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QUALITY OF SERVICE ATTRIBUTES BASED HYBRID DECISION-MAKING FRAMEWORK FOR RANKING CLOUD SERVICE PROVIDERS UNDER FERMATEAN FUZZY ENVIRONMENT

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Abstract: Cloud Computing has gained substantial popularity due to its ability to offer diverse and dependable computing services suited to clients demands. Given the rapid expansion of this technology, an increasing number of IT service providers are competing to deliver cloud services that are both of excellent quality and cost-efficient, in order to best meet the requirements of their clients. With the extensive range of options available, selecting the best Cloud Service Provider (CSP) has become a challenging dilemma for the majority of cloud clients. When evaluating services offered by many CSPs, it is important to consider multiple attributes. Efficiently addressing the selection of the best CSP involves tackling a challenging Multi-Attribute Decision Making (MADM) problem. Several MADM techniques have been proposed in academic literature for evaluating CSPs. However, the persisting problems of inconsistency, uncertainty, and rank reversal remain unresolved. In this paper the authors present a hybrid MADM framework to rank eight CSPs using nine Quality of Service (QoS) attributes. In order to achieve this objective, Fermatean fuzzy sets-full consistency method (FFS-FUCOM) is combined with Grey–Relational–Analysis and the Technique–for–Order–Preference–by–Similarity–to–Ideal–Solution (Grey-TOPSIS) technique. The framework successfully resolved the aforementioned problems. Sensitivity analysis is conducted to assess the stability and robustness of the results produced by the proposed framework. The sensitivity analysis results indicate that the proposed framework offers an accurate and robust solution. A systematic ranking test is undertaken to ensure that the results are ranked in a systematic manner. Additionally, a comparative analysis is carried out with the most relevant study.

Keywords: Cloud Computing, Cloud Service Providers, Fermatean Fuzzy Sets, MADM, FUCOM, Grey-TOPSIS.

MSC: 90C31, 90C70, 62C86, 68P10, 68U35.

1. INTRODUCTION

Nowadays, researchers are intensively studying the emergence of the 5th industrial revolution and the crucial role of artificial intelligence within this revolution [1]. Nevertheless, the majority of sizable and moderately-sized corporations have yet to adopt sophisticated artificial intelligence technology and have not fully accomplished their digital transformation. The emergence and advancement of the 4th industrial revolution (Industry 4.0) can still be observed in industry and production, particularly in developing economies.

The advent of Industry 4.0 has highlighted the need for connection in various domains. The formation of Industry 4.0 has brought along advanced technology that allows for instantaneous connectivity, monitoring, and accessible across several systems [2]. Cloud computing technology is a fast-growing technology within Industry 4.0. The literature highlights several advantages of cloud computing technology, including its accessibility, cost-effectiveness, and ability to facilitate speedy decision-making [3], [4]. Cloud computing technology is a model that allows for easy and immediate access to a shared pool of customisable computer resources, such as networks, storage, servers, services, and applications. This technology facilitates the transfer of basic computing operations from local servers to distant servers, potentially resulting in less information technology expenditure and reduced maintenance expenses. Large organisations are increasingly replacing their commercial information technology expenditures with outsourcing agreements due to the availability of high technology requirements through cloud computing technology services, which offer 24/7 accessibility and relatively cheap investment costs [5].

Cloud computing encompasses a variety of services provided by Cloud Service Providers (CSPs) to fulfil client requirements [6]. Leading IT corporations such as Amazon, Microsoft, and Google are presently competing to offer clients reliable and cost-effective services that most effectively meet their demands. The competitive This competitive environment fosters the growth of cloud computing technologies and motivates numerous IT companies to enhance their Quality of Service (QoS).

The CSPs provide comparable services with varying costs, levels of quality, and sets of features. Although a particular provider may offer affordable storage services, it could be costly for computing tasks. With the wide range of cloud services available, consumers face the substantial challenge of choosing the CSP that most effectively meets their needs. Ensuring future performance and adhering to rules, policies, and laws [7], [8] is crucial.

However, selecting an inappropriate CSP can result in future service delivery failures, compromised data security or integrity, and non-compliance with cloud data storage usage.

The process of cloud service selection involves identifying the best suitable CSP by aligning the user's requirements with the characteristics offered by different CSPs [9]. The rapid growth of CSPs, together with their vast range of services offered at variable prices and quality levels, has resulted in challenges when ranking and choosing the most suitable CSP based on user preferences [10], [11], [12].

Moreover, it is important to consider several attributes when choosing the most appropriate CSP. QoS attributes, such as reliability and performance, play an important role in assessing the quality of CSPs. Cloud customers also place great attention on the security attributes of the services. The consumer may find some selection attributes unclear, such as the lack of transparency from CSPs regarding the access and authorization of cloud resources. Some attributes, such as security and usability, are difficult to measure precisely [13]. Furthermore, it is important to consider that there may be trade-offs between these attributes, such as price and performance [14]. To determine the most suitable CSP that aligns most closely with user preferences, it is necessary to analyse a broad range of distinct evaluation attributes that define the various cloud services provided by multiple CSPs. Hence, the process of choosing the appropriate CSP involves a complicated Multiple Attributes Decision-Making (MADM) issue, wherein many options must be assessed and ranked based on different attributes [15], taking into account the user's specific preferences (i.e., the importance level of each of the attribute) [16], [17], [18], [19].

1.1. Research Problem

While MADM techniques have been extensively examined in the academic literature, they still have certain shortcomings, such as inadequate consistency in comparisons, complicated comparison systems, and an overall rise in computing complexity [20]. These weaknesses provide a substantial obstacle when selecting CSPs [21]. Another issue that arises in the process of ranking and selecting CSPs is uncertainty [22]. In addition, several MADM techniques have a rank reversal issue [23], [24], wherein the addition or removal of a CSP from the repository causes a non-ideal CSP to be ranked as ideal. An unexpected change in the ranking of CSPs misleads a cloud user and leads to significant financial losses over time due to the incorrect selection of services. Therefore, it would be advantageous to establish a framework for choosing CSPs that are resilient to inconsistency, rank reversals and uncertainty issues.

1.2. Limitations of MADM Techniques

Based on the literature reviewed in Section 2, numerous MADM techniques have been employed to rank CSPs in order to identify the most effective and optimal CSP. The subsequent sections will examine MADM ranking and weighting techniques, along with the applications of fuzzy set theory.

1.2.1 MADM Ranking Techniques

MADM ranking techniques include TOPSIS, PROMETHEE, VIKOR, ELECTRE, Grey relational analysis, and multi-objective programming. Each technique has its own advantages and disadvantages, as well as different situations where it might be applied

[25]. No technique stands out as superior to the others [26]. Several techniques can be used to solve the MADM problem, hence improving the dependability of decision-related information. According to our examination outlined in Section 2.1, TOPSIS was the most commonly used technique for ranking CSPs.

TOPSIS is a prominent ranking technique employed for determining the optimal alternative among set of alternatives. It has been widely selected to rank CSPs. In these studies, it has been extended under different fuzzy environments such as triangular fuzzy numbers [27], [28], [29], [30], 2-tuple fuzzy linguistic [31], IFS [32] [33], [34], single-valued NFS [35], interval-valued fuzzy set [36], and interval, IFS and NFS [23]. Nevertheless, the application of Euclidean distance in the traditional TOPSIS is associated with several drawbacks. Firstly, it is not sensitive to small values [37]. Secondly, it results in a relatively small distance between the positive-ideal-solution and negative-ideal-solution [38]. Thirdly, it distorts the original information [39]. Fourthly, it exhibits rank reversal defects [40]. Accordingly, several enhancements of TOPSIS have been proposed in the academic literature to address these drawbacks [37]. Alternative measures such as, contact-vector-distance [41], hamming-distance [42], Canberra-distance [37], M-TOPSIS [43], and generalized-hybrid-distance [39] have been suggested as substitutes for Euclidean distance. In pursuit of the same objective, many academics integrated Grey-relational-analysis with TOPSIS (namely Grey-TOPSIS technique) [38], [44], [45], [46], [47], [48].

Deng initially introduced the Grey-relational-analysis technique, which has been extensively employed to address issues of vagueness and insufficient information [49]. The main benefits of the Grey-relational-analysis technique include making decisions based on the original data, being one of the most efficient approaches for making business decisions, and facilitating simple and direct computations [49]. Furthermore, Grey-relational-analysis possesses an ability to handle intricate decision-making scenarios, such as those with ambiguous, inaccurate, and incomplete data [46].

Although the Grey-TOPSIS technique [50] has advantages, it lacks the ability to assign weights to attributes based on their importance. Consequently, researchers employed alternative approaches, such as AHP or BWM, to achieve this goal.

1.2.2 MADM Weighting Techniques

Assessing alternatives involves considering the importance of the assessment attributes in the decision-making process [51], [52]. The assessment attributes have different levels of importance, causing certain attributes to have a greater influence on the evaluation than others [21]. Attributes weight is determined by many MADM techniques, which are categorised as either objective or subjective techniques [53]. The objective weighting techniques involve calculating attribute weights based on the variance of data in the decision matrix [54]. Objective attribute weights can be determined by many techniques, such as Gini index, standard deviation, or entropy [55]. By using the given techniques, the need for expert input is reduced, which helps in creating autonomous decision support systems. However, there are often situations where it is challenging to estimate the weights of the attributes only from the decision matrix. This presents a challenge in verifying that the derived weights are valid in light of their actual importance as determined by the experts.

