



HYBRID INTELLIGENCE FOR CLOUD SERVICE EVALUATION: INTEGRATING PCA-FEATURE DE-CORRELATION AND BEST ONLY WEIGHT GENERATION

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ARTICLE INFO

Article History

Received: February 10, 2026

Reviewed: April 17, 2026

Accepted: May 17, 2026

Published: June 30, 2026

Keywords:

Cloud Service Selection,
Hybrid MCDM,
PCA,
BOM,
Quality of Service.

ABSTRACT

Choosing a cloud service has become a very important multi-criteria decision-making (MCDM) problem because there are more and more providers that offer different quality-of-service (QoS) features. Conventional MCDM methodologies, including the Analytic Hierarchy Process (AHP) and the Best–Worst Method (BWM), frequently encounter challenges related to inconsistency, subjectivity, and scalability, particularly when addressing numerous criteria and alternatives. This study introduces an innovative hybrid framework that combines Principal Component Analysis (PCA) with the Best-Only Method (BOM) to achieve efficient and consistent ranking of cloud service providers (CSPs). PCA is used to get rid of duplicate and correlated QoS criteria, which makes dimensionality reduction more objective. BOM, on the other hand, uses the fewest pairwise comparisons possible to find relative criteria weights, which makes the process more efficient. The integrated PCA-BOM method is also linked to a ranking system that lets you compare different CSP options. The experimental results show that the proposed framework has a better rank conformance with the baseline BOM, a perfect consistency ratio (CR = 0.00), and a high Ranking Stability Index (RSI), which means it is strong in different decision-making situations. It also needs up to 83% fewer comparisons than AHP and 48% fewer than BWM, which shows that it can be used in practice. The hybrid PCA-BOM framework is a structured, reliable, and computationally efficient way to rank cloud services based on more than one criterion.



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I. INTRODUCTION

Cloud computing has completely changed the way technology works in the 21st century [1]. What used to be a high-end luxury is now a basic need for businesses around the world. This change means moving away from traditional on-premise IT infrastructure and toward a model that is very flexible, always available, and needs very little management [2]. Using virtualized resources that are delivered over the internet, businesses can now meet their complicated computing and storage needs on a subscription or pay-per-use basis [3]. This takes care of the technical and administrative problems that come with having hardware on-site. Cloud computing is getting bigger and offers a lot of services that are tailored to each user. Most of the time, these services are divided into three main delivery models: Software as a Service (SaaS), Infrastructure as a Service (IaaS), and Platform as a Service (PaaS) [4]. All of these services have strict Service Level Agreements (SLAs) that they must follow. Cloud technologies have many benefits, such as the ability to quickly scale up, save money, and access on-demand [3]. But the huge growth in the number of cloud service providers (CSPs) has made it hard for people to pick one [5]. Microsoft, Amazon, Google, and IBM are just a few of the big IT companies that compete to offer services that do the same things but cost different amounts and are of different quality.

This makes it harder for cloud customers to find the provider that best meets their needs [6], [7]. Choosing the wrong provider can have serious effects, such as service failures that are catastrophic, breaches of data integrity, and not following new international storage standards [8]. This problem is made worse by the fact that many quality indicators are often contradictory or hard to measure, which makes the selection process a complicated Multi-Criteria Decision-Making (MCDM) problem [9], where the final outcome depends critically on (i) the criteria set, (ii) how weights are derived, and (iii) how alternatives are ranked under uncertainty and varying user preferences [10], [11]. Many MCDM algorithms have been developed for cloud service selection problem [12-18]. However, these algorithms have their pros, cons and applicability. An important limitation that persists across many MCDM-based CSP ranking models is the implicit assumption that QoS criteria are independent. In real cloud datasets, QoS attributes often exhibit redundancy and correlation (e.g., throughput–response time, availability–reliability, or cost–performance tradeoffs) [19], [20]. If correlated criteria are used directly in MCDM, the decision matrix may over-emphasize duplicated information and distort weights and rankings. To overcome these constraints, recent academic initiatives have concentrated on the creation of hybrid Multi-Criteria Decision-Making (MCDM) frameworks that amalgamate various mathematical methodologies—including the Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and the Best-Worst Method (BWM)—to deliver more consistent, efficient, and dependable ranking solutions [8], [10], [11], [21], [22].

The Analytic Hierarchy Process (AHP) comparison complexity ($n(n-1)/2$) [23] and the Best Worst Method (BWM) comparison complexity ($2n-3$) [24] are two traditional MCDM methods that are often used to find the weights of QoS criteria in cloud service ranking. But these methods often have problems with scalability and subjective inconsistency because they require so many pairwise comparisons. Also, if there is a strong correlation between QoS criteria, it can cause redundancy and bias in the ranking result. The Best-Only Method (BOM) has also become a very effective way to weight things. This is because it only needs best-to-others comparisons complexity ($n-1$), which cuts down on the number of comparisons by a lot while still getting perfect or almost perfect consistency in the weights [25]. In the work [26], the author investigates the relationships among various QoS attributes; however, the methodology for analyzing these correlations is not detailed. The study [27] delineates a correlation model predicated on business services; however, it exclusively concentrates on modeling components and fails to implement the model in the service selection process. The research [15] examines a PCA-based methodology for the selection of web services.

This article employs the PCA methodology to alleviate the interconnection among QoS attributes; however, the author overlooks the importance of QoS attribute weight information, which is essential in the service selection process. [14] Looks at a way to use weighted PCA to choose multimedia services. This study lacks flexibility in weight assignment for QoS attributes, particularly in the accurate and efficient distribution of pertinent QoS weight data. This study introduces a hybrid PCA-BOM decision framework designed to tackle these challenges. It combines Principal Component Analysis (PCA) for eliminating correlations with the Best-Only Method (BOM) to derive robust criteria weights from minimal pairwise inputs. The proposed method emphasizes consistency, efficiency, and scalability in cloud service ranking. Empirical results show that our framework not only outperforms traditional AHP and BWM in reducing comparison overheads but also achieves perfect consistency ratio ($CR = 0.00$) and maintains high Ranking Stability Index (RSI), making it suitable for real-world cloud environments. The rest of the paper is arranged as follows. A review of related work was given in Section II. The proposed PCA-BOM method is given in Section III. In Section IV, an experimental study is presented. Section V is about discussion of results. Finally, Section VI concludes our study and discusses its limitations and future work.

