance from Step 4 using the CoCoSo method presented in Section 3.4 using Eqs. (17)–(22).

After finding the accuracy with Eq. (7) and normalizing them with Eq. (11), the weighted normalized accuracy was computed using Eq. (17). The multi-stage compromise solutions, i.e. sum, minimum, and maximum, were computed using Eqs. (18)–(20), respectively. Eq. (21) was then used to aggregate the compromise solutions as the sum of the arithmetic and geometric mean of these solutions. Finally, the net-ranking index was computed using Eq. (22), multiplying all the compromise solutions raised to its corresponding expert weights.

Table 5 presents the net-ranking index of each expert, D_1, D_2, and D_3, and the cumulative net-ranking index for all the CVs, $A_1, A_2, \dots, A_7$. From Table 5, it can be concluded that the ranking order of the CVs is

$A_4 > A_1 > A_6 > A_2 > A_7 > A_3 > A_5$ with A_4 being the viable candidate for the process followed by A_1, A_6, and so on.

5. Results & Discussion

5.1. *Sensitivity Analysis*

This section attempts to understand the effect of criteria weights on the ordering of CVs. For this purpose, we performed weight rotation using a left shift operator that swaps weights between the criteria set to form new weight sets so that every weight value is assigned to every criterion once. Additionally, this gave us ten sets of weight vectors, each of 1×10 order, that were fed as input to the ranking model to determine rank vectors of

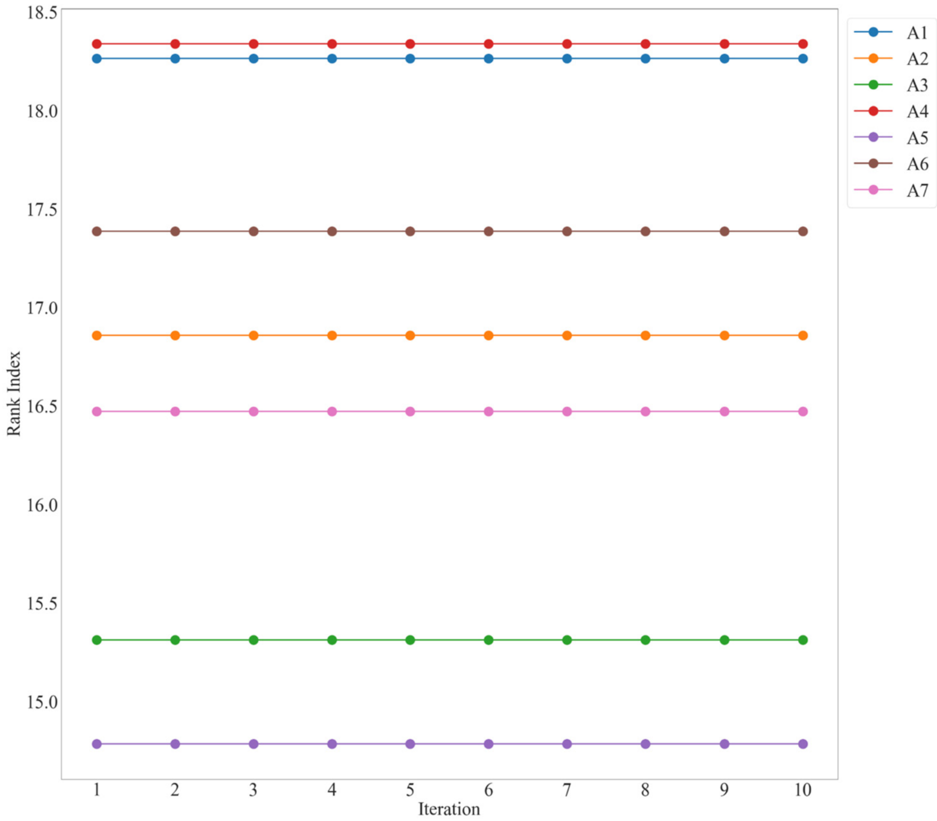

Fig. 3. Sensitivity graph of the framework.

CVs for different sets. The procedure described in Section 3.4 was utilized to determine CV rank for each weight set.