The subjective weighting techniques have been established to precisely capture the decision-maker's opinion [56], [57]. They facilitate the assessment of the importance of attributes systematically. Subjective techniques for determining attributes' weight allow decision-makers to evaluate the importance of a specific attribute in relation to others in a certain decision context [58]. These techniques can determine the importance of assessment attributes, perform pairwise comparisons, or establish connections between assessment attributes. The weight vector used to determine the importance of attributes is based entirely on decision-makers' knowledge [24], [59]. The AHP, ANP, and BWM are well-known subjective techniques utilised for calculating attributes' weight [60].

The accuracy of the weights in AHP is dependent upon successfully passing consistency test for pairwise comparison matrices [61]. These matrices incorporate numerical scales determined by decision-makers based on their expertise, which can result in inconsistencies owing to limited experience and the complicated nature of the decision problem. The number of comparisons rises proportionally with the number of attributes, leading to a potential escalation of inconsistency. In contrast, BWM, another MADM technique, necessitates a lesser number of pairwise comparisons in comparison to AHP. BWM employs a scale ranging from 1 to 9 to make comparisons, doing reference comparisons to identify the most favourable attribute and attributes preferences over the least favourable attribute. The application of this strategy effectively decreases the number of pairwise comparisons required from $n(n-1)/2$ in AHP to $2n-3$ in BWM [62]. Nevertheless, BWM has difficulties in determining the optimal and suboptimal attributes, as well as their respective importance. Minimising the use of fractional numbers improves comprehension for decision-makers, while this approach still requires significant cognitive effort due to the subjective nature of comparisons. In general, the pairwise and reference comparisons in these techniques result in considerable time consumption and difficulties in providing natural comparisons.

Recently, a Full-Consistency-Method (FUCOM) [62] was proposed to address the issue of inconsistency that is often observed with the AHP and BWM techniques. The FUCOM relies on the principles of comparing pairs and validating outcomes by measuring the deviation from maximum consistency (DMC). The key advantages of using FUCOM are a limited number of pairwise comparisons of attributes (specifically, only $n-1$ comparisons), the possibility of validating results by setting the DMC of comparison, and the ability to take into account transitivity in pairwise comparisons of attributes. The FUCOM incorporates the subjective influence of a decision-maker on the final weight value of attributes. Within FUCOM, decision-makers prioritise the attributes based on their preferences and conduct pairwise comparisons of the evaluated attributes. In contrast to previous techniques, FUCOM has exhibited slight variations in the acquired weights of attributes from the ideal values. In addition, the mathematical technique of FUCOM resolves the issue of redundant pairwise comparisons of attributes, a problem that is present in some subjective techniques used to estimate the weights of attributes. Therefore, FUCOM is considered as the most appropriate method for determining the weight of the QoS attributes. However, like AHP and BWM, the uncertainty issue remained an open issue that cannot be handled by employing the original version of FUCOM.

1.2.3 Fuzzy Set Theory

Multiple types of uncertainty can be found in the literature, caused by the decision-making process. They are involved in identifying attributes, assessing connections among attributes, assessing alternatives, generating attributes weight based on expert opinions, and selecting aggregation operators [63]. The uncertainties in the input data of a MADM problem mainly include evaluating many alternatives and establishing the weights of the attributes. Traditional MADM techniques typically need exact input values, even though it is common to include uncertain data in decision-making [63]. Meeting this condition is a difficulty for decision-making, as obtaining accurate values is often difficult, if not impossible. Therefore, when input data is ambiguous, specific techniques like fuzzy sets or probabilities are required for ranking [63]. This work utilises fuzzy set theory to address the uncertainty raised by depending on expert opinions in generating the weight of attributes using FUCOM.

In this regard, Zadeh invented the notion of [64] (FS) to address uncertainties in real-life problems. The utilisation of FS allows for the assignment of varied degrees of membership (μ) to alternative, with respect toothier numbers. However, Zadeh's influential research failed to consider the consequences of incorporating a degree of non-membership (v). Atanassov [65] introduced a notable concept of intuitionistic fuzzy set (IFS), which incorporates the consideration of both μ and v. This concept is restricted by the condition $\mu + v \leq 1$. The concept of IFS has proven to be valuable in addressing numerous practical problems by considering the value of indeterminacy. However, the researchers highlighted the inefficiency of the method in handling uncertainties when the summation of the μ and v exceeds 1. Yager [66] introduced the Pythagorean fuzzy set (PyFS) as a solution to address this problem. The notion of PyFS is subject to the condition $(\mu)^2 + (v)^2 \leq 1$. However, the inefficiency of the PyFS appeared when the square sum of the μ and v exceeds 1. Later, Yager [67] introduced an extended and generalised FS version named q-rung orthopair fuzzy sets (q-ROFSs). This version includes the condition $(\mu)^q + (v)^q \leq 1$. Senapati and Yager [68] proposed the concept of Fermatean fuzzy set (FFS) as a specific instance of q-ROFSs, where q is equal to 3, developing upon the ideas of IFS and PyFS. FFS demonstrates superior flexibility and efficiency in managing uncertainty when compared to IFS and PyFS, as shown in Figure 1. Consequently, the utilisation of FFS is gradually growing as a means to address numerous MADM issues. A q-ROFS offers greater flexibility compared to FFS, but it also introduces additional complexity. FFS provides analysts with a substantial degree of flexibility.

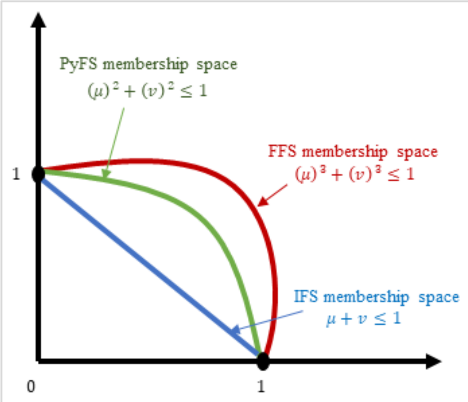

Figure 1: Membership space analysis between IFS, PyFS and FFS.

Thus, FFS-FUCOM is aimed to make more flexible and realistic decisions [69]. In the proposed MADM farmwork, the FFS-FUCOM is adopted to determine the weighting coefficients of the evaluation attributes. In this paper, the FFS-FUCOM proposed by [69] is modified by using modified Euclidean distance measure to process uncertain information.

1.3. Research Motivation

In this paper, we are motivated to hybrid MADM framework under fuzzy environment for ranking CSPs. The framework combines Grey-relational-analysis and Technique-for-Order-Preference-by-Similarity-to-Ideal-Solution (Grey-TOPSIS) technique and Fermatean fuzzy sets-full consistency method (FFS-FUCOM) based distance measurement that is resistant to ranking reversal, inconsistency, and uncertainty issues. To the best of our knowledge, there is no existing study in the literature that combines the FFS-FUCOM and Grey-TOPSIS for the purpose of ranking CSPs or any other case study. Initially, the FFS-FUCOM based distance measurement is proposed to estimate the final weights of the QoS attributes and assess their relative levels of importance. Furthermore, the Grey-TOPSIS technique was adopted to rank the chosen CSPs based on the weighting results derived by FFS-FUCOM based distance measurement. Furthermore, the proposed framework's effectiveness, efficiency, and robustness were evaluated using an experiment, sensitivity analysis, and comparative analysis.

1.4. Research Contributions

The main contributions of this study can be summarised as follows:

- This paper adjusts FFS-FUCOM based distance measurement to obtain the final weights of the QoS attributes and determine their importance level. This method is utilised as a means to address the issues of inconsistency and uncertainty that are present in earlier techniques.
- This paper utilise Grey-TOPSIS technique for ranking CSPs as a solution to address the issue of rank reversal that is associated with earlier MADM solutions.

- This paper presents a hybrid MADM framework that combines the Grey-TOPSIS technique with the FFS-FUCOM based distance measurement to rank eight CSPs based on nine QoS attributes.

The subsequent sections of this paper are organised as follows: Section 2 presents a comprehensive examination of the CSPs ranking techniques using MADM. Section 3 provides a brief overview of some definitions that are relevant to the remaining contents of the paper. Section 4 provides a detailed explanation of the proposed methods, specifically focusing on the FFS-FUCOM based distance measurement and Grey-TOPSIS technique. The overall findings are reported in Section 5. The validation and evaluation are presented in Section 6. Section 7 serves as the conclusion of our paper, where we discuss the limitations and potential for future studies.

2. RANKING OF CSPS RANKING

An examination of MADM-based techniques that utilised fuzzy sets to determine the most optimal CSP is presented in this section. Researchers have shown significant interest in evaluating the performance of CSPs across various applications due to their widespread availability [70], [71]. The objective of this research is to systematically rank the performance of CSPs and develop approaches for determining the most efficient and optimal CSP. Prior research has commonly utilised MADM techniques to tackle decision-making difficulties in many sectors [72], [73]. The study conducted by [74] presents an alternative classification of metrics utilised for ranking cloud services, taking into account their degree of fuzziness. Additionally, they proposed fuzzy analytic hierarchy process (AHP) approach that enables the evaluation of cloud services based on a diverse model of service features. The researchers in [75] introduced an MADM framework that combines interpretive structural modelling and Analytic Network Process (ANP) approaches by employing triangular fuzzy numbers. The aim of this framework was to depict the relationships between the evaluation qualities of cloud computing and big data, while also considering uncertainties in the data. The authors of [22] presented a hybrid MADM approach for selecting the most suitable IaaS among several cloud providers for firms' users. This study utilised a combination of the balanced scorecard and AHP technique, incorporating triangular fuzzy numbers, for the mentioned purpose. The authors of [70] introduced a fuzzy MADM framework to choose a Cloud service. They utilised AHP and fuzzy ontology to represent uncertain connections between objects in databases for service matching.