II. RELATED WORK

Over the past decade, the problem of cloud service selection has attracted considerable attention from the research community. In past years many academics have concentrated on more and more hybrid approaches employing current MCDM techniques to overcome the limits of individual MCDM methods and to make customers more pleased and try to acquire more precise decision-making. According to [28] introduce SMICloud, a system for comparing cloud services offered by multiple providers with varying prices and quality of service. The system employs the Service Measurement Index (SMI) to identify essential quality-of-service (QoS) attributes, this research serves as a foundational approach for utilizing SMI and AHP in ranking cloud services based on QoS. In turn [10] suggest a QoS-aware selection model that shows QoS in a three-level hierarchy, information from the provider, third-party monitoring tools, and user reviews. This way, both new and experienced users can set different levels of requirements. Model uses MCDM methods (AHP for weighting and SAW for scoring) to rank providers. It also runs the whole process as a simulation tool on a cloud platform. Testing with real-world CSP data shows that multi-level QoS modeling can change rankings compared to single-level selection. This makes decision-making more realistic. By [29] suggest a combined MCDM framework (AHP + TOPSIS) to choose the best cloud service when many providers offer similar features but have different levels of quality of service (QoS). A real-world cloud case study (Cloud Harmony data) shows that the method works, and sensitivity analysis is used to check how well the ranking holds up.

Overall, this work is a good starting point for a hybrid method for QoS-driven CSP ranking that uses both classic AHP-weighting and TOPSIS-ranking. In turn [30] examine cloud service selection as a multi-attribute decision problem characterized by variations in Quality of Service (QoS) and pricing. They use AHP and ANP to find the weights for the criteria and compare TOPSIS and Fuzzy TOPSIS for ranking cloud options. Results show that both TOPSIS and Fuzzy TOPSIS can reliably find the best service based on the given preference structure. However, fuzzy TOPSIS is better when QoS values are unclear or uncertain. The work offers a valuable foundation for traditional AHP/ANP weighting combined with distance-based ranking in the selection of CSPs. According to [8] propose a hybrid approach (H-MCDM) that combines ANP and VIKOR: ANP (with a BOCR structure) computes local rankings of CSPs within benefit/opportunity/cost/risk subnets, and VIKOR produces the global compromise ranking. The method considers both beneficial and non-beneficial criteria. Results and sensitivity analysis indicate the hybrid approach provides stable rankings and improves decision reliability compared to using ANP or VIKOR alone. By [31] propose a pragmatic, cohesive MCDM framework for cloud service selection characterized by frequently linguistic and ambiguous QoS evaluations.

They use a cloud model to turn qualitative language ratings into quantitative forms that show both fuzziness and randomness. To make things less subjective, they figure out dynamic expert weights by looking at how similar each expert's cloud evaluation is to the group's mean cloud model. For ranking, they enhance TOPSIS with Grey Relational Analysis (GRA) and formulate a multi-objective optimization model to estimate criteria weights objectively. The approach is validated on a real cloud adoption case (a mining company platform) and shows robust rankings via comparative and sensitivity analysis. According to [32] propose FBM, a cloud-broker-centric framework for service ranking and selection in federated clouds where services are heterogeneous and user feedback is often linguistic (vague). The broker maintains a repository combining service characteristics and user feedback, and converts linguistic QoS inputs into numeric values using fuzzy logic (triangular fuzzy numbers) and defuzzification. To compute QoS importance while considering dependencies and sub-attributes, the method integrates fuzzy ANP for weighting and fuzzy TOPSIS for ranking services. The approach is validated via a numerical example and CloudSim-based simulations (250–1000 services), reporting improvements on MAE/RMSE and utilization compared to baseline TOPSIS/fuzzy-AHP. In turn [33] propose MRM-C, a cloud service selection framework that prioritizes reliability by combining multiple reliability criteria with a Markov chain model to capture dynamic service behavior over time. The method first forms an overall evaluation matrix using weighted reliability criteria and then builds a transition probability matrix to estimate steady-state reliability for each service. Finally, a utility-based scoring system is used to rank services more accurately when there is uncertainty. A lot of testing with multi-level sensitivity analysis and comparisons to baseline methods shows that selection accuracy can improve by up to 17% and failure rates can drop by up to 12%. This means that service provisioning is more stable and reliable.

For cloud service provider (CSP) selection, [22] suggest a hybrid MCDM approach that simultaneously models objective QoS evidence and subjective customer preferences. The framework calculates subjective criteria weights using AHP (to capture user priorities with consistency checking) and objective criteria weights using the Entropy method (to reduce bias and handle quantitative QoS variations). These weights are then combined and fed into TOPSIS to rank CSP alternatives based on closeness to ideal/anti-ideal solutions. The study validates the approach using real QoS data (e.g., CloudHarmony/QWS-type datasets [34-36]) and shows that the combined weighting yields more balanced rankings than using only objective or only subjective weights. Sensitivity and rank-correlation analysis further demonstrate that the best-ranked services remain stable under weight perturbations, supporting robustness for practical CSP selection. By [37] address cloud service provider (CSP) selection as a multi-criteria problem under uncertainty by using pentagonal intuitionistic fuzzy numbers (PIFN) with a hybrid AHP–TOPSIS decision pipeline. The method first computes fuzzy weights of criteria via AHP-based comparison matrices from decision-makers, and then applies fuzzy TOPSIS to obtain the final CSP ranking. The study further performs sensitivity and comparative analyses to examine how rankings change and to identify the most sensitive criteria, supporting robustness and future refinement. Overall, the paper shows that modelling linguistic/uncertain judgments with intuitionistic fuzzy representations can make CSP ranking more realistic than crisp scoring. In turn [38] present an integrated trapezoidal fuzzy BWM–VIKOR framework to handle MCDM decisions under linguistic uncertainty.

BWM is used to derive criteria weights with fewer comparisons than AHP, while VIKOR produces a compromise ranking by balancing group utility and individual regret. The method is validated through a real case study selecting an SWTP location using multiple criteria/sub-criteria and five alternatives, and the authors report robustness via comparative and sensitivity analyses. Methodologically, this work is relevant to cloud service ranking because it demonstrates how hybrid BWM–VIKOR improves weighting efficiency and ranking stability in uncertain decision environments. In turn [39] propose a dynamic cloud service selection framework that explicitly integrates user feedback into MCDM-based CSP ranking. AHP is used to determine the criteria weights, TOPSIS is used to generate an initial ranking, and a Markov chain that incorporates both recent and past feedback to capture changing user experience is used to refine the ranking. Instead of depending on static QoS snapshots, the method updates rankings over time by modeling feedback transitions (high/medium/low) and using steady-state probabilities. Sensitivity/rank-conformance analysis and a real-data case study (CloudHarmony) demonstrate that the optimal choice is consistent across scenarios and that the framework mitigates rank-reversal effects, making it applicable to dynamic cloud markets. CCS-OSSR, a cloud service selection and ranking framework proposed by [5], views CSP selection as an MCDM problem motivated by competing QoS criteria. The framework employs a hybrid BWM–TOPSIS pipeline, in which TOPSIS ranks cloud service options according to proximity to ideal/anti-ideal solutions and BWM determines QoS weights with fewer and more consistent pairwise comparisons than AHP. Using a real QoS dataset (QWS [34-36]), the authors validate the method and demonstrate ranking agreement with AHP/AHP-TOPSIS while enhancing consistency and lowering computational load. Robustness is supported by sensitivity analysis, which shows that the top-ranked option is stable under weight changes.

