QMADM-W: A Hybrid MADM Framework for Cloud Service Selection with Unavailable Data

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***Abstract*—The rapid expansion of cloud computing has made it increasingly difficult for users to determine the most appropriate cloud service provider (CSP). The provider offers diverse services, typically assessed based on quality of service (QoS) attributes, including throughput, reliability, availability, latency, and response time. Researchers often present these QoS attributes in a decision matrix and apply multi-attribute decision-making (MADM) algorithms to evaluate and rank the CSPs. However, in practical scenarios, not all CSPs satisfy every QoS attribute, leading to unavailable performance measure values in a decision matrix. To address this challenge, we develop a hybrid MADM framework for CSP selection that handles an incomplete decision matrix. The framework integrates QoS-aware MADM (QMADM) algorithms, QTOPSIS-W and QVIKOR-W with attribute weights (QMADM-W). It employs three imputation techniques to determine unavailable performance values: minimum (min), maximum (max), and mean. The weights are derived using the analytic hierarchy process (AHP) and the analytic network process (ANP). Simulation results using the QoS for web services (QWS) dataset demonstrate the framework's effectiveness in QTPOSIS-W, with consistent and robust performance observed under the mean imputation technique through sensitivity analysis. The proposed algorithms offer a reliable solution for selecting an optimal CSP, even for an incomplete decision matrix.**

***Index Terms*—Analytic Hierarchy Process, Analytic Network Process, Cloud Service Selection, Imputation, Multi-Attribute Decision-Making, Quality of Service, Sensitivity.**

I. Introduction

The rapid expansion of cloud computing has revolutionized how computing resources are accessed by users and managed by CSPs [1], [2]. CSPs offer diverse services measured through various QoS attributes, including throughput, reliability, availability, latency, and response time [3]. However, selecting the most suitable CSP is challenging due to variations in performance measure values across CSPs [4]. MADM algorithms have been developed to rank CSPs based on QoS attributes [5], [6] to address this. Nevertheless, the selection process is quite challenging with unavailable or incomplete QoS data in a decision matrix, as many CSPs do not satisfy all QoS attributes [7], [8]. Some other challenges include categorizing QoS attributes, determining weights, and adapting to evolving user requirements [9], [10].

This paper proposes a hybrid MADM framework for selecting the best CSP from m CSPs. Each CSP is characterized by n QoS attributes, with each QoS attribute assigned a corresponding weight, hence called QMADM-W. The QoS attribute weights are derived using the AHP and the ANP. QMADM-W uses two QMADM algorithms, namely the technique for order preference by similarity to ideal solution (TOPSIS) and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) from our earlier study [11], [12], hence called QTOPSIS-W and QVIKOR-W, and three imputation techniques, min, max, and mean, to determine unavailable performance values in the decision matrix. The simulation results are presented for both QMADM algorithms with and without unavailable performance measure values, using the QWS dataset. The results indicate that the mean imputation technique consistently provides more stable and reliable rankings than other techniques in the QTOPSIS-W algorithm. This paper uses sensitivity analysis to determine the robustness of the proposed framework, which can be applied to select CSPs in real-life scenarios.

To motivate the significance of the problem addressed in this paper, consider three CSPs: Amazon web services (AWS), Google cloud platform (GCP), and Microsoft Azure. While all offer core compute services, such as AWS elastic compute cloud, GCP compute engine, and Azure virtual machines, their support for advanced features varies. For instance, Azure supports blockchain-as-a-service, while AWS and GCP do not. AWS and Azure provide edge artificial intelligence (AI) through Panorama and Azure percept, respectively, but GCP lacks a native counterpart. The presence and absence of specialized services can significantly impact the decision-making process. Therefore, selecting the most appropriate CSP becomes challenging when specific performance measure values are unavailable or inconsistently supported across CSPs [13].

The rest of this paper is structured as follows: Section II discusses related work and its insights. Section III defines the problem statement. Section IV introduces the proposed framework. Section V presents the simulation results and sensitivity analysis. Finally, Section VI recaps the paper and presents future work.