The selection of the most suitable CSP among set of alternatives was tackled by many other studies such as [27], [28], [29], [30] integrated AHP and TOPSIS under triangular fuzzy numbers, [71] integrated AHP under triangular fuzzy numbers with Weighted Aggregated Sum-Product Assessment (WASPAS) techniques, [31] introduced 2-tuple fuzzy linguistic MADM technique based on TOPSIS, [33], [34] extended TOPSIS under intuitionistic fuzzy set (IFS), [76] extended Best Worst Method (BWM) under triangular fuzzy numbers, [77] integrated AHP, Revised AHP under Fuzzy Geometric mean and Weighted Sum Model (WSM), [78] utilized IFS score function, [79] developed cloud testing adoption assessment model under triangular fuzzy numbers, [80] integrated interval-valued IFS with WASPAS, [81] extended distance-based approach (DBA) under triangular fuzzy numbers, [82] introduced Shapley-TOPSIS under IFS, [83] used TOPSIS with triangular fuzzy numbers, [84] used AHP with triangular fuzzy numbers, [85] employed Sugeno Fuzzy inference system, [86] utilised data envelopment analysis method under neutrosophic fuzzy set (NFS), [35] extended TOPSIS under single-valued NFS, [36] extended TOPSIS with interval-valued fuzzy set, [87] proposed a grey wolf-based approach that uses entropy and hesitant fuzzy sets, [23] proposed rank reversal robust modular TOPSIS technique with crisp, interval, IFS and NFS, and [32] used AHP and TOPSIS under IFS. It was observed that TOPSIS, AHP, and BWM were the most widely utilised techniques for ranking CSPs [51].

3. PRELIMINARIES

In order to ensure the self-sufficiency of this study, a brief introduction to some definitions that are relevant to the remaining content is provided.

3.1 FFS

Definition 1. [68], [88] *Let X be a non-empty universe. A FFS $\tilde{\mathcal{R}}$ in X is determined by a membership $\mu_{\mathcal{R}}(x): X \to [0.1]$, and a non-membership $v_{\mathcal{R}}(x): X \to [0.1]$ functions. The set $\tilde{\mathcal{R}}$ is represented as follows:*

$$\tilde{\mathcal{R}} = \{\langle x, \mu_{\mathcal{R}}(x), v_{\mathcal{R}}(x)\rangle : x \in X\}, \tag{1}$$

with the condition that $0 \le (\mu_{\mathcal{R}}(x))^3 + (v_{\mathcal{R}}(x))^3 \le 1$.

Additionally, the indeterminacy degree is $\pi_{\mathcal{R}}(x) = \sqrt[3]{1 - (\mu_{\mathcal{R}}(x))^3 - (v_{\mathcal{R}}(x))^3}$. The element $\langle x, \mu_{\mathcal{R}}(x), v_{\mathcal{R}}(x)\rangle$ is Fermatean fuzzy number (FFN) in $\tilde{\mathcal{R}}$. For convenience a FFN is denoted by $\tilde{\mathcal{R}} = (\mu_{\mathcal{R}}, v_{\mathcal{R}})$ with $\mu, v \in [0,1]$.

Definition 2. *Let $\tilde{\mathcal{R}} = (\mu_{\mathcal{R}}, v_{\mathcal{R}})$ and $\tilde{\mathcal{S}} = (\mu_{\mathcal{S}}, v_{\mathcal{S}})$ be two FFSs, and $\lambda > 0$. Then, the subsequent operators for FFSs may be expressed* [88]*:*

$$\tilde{\mathcal{R}} \oplus \tilde{\mathcal{S}} = \left(\sqrt[3]{\mu_{\mathcal{R}}^3 + \mu_{\mathcal{S}}^3 - \mu_{\mathcal{R}}^3\mu_{\mathcal{S}}^3}, v_{\mathcal{R}}v_{\mathcal{S}}\right) \tag{2}$$

$$\tilde{\mathcal{R}} \otimes \tilde{\mathcal{S}} = \left(\mu_{\mathcal{R}}\mu_{\mathcal{S}}, \sqrt[3]{v_{\mathcal{R}}^3 + v_{\mathcal{S}}^3 - v_{\mathcal{R}}^3 v_{\mathcal{S}}^3}\right) \tag{3}$$

$$\lambda.\tilde{\mathcal{R}} = \left(\sqrt[3]{1 - (1 - \mu_{\mathcal{R}}^3)^\lambda}, v_{\mathcal{R}}^\lambda\right) \tag{4}$$

$$\tilde{\mathcal{R}}^\lambda = \left(\mu_{\mathcal{R}}^\lambda, \sqrt[3]{1 - (1 - v_{\mathcal{R}}^3)^\lambda}\right) \tag{5}$$

Definition 3. *Let $\tilde{\mathcal{R}} = (\mu_{\mathcal{R}}, v_{\mathcal{R}})$ be an FFS. The accuracy-function ($\mathcal{A}$) and score-function ($\mathcal{T}$) for this FFS are expressed in* Equations *(6) and (7)* [88]:

$$\mathcal{A}(\tilde{\mathcal{R}}) = \mu_{\mathcal{R}}^3 + v_{\mathcal{R}}^3 \tag{6}$$

$$\mathcal{T}(\tilde{\mathcal{R}}) = \mu_{\mathcal{R}}^3 - v_{\mathcal{R}}^3 \tag{7}$$

These equations can be utilised to compar two FFSs, specifically $\tilde{\mathcal{R}} = (\mu_{\mathcal{R}}, v_{\mathcal{R}})$ and $\tilde{\mathcal{S}} = (\mu_{\mathcal{S}}, v_{\mathcal{S}})$. When comparing them, there are differences in conditions [88]:

1. If $\mathcal{T}(\tilde{\mathcal{R}}) < \mathcal{T}(\tilde{\mathcal{S}})$, then $\tilde{\mathcal{R}} < \tilde{\mathcal{S}}$;

2. If $\mathcal{T}(\tilde{\mathcal{R}}) > \mathcal{T}(\tilde{\mathcal{S}})$, then $\tilde{\mathcal{R}} > \tilde{\mathcal{S}}$;
3. If $\mathcal{T}(\tilde{\mathcal{R}}) = \mathcal{T}(\tilde{\mathcal{S}})$, then
   i. If $\mathcal{A}(\tilde{\mathcal{R}}) < \mathcal{A}(\tilde{\mathcal{S}})$, then $\tilde{\mathcal{R}} < \tilde{\mathcal{S}}$;
   ii. If $\mathcal{A}(\tilde{\mathcal{R}}) > \mathcal{A}(\tilde{\mathcal{S}})$, then $\tilde{\mathcal{R}} > \tilde{\mathcal{S}}$;
   iii. If $\mathcal{A}(\tilde{\mathcal{R}}) = \mathcal{A}(\tilde{\mathcal{S}})$, then $\tilde{\mathcal{R}} = \tilde{\mathcal{S}}$.

Definition 4. *The FFS complement $\tilde{\mathcal{R}} = (\mu_{\mathcal{R}}, v_{\mathcal{R}})$ may be expressed as follows* [88]:

$$\mathrm{Com}(\tilde{\mathcal{R}}) = (v_{\mathcal{R}}, \mu_{\mathcal{R}}) \tag{8}$$

Definition 5. *Let $\tilde{\mathcal{R}}_i = \left(\mu_{\mathcal{R}_i}, v_{\mathcal{R}_i}\right)(i = 1,2,\dots,n)$ is a set of n FFSs, and $w = (w_1, w_2, \dots, w_n)^T$ is the equivalent weight vector for $\tilde{\mathcal{R}}_i(\sum_i w_i = 1)$. Then, the Fermatean fuzzy weighted average (FFWA) aggregation operator can be expressed as follows* [89]:

$$\mathrm{FFWA}\left(\tilde{\mathcal{R}}_1, \tilde{\mathcal{R}}_2, \dots, \tilde{\mathcal{R}}_n\right) = \left(\sum_{i=1}^{n} w_i \mu_{\mathcal{R}_i}, \sum_{i=1}^{n} w_i v_{\mathcal{R}_i}\right) \tag{9}$$

Definition 6. [90] *Let $\tilde{\mathcal{R}} = (\mu_{\mathcal{R}}, v_{\mathcal{R}})$ is an FFS. $\mathcal{T}(\tilde{\mathcal{R}})$ can be vary from -1 to 1. The establishment of a positive scoring function for an FFS within this specified range, ensuring a positive defuzzified results return.*

$$\mathcal{T}^P\left(\tilde{X}_{ij}\right) = 1 + \mathcal{T}\left(\tilde{X}_{ij}\right) \tag{10}$$

Definition 7. [91] *Let $\tilde{\mathcal{R}} = (\mu_{\mathcal{R}}, v_{\mathcal{R}})$ and $\tilde{\mathcal{S}} = (\mu_{\mathcal{S}}, v_{\mathcal{S}})$ be two FFSs. The definition of a modified Euclidean distance measure $D_{FFS}(\mu, v)$ between the two FFSs is given as:*

$$D_{\mathrm{FFS}}(\mathcal{R}, \mathcal{S}) = \left(\frac{1}{2n} \sum_{x_i \in X} \left(|\mu_{\mathcal{R}}^3 - \mu_{\mathcal{S}}^3|^2 + |v_{\mathcal{R}}^3 - v_{\mathcal{S}}^3|^2 + |\theta_{\mathcal{R}}^3 - \theta_{\mathcal{S}}^3|^2\right)\right)^{1/2}. \tag{11}$$

3.2 Classical FUCOM

The algorithm of classical FUCOM [] can be summarised as follows:

Step 1. Ranking attributes based on decision-makers' opinion of their importance. Let $Att = \{Att_1, Att_2, Att_3, \dots, Att_n\}$ be the set of attributes, listed in the order of preference by the decision-makers.