While noting future extensions for managing interrelated criteria and changing user requirements, the study concludes that CCS-OSSR provides a useful, consistent decision aid.

By combining TOPSIS for final ranking with BWM (Best–Worst Method) for dependable criterion weighting, Youssef [11] suggests an integrated MCDM framework for cloud service provider (CSP) selection. The key motivation is that many QoS criteria (e.g., security, usability) are difficult to score directly, and classic pairwise methods like AHP become computationally heavy and inconsistent as criteria increase. In the proposed approach, BWM reduces the number of comparisons (only best-to-others and others-to-worst), improving consistency, while TOPSIS computes closeness to the ideal and anti-ideal CSP. A use-case with multiple CSPs and criteria demonstrates effective ranking, and comparisons show the method outperforms AHP in efficiency and consistency. This work supports using lightweight hybrid MCDM pipelines for practical cloud selection under qualitative and quantitative QoS requirements. According to [40] propose OPTCLOUD, a QoS-driven cloud service selection framework that explicitly treats cloud ranking as an MCDM problem where many QoS attributes are interrelated (correlated). The paper argues that conventional weighted-sum scoring can produce inaccurate results when QoS criteria are correlated, so it first applies PCA to reduce dimensionality and remove multicollinearity among QoS indicators. User preference is then incorporated through the Best–Worst Method (BWM) to compute consistent criterion weights with fewer comparisons than AHP. The integrated PCA–BWM scheme yields a final comprehensive score used to rank candidate CSPs and is validated using QoS datasets with sensitivity and comparative analysis, showing improved robustness and practicality for real cloud selection scenarios. In turn [41] suggest a mixed MCDM framework for ranking cloud service providers. They do this by first using the Best–Worst Method (BWM) to guess the weights of the criteria and then using TOPSIS, ARAS, and COPRAS to rank them.

The paper confirms the method by using it in several use-case scenarios with different numbers of criteria and CSP options. It shows that BWM-ARAS and BWM-COPRAS give almost the same rankings, while BWM-TOPSIS gives slightly different rankings when the criteria/CSP set changes. A significant discovery is that BWM requires substantially fewer pairwise comparisons than AHP, enhancing efficiency while ensuring dependable prioritization. The study finds that criteria weights are the main factor that determines ranking. It also suggests that BWM should be improved by adding more MCDM techniques in the future. By [42] put forward a QoS-focused MADM (QMADM) approach for choosing a cloud service when the decision matrix is not complete (for example, when some CSP-QoS values are missing). They use three imputation methods (min, max, and mean) to fill in missing QoS entries, and they combine this method with seven MADM algorithms to rank CSPs. They use the QWS benchmark dataset [34-36] to compare rankings with and without QMADM. They find that 6 out of 7 algorithms work the same way, regardless of which imputation method is used. The study conducts sensitivity analysis to validate the robustness of rankings and emphasizes that neglecting absent QoS values diminishes the practical relevance of cloud ranking models. Mostafa [25] suggests the Best-Only Method (BOM) as a novel MCDM strategy for selecting a cloud service provider (CSP), aimed at minimizing decision-maker effort and enhancing reliability. BOM only needs the best-to-others comparisons to figure out the weights for criteria (and CSP), which makes the process easier and more consistent than AHP and BWM.

The study demonstrates that utilizing a SMI-based use case, BOM necessitates significantly fewer comparisons while attaining CR = 0% and TD = 0, signifying flawless consistency and precise weight ratios. The paper concludes that BOM is more efficient and reliable for QoS-driven CSP ranking, although results for qualitative criteria still rely on expert evaluations. According to [43] conceptualize cloud provider selection as a multi-criteria decision-making (MCDM) challenge influenced by varying QoS requirements. They suggest a hybrid framework that uses the Best-Only Method (BOM) to weight criteria more efficiently (with fewer comparisons) and RE-TOPSIS (a modified version of TOPSIS) to fix the problem of rank reversal. The framework employs a cloud-broker configuration and assesses CSPs via a case study incorporating various QoS criteria. Their comparative analysis with AHP, BOM, BOM-TOPSIS, and BWM-TOPSIS demonstrates enhanced efficiency, elevated consistency, and resilient ranking behavior. Mostafa [21] suggests a hybrid MCDM framework for ranking cloud services by combining Markov chains with the Best-Only Method (BOM). The Markov chain module tracks changes in user requirement priorities over time and derives the final priority vector, addressing the dynamic nature of QoS preferences. BOM then computes QoS criteria weights using fewer pairwise comparisons and guarantees full consistency. Finally, cloud services are ranked using normalized QoS benchmark data, and the method is validated on a Cloud Harmony dataset with performance, rank conformance, and sensitivity analyses, showing robustness to rank reversal.

III. PROPOSED METHODS

In this paper we proposed Hybrid MCDM approach for cloud computing service selection. The proposed approach can be utilized as the core of a cloud broker system to obtain user requirements and provide a ranked list of viable cloud services, reducing the complexity of service selection for cloud users. The steps of the proposed method are summarized in the flowchart shown in Fig. 1 and are as follows:

Step 1 (Determine the Selected Set of Criteria): Suppose the selected set of criteria is $C = \{C_1, C_2, C_3, \dots, C_n\}$, where n is the number of Quality of Service criteria.

Step 2 (Determine the Selected Set of CSPs): Suppose the selected set of CSPs is $CSP = \{CSP_1, CSP_2, CSP_3, \dots, CSP_m\}$, where m is the number of Cloud Service Providers.

Input – Decision Matrix (QoS Parameter Values) : We construct a decision matrix DM of $m \times n$, where n is the number of QoS criteria for selecting the optimal cloud service provider, and m is the number of eligible cloud service alternatives denoted by (CSP_i) that satisfy the functional and non-functional requirements of the cloud customer.