II. Previous Studies

The selection of a CSP is a challenging MADM problem, as it relies on various QoS attributes and their associated weights. Several MADM algorithms, especially TOPSIS and VIKOR, have been widely used in the literature. A brief overview of the various application domains where researchers have utilized these algorithms is stated as follows. Singh and Sidhu [14] have employed the AHP algorithm to calculate attribute weights. They have integrated it with the TOPSIS algorithm to rank CSPs, thereby evaluating the performance of cloud services. Lee et al. [15] have proposed

MADM algorithms, including the weighted sum method and TOPSIS, to rank renewable energy sources in Taiwan's electricity generation. Rafieyan et al. [9] have developed a framework for cloud computing by integrating the best-worst and VIKOR algorithms. Their results have shown improved performance over existing algorithms, making it effective for large-scale cloud systems.

Kumar et al. [16] have proposed a framework to choose the CSP using MADM algorithms. Their framework has combined the AHP and the TOPSIS algorithms to identify the best CSP. Their approach has offered users a systematic and effective decision-making tool, enhancing their ability to make informed cloud service choices and improving user satisfaction and trust in cloud computing environments. Saha et al. [17] have applied MADM algorithms, TOPSIS, and VIKOR, to find the best CSP by assessing QoS attributes. Zoel et al. [18] have proposed a hybrid Internet of things (IoT) selection framework combining TOPSIS and VIKOR algorithms, with criteria weights derived using the best-worst method from multiple decision-makers. Their approach has delivered consistent and robust rankings. However, most existing studies assume a complete decision matrix, where all QoS attributes are available. Some QoS attributes may be unavailable in practice, especially in dynamic cloud environments. This gap motivates our work on CSP selection under the incomplete decision matrix.

III. Problem Statement

Let us consider a set of m CSPs, denoted as CSP = $\{CSP_1, CSP_2, CSP_3, \ldots, CSP_m\}$, and a set of n attributes, A = $\{A_1, A_2, A_3, \ldots, A_n\}$, where $n \gg m$. Each attribute A_j, $1 \leq j \leq n$, is associated with a weight W_j and is categorized as beneficial (to be maximized) or non-beneficial (to be minimized). The sum of the weights of the QoS attributes need not be equal to 1. Mathematically, $\sum_{j=1}^{n} W_j \neq 1$. The decision matrix consists of m rows and n columns, where each value P_{ij} represents the performance value of the CSP, CSP_i, $1 \leq i \leq m$, with respect to the QoS attribute A_j, $1 \leq j \leq n$. The objective is to identify the best CSP and rank the CSPs based on the QoS attributes when some performance measure values are unavailable.

IV. Proposed Hybrid MADM Framework

This section outlines the proposed hybrid MADM framework incorporating AHP and ANP algorithms to determine QoS attribute weights (Algorithms 1 and 2) and two MADM algorithms, QTOPSIS-W and QVIKOR-W, to rank CSPs and identify the best CSP (Algorithms 3 and 4), in order to handle the unavailable performance measure values in the decision matrix. AHP forms a comparison matrix by taking every pair of QoS attributes and assessing their relative importance on a 1 to 9 scale. The matrix is then normalized, and the average of each row gives the final weights, which reflect the priority of attributes. A consistency check is also performed to ensure the weight calculation is logically consistent and reliable [19]. Unlike AHP, which assumes attributes are independent, ANP considers the interdependencies and feedback among them. Pairwise comparisons are used to build a supermatrix, which is then normalized and raised to a limit to obtain the final weights, reflecting more realistic priorities of QoS attributes [19]. These QoS attribute weights are subsequently used in the QTOPSIS-W and QVIKOR-W algorithms. Further, we use three imputation techniques: min, max, and mean to handle these values. The detailed description of two MADM algorithms is discussed in the following subsections.

Algorithm 1 Weight Calculation using the AHP Algorithm

Inputs: A set of n QoS attributes
Output: A set of n weights, $W = \{W_1, W_2, \ldots, W_n\}$

1: **for** $j = 1$ to n **do**
2: **for** $j' = 1$ to n **do**
3: **if** $j = j'$ **then**
4: Set $M_{jj'} = 1$
5: **else if** $j \neq j'$ **then**
6: Set $M_{jj'}$ = relative importance of attribute j over j'
7: Set $M_{j'j} = \frac{1}{M_{jj'}}$
8: **end if**
9: **end for**
10: **end for**
11: **for** $j = 1$ to n **do**
12: **for** $j' = 1$ to n **do**
13: Set $M^*_{jj'} = \frac{M_{jj'}}{\sum_{i=1}^{n} M_{jj'}}$
14: **end for**
15: **end for**
16: **for** $j' = 1$ to n **do**
17: Set $W_{j'} = \frac{1}{n} \sum_{j=1}^{n} M^*_{j'j}$
18: **end for**