$Att_{j(1)} \succ Att_{j(2)} \succ Att_{j(3)} \succ \cdots Att_{j(k)}$, where k is the attribute's rank.

Step 2. Determining the relative importance of the attributes. The relative importance of attribute $Att_{j(k)}$ compared to $Att_{j(k+1)}$ is expressed as $\Phi_{\mathrm{k/(k+1)}}$. The relative importance can be characterised in two ways: according to the decision-maker's opinion or based on a predetermined scale. A total of $(n-1)$ comparisons will be performed, with the first ranked attribute being compared to itself due to its perceived importance.

Step 3. Determining the final weight values of the attributes which can be derived based on the following two conditions:

$$\frac{\mathrm{w_k}}{\mathrm{w_{k+1}}} = \Phi_{\mathrm{k/(k+1)}} \tag{12}$$

Mathematical transitivity:

$$\frac{\mathrm{w_k}}{\mathrm{w_{k+2}}} = \varphi_{\mathrm{k/(k+1)}} \otimes \varphi_{\mathrm{(k+1)/(k+2)}} \tag{13}$$

Step 4. Defining the final model. Full consistency can be obtained if deviation from full consistency is minimised and meets the conditions outlined in Step 3. The final model is as follows:

$$\begin{aligned} & min\chi \\ & \text{s.t.} \\ & \left|\frac{w_{j(k)}}{w_{j(k+1)}} - \varphi_{k/(k+1)}\right| \le \chi, \forall j \\ & \left|\frac{w_{j(k)}}{w_{j(k+2)}} - \varphi_{k/(k+1)} \otimes \varphi_{(k+1)/(k+2)}\right| \le \chi, \forall j \\ & \sum_{j=1}^{n} w_j = 1, \forall j \\ & w_j \ge 0, \forall j \end{aligned} \tag{14}$$

3.3 Classical TOPSIS Technique

Step 1. Creating the normalised decision matrix.
Step 2. Creating of weighted normalised decision matrix.
Step 3. Determination of positive-ideal-solution and negative-ideal-solution.
Step 4. Calculating the Euclidean distance for each alternative in the weighted normalised decision matrix from the positive-ideal-solution.
Step 5. Computing the relative closeness to the ideal-solution.
Step 6. Ranking alternatives based on the closeness coefficient values.

3.4 Grey relational analysis

Step 1. Computing the normalised decision matrix.
Step 2. Computing the weighted normalised decision matrix.
Step 3. Identifying the positive-ideal-solution and negative-ideal-solution.
Step 4. Computing the grey relational coefficient.
Step 5. Computing the relative grey relational grade.
Step 6. Ranking alternatives based on the greyrelational grade.

4. PROPOSED METHODS

In this section, the proposed framework is explained in details. We dive into the prioritisation of attributes using the FFS-FUCOM based distance measurement in Section 4.1, and the ranking of CSPs using the Grey-TOPSIS technique in Section 4.2. Figure 2 illustrates the sequential steps that make up the research framework utilised in this study.

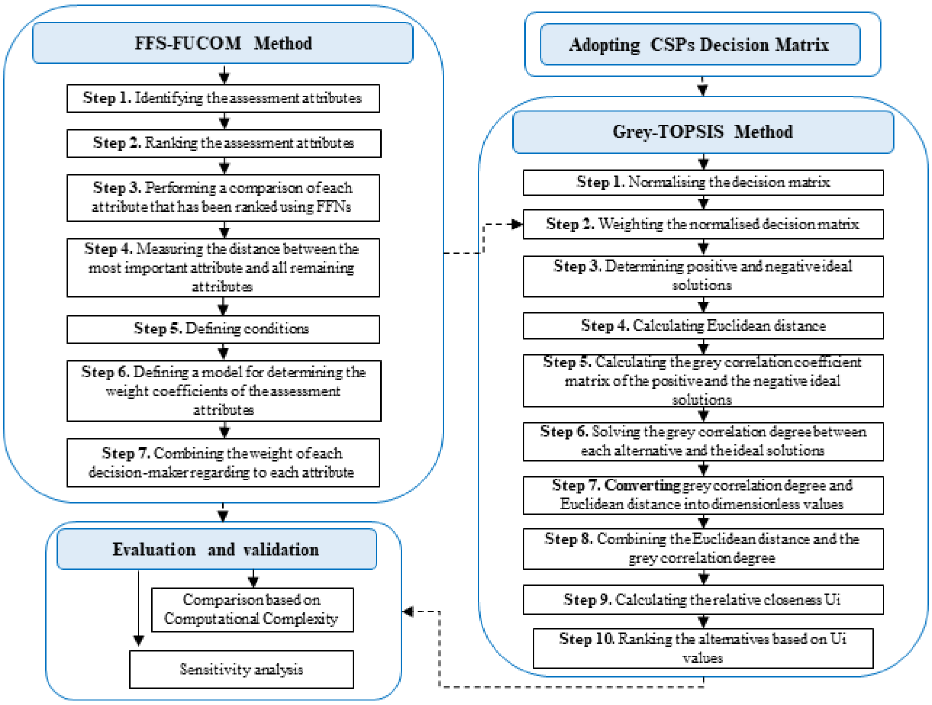

Figure 2: Proposed framework.

4.1 FFS-FUCOM Based Distance Measurement

Suppose there are n assessment attributes denoted as w_j, where $j = 1,2,\ldots,n$, and their weight coefficients need to be calculated in a MADM scenario. Subjective approaches for generating weights based on pairwise comparison of attributes require decision-makers to assess the level of attribute i's influence on attribute j. The influence of attribute i on attribute j can be expressed as the comparison value (a_{ij}). Given that the resulting values of comparison a_{ij} are not derived from precise measurements, but rather from subjective assessments, it is possible to represent existing uncertainties using fuzzy numbers. Linguistic terms are commonly employed to compare two variables. Therefore, the fuzzy linguistic terms [69] provided in Table 1 are regarded as a representation of the decision-maker's preferences in the FFS-FUCOM.

Table 1: The linguistic terms and FFNs [69].

Linguistic Terms	FFNs		Linguistic Terms	FFNs		Linguistic Terms	FFNs	
	μ	v		μ	v		μ	v
Very very low (VVL)	0.1	0.9	Medium low (ML)	0.4	0.5	High (H)	0.7	0.2
Very low (VL)	0.1	0.75	Medium (M)	0.5	0.4	Very high (VH)	0.8	0.1
Low (L)	0.25	0.6	Medium high (MH)	0.6	0.3	Very very high (VVH)	0.9	0.1

In this paper, the FFS-FUCOM proposed by [69] is extended by using modified Euclidean distance measure for determining the weights of QoS attributes. The modified algorithm of FFS-FUCOM is described in seven sequential steps.

Step 1. Identifying the assessment attributes. As previously stated, there are n decision attributes, represented by Att = $\{At_1, At_2, ..., At_n\}$, where j ranges from 1 to n. These attributes are identified based on previous study [11]. A brief definition of each attribute is given below.

Scalability (At_1): it refers to a CSP's ability to manage an increasing demand or to be expanded efficiently to support the growth without sacrificing performance.

Sustainability (At_2): it refers to how environmentally sustainable a CSP's infrastructure and operations are, considering aspects such as use of renewable energy, waste reduction, and minimising carbon footprint.

Usability (At_3): it refers to how easy it is for consumers, developers, and managers to use and access the services provided by the CSP.

Interoperability (At_4): it refers to the ability of a CSP's services to easily connect and interact with another systems, applications, and technologies.

Security management (At_5): it refers to the procedures and policies implemented by the CSP that ensure the confidentiality, integrity, and availability of data and resources.

Cost (At_6): it refers to CSP's costs such as initial charges, usage-based billing, discounts, and contract conditions.

Maintainability (At_7): it refers to the simplicity and cost-effectiveness of managing and updating a CSP's services over time.

Service response time (At_8): it refers to the CSP's effectiveness in handling customer demands and providing resources or data during regular and high-demand periods.

Reliability (At_9): it refers to the consistency, stability, and availability of the CSP's services.

Step 2. Ranking the assessment attributes. Decision-makers initially determine a ranking of attributes based on their subjective preferences regarding the importance of each attribute. The first rank is assigned to an attribute that is anticipated to possess the highest weight coefficient, followed by subsequent ranks assigned to attributes of decreasing relevance. The attribute that have the lowest weight value holds the final position. Therefore, the attributes are ranked based on the anticipated values of the weight coefficients, as given in Equation (15).

$$At_{j(1)} > At_{j(2)} > \cdots > At_{j(k),} \tag{15}$$

where k denotes the ranking position of the certain attribute. In the case where two or more attributes are deemed to have equal importance, the "=" symbol, is used instead of the ">" symbol to indicate this in Equation (15).