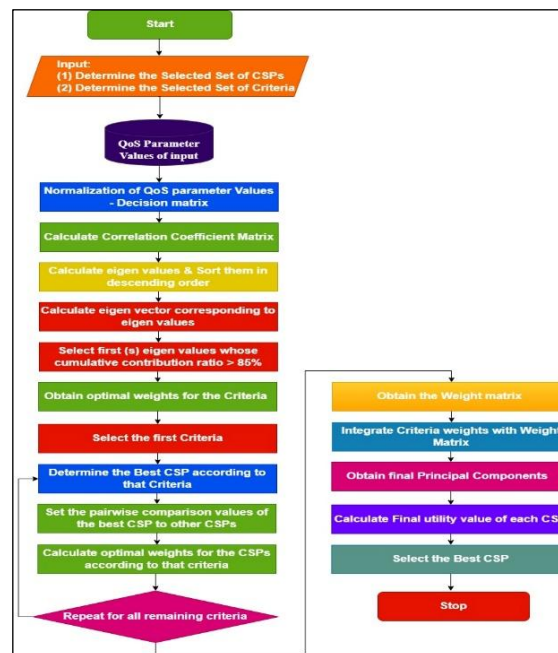


Figure 1: A Flowchart summarizing the steps of the proposed approach.
Source: Authors, (2026).

Step 3 (Normalization of Decision Matrix): Various measuring units and ranges are used to estimate the values of QoS criteria due to their vast diversity. Comparatively speaking, this could result in inconsistent results. Therefore, in order to achieve a consistent comparison, each QoS criterion value of the matrix DM is normalized using Standard deviation method in this step.

For j = 1 to n

$$\text{Calculate } \overline{DM_j} = \frac{\sum_{i=1}^m DM_{ij}}{m} \text{ and } \sigma_j = \sqrt{\frac{\sum_{i=1}^m (DM_{ij} - \overline{DM_j})^2}{n-1}}$$

For i=1 to m do

For j=1 to n do

$$N_{ij} = \frac{DM_{ij} - \overline{DM_j}}{\sigma_j}$$

Step 4 (Calculate the correlation coefficient matrix): Correlation measures both the strength and direction of the linear relationship between two variables, indicating how much they change in relation to each other. To identify these correlations, we compute the correlation matrix $R = (r_{ij})_{n \times n}$ of Decision matrix N using Pearson correlation coefficient, Where r_{ij} reflects the correlations coefficient between nx_i and nx_j for QoS criteria.

For i=1 to n do

For j=1 to n do

$$R = (r_{ij})_{n \times n} = \frac{\sum_{k=1}^n (nx_{kj} - nx_i)(nx_{kj} - nx_j)}{\sqrt{\sum_{k=1}^n (nx_{kj} - nx_i)^2 \sum_{k=1}^n (nx_{kj} - nx_j)^2}}$$

Step 5 (Calculate the Eigenvalues of the correlation coefficient matrix & sort them in descending order): Eigen values show the data magnitude. By using the characteristic equation $|\lambda I - R|$, we calculated the p eigenvalues (λ) of the correlation matrix R and sort them as $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_p \geq 0$.

Step 6 (Calculate the Eigenvectors corresponding to the Eigenvalues): Eigen vectors shows data direction. We calculated the eigenvector X_i corresponding to the eigenvalues λ_i , $i=1,2,\dots, p$.

Step 7 (Compute the contribution ratio and cumulative contribution ratio): Contribution ratio is the term that gives us an idea of the amount of total variance that has been retained by selecting the principal components instead of the original feature space.

$$Tk = \frac{\lambda_k}{\sum_{i=1}^p \lambda_i} \quad k = 1,2,\dots, p \quad \text{CCRM} = \sum_{k=1}^m Tk \quad m = 1,2,\dots, p$$

Step 8 (Select the first (s) Eigenvectors also called PC loadings $X_1, X_2, \dots, X_s$ ($s \leq p$) whose Cumulative Contribution ratio is higher than 85%): Here we can either consider the number of Eigenvectors also called PC loadings of any value of our choice (s) or limit the contribution ratio.

Step 9 (Choose the Best Criterion): Assume that C_B , where $C_B \in C$, is best criterion.

Step 10 (Obtain the Pairwise Comparison Values between the Best and Other Criteria

$$(A_B) = (A_{B1}, A_{B2}, \dots, A_{Bn}) \text{ using a Saaty's scale of 1-9.}$$

Step 11 (Compute the Optimal Weights of the Criteria by solving the system of linear equations): Suppose that W is a vector of n elements that represents the optimal weights of the criteria. The following problem should be solved to obtain the optimal weight values:

$$\frac{WB}{W_i} = A_{Bi} \quad \text{for } A_{Bi} \in A_B$$

$$\sum_{i=1}^n W_i = 1$$

Step 12 (Choose the First Criterion and Choose the Best CSPs according to this criterion)

Step 13 (Obtain the Pairwise Comparison Values of the Best CSPs to other CSPs $(CSP_A_B) = (CSP_A_{B1}, CSP_A_{B2}, \dots, CSP_A_{Bn})$ using a Saaty's scale of 1-9.)

Step 14 (Compute the optimal weights of the CSPs according to selected criteria by solving the system of linear equations):

$$\frac{CSP_B}{W_i} = CSP_A_{Bi} \quad \text{for } CSP_A_{Bi} \in CSP_A_B$$

$$\sum_{i=1}^m W_i = 1$$

Step 15 (Repeat step 12 to 14 for all remaining criteria and obtain the weights of CSPs): Here we get the weight matrix CSP_W , where each row of the matrix represents the optimal weights of the CSPs with respect to the criterion corresponding to that row.

Step 16 (Integrate Criteria weights W with weight matrix CSP_W): Here we get new weighted matrix (CSP_W^*) where Criteria weight is multiplied with the optimal weights of the CSPs with respect to the criterion corresponding to that row.

Step 17 (Obtain final Principal components $PC = (PC_1, PC_2, \dots, PC_s)$ by multiplying weighted matrix CSP_W^* with selected (s) eigenvectors obtain in step 8.

Step 18 (Calculate the Final Utility Value using following Equation to rank the CSP):

$$F_{\text{utility } j} = \sum_{k=1}^s \frac{\lambda_k}{\sum_{i=1}^p \lambda_i} * PC_{kj}$$

For $j = 1$ to m where m is no of CSP.

IV. RESULTS AND DISCUSSIONS

In this section, we evaluate the appropriateness of our proposed approach from different perspectives: Rank conformance analysis, efficiency (number of pairwise comparisons), Spearman's Rank Correlation Coefficient, Sensitivity analysis, Ranking Stability Index (RSI) and consistency ratio (CR).