Algorithm 2 Weight Calculation using the ANP Algorithm

Inputs: A set of n QoS attributes, t iterations, and ϵ tolerance
Output: A set of n weights, $W = \{W_1, W_2, \ldots, W_n\}$

1: Steps 1 to 10 are same as Steps 1 to 10 of AHP algorithm
11: **for** j = 1 to n **do**
12: Set $W_j = \frac{1}{n} \sum_{j'=1}^{n} M_{jj'}$ ▷ Local priority vector
13: **end for**
14: **for** $j = 1$ to n **do**
15: **for** $j' = 1$ to n **do**
16: Set $SM_{jj'} = W_j$ ▷ SM = Supermatrix
17: **end for**
18: **end for**
19: Initialize $SM_{limit} = SM$ ▷ SM_{limit} = Limit supermatrix
20: **for** $l = 1$ to t **do**
21: Set $SM_{new} = SM_{limit} \times SM$
22: **if** $|SM_{new} - SM_{limit}| < \epsilon$ **then**
23: **break**
24: **end if**
25: Set $SM_{limit} = SM_{new}$
26: **end for**
27: **for** $j = 1$ to n **do**
28: Set $W_j = SM_{limit}(j, 1)$
29: **end for**
30: **for** $j = 1$ to n **do**
31: Set $W_j = \dfrac{W_j}{\sum_{j'=1}^{n} W_{j'}}$
32: **end for**

A. QTOPSIS-W Algorithm

QTOPSIS-W is a QMADM algorithm that is based on an ideal CSP. It selects the CSP with the greatest geometric distance from the ideal worst-performing CSP and the smallest distance from the ideal best-performing CSP. This algorithm consists of five steps: normalization, handling unavailable performance measure values, determining the product, value selection and distance measurement, and CSP selection. These steps are described as follows.

1) Normalization: It is the ratio between the performance measure value and the square root of the sum of all the squared performance measure values. Mathematically,

$$NV_{ij} = \frac{P_{ij}}{\sqrt{\sum_{i=1}^{m}(P_{ij})^2}} \tag{1}$$

2) Handling Unavailable Performance Measure Values: Unavailable performance measure values create a significant challenge in the decision matrix and conducting subsequent analysis [11], [12]. To address this, we apply imputation techniques as follows. We mitigate the unavailable performance measure values by replacing them with the minimum normalized value corresponding to the respective QoS attribute. Mathematically,

$$x_{ij} = min(NV_{kj}), 1 \leq i, k \leq m, 1 \leq j \leq n \tag{2}$$

where x_{ij} is the unavailable performance measure value, NV_{kj} is the normalized value of attribute A_j irrespective of the CSP, and min is a pre-defined function to find the minimum of a set of normalized values. Similarly, we substitute the maximum normalized value for the unavailable performance measure value. Mathematically,

$$x_{ij} = max(NV_{kj}), 1 \leq i, k \leq m, 1 \leq j \leq n \tag{3}$$

where max is a pre-defined function to find the maximum of a set of normalized values. Similarly, we substitute the mean normalized value for the unavailable performance measure value. Mathematically,

$$x_{ij} = \frac{1}{m}\sum_{k=1}^{m} NV_{kj}, 1 \leq i \leq m, 1 \leq j \leq n \tag{4}$$

3) Determine the Product: QTOPSIS-W algorithm computes the product of normalized QoS attribute weights and normalized performance measure values.

4) Determine Best and Worst Solutions: The max (mx_j) and min (mn_j) normalized performance measure values concerning each attribute A_j, $1 \leq j \leq n$, are stated as follows.

$$mx_j = max(NV_{kj}), 1 \leq k \leq m, 1 \leq j \leq n \tag{5}$$

$$mn_j = min(NV_{kj}), 1 \leq k \leq m, 1 \leq j \leq n \tag{6}$$

Then the Euclidean distance, ED_{kbest} (ED_{kworst}), $1 \leq k \leq m$, between the normalized performance measure values of each CSP over the attributes and the $best$ ($worst$) normalized performance measure values among the CSPs over the attributes is determined. Note that the $best$ ($worst$) normalized performance measure value is the maximum (minimum) value for beneficial and the minimum (maximum) for non-beneficial QoS attributes. Mathematically,

$$ED_{kbest} = \sqrt{\sum_{j=1}^{n}(NV_{kj} - mx_j \text{ or } mn_j)^2} \tag{7}$$

$$ED_{kworst} = \sqrt{\sum_{j=1}^{n}(NV_{kj} - mn_j \text{ or } mx_j)^2} \tag{8}$$