It is important to note that decision-makers should have expertise in the topic of research, such as CSPs. The researchers performed a bibliometric analysis on the authors and co-authors of publications that focused on developing CSPs. This analysis formed the basis for the decision-makers' selection used in this study. According to [15], [92], at least three decision-makers should be selected to rank the attributes.

Step 3. Performing a comparison of each attribute that has been ranked using FFNs. The attributes are thereafter compared by utilising Table 1. The comparison is conducted based on the attribute that is ranked first. Therefore, the fuzzy attribute importance ($\tilde{\varpi}_{At_{j(k)}}$) is determined for all attributes. Given that the most important attribute is being compared to itself, it is necessary to make $n-1$ comparisons of the remaining attributes. The fuzzy comparative importance $\tilde{\varphi}_{k/(k+1)}$ is computed by applying Equation (16), based on the defined importance of the attributes.

$$\tilde{\varphi}_{k/(k+1)} = \frac{\tilde{\varpi}_{At_{j(k+1)}}}{\tilde{\varpi}_{At_{j(k)}}} = \frac{\left(\varpi^{\mu}_{At_{j(k+1)}}, \varpi^{v}_{At_{j(k+1)}}\right)}{\left(\varpi^{\mu}_{Att_{j(k)}}, \varpi^{v}_{At_{j(k)}}\right)} \tag{16}$$

Therefore, a fuzzy vector of the comparative importance of the assessment attributes is determined by utilising Equation (17).

$$\Phi = \left(\varphi_{1/2}, \varphi_{2/3}, \dots, \varphi_{k/(k+1)}\right) \tag{17}$$

where $\varphi_{k/(k+1)}$ represents the priority assigned to the attribute of the $At_{j(k)}$ ranking in relation to the attribute of the $Att_{j(k+1)}$ ranking.

Step 4. Measuring the distance between the most important attribute and all remaining attributes using modified Euclidean distance measure given in Definition 7.

Step 5. Defining a model to determine the weight values of the assessment attributes $(w_1, w_2, \dots, w_n)^T$ using Equation (14) based on the conditions given in Equations (12) and (13). The derived weights indicate the importance of each attribute according to the preferences of each decision maker.

Step 6. Combining the weight of each decision-maker regarding to each attribute, as follows:

$$W_j = \frac{w_{dm1j} \times w_{dm2j} \times w_{dm3j}}{\sum_{j=1}^{n} w_{dm1j} \times w_{dm2j} \times w_{dm3j}}, \mathrm{i} = 1,2, \dots, \mathrm{m}; \mathrm{j} = 1,2, \dots, \mathrm{n} \tag{18}$$

where w_{dm1j}, w_{dm2j}, and w_{dm3j} represent the weights of a certain attribute based on the preferences of decision-maker$_1$, decision-maker$_2$, and decision-maker$_3$, respectively.

4.2 Adaptation of Grey-TOPSIS Technique

Let x_{ij} be the decision given to the CSP_i's alternative based on At_j's attributes, with weight w_j, for $i = 1, \dots, m$ and $j = 1, \dots, n$. Hence, the initial decision matrix is given in Equation (19).

$$X = \left(x_{ij}\right)_{\substack{1 \le i \le n \\ 1 \le j \le m}} . \tag{19}$$

The Grey-TOPSIS technique [50] is based on the ten steps below.

Step 1. Normalising the decision matrix using Equation (20).

$$S_{ij} = \; x_{ij} / \left(\sum_{i=1}^{k} \left(x_{ij}\right)^2\right)^{1/2} \tag{20}$$

where x_{ij} represents the value of the cell at the intersection of the i_{th} row and j_{th} column in the decision matrix. Let k be the number of alternatives considered, while m represents the number of attributes.

Step 2. Weighting the normalised decision matrix using Equation (21). The set of weight values $\mathrm{w} = \mathrm{w}_1, \mathrm{w}_2, , \cdots, \mathrm{w}_\mathrm{m}$, which were obtained in Section 4.1, are used in this phase as follows:

$$V_{ij} = W_j \; * \; S_{ij}, \text{ where } W = [W_1 \quad W_2 \quad \dots \quad W_m]. \tag{21}$$

Step 3. Determining positive-ideal-solution A^+ and negative-ideal-solution A^- as follows:

$$A^+ = \; (v_1^+, v_2^+, v_3^+, \dots \dots, v_m^+), \tag{22}$$

$$A^- = \; (v_1^-, v_2^-, v_3^-, \dots \dots, v_m^-), \tag{23}$$

where $A_j^+ = \max_i v_{ij}$, $A_j^- = \min_i v_{ij}$, $i = 1, 2, 3, \dots, k$ and $j = 1, 2, 3, \dots, m$.

Step 4. Calculating Euclidean distance between the evaluation alternative and the ideal solution using Equation (24).

$$d_i^+ = \left[\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2\right]^{1/2}, d_i^- = \left[\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2\right]^{1/2} . \tag{24}$$

Step 5. Calculating the grey correlation coefficient matrix of the positive $R^+ = \left(r_{ij}^+\right)_{\mathrm{mxn}}$ and the negative $R^- = \left(r_{ij}^-\right)_{\mathrm{mxn}}$ ideal solutions, as follows:

$$r_{ij}^+ = \frac{m^+ + \xi M^+}{\left|v_j^+ - v_{ij}\right| + \xi M^+}, r_{ij}^- = \frac{m^- + \xi M^-}{\left|v_j^- - v_{ij}\right| + \xi M^-}, \tag{25}$$

where

$$m^+ = \min_i \min_j \left|v_j^+ - v_{ij}\right|, M^+ = \max_i \max_j \left|v_j^+ - v_{ij}\right|,$$

$m^{-} = \min_{i} \min_{j} \left| v_j^{-} - v_{ij} \right|, M^{-} = \max_{i} \max_{j} \left| v_j^{-} - v_{ij} \right|,$
ξ represents the resolution coefficient and its equal to 0.5 in this paper.

Step 6. Solving the grey correlation degree between each alternative and the ideal solutions as follows:

$$r_i^{+} = \frac{1}{n} \sum_{j=1}^{n} r_{ij}^{+}, r_i^{-} = \frac{1}{n} \sum_{j=1}^{n} r_{ij}^{-}. \tag{26}$$

Step 7. Incorporating both shape and position, the grey correlation degree and the preceding Euclidean distance must be converted into dimensionless values, as follows:

$$R_i^{+} = \frac{r_i^{+}}{\max_{i} r_i^{+}}, R_i^{-} = \frac{r_i^{-}}{\max_{i} r_i^{-}}. \tag{27}$$

$$D_i^{+} = \frac{d_i^{+}}{\underset{i}{\max}{}^{+}}, D_i^{-} = \frac{d_i^{-}}{\max d_i^{-}}. \tag{28}$$

Step 8. Uniting the Euclidean distance and the grey correlation degree. A lesser Euclidean distance from the positive-ideal-solution indicates a superior alternative in terms of distance. The alternative is considered to have a better shape when the degree of grey correlation of the positive-ideal-solution is higher. Thus, they are merged based on these factors:

$$u_i^{+} = \alpha D_i^{-} + \beta R_i^{+}, u_i^{-} = \alpha D_i^{+} + \beta R_i^{-}, \tag{29}$$

where α and β represent the ratio of the two angles that determine the position and shape in the alternative.

Step 9. Calculating the relative closeness U_i by replacing d_i^{+} and d_i^{-} with u_i^{+} and u_i^{-}, respectively.

$$U_i = \frac{u_i^{+}}{u_i^{+} + u_i^{-}}. \tag{30}$$

Step 10. Ranking the alternatives based on the score values obtained from Equation (30). The alternative's superiority is directly proportional to its score; a higher score indicates a better alternative, while a lower score indicates the opposite.

5. RESULTS AND DISCUSSION

5.1 QoS Attributes Weighting Results

This section presents the weighting outcomes of the QoS Attributes using the FFS-FUCOM based distance measurement presented in Section 4.1. A collection of nine assessment attributes, denoted as Att, has been selected to rank CSPs, as mentioned in Step1. The attributes are Att_1- Att_9. As previously mentioned, the choice of these attributes was determined by prior research [11]. The initial step of the FFS-FUCOM involves identifying the assessment attributes. These attributes, namely At_1, At_2, At_3, At_4, At_5, At_6, At_7, At_8, and At_9, correspond to scalability, sustainability, usability, interoperability, security management, cost, maintainability, service response time, and reliability, respectively. Then, three decision-makers determined the ranking of attributes based on their subjective preferences regarding the importance of each attribute, as explained in Step 2. For this purpose, the decision-makers utilised a nine-point Likert scale consisting of linguistic terms as presented in Table 1. The decision-makers' preferences for each of the attributes are provided in Table 2, as presented in Step 3.

Table 2: Decision-makers' preferences for each attribute.

Decision-makers/Attributes	**At_1**	**At_2**	**At_3**	**At_4**	**At_5**	**At_6**	**At_7**	**At_8**	**At_9**
Decision-maker$_1$	H	VVL	MH	VH	VVL	ML	VL	H	MH
Decision-maker$_2$	M	VVL	MH	VVL	H	L	M	VH	ML
Decision-maker$_3$	H	M	VH	VVL	VVL	VL	H	M	ML

Subsequently, FFNs are utilised to compare each ranking attribute. At this step, each linguistic term is substituted with its corresponding FFN. After that, the fuzzy vector representing the comparative importance of the assessment attributes for each decision-maker is derived, as given in Table 3.