IV.1 RANK CONFORMANCE ANALYSIS

We have analyze the performance of the proposed methodology by comparing with Traditional BOM [25]. The Proposed PCA-BOM framework maintains consistency with traditional BOM for top-ranked CSPs (CSP 4 ranks 1st, CSP 1 ranks 2nd and CSP 11 ranks 3rd in both PCA-BOM and BOM) but provides a more differentiated and statistically grounded ranking for mid- and lower-ranked providers. PCA-BOM places remaining CSPs (except CSP2 and 3) higher than BOM, possibly due to their stronger performance in the principal components retained after dimensionality reduction. PCA-BWM method demonstrates slightly more dispersion in rankings suggesting BWM's higher sensitivity to expert subjectivity. Overall, the Proposed PCA-BOM approach maintains superior rank conformance for critical providers (e.g., CSP1, CSP4, CSP11), reduces inconsistency seen in BOM and PCA-BWM rankings, and shows greater generalization by minimizing criteria redundancy.

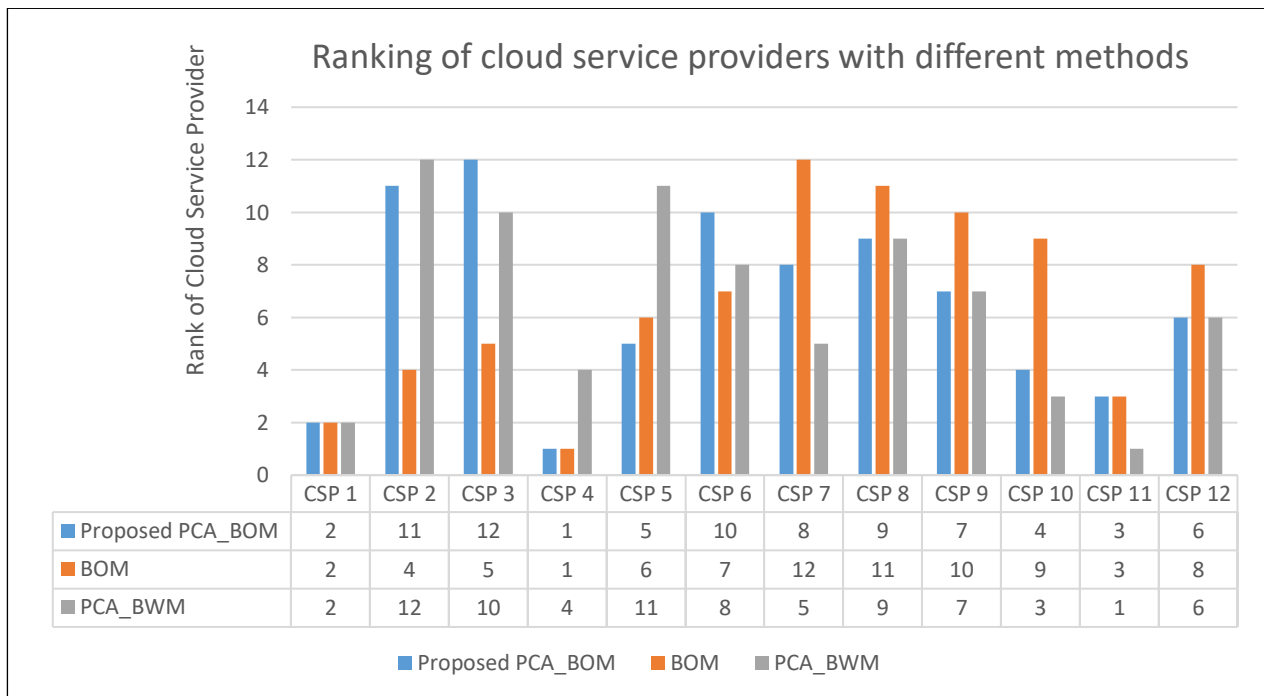


Figure 2: Ranking of cloud service providers with different methods.

Source: Authors, (2026).

IV.2 COMPARATIVE ANALYSIS – EFFICIENCY

To evaluate the efficiency gains of the proposed approach, we compared the computational effort required by the PCA_BOM method with that of traditional MCDM methods, such as BWM [24] and AHP [23]. The suggested approach demonstrates the highest reduction in computational effort compared to AHP ($\approx 83\%$ fewer comparisons) and BWM ($\approx 48\%$ fewer comparisons). This supports the claim that proposed approach is efficient, scalable and useful because it is light and still makes good decisions. Especially when there are a lot of options (CSPs) and criteria to choose from.

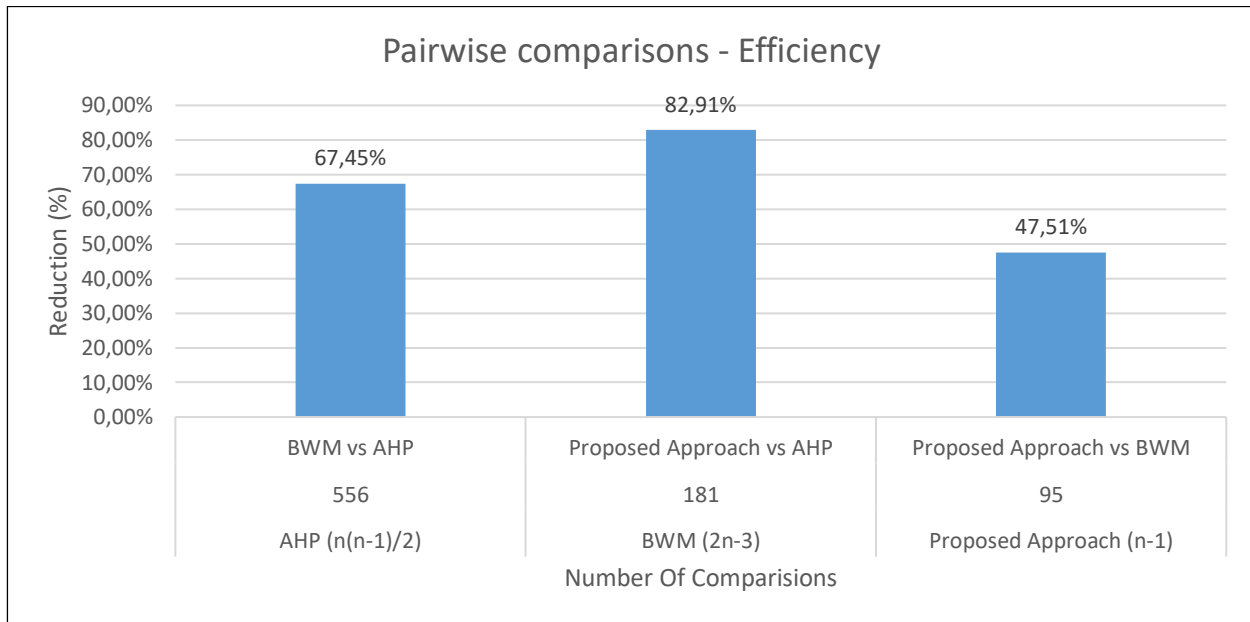


Figure 3: Pairwise Comparisons in weighting method.
Source: Authors, (2026).