For each weight set, parameter values are determined for each expert, and net values are calculated. This results in a 1×7 vector obtained for each set. These values are plotted in Fig. 3, which reveals that the ordering is intact and the developed approach is robust to criteria weight shift.

5.2. *Comparative Analysis*

This section provides a bidirectional comparison between the application and method perception. In the application context for CV selection, the authors considered extant models that use IFS and its extensions in the method context. The proposed model was compared with the extant models to understand its efficacy. From the application perspective, models like those proposed by Krishankumar *et al.* (2020), Dahooie *et al.* (2020), Hussain *et al.* (2020a), Hussain *et al.* (2020b), and Hang Nguyen *et al.* (2023) were compared with proposed model to understand its efficacy from the application perspective. A comparison of the proposed model and extant models is presented in Table 6.

Table 6
Comparison of the proposed model with existing models.

Features	Proposed model	Hang Nguyen *et al.* (2023)	Hussain *et al.* (2020a)	Hussain *et al.* (2020b)	Dahooie *et al.* (2020)	Krishankumar *et al.* (2020)
Rating	FFS	PULTS	Crisp	Triangular fuzzy numbers	IVIFS	IFS
Subjective randomness	Captured	n/a	n/a	n/a	Captured	Captured
Preference flexibility	Highly flexible	Highly flexible	n/a	n/a	Moderately flexible	Less flexible
Uncertainty modelling	Better	Better	n/a	n/a	Good	Good
Experts' importance	Determined	n/a	n/a	n/a	n/a	n/a
Experts' hesitation	Captured	n/a	n/a	n/a	n/a	Captured
Criteria type	Considered during weight calculation and ranking	–Considered during ranking–				
Personalized ranking	Possible	n/a	n/a	n/a	n/a	n/a
Weight consideration	Both expert and criteria weights	–Only criteria weights–				

Note: FFS – Fermatean fuzzy sets; PULTS – probability uncertainty linguistic term set; IVIFS – interval-valued intuitionistic fuzzy set; IFS – intuitionistic fuzzy set.

Some innovative features of the developed model are provided below:

- FFS is considered the preference information that could model uncertainty from three zones, i.e. preference, non-preference, and hesitancy, with a broader scope for preference expression, unlike the other fuzzy variants shown in Table 6. Owing to the flexibility in terms of the q parameter, the range of expression is broadened, thereby allowing better expression of choices. Also, FFS handles subjective randomness effectively, as it is a crucial property of an orthopair fuzzy set.
- Human intervention is managed effectively by calculating parameter values rather than direct assignment. As a result, the bias and inaccuracy in the decision process are reduced, thereby providing rationality in the decision process. Furthermore, the hesitation of experts is handled effectively by the developed methods, along with the scope for better discrimination of criteria based on their importance and values. Also, the consideration of the reliability of experts and criteria type allows for rational weight assessment, unlike other methods.
- Since experts play a crucial role in the decision process, consideration of their weights/importance during criteria weight calculation and ranking is crucial. Unlike other models, in this case, the importance of experts is considered during criteria weight calculation, and both criteria and experts' weights are considered during the ranking of