Table 3: Fuzzy vector of the assessment attributes comparative importance of each decision-maker.

Decision-makers/ Attributes	**At_1**		**At_2**		**At_3**		**At_4**		**At_5**		**At_6**		**At_7**		**At_8**		**At_9**	
	μ	v	μ	v	μ	v	μ	v	μ	v	μ	v	μ	v	μ	v	μ	v
Decision-maker$_1$	0.7	0.2	0.1	0.9	0.6	0.3	0.8	0.1	0.9	0.1	0.4	0.5	0.1	0.75	0.7	0.2	0.6	0.3
Decision-maker$_2$	0.5	0.4	0.1	0.9	0.6	0.3	0.9	0.1	0.6	0.3	0.25	0.6	0.5	0.4	0.8	0.1	0.4	0.5
Decision-maker$_3$	0.7	0.2	0.5	0.4	0.8	0.1	0.1	0.9	0.9	0.1	0.1	0.75	0.7	0.2	0.5	0.4	0.4	0.5

At that point, the modified Euclidean distance measure is utilised to calculate the distance between the most important attribute and all other attributes, as described in Step 4 and given in Table 4.

Table 4: Distance between the most important attribute and all other attributes.

Decision-makers/Attributes	**At_1**	**At_2**	**At_3**	**At_4**	**At_5**	**At_6**	**At_7**	**At_8**	**At_9**
Decision-maker$_1$	1.5410	2.0295	1.7078	1.3069	1	1.8662	1.8952	1.5410	1.7078
Decision-maker$_2$	1.8133	2.0295	1.7078	1	1.7078	1.8964	1.8133	1.3069	1.8662
Decision-maker$_3$	1.5410	1.8133	1.3069	2.0295	1	1.8952	1.5410	1.8133	1.8662

Then, two conditions are defined that must be met in order to calculate the final values of the weight coefficients. Accordingly, the mathematical model given in Step 5 is defined to ascertain the weight coefficients of the assessed attributes. The weights assigned to the attributes, taking into account the preferences of each decision-maker, are provided in Table 5.

Table 5: Weight values based on each decision-maker and the final weights.

Decision-makers/Attributes	**At_1**	**At_2**	**At_3**	**At_4**	**At_5**	**At_6**	**At_7**	**At_8**	**At_9**
Decision-maker$_1$	0.1118	0.0852	0.1016	0.1318	0.1717	0.0933	0.0911	0.1121	0.1014
Decision-maker$_2$	0.0986	0.0881	0.1046	0.1786	0.1046	0.0944	0.0986	0.1366	0.0959
Decision-maker$_3$	0.1136	0.0964	0.1337	0.0861	0.1749	0.0919	0.1136	0.0964	0.0935
Final weights	0.0980	0.0566	0.1112	0.1585	**0.2459**	0.0634	0.0799	0.1154	0.0711

The weights assigned to the attributes, based on the preferences of each decision-maker, are combined in Step 6 using Equation (18), as provided in Table 5. The security management attribute represented by At_5 received the highest weight value of 0.2459. The attributes At_4, At_8, and At_3 represent interoperability, service response time, and usability, respectively. They got weight values of 0.1585, 0.1154, and 0.1112. The attributes At_1, At_7, At_9, and At_6 represent scalability, maintainability, reliability, and cost, respectively. They received weight values of 0.0980, 0.0799, 0.0711, and 0.0634. At_2, which represents the sustainability attribute, assigned the lowest weight value of 0.0566. These weights are fed to Grey-TOPSIS technique to rank the CSPs.

5.2 CSPs Ranking Results

This section presents the ranking outcomes of CSPs using Grey-TOPSIS technique. The decision matrix utilised in this paper is derived from a prior study [11]. This matrix had eight CSPs, namely CSP_1, CSP_2, CSP_3, CSP_4, CSP_5, CSP_6, CSP_7, and CSP_8, which corresponded to HP, Amazon, Google, GoGrid, Azure, Rackspace, Joynet, and Linode. These CSPs crossed with nine assessment attributes, as given in Table 6.

Table 6: CSPs decision matrix.

CSPs/Atts	**At_1**	**At_2**	**At_3**	**At_4**	**At_5**	**At_6**	**At_7**	**At_8**	**At_9**
CSP_1	12.81	15.47	31.11	7.81	8.05	20.75	6.89	2.43	7.32
CSP_2	29.24	8.11	13.2	6.69	18.79	10.37	2.9	17.95	6.27
CSP_3	19.21	10.14	5.66	11.71	2.68	6.92	10.33	9.58	8.78
CSP_4	9.61	34.69	6.6	5.86	32.21	2.53	13.78	13.08	10.98
CSP_5	12.81	3.2	19.8	33.97	10.07	5.19	8.27	7.67	34.51
CSP_6	2.23	13.52	13.2	22.25	13.42	32.12	10.33	12.78	20.56
CSP_7	7.69	6.76	2.51	2.34	8.05	8.3	13.78	30.12	2.79
CSP_8	6.4	8.11	7.92	9.37	6.71	13.83	33.72	6.39	8.78

In the Step 1 of Grey-TOPSIS technique, the decision matrix is normalised to produce normalised decision matrix, as given in Table 7.

Table 7: Normalised decision matrix.

CSPs/Atts	**At_1**	**At_2**	**At_3**	**At_4**	**At_5**	**At_6**	**At_7**	**At_8**	**At_9**
CSP_1	0.3063	0.3534	0.7227	0.1738	0.1870	0.4746	0.1600	0.0579	0.1641
CSP_2	0.6990	0.1853	0.3066	0.1489	0.4364	0.2372	0.0673	0.4277	0.1406
CSP_3	0.4593	0.2317	0.1315	0.2606	0.0622	0.1583	0.2399	0.2283	0.1969
CSP_4	0.2297	0.7926	0.1533	0.1304	0.7481	0.0579	0.3200	0.3117	0.2462
CSP_5	0.3063	0.0731	0.4600	0.7559	0.2339	0.1187	0.1920	0.1828	0.7738
CSP_6	0.0533	0.3089	0.3066	0.4951	0.3117	0.7347	0.2399	0.3045	0.4610
CSP_7	0.1838	0.1544	0.0583	0.0521	0.1870	0.1899	0.3200	0.7177	0.0626
CSP_8	0.1530	0.1853	0.1840	0.2085	0.1558	0.3164	0.7830	0.1523	0.1969

In Step 2, each value in this matrix is multiplied by the weight values of the attributes, which are derived using the FFS-FUCOM, as provided in Table 8. The ideal solutions of positive A^+ and negative A^- are derived, as detailed in Step 3 and given in Table 8. It is important to note that all attributes are beneficial except for the cost attribute (Att_6), which is considered a non-beneficial attribute.

Table 8:Normalised weighted decision matrix.

CSPs/Atts	**At_1**	**At_2**	**At_3**	**At_4**	**At_5**	**At_6**	**At_7**	**At_8**	**At_9**
CSP_1	0.0300	0.0200	0.0803	0.0276	0.0460	0.0301	0.0128	0.0067	0.0117
CSP_2	0.0685	0.0105	0.0341	0.0236	0.1073	0.0150	0.0054	0.0494	0.0100
CSP_3	0.0450	0.0131	0.0146	0.0413	0.0153	0.0100	0.0192	0.0264	0.0140
CSP_4	0.0225	0.0449	0.0170	0.0207	0.1840	0.0037	0.0256	0.0360	0.0175
CSP_5	0.0300	0.0041	0.0511	0.1198	0.0575	0.0075	0.0153	0.0211	0.0550
CSP_6	0.0052	0.0175	0.0341	0.0785	0.0766	0.0466	0.0192	0.0352	0.0328
CSP_7	0.0180	0.0087	0.0065	0.0083	0.0460	0.0120	0.0256	0.0828	0.0045
CSP_8	0.0150	0.0105	0.0205	0.0331	0.0383	0.0200	0.0625	0.0176	0.0140
$\boldsymbol{A^+}$	0.0685	0.0449	0.0803	0.1198	0.1840	0.0037	0.0625	0.0828	0.0550
$\boldsymbol{A^-}$	0.0052	0.0041	0.0065	0.0083	0.0153	0.0466	0.0054	0.0067	0.0045

In Step 4, Euclidean distance is computed between each alternative and the d^+ and d^-, as given in Table 9.

Table 9: Positive and negative ideal solutions.

CSPs	CSP_1	CSP_2	CSP_3	CSP_4	CSP_5	CSP_6	CSP_7	CSP_8
d^+	0.2013	0.1581	0.2175	0.1447	0.1614	0.1631	0.2117	0.2064
d^-	0.0895	0.1279	0.0695	0.1842	0.1457	0.107	0.0923	0.0752

Upon performing calculations, the values for m^{+}, m^{-}, M^{+}, and M^{-} were determined to be 0, 0, 0.1687, and 0.1687, respectively, as presented in Step 5. These values are utilised to compute the grey correlation coefficient matrix for the positive $R^{+} = \left(r_{ij}^{+}\right)_{\mathrm{mxn}}$ and the negative $R^{-} = \left(r_{ij}^{-}\right)_{\mathrm{mxn}}$ideal solutions, as given in Tables 10 and 11.