IV.3 SPEARMAN'S RANK CORRELATION COEFFICIENT

The Spearman Rank Correlation Coefficient (RCC) matrix quantifies the degree of similarity between the proposed ranking method PCA_BOM and other benchmark methods such as BOM [25] and PCA_BWM [39]. Proposed variant aligns well strong agreement with other PCA-integrated approaches. This suggests good consistency and generalization across PCA-based decision strategies. It shows a relatively low (weak agreement) compared to traditional BOM. This suggests that PCA integration changes the way priorities are set, which may be more in line with the underlying data variance than with expert-driven judgments alone. The standalone BOM approach shows weak alignment, which means that BOM is more subjective or expert-driven in its structure. On the other hand, PCA-enhanced versions are data-driven and show strong consistency.

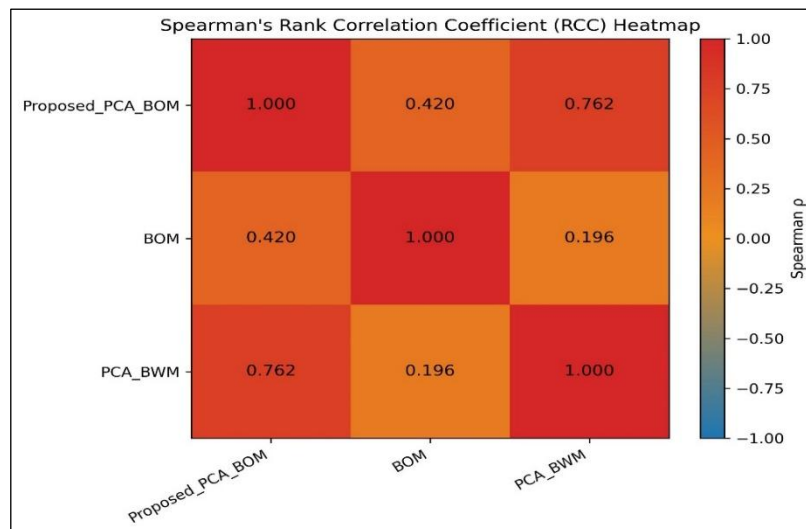


Figure 4: Spearman's Rank Correlation Coefficient.
Source: Authors, (2026).

IV.4 SENSITIVITY ANALYSIS

The figure shows a thorough sensitivity analysis that tests how well the computed rankings of Cloud Service Providers (CSPs) hold up when the weights of the decision criteria change. In this experiment, the initial set of weights underwent a sequence of pairwise exchanges among various criteria (e.g., $C1 \leftrightarrow C2$, $C2 \leftrightarrow C3$, etc.), emulating potential alterations in expert preference or stakeholder assessment. CSP 4 and CSP 1 consistently hold the top two spots (Rank 1 and 2) in all perturbation cases. This shows that they are very stable and strong when decision contexts change. The results show that the top-ranked CSPs are very stable, with only small or no changes in rank in most cases. This shows that the core decision outcomes stay the same even when the importance of the criteria changes a lot. Mid- and lower-ranked CSPs, on the other hand, show moderate changes in their ranks. This analysis gives real-world evidence that the MCDM model is reliable. It shows that even though small changes in preferences are to be expected, the main prioritization stays mostly the same for the best options.

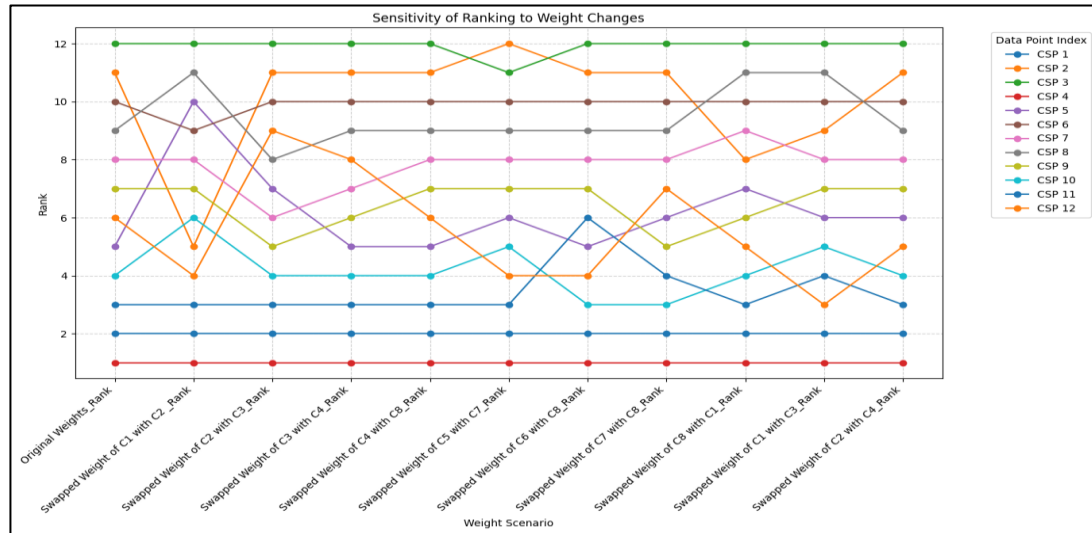


Figure 5: Sensitivity Analysis.
Source: Authors, (2026).

IV.5 RANKING STABILITY INDEX (RSI)

The Ranking Stability Index (RSI) measures how consistently each alternative (CSP) keeps its rank when the weight changes. It shows how much the rankings change when the input weights change. The average Ranking Stability Index (RSI) for the 12 CSPs in 11 weight-change scenarios is 0.9251. This shows that the ranking system is very strong and reliable, even when the input weights change a little bit.