Next, QTOPSIS-W finds the similarity index, S_k, $1 \leq k \leq m$, as follows.

$$S_k = \frac{ED_{kworst}}{ED_{kbest} + ED_{kworst}} \tag{9}$$

If S_k = 1 (S_k = 0), then the CSP CSP_k is the best (worst) CSP over all the CSPs.

5) Ranking the CSPs: QTOPSIS-W algorithm ranks the CSPs and selects the CSP with the maximum S_k, $1 \leq k \leq m$. The decreasing order of the S_k determines the rank of the CSPs.

Algorithm 3 QTOPSIS-W Algorithm

Inputs: A decision matrix with m CSPs and n QoS attributes with weights W_j using AHP/ANP
Output: Ranking of CSPs

```
Normalize the decision matrix using Eq. (1)
for each unavailable performance measure value do
    Replace the value with min, max, or mean normalized performance
    measure value concerning the corresponding QoS attribute
end for
Find the sum of the product.
for j = 1 to n do
    Determine the max and min normalized performance measure
    values with respect to each attribute by using the Eqs. (5) and (6)
end for
for k = 1 to m do
    Calculate the ideal best-performing CSP using Eq. (7) and ideal
    worst-performing CSP using Eq. (8)
end for
for k = 1 to m do
    Calculate the S_k using Eq. (9)
end for
Select the CSP with the maximum S_k
```

B. QVIKOR-W Algorithm

QVIKOR-W is a QMADM algorithm that undergoes five steps: normalization, handling unavailable performance measure values, weighted and normalized distance, total score, and CSP selection. Note that the process for handling unavailable performance measure values in QVIKOR-W is the same as QTOPSIS-W.

1) Normalization: The performance measure values are normalized based on whether a QoS attribute is beneficial or non-beneficial. The normalized value for a beneficial QoS attribute is the ratio between the performance measure value and the maximum performance value among all CSPs concerning the corresponding attribute. Mathematically,

$$NV_{kj} = \frac{P_{kj}}{P_{jmax}}, 1 \leq k \leq m, 1 \leq j \leq n \tag{10}$$

On the contrary, for a non-beneficial QoS attribute, the normalized value is the ratio between the minimum performance value among all CSPs concerning the corresponding attribute and the performance measure value. Mathematically,

$$NV_{kj} = \frac{P_{jmin}}{P_{kj}}, 1 \leq k \leq m, 1 \leq j \leq n \tag{11}$$

Once the performance measure values are normalized, QVIKOR-W checks for unavailable performance measure values and replaces these values as explained in the Section IV-A2.

2) Weighted Normalized Distance: QVIKOR-W algorithm calculates the weighted normalized Manhattan distance (Q), as shown in Eq. (12), and the weighted normalized Chebyshev distance (R), as shown in Eq. (13).

$$Q_k = \sum_{j=1}^{n} \frac{W_j \times (mx_j - NV_{kj})}{mx_j - mn_j}, 1 \leq k \leq m \tag{12}$$

$$R_k = max(\frac{W_j \times (mx_j - NV_{kj})}{mx_j - mn_j}), 1 \leq k \leq m \tag{13}$$

3) Total Score: QVIKOR-W algorithm calculates the total score (TS_k) by taking both Q and R values. Mathematically,

$$TS_k = \frac{v(Q_k - min(Q))}{max(Q) - min(Q)} + \frac{(1-v)(R_k - min(Q))}{max(Q) - min(Q)} \tag{14}$$

where v and $(1 - v)$ are the weights of maximum group utility and individual regret.

4) Ranking of CSPs: QVIKOR-W selects the minimum total score. On the other hand, the increasing order of the TS_k values specifies the rank of the CSPs.