Table 10: Grey correlation coefficient matrix for the positive-ideal-solution.

CSPs/Atts	**At$_1$**	**At$_2$**	**At$_3$**	**At$_4$**	**At$_5$**	**At$_6$**	**At$_7$**	**At$_8$**	**At$_9$**
CSP$_1$	0.6866	0.7723	1	0.4774	0.3793	0.7615	0.6289	0.5254	0.6604
CSP$_2$	1	0.7104	0.6458	0.4670	0.5239	0.8812	0.5960	0.7158	0.6518
CSP$_3$	0.7821	0.7265	0.5620	0.5178	0.3333	0.9298	0.6603	0.5988	0.6726
CSP$_4$	0.6471	1	0.5712	0.4595	1	1	0.6952	0.6428	0.6920
CSP$_5$	0.6866	0.6743	0.7427	1	0.4001	0.9563	0.6412	0.5773	1
CSP$_6$	0.5713	0.7549	0.6458	0.6710	0.4400	0.6628	0.6603	0.6387	0.7912
CSP$_7$	0.6255	0.7001	0.5331	0.4304	0.3793	0.9098	0.6952	1	0.6250
CSP$_8$	0.6118	0.7104	0.5847	0.4928	0.3667	0.8373	1	0.5637	0.6726

Table 11: Grey correlation coefficient matrix for the negative-ideal-solution.

CSPs/Atts	**At$_1$**	**At$_2$**	**At$_3$**	**At$_4$**	**At$_5$**	**At$_6$**	**At$_7$**	**At$_8$**	**At$_9$**
CSP$_1$	0.7729	0.8416	0.5331	0.8138	0.7333	0.8365	0.9193	1	0.9211
CSP$_2$	0.5713	0.9300	0.7534	0.8460	0.4782	0.7278	1	0.6639	0.9382
CSP$_3$	0.6795	0.9038	0.9120	0.7184	1	0.6977	0.8596	0.8109	0.8982
CSP$_4$	0.8299	0.6743	0.8887	0.8716	0.3333	0.6628	0.8069	0.7422	0.8659
CSP$_5$	0.7729	1	0.6538	0.4304	0.6664	0.6835	0.8944	0.8540	0.6250
CSP$_6$	1	0.8634	0.7534	0.5456	0.5789	1	0.8596	0.7476	0.7484
CSP$_7$	0.8683	0.9482	1	1	0.7333	0.7095	0.8069	0.5254	1
CSP$_8$	0.8962	0.9300	0.8579	0.7727	0.7856	0.7608	0.5960	0.8856	0.8982

Based on these matrices the grey correlation degree between all alternatives and the ideal solutions r_i^{+} and r_i^{-} are determined, as given in Step 6. The grey correlation degree and Euclidean distance are transformed into dimensionless values by computing R_i^{+}, R_i^{-}, D_i^{+}, and D_i^{-} using Equations (27) and (28), as described Step 7. In the following Step 8, Equation (29) is employed to combine the Euclidean distance and grey correlation degree by determining the values of u_i^{+} and u_i^{-}. In Step 9, the relative closeness U_i is calculated using these values. It's worth mentioning that the α and β values in Equation (29) are selected to be 0.1 and 0.9, respectively, to determine relative closeness U_i. Finally, the eight CSPs are ranked according to the score values derived from Equation (30), as given in Step 10. A higher CSP score signifies a superior alternative, whilst a lower score signifies the contrary. The overall results of Step 6 to Step10 are given in Table 12.

Table 12: Overall results of Grey-TOPSIS.

CSPs	r^+	r^-	R^+	R^-	D^+	D^-	$\alpha = 0.1, \beta = 0.9$			
							u^+	u^-	U	Ranks
CSP_1	0.6547	0.8191	0.8784	0.9710	0.9256	0.4859	0.5251	0.9301	0.4647	5
CSP_2	0.6880	0.7677	0.9231	0.9101	0.7271	0.6941	0.7170	0.7454	0.5024	3
CSP_3	0.6426	0.8311	0.8622	0.9853	1	0.3770	0.4255	0.9985	0.4519	8
CSP_4	0.7453	0.7417	1	0.8793	0.6653	1	1	0.6867	0.5382	1
CSP_5	0.7421	0.7312	0.9956	0.8668	0.7420	0.7909	0.8114	0.7545	0.5330	2
CSP_6	0.6485	0.7885	0.8701	0.9348	0.7501	0.5806	0.6095	0.7686	0.4786	4
CSP_7	0.6554	0.8435	0.8793	1	0.9733	0.5012	0.5390	0.9760	0.4576	7
CSP_8	0.6489	0.8203	0.8706	0.9725	0.9490	0.4082	0.4544	0.9513	0.4594	6

According to the data presented in Table 12, CSP_4 achieved the highest ranking with a score of 0.5382. Subsequently, CSP_5, CSP_2, CSP_6, and CSP_1 were ranked with score values of 0.5330, 0.5024, 0.4786, and 0.4647, respectively. The CSP_8, CSP_7, and CSP_3 received the lowest ranks, with score values of 0.4594, 0.4576, and 0.4519, respectively.

6. EVALUATION AND VALIDATION

6.1 Sensitivity Analysis

This section focuses on measuring the sensitivity of the proposed framework for ranking CSPs. This is achieved by (i) altering the α and β values, and (ii) adjusting the weights assigned to the attributes. Firstly, the combination of the Euclidean distance and grey correlation degree, as defined in Equation (20), are iterated four more times using different values of α (0.3, 0.5, 0.7, 0.9) and β (0.7, 0.5, 0.3, 0.1). Figure 4 shows that the ranking results of the eight CSPs are slightly changed with the alteration of the α and β values.

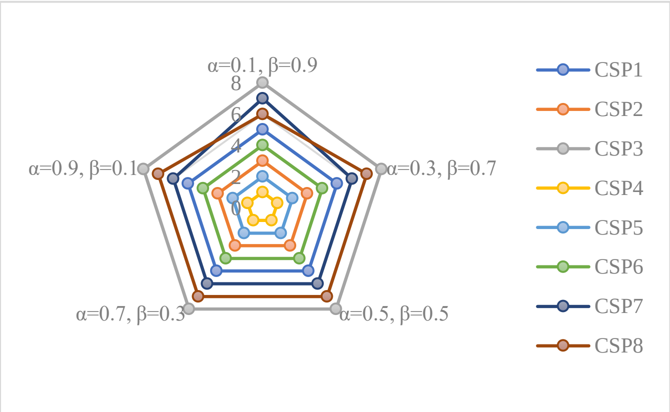

Figure 4: Impacts of altering the α and β values on the CSPs ranking results.

The ranking positions of CSP_1-CSP_6 remained consistent across all α and β values in comparison to the original ranking, specifically when $\alpha = 0.1$ and $\beta = 0.9$. The positions of CSP_7 and CSP_8 were reversed across all α and β values in comparison to the original ranking.

Secondly, the effect of adjusting the weight coefficients of attributes on the ranking of CSPs. The weighting coefficients for the attributes are adjusted in 9 different scenarios (S_1-S_9) to evaluate the sensitivity of the proposed framework, as stated in references [15], [25]. Table 13 provides the adjusted weights and elasticity weight coefficient α_c values for each of the aforementioned scenarios.

Table 13: Adjusted weights and α_c values of each scenario.

Attributes	**At_1**	**At_2**	**At_3**	**At_4**	**At_5**	**At_6**	**At_7**	**At_8**	**At_9**
Original Weights	0.0980	0.0566	0.1112	0.1585	**0.2459**	0.0634	0.0799	0.1154	0.0711
S_1	0.1299	0.0751	0.1474	0.2102	**0.0000**	0.0840	0.1059	0.1531	0.0943
S_2	0.1137	0.0657	0.1290	0.1840	0.1250	0.0735	0.0927	0.1339	0.0825
S_3	0.0974	0.0563	0.1106	0.1577	0.2500	0.0630	0.0794	0.1148	0.0708
S_4	0.0812	0.0469	0.0921	0.1314	0.3750	0.0525	0.0662	0.0957	0.0590
S_5	0.0650	0.0375	0.0737	0.1051	0.5000	0.0420	0.0529	0.0765	0.0472
S_6	0.0487	0.0281	0.0553	0.0788	0.6250	0.0315	0.0397	0.0574	0.0354
S_7	0.0325	0.0188	0.0369	0.0526	0.7500	0.0210	0.0265	0.0383	0.0236
S_8	0.0162	0.0094	0.0184	0.0263	0.8750	0.0105	0.0132	0.0191	0.0118
S_9	0.0000	0.0000	0.0000	0.0000	**0.9999**	0.0000	0.0000	0.0000	0.0000
α_c	0.1299	0.0751	0.1474	0.2102	0.3261	0.0840	0.1059	0.1531	0.0943

In addition, the degree of alteration (δ) is found to be within the range of -0.2459 and 0.7541. The impact of the new implemented weights on the ranking of the CSPs is depicted in Figure 5. Subsequently, the revised rankings of CSPs are compared to their initial rankings.