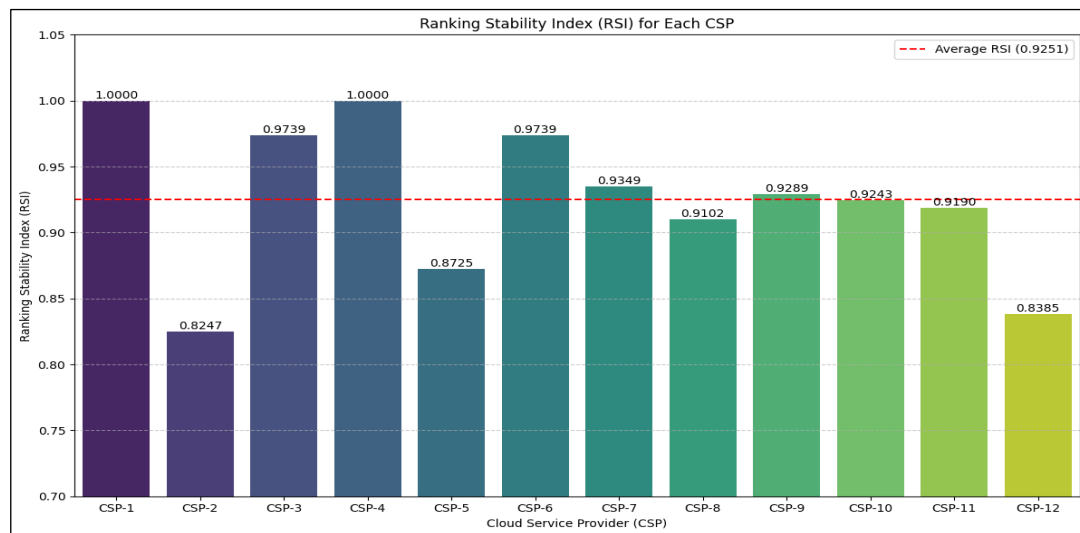


Figure 6: Ranking Stability Index (RSI).
Source: Authors, (2026).

IV.6 CONSISTENCY RATIO (CR)

If the Consistency Ratio (CR) is less than 0.1, it means that the judgments are consistent enough. In this proposed approach, CR = 0.0, which means that all of the pairwise comparisons are perfectly consistent. This is perfect and shows that the input values follow transitive preferences, which is what you would expect in the Analytic Hierarchy Process (AHP). So, the weights that come out are reliable and strong enough to use for more decision-making or sensitivity analysis.

V. CONCLUSIONS

This study introduced an innovative hybrid decision-making framework that combines PCA with the BOM for efficient, reliable, and scalable CSP selection. The proposed PCA-BOM Variant underwent a systematic evaluation across various dimensions, including rank conformity, computational efficiency, correlation consistency, sensitivity to perturbations, and ranking stability. The results show that PCA-BOM Variant has a better rank conformance with baseline BOM, shows a lot of consistency and strong generalization, needed up to 83% fewer pairwise comparisons than AHP and 48% fewer than BWM, kept a high Ranking Stability Index (RSI), showing that it is reliable when decision contexts change, and got a Consistency Ratio (CR) of 0.00, which means that the pairwise comparisons were perfectly coherent. PCA-BOM Variant is a scalable, reliable, and cognitively efficient way to choose a cloud service that is better than traditional MCDM methods.

VI. AUTHOR'S CONTRIBUTION

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VII. REFERENCES

- [1] D. Gurung, S. M. Z. U. Rashid, Z. Zain ul Abdeen, and S. Rath, "Cloud Revolution: Tracing the Origins and Rise of Cloud Computing," arXiv, arXiv:2512.06800, Dec. 7, 2025, doi: 10.48550/arXiv.2512.06800.
- [2] S. G. Patel and S. P. Patel, "Cloud Service Provider Selection: A Complex Multi-Criteria Decision Making Problem," Journal of Electrical Systems, vol. 20, no. 10s, pp. 1200–1207, Jul. 2024. [Online]. Available: <https://journal.esrgroups.org/jes/article/view/5231>
- [3] Buyya, R., Yeo, C.S., Venugopal, S., Broberg, J., Brandic, I.: Cloud computing and emerging it platforms: vision, hype, and reality for delivering computing as the 5th utility. Futur. Gener. Comput. Syst. 25(6), 599–616 (2009)
- [4] B. P. Rimal, E. Choi, and I. Lumb, "A taxonomy and survey of cloud computing systems," in Proceedings of the Fifth International Joint Conference on INC, IMS and IDC, Seoul, South Korea, 2009, pp. 44–51.
- [5] R. R. Kumar, B. Kumari, and C. Kumar, "CCS-OSSR: A framework based on Hybrid MCDM for Optimal Service Selection and Ranking of Cloud Computing Services," Cluster Computing, vol. 24, pp. 867–883, 2021, doi: 10.1007/s10586-020-03166-3.
- [6] C. N. Höfer and G. Karagiannis, "Cloud computing services: Taxonomy and comparison," J. Internet Services Appl., vol. 2, no. 2, pp. 8194, Sep. 2011.
- [7] F. Nawaz, N. K. Janjua, O. K. Hussain, F. K. Hussain, E. Chang, and M. Saberi, "Event-driven approach for predictive and proactive management of SLA violations in the cloud of things," Future Gener. Comput. Syst., vol. 84, pp. 7897, Jul. 2018.
- [8] M. Saha, S. K. Panda, and S. Panigrahi, "A hybrid multi-criteria decision making algorithm for cloud service selection," International Journal of Information Technology, vol. 13, no. 4, pp. 1417–1422, Aug. 2021, doi: 10.1007/s41870-021-00716-9.
- [9] Tomar, A., Jana, P.K.: A multi-attribute decision making approach for on-demand charging scheduling in wireless rechargeable sensor networks. Computing 1–25 (2020)
- [10] M. Eisa, M. Younas, K. Basu, and I. Awan, "Modelling and simulation of QoS-aware service selection in cloud computing," Simulation Modelling Practice and Theory, vol. 103, p. 102108, 2020, doi: 10.1016/j.simpat.2020.102108.
- [11] A. E. Youssef, "An integrated MCDM approach for cloud service selection based on TOPSIS and BWM," IEEE Access, vol. 8, pp. 71851–71863, 2020, doi: 10.1109/ACCESS.2020.2987111.
- [12] Kumar GS, Steve V, Rajkumar B (2013) A framework for ranking of cloud computing services. Fut Gener Comput Syst 29(4):1012–1023
- [13] Chandrashekar J, Gangadharan GR, Ugo F, Rajkumar B (2019) Selcloud: a hybrid multi-criteria decision-making model for selection of cloud services. Soft Comput 23(13):4701–4715
- [14] Kheybari S, Rezaie FM, Farazmand H (2020) Analytic network process: an overview of applications. Appl Math Comput 367:124780
- [15] Gao Z, Liang RY, Xuan T (2019) Vikor method for ranking concrete bridge repair projects with target-based criteria. Results Eng 3:100018
- [16] Tapoglou N, Mehnen J (2016) Cloud-based job dispatching using multi-criteria decision making. Procedia CIRP 41:661–666
- [17] Wang M, Liu Y (2013) Qos evaluation of cloud service architecture based on anp. In: Proceedings of the international symposium on the analytic hierarchy process
- [18] Sen L, Chan Felix TS, Wenxue R (2016) Decision making for the selection of cloud vendor: an improved approach under group decision-making with integrated weights and objective/subjective attributes. Expert Syst Appl 55:37–47
- [19] L. Qi, W. Dou, and J. Chen, "Weighted principal component analysis-based service selection method for multimedia services in cloud," Computing, vol. 98, no. 1–2, pp. 195–214, 2016.
- [20] G. Kang, J. Liu, M. Tang, and B. Cao, "Web service selection algorithm based on principal component analysis," Journal of Electronics, vol. 30, no. 2, pp. 204–212, 2013.
- [21] A. M. Mostafa, "A hybrid framework for ranking cloud services based on Markov chain and the Best-Only Method," IEEE Access, vol. 11, pp. 50–66, 2023, doi: 10.1109/ACCESS.2022.3232746.
- [22] A. Tomar, R. R. Kumar, and I. Gupta, "Decision making for cloud service selection: a novel and hybrid MCDM approach," Cluster Computing, vol. 26, pp. 3869–3887, 2023, doi: 10.1007/s10586-022-03793-y.
- [23] T. L. Saaty, "How to make a decision: The analytic hierarchy process," European Journal of Operational Research, vol. 48, no. 1, pp. 9–26, 1990.
- [24] M. Rezaei, "Best-worst multi-criteria decision-making method," Omega, vol. 53, pp. 49–57, 2015.