Algorithm 4 QVIKOR-W Algorithm

Inputs: A decision matrix with m CSPs and n QoS attributes with weights W_j using AHP/ANP
Output: Ranking of CSPs

1: Normalize the decision matrix using Eq. (10) and Eq. (11)
2: Steps 2 to 4 are the same as Steps 2 to 4 of the QTOPSIS-W algorithm
3: Steps 5 to 7 are the same as Steps 6 to 8 of the QTOPSIS-W algorithm
8: **for** $k = 1$ to m **do**
9: Compute Q_k and R_k using Eq. (12) and Eq. (13)
10: **end for**
11: **for** $k = 1$ to m **do**
12: Calculate the TS_k for each CSP using Eq. (14)
13: **end for**
14: Select the CSP with the minimum TS_k

V. Simulation Results and Sensitivity Analysis

The simulation runs were conducted on a system with an Intel(R) Core(TM) i7-9700 central processing unit (CPU) @ 3.00 GHz, 4.00 GB random access memory (RAM), running a 64-bit Windows 10 Home operating system (OS) on an x64-based architecture, using Python. The QWS dataset [20] was used to evaluate QTOPSIS-W and QVIKOR-W algorithms by considering the QoS attribute weights from AHP and ANP algorithms under three imputation techniques, namely, min, max, and mean, to identify the best five CSPs. QTOPSIS-W algorithm (QVIKOR-W algorithm) simulation results, obtained using AHP and ANP algorithms, are compared with the traditional TOPSIS algorithm (VIKOR algorithm). The comparison, conducted on both incomplete and complete decision matrices, is presented in Fig. 1 and Fig. 2 (Fig. 3 and Fig. 4), respectively.

The QoS attribute weights of the AHP algorithm are 0.22, 0.12, 0.07, 0.06, 0.13, 0.04, 0.03, and 0.32, respectively. Similarly, the weights of the ANP algorithm are 0.23, 0.16, 0.12, 0.14, 0.08, 0.10, 0.07, and 0.08, respectively. Note that the results corresponding to each imputation technique in the QTOPSIS-W algorithm (QVIKOR-W algorithm) are denoted as QTOPSIS-WMin algorithm (QVIKOR-WMin algorithm), QTOPSIS-WMax algorithm (QVIKOR-WMax algorithm), and QTOPSIS-WMean algorithm (QVIKOR-WMean algorithm). In each figure, the x-axis denotes the ranks (1 to 5), while the y-axis indicates the CSP numbers. The results show minimal variation in rankings across imputation techniques. Notably, the QTOPSIS-WMean algorithm yields identical top five CSPs as the TOPSIS algorithm under the AHP and ANP algorithms, indicating strong consistency. In contrast, QTOPSIS-WMin and QTOPSIS-WMax algorithms exhibit some ranking deviations. Similarly, QVIKOR-WMean algorithm aligns closely with VIKOR algorithm, especially under AHP algorithm weighting, as seen in Fig. 3, where CSP 1161 consistently ranks first except under the max imputation. Greater differences in ranking are observed for QVIKOR-WMin and QVIKOR-WMax algorithms with ANP algorithm weights (Fig. 4). These observations affirm that the mean imputation technique provides more stable and robust rankings within the hybrid MADM framework, maintaining performance even with unavailable data.

A. Sensitivity Analysis

Sensitivity analysis is performed to evaluate CSPs' ranking stability and robustness against variations in QoS attribute weights. We consider ten distinct scenarios, C_1 to C_{10}. They are defined by pairwise exchanges (denoted as $\leftrightarrow$) of weights between selected QoS attributes: ($A_1 \leftrightarrow A_2$), ($A_2 \leftrightarrow A_3$), ($A_3 \leftrightarrow A_4$), ($A_4 \leftrightarrow A_5$), ($A_5 \leftrightarrow A_6$), ($A_6 \leftrightarrow A_7$), ($A_7 \leftrightarrow A_8$), ($A_1 \leftrightarrow A_8$), ($A_2 \leftrightarrow A_4$), and ($A_4 \leftrightarrow A_6$). These variations allow us to examine how changes in the relative importance of QoS attributes influence the ranking of CSPs. The results are illustrated in Fig. 5 and Fig. 6, which show the ranking variations using the QTOPSIS-W algorithm with the AHP algorithm and the QVIKOR-W algorithm with the ANP algorithm, respectively. The x-axis represents the ten scenarios in each figure, while the y-axis denotes the CSP numbers. The figures visualize mostly stable rankings across scenarios, offering insight into each algorithm's resilience to QoS attribute weight changes.