Based on the recent ranking results of CSPs displayed in Figure 5, the top-ranked alternative, namely CSP_4, maintained its position in seven scenarios but slipped to second place in S_1 and S_2. CSP_5, the alternative ranked second, maintained its position in S_3 and S_4. However, it rose to the top rank in S_1 and S_2, and dropped to the third and fourth positions in S_5 and S_6, and S_7-S_9, respectively. CSP_2, the alternative placed third, maintained its position in four scenarios (S_1-S_4) but moved to second place in scenarios S_5-S_9. CSP_6, the alternative ranked fourth, maintained its position in five scenarios (S_2-S_6), but fell to fifth place in S_1 and rose to third place in S_7-S_9. CSP_1, the alternative ranked fifth, maintained its position across eight scenarios (S_2-S_9) but fell to sixth place in S_1. CSP_8, which placed sixth, maintained its position in S_2 and S_3 but fell to seventh place in the remaining scenarios. The alternative ranked seventh, named CSP_7, maintained its position in only one scenario (S_3), but fell to eighth place in S_1 and S_2, and rose to sixth place in S_4-S_9. CSP_3, the eighth-ranked alternative, maintained its position in seven scenarios (S_3-S_9) but rose to the fourth and seventh places in S_1 and S_2, respectively.

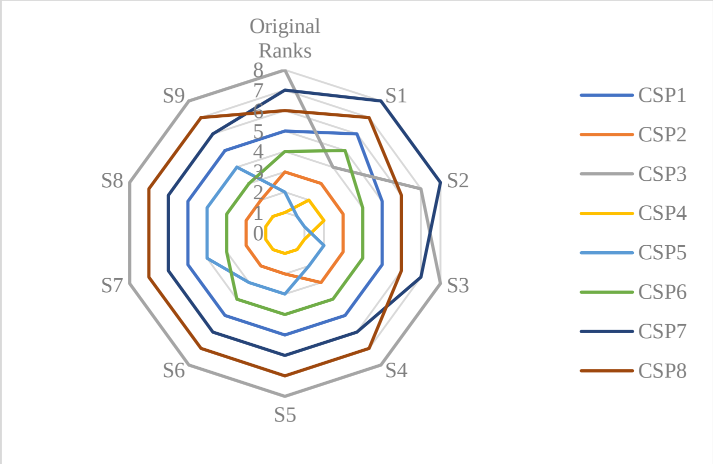

Figure 5: New ranking results of CSPs across nine scenarios.

At this point, the correlation coefficients are calculated between the new ranking orders and the original ranking orders. Spearman's rho correlation is used to analyse the overall results of sensitivity analysis and measure the strength and direction (positive/negative) of the correlation between the original and new rankings. Figure 6 displays the correlation of CSPs ranks in 9 different scenarios.

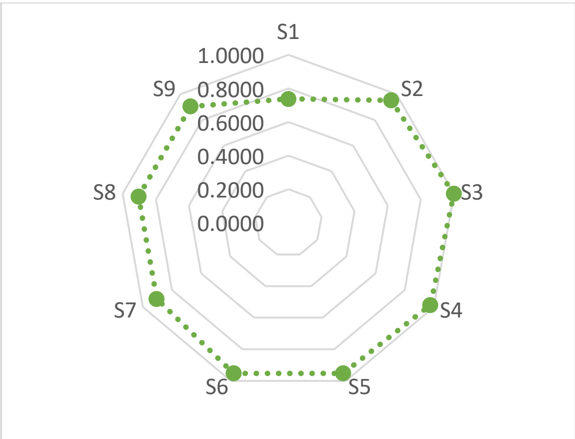

Figure 6: Correlation of CSPs ranks in 9 different scenarios.

The correlation between the initial and new ranks in eight scenarios (S_2–S_9) ranged from 0.9 to 1.0, indicating a strong and positive relationship (Figure 6). The correlation coefficient between the initial and new ranks in S_1 was 0.7, indicating a moderate and positive relationship. The correlation coefficient produced an average value of 0.9, indicating a strong and positive relationship.

6.2 Systematic Ranking Test

Many academics performed a systematic ranking test to evaluate the efficacy of their MADM techniques in the current literature [61]. Validation includes categorising the chosen alternatives/CSPs into groups and then confirming the ranking results. Each group comprised several CSPs. The number of CSPs in each group varies based on the total number of CSPs. The validation results were not affected by the number of groups or alternatives used in the assessment, as reported by [61], [92]. The validity of the ranking results can be verified by the following steps: In order to verify that the CSPs were arranged in a systematic manner, the following steps are taken: (i) the values within the weighted normalised matrix are aggregated for each CSP; (ii) the aggregated values and their corresponding CSPs are ordered based on the ranking outcomes; (iii) the CSPs are categorised into distinct groups; and (iv) the average value of each group is computed.

The comparisons were based on the average value of each group. If $Group_1$ achieves the highest average value, it confirms that the ranking results are systematically ranked. The average of $Group_2$ must fall between the averages of $Group_3$ and $Group_1$. It is important for the subsequent groups to follow the same process, making sure that each group's average value is more than or equal to the next group's average and less than or equal to the preceding group's average. The assessment findings are reported in Table 14.

Table 14: Systematic ranking results.

Groups	CSPs	Mean Values
$Group_1$	CSP_4 and CSP_5	0.0407
$Group_2$	CSP_2 and CSP_6	0.0372
$Group_3$	CSP_1 and CSP_8	0.0276
$Group_4$	CSP_7 and CSP_3	0.0228

The CSPs are classified into four distinct groups, with two CSPs in each group. The average of $Group_1$ (0.0407) exceeds that of $Group_2$, $Group_3$, and $Group_4$. The average of $Group_2$ (0.0372) is higher than that of $Group_3$ (0.0276) and $Group_4$ (0.0228). $Group_3$'s average value exceeds $Group_4$'s average value. The finding shows that the ranking results of the CSPs are accurate and consistent.

6.3 Comparative Analysis

This section compares the proposed method (Grey-TOPSIS technique with the FFS-FUCOM based distance measuring) to the study reported by [11]. The authors of [11] utilised TOPSIS and BWM to evaluate and rank the CSPs according to nine QoS criteria. The present study and the study of [11] both provided the ranking orders of the 8 CSPs as shown in Table 15. Five out of eight CSPs, accounting for 62.5%, had similar ranking orders. Three out of the eight CSPs, representing 37.5%, had different ranking orders.

Table 15: Comparing the ranking orders of the two studies.

Studies	Ranking orders	Similarities	Differences
Present study	$CSP_4 > CSP_5 > CSP_2 > CSP_6 > CSP_1 > CSP_8 > CSP_7 > CSP_3$	5 CSPs of 8 (62.5%)	3 CSPs of 8 (37.5)
Study of [11]	$CSP_4 > CSP_5 > CSP_2 > CSP_6 > CSP_1 > CSP_7 > CSP_3 > CSP_8$		

The present study utilised the Grey-TOPSIS technique to rank the selected CSPs, addressing the shortcomings of the traditional TOPSIS technique mentioned in Section 1.2.1. The problem of rank reversal in TOPSIS [11] and other MADM techniques is solved by implementing the Grey-TOPSIS technique [40]. Furthermore, employing Grey-relational-analysis technique with TOPSIS may manage complex decision-making situations involving uncertain, imprecise, and insufficient data [46].

In the same context, FFS-FUCOM based distance measurement has been utilised to determine the weight values of assessment attributes within the same context. The inconsistency of the results rises as the number of comparisons required rises, as stated in Section 1.2.2. The FUCOM consistently requires fewer pairwise comparisons than the BWM technique to calculate attributes' weight. Therefore, the FUCOM requires less processing effort and is hence more efficient than BWM [11]. Furthermore, combining FFS with FUCOM based distance measurement aims to tackle uncertainty found in previous methods. Overall, the proposed framework for ranking CSPs based on multiple QoS attributes demonstrates better performance compared to the prior study.

7. CONCLUSION

This paper proposed a hybrid decision-making framework for ranking CSPs based on multiple QoS attributes. The FFS-FUCOM based distance measurement is formulated to obtain the final weights of the QoS attributes and determine their importance level. This method is utilised as a means to address the issues of inconsistency and uncertainty that are present in earlier techniques. Then, Grey-TOPSIS technique is adopted for ranking CSPs as a solution to address the issue of rank reversal that is associated with earlier MADM techniques based on the attributes’ weight derived by FFS-FUCOM based distance measurement.

The proposed method can be generalised to rank another CSPs such as IBM Cloud, Oracle Cloud, Alibaba Cloud, DigitalOcean, VMware Cloud, Salesforce Cloud, Red Hat OpenShift, CenturyLink Cloud, SAP Cloud Platform, and Tencent Cloud based on the same QoS attributes. In addition, another QoS attributes can be included in the ranking of CSPs. The ranking and selecting CSPs promotes better decision, competition, and development in the cloud computing sector. In addition, it has numerous implications for both service providers and clients. It can aid clients in making well-informed decisions when choosing services that are in line with their particular requirements. Service providers are motivated to consistently develop and innovate in order to improve their QoS.

Although the proposed framework has apparent advantages, it also has certain limits. Initially, the FFS-FUCOM solely employed Euclidean distance in its formulation. Furthermore, all decision-makers were given equal treatment, irrespective of their level of knowledge. Furthermore, the FUCOM technique has not been extended with more sophisticated fuzzy set.

This study can serve as a foundation for future research endeavours. Firstly, the FFS-FUCOM can be explored with additional distance metrics. Furthermore, experts can be rated and assigned values according to their level of knowledge. Finally, the FUCOM can be extended with new fuzzy sets such as spherical fuzzy sets or epistemic random fuzzy sets.

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