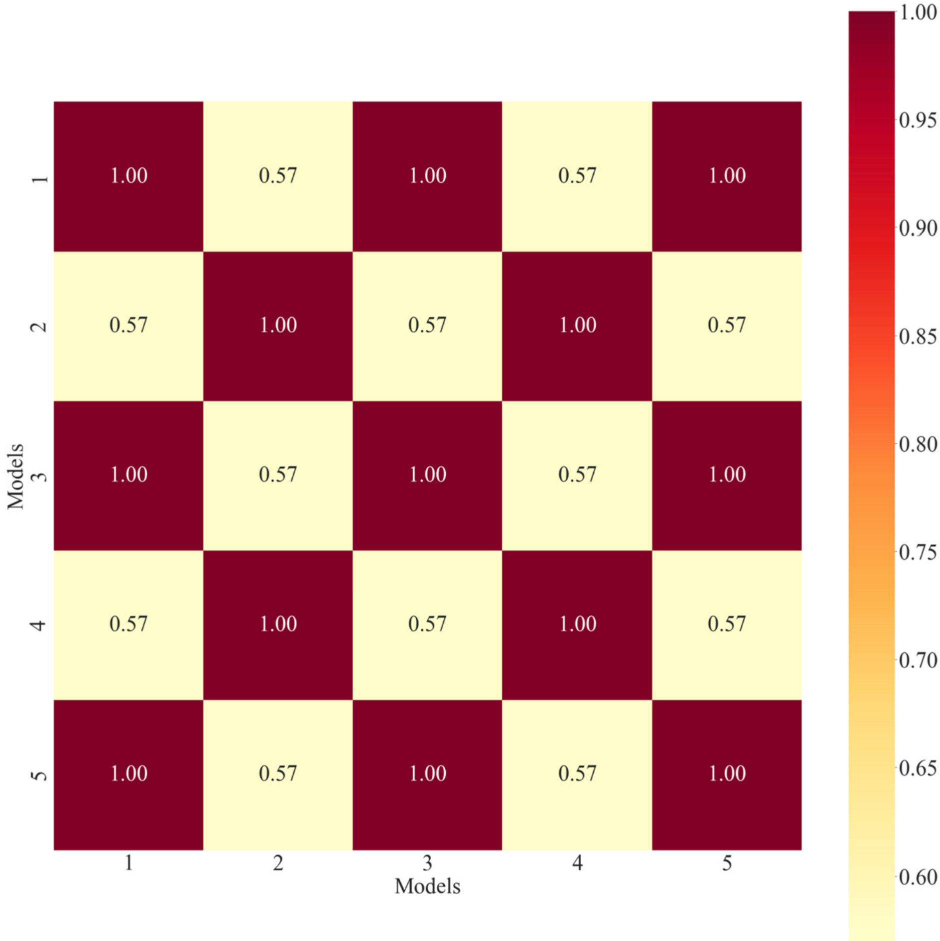

Fig. 4. Spearman correlation of rank orders obtained. *Methods considered*: 1 – Proposed; 2 – Senapati and Yager (2020); 3 – Mishra, Rani *et al.* (2022); 4 – Rani and Mishra (2021); and 5 – Zeng *et al.* (2023).

CVs. Such a connected decision system allows rational ranking of CVs with better consistency.

- Finally, the ranking of CVs is done in two ways, i.e. personalized and cumulative ways, which needs to be improved in the extant models. Also, the consistent rank fusion with the help of weights of experts and consideration of criteria weights during rank estimation makes the developed model well-connected and systematic, unlike other CV selection approaches.

From the method perspective, the models proposed by Senapati and Yager (2020), Mishra *et al.* (2022b), Rani and Mishra (2021), and Zeng *et al.* (2023) were compared with the developed framework to determine its consistency level by applying Spearman correlation to the rank orders obtained from each method. It can be noted from Fig. 4 that the proposed framework is consistent with the other decision models with coefficient