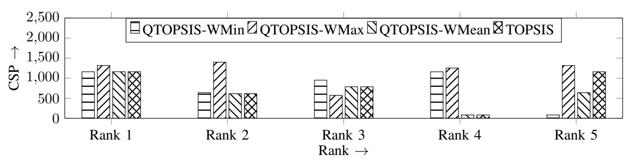

Fig. 1. Comparison of best five CSPs using three imputation techniques for QTOPSIS-W and TOPSIS using AHP.

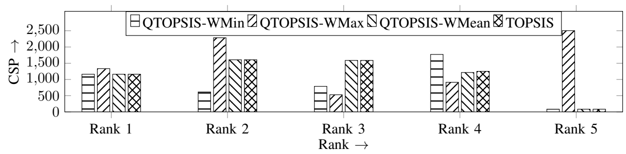

Fig. 2. Comparison of best five CSPs using three imputation techniques for QTOPSIS-W and TOPSIS using ANP.

Our analysis shows that the QTOPSIS-W and QVIKOR-W algorithms consistently rank CSP 1161 as the best CSP across different weight configurations, except when using the max imputation technique. Under this technique, CSP 1333 is ranked best by the QTOPSIS-WMax algorithm with the AHP algorithm, while CSP 1190 is ranked best by the QVIKOR-WMax algorithm with the ANP algorithm. These results suggest that both algorithms demonstrate strong consistency and robustness, even in the presence of unavailable data. Additionally, the CSP rankings remain largely stable across different imputation techniques. This highlights the importance of using reliable decision-making processes to manage uncertainty in performance data. Overall, the findings confirm that these algorithms maintain stable rankings despite variations in QoS attribute weights.

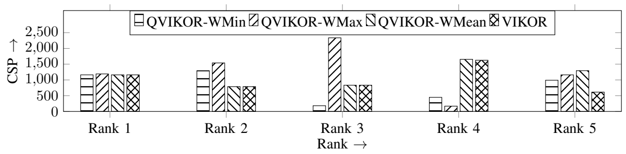

Fig. 3. Comparison of best five CSPs using three imputation techniques for QVIKOR-W and VIKOR using AHP.

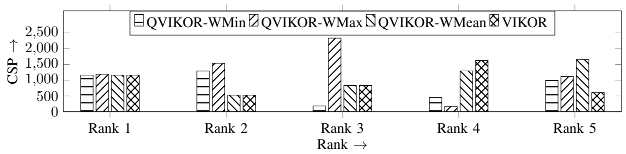

Fig. 4. Comparison of best five CSPs using three imputation techniques for QVIKOR-W and VIKOR using ANP.

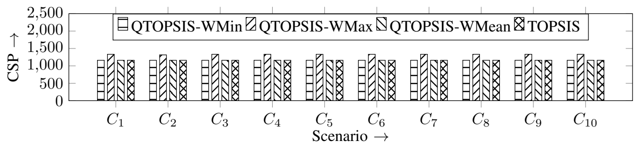

Fig. 5. Sensitivity analysis of QTOPSIS-W and TOPSIS algorithms using AHP in ten different scenarios.

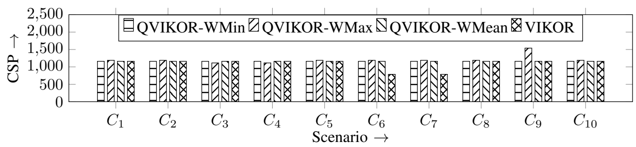

Fig. 6. Sensitivity analysis of QVIKOR-W and VIKOR algorithms using ANP in ten different scenarios.

VI. Conclusion

This study has proposed a hybrid MADM framework for CSP selection that effectively addresses unavailable performance measure values in the decision matrix. Specifically, two QMADM algorithms, QTOPSIS-W and QVIKOR-W, are demonstrated in combination with two QoS attribute weighting algorithms, AHP and ANP, to capture dependencies among criteria and three imputation techniques to identify the best CSPs while managing unavailable data. Our analysis shows that imputation significantly helps in CSP rankings, which remains stable even with unavailable data, as per the sensitivity analysis. In particular, the mean imputation technique demonstrates superior consistency. This framework enables informed decision-making even with unavailable data. Future work could explore advanced imputation techniques, like machine learning-based techniques, and adapt the framework for dynamic environments.

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