- [25] A. M. Mostafa, "An MCDM approach for cloud computing service selection based on best-only method," *IEEE Access*, vol. 9, pp. 155072155086, 2021.
- [26] F. Wagner, A. Klein, B. Klöpper, F. Ishikawa, and S. Honiden, "Multi-objective service composition with time-and input dependent QoS," in *Proceedings of the 2012 IEEE 19th International Conference on Web Services*, pp. 234–241, IEEE, HI, USA, June 2012.
- [27] Y. Luo, Y. Fan, and H. Wang, "Business correlation-aware modelling and services selection in business service ecosystem," *International Journal of Computer Integrated Manufacturing*, vol. 26, no. 8, pp. 772–785, 2013.
- [28] S. K. Garg, S. Versteeg, and R. Buyya, "A framework for ranking of cloud computing services," *Future Generation Computer Systems*, vol. 29, no. 4, pp. 1012–1023, 2013, doi: 10.1016/j.future.2012.06.006.
- [29] R. R. Kumar, S. Mishra, and C. Kumar, "A Novel Framework for Cloud Service Evaluation and Selection Using Hybrid MCDM Methods," *Arabian Journal for Science and Engineering*, vol. 43, pp. 7015–7030, 2018, doi: 10.1007/s13369-017-2975-3.
- [30] A. Jaiswal and R. B. Mishra, "Cloud Service Selection Using TOPSIS and Fuzzy TOPSIS with AHP and ANP," in *Proc. 2017 International Conference on Machine Learning and Soft Computing (ICMLSC'17)*, 2017, doi: 10.1145/3036290.3036312.
- [31] L. Liu, C. Lu, F. Xiao, R. Liu, and N. N. Xiong, "A Practical, Integrated Multi-Criteria Decision-Making Scheme for Choosing Cloud Services in Cloud Systems," *IEEE Access*, vol. 9, pp. 88391–88404, 2021, doi: 10.1109/ACCESS.2021.3089991.
- [32] S. S. Chauhan, A. Dodiya, P. Gamit, S. Patel, and A. Chaudhari, "FBM: A Fuzzy Brokering Model for Service Selection in Federated Cloud," *Procedia Computer Science*, vol. 258, pp. 2723–2736, 2025, doi: 10.1016/j.procs.2025.04.533.
- [33] W. Jin, K. Wang, and E. Zhu, "A framework based on multiple reliability criteria and Markov chain for optimal selection of cloud services," *Computing*, vol. 107, Art. no. 230, 2025, doi: 10.1007/s00607-025-01575-z.
- [34] Al-Masri, E., & Mahmoud, Q. H. (2007). Discovering the best web service. In *Proceedings of the 16th International Conference on World Wide Web* (pp. 1257–1258).
- [35] Al-Masri, E., & Mahmoud, Q. H. (2007). QoS-based discovery and ranking of web services. In *2007 16th International Conference on Computer Communications and Networks* (pp. 529–534). IEEE.
- [36] Al-Masri, E., & Mahmoud, Q. H. (2008). Investigating web services on the World Wide Web. In *Proceedings of the 17th International Conference on World Wide Web* (pp. 795–804).
- [37] N. Ghorui, S. P. Mondal, B. Chatterjee, A. Ghosh, A. Pal, D. De, and B. C. Giri, "Selection of cloud service providers using MCDM methodology under intuitionistic fuzzy uncertainty," *Soft Computing*, vol. 27, pp. 2403–2423, 2023, doi: 10.1007/s00500-022-07772-8.
- [38] K. Debnath, P. Debnath, S. Choudhury, A. K. Saha, and A. Majumdar, "An integrated decision-making approach using Best-Worst method and VIKOR in uncertain environment," *Journal of Ambient Intelligence and Humanized Computing*, vol. 16, pp. 33–49, 2025, doi: 10.1007/s12652-024-04870-3.
- [39] F. Latifi, R. Nassiri, M. Mohsenzadeh, and H. Mostafaei, "A Markov chain-based multi-criteria framework for dynamic cloud service selection using user feedback," *The Journal of Supercomputing*, vol. 81, Art. no. 89, 2025, doi: 10.1007/s11227-024-06508-9.
- [40] R. R. Kumar, A. Tomar, M. Shameem, and M. N. Alam, "OPTCLOUD: An Optimal Cloud Service Selection Framework Using QoS Correlation Lens," *Computational Intelligence and Neuroscience*, vol. 2022, Art. ID 2019485, 2022, doi: 10.1155/2022/2019485.
- [41] A. Mishra and R. Kumar, "Ranking of cloud services by applying BWM-TOPSIS, BWM-ARAS, and BWM-COPRAS hybrid MCDM methods," *International Journal of Data Science and Analytics*, vol. 20, pp. 5301–5319, 2025, doi: 10.1007/s41060-025-00775-2.
- [42] P. Navya, S. K. Panda, and R. R. Rout, "Quality of service-centric multi-attribute decision-making algorithms for handling unavailable performance data in cloud service selection," *Cluster Computing*, vol. 28, p. 561, 2025, doi: 10.1007/s10586-025-05222-2.
- [43] K. Tiwari, A. K. Sharma, and R. K. Tiwari, "An Optimized Framework for Cloud Provider Selection using Best Only Method and RE-TOPSIS," *Journal of Engineering Science and Technology Review*, vol. 18, no. 6, pp. 128–141, 2025, doi: 10.25103/jestr.186.14.