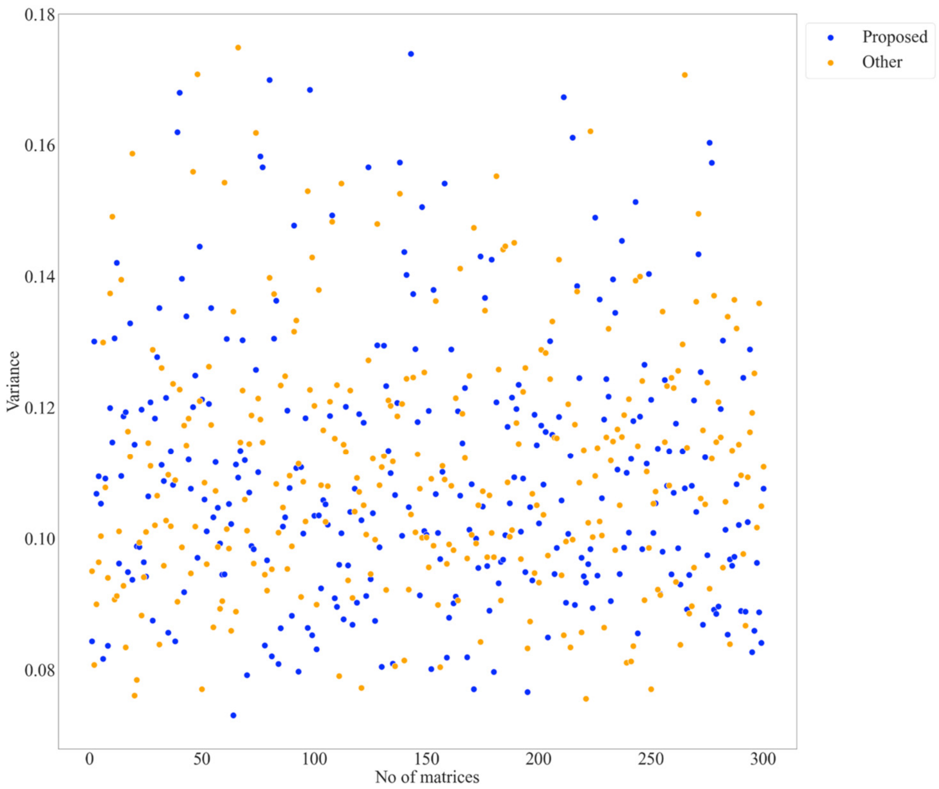

Fig. 5. Broadness analysis of the proposed model against other models.

values of 1, 0.57, 1, 0.57, and 1 for proposed versus other models. Fig. 4 provides the complete correlation plot to show the net consistency effect of the proposed model with respect to other decision models.

Apart from consistency, we also explored the broadness aspect of the proposed model to give stakeholders a convenient ordering of CVs that would facilitate better backup planning and management. For this, we performed a simulation study with a set of 300 matrices with a 7×10 dimension. The criteria weights were considered as calculated in Section 4. It must be noted that in each set, there are three matrices. All of these matrices were fed as input to the proposed and compared models to determine the rank values of CVs. As a result, we obtained 300 vectors of 1×7 dimension, and the variability was determined for each vector. Subsequently, two vectors with 300 points each were derived, as plotted in Fig. 5. In the proposed framework, rank values from each of the three matrices from a single matrix set were determined and finally fused to determine the cumulative values, upon which variance measure was applied to determine the rank variability. In the model by Mishra *et al.* (2022b), the three matrices with a single matrix set were first aggregated and later fed to the ranking model to determine rank values. From the plot, it is clear that there are situations where the proposed framework outperforms the extant models and vice versa. Moreover, it is evident that the proposed model can be promptly used by policymakers and experts to gain broad rank values for better planning of the backup strategy and also to gain insights into the ordering of CVs based on individual experts, which otherwise is not possible. Hence, along with broad ranks, we are able to facilitate the personalization aspect better, followed by the cumulative aspect, which is lacking in the extant models.

5.3. *Discussion*

CV selection is an important decision problem aimed at supporting diverse sectors to manage data and resources properly. Since the health industry is packed with crucial and private data, health industries need to maintain such data efficiently and less expensively. Besides, data management must help the health sector's daily activity; in this aspect, cloud technology is a prominent DT that meets the industry's demand. However, the hurdle lies in choosing a suitable CV based on diverse criteria and uncertain preferences.

To tackle the challenge, we propose a model possessing integrated decision approaches focusing on the methodical determination of parameter values and reduced human intervention to alleviate biases and inaccuracies in the process. The selection problem involves the consideration of multiple criteria that are QoS presented by the CSMIC as benchmarking factors for aiding appropriate CV selection. Since there are multiple criteria and the opinion of a CV with respect to these criteria is uncertain, the problem is mapped to MCDM. Here, criteria weights are methodically derived, and from the values in Section 4, it is seen that scalability, user-friendliness, and total cost are highly preferred criteria, followed by privacy breach and assurance. Likewise, other criteria preferences are gained. Based on the ranking algorithm, CV A_4 is highly preferred, followed by A_1, A_6, and so on.

The efficacy of the framework was investigated from both the application and methodology perspectives based on Table 6, Fig. 4, and Fig. 5. It is inferred that the proposed framework is methodical and reduces human intervention, subjectivity, and biases. Furthermore, the model demonstrated consistency with respect to other models and the ability to showcase both individualistic and cumulative ranking of CVs with an acceptable level of broadness, which the other models need to improve.

6. Conclusion

The framework developed in this article is valuable for the rational selection of CVs to manage utility activities in the health industry effectively. Primarily, the framework focuses on better modelling uncertainty and reducing human intervention to tackle the issues of bias and subjectivity. Weights of experts and criteria are methodically determined with better capturing of hesitation of experts during preference articulation along with personalized rank orders of CVs, which aids in mitigating subjectivity and biases. The model provides both cumulative and personalized ordering of CVs that offers better planning and rationale toward a specific selection. Utilization of FFN for data models uncertainty effectively from three dimensions, i.e. membership, hesitancy, and non-membership, gives a broader window for preference expressions. Variance and LOPCOW methods are presented for determining the weights of entities, and later, a ranking algorithm with CoCoSo and rank fusion is put forward for determining the rank values of CVs at both the individualistic and cumulative levels.

From Table 6, Fig. 3, and Fig. 4, the efficacy of the framework is clarified from both the application and method perspectives. Some notable aspects of the proposed framework include consistency, broad rank values, and methodical parameter calculations. Further, some implications of the framework include: (i) is a ready-to-use module that can supplement decisions from stakeholders; (ii) reduces human intervention and provides a methodical approach for calculating decision parameters that reduce inaccuracies and subjectivity; (iii) can be used both by users and CVs for their respective purposes, such as aiding selection and planning strategies to improve market growth, respectively; (iv) offers both sense of personalization and cumulative rank estimation that adds value to stakeholders at the decision-making process; (v) uncertainty is handled from three dimensions – preference, non-preference, and hesitancy; (vi) subjective randomness issue and bias from the system is handled via methodical calculation of entities; and (vii) can be used by policymakers and other stakeholders after training which can be facilitated via seminars, hands-on sessions, and workshop.

Some limitations of the work are: (i) data are assumed to be complete, and if, due to hesitation, some instances are not available, the system cannot handle the issue; (ii) partial information about entities cannot be considered in the present formulation; (iii) customized ranking; (iii) pre-defined terms are being used, which in some sense restricts the experts from flexibly providing her/his rating; and (iv) functional criteria are considered for rating CVs, but social and environmental factors are not included in the present study. In terms of future research scope, we plan to address the limitations and extend the framework to different MCDM applications from supply chains, energy, sustainability, environment sectors, and so on. Further, we also anticipate extending different fuzzy versions, such as interval and probabilistic variants of orthopair fuzzy sets, hesitant fuzzy sets, neutrosophic fuzzy sets, and alike, to better understand uncertainty modelling for CV selection. Also, the data-preprocessing module is planned to enhance the rating information with consistent preference information from experts either via feedback mechanism or methodical data entry. Finally, concepts of machine learning and recommender systems can be integrated with the proposed framework to perform large-scale decision-making better.

Author contributions

S. Dhruva – Conceptualization, Data curation, Prototyping, Implementation, Writing and Editing.
R. Krishankumar – Conceptualization, Data curation, Implementation, Writing and Editing.

E.K. Zavadskas – Implementation, Supervision, Review, Writing and Editing.
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Declarations

Conflict of interest: The authors declare no competing interest.

A. Appendix

Table A1
Terms and their abbreviations.

Term	Abbreviation
AHP	Analytical hierarchical process
ARAS	Additive ratio assessment
CA	Comparative analysis
CFFEWAA	Complex Fermatean fuzzy Einstein weighted average aggregation
CFFEOWAA	Complex Fermatean fuzzy Einstein ordered weighted average aggregation
CFFEHAA	Complex Fermatean fuzzy Einstein hybrid average aggregation
CoCoSo	Combined compromise solution
CODAS	Combinative distance-based assessment
COPRAS	Complex proportional assessment
CRADIS	Compromise ranking of alternatives from distance to ideal solution
CRITIC	Criteria importance through inter-criteria correlation
CV	Cloud vendor
D-CRITIC	Distance correlation criteria importance through inter-criteria correlation
DHHFLTS	Double hierarchy hesitant fuzzy linguistic term set
DOBI	Dombi Bonferroni
EDAS	Evaluation based on distance from average solution
EVCS	Electric vehicle charging station
FF	Fermatean fuzzy
FFD	Fermatean fuzzy data
FFN	Fermatean fuzzy number
FFS	Fermatean fuzzy set
FLBWM	Fuzzy linear best-worst method
FUCOM	Fuzzy composite evaluation method
IF-VIKOR	Intuitionistic fuzzy viekriterijumsko kompromisno rangiranje
IFS	Intuitionistic fuzzy set
IFSV	Intuitionistic fuzzy statistical variance
IoT	Internet of things
IVFFS	Interval-valued Fermatean fuzzy sets
IVFNN	Interval-valued fuzzy neutrosophic number
IVHFFS	Interval-valued hesitant Fermatean fuzzy sets
IVIFS	Interval-valued intuitionistic fuzzy set
LCC	Low carbon city
LGSWA	Logarithmic generalized spherical weighted averaging
LGSWG	Logarithmic generalized spherical weighted geometric
LOPCOW	Logarithmic percentage change-driven object weighting
MCDM	Multi-criteria decision making

(*continued on next page*)

Table A1
(*continued*)

Term	Abbreviation
MCDP	Multi-criteria decision problem
MCRAT	Multiple-criteria ranking by alternative trace
MEREC	Method based on removal effect of criteria
MMS	Micro mobility solutions
MOSS	Methodology for optimal service selection`
MULTIMOORA	Multiplicative form of multi-objective optimization based on ratio analysis and reference point approach
PFS	Pythogorean fuzzy set
PIFN	Pentagonal intuitionistic fuzzy number
PROMTHEE	Perference ranking organization method for enrichment evaluation
PSI	Preference selection index
PULTS	Probabilistic uncertainty linguistic fuzzy set
QoS	Quality of service
SA	Sensitivity analysis
SAW	Simple additive weighting
SMART	Simple multi-attribute rating technique
SWARA	Step-wise weight assessment ratio analysis
T2NN	Type-2 neutrosophic number
TODIM	Tomada de decisão interativa e multicritério
TOPSIS	Technique for order preference by similarity to ideal solution
WASPAS	Weighted aggregated sum product assessment

Table A2
Symbols and their definitions.

Symbol(s)	Definition	Symbol(s)	Definition
H	Fixed set	c	No of criteria
N	Fixed set	j	Criteria number
$\overline{N}$	IFS	V_{ij}^{l}	FFN of ith CV, jth criteria, and lth expert
h	Value belonging to set H	$A(V_{ij}^{l})$	Accuracy of V_{ij}^{l}
$\mu_{\overline{N}}(h)$	Degree of truth in IFS	$AN(V_p)$	Normalized accuracy of V_{ij}^{l}
$\upsilon_{\overline{N}}(h)$	Degree of false in IFS	υ_{j}^{l}	Variance of jth criteria and lth expert
$\pi_{\overline{N}}(h)$	Degree of hesitance in IFS	w_l	Weight of lth expert
$\overline{V}$, V	FFS	V_{lj}	FFN of jth criteria and lth expert
$\mu_{\overline{V}}(h)$, μ_p	Preference value of FFS	$A(V_{lj})$	Accuracy of V_{lj}
$\upsilon_{\overline{V}}(h)$, ν_p	Non-preference value of FFS	$AN(V_{lj})$	Normalized accuracy of V_{lj}
V_p, V_1, V_2	FFN	pv_j	Percentage value of jth criteria
η	Constant	w_j	Weight of jth criteria
$A(V_p)$	Accuracy of FFN	$WAN(V_{ij}^{l})$	Weighted normalized accuracy of V_{ij}^{l}
$S(V_p)$	Score of FFN	X_{i1}^{l}	First compromise solution of ith CV and lth expert
d	Number of experts	X_{i2}^{l}	Second compromise solution of ith CV and lth expert
l	Expert number	X_{i3}^{l}	Third compromise solution of ith CV and lth expert
x	No of CVs	X_{i}^{l}	Combined compromise solution of ith CV and lth expert
i	CV number	X_i	Net-ranking index of ith CV

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