

Original Article

Optimized Cloud Service Ranking through PCA-based Dimensionality Reduction and BOM Weight Synthesis

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Abstract - Selecting a cloud service from many competing providers is a multi-criteria decision problem in which the Quality of Service (QoS) criteria are often strongly correlated. Methods such as AHP, BWM and TOPSIS treat these criteria as independent and need many pairwise comparisons. An earlier study by the authors combined Principal Component Analysis (PCA) with a two-level Best-Only Method (BOM), in which an expert also compared every provider under every criterion, at a cost of 95 judgements for eight criteria and twelve providers. The present paper keeps the PCA stage, the BOM weighting of the criteria and the variance-weighted utility of that study, and removes the provider-level elicitation. BOM weights are applied directly to the standardised QoS data, so only $n - 1$ judgements are needed (7 instead of 95) and the effort no longer grows with the number of providers. The two versions are compared on the same twelve QWS services and under the same two preference profiles. Under the reliability-focused profile of the earlier study, both select the same three leading services, and their rankings are significantly correlated (Spearman's $\rho = 0.80$); under the response-time profile, the agreement is weaker ($\rho = 0.56$). In all four common-basis sensitivity settings, the single-level version is the more stable (mean ρ 0.93–0.98 against 0.82–0.94). Its ranking also agrees with PCA-BWM ($\rho = 0.98$) and Weighted PCA ($\rho = 0.94$). The final component scores are shown to be uncorrelated only for equal weights.

Keywords - Best-Only Method, Cloud Service Selection, Multi-Criteria Decision Making, Principal Component Analysis, Quality of service.

1. Introduction

Cloud computing has transformed how organizations acquire and utilize IT resources, offering unprecedented flexibility, scalability, and cost-effectiveness [1]. The “pay-as-you-go” model and on-demand resource provisioning have made cloud services an attractive alternative to traditional on-premise infrastructure [3]. This growing adoption has led to a burgeoning market with numerous Cloud Service Providers (CSPs) offering a wide array of services (Software as a Service (SaaS), Platform as a Service (PaaS), Infrastructure as a Service (IaaS), etc.), each with varying Quality of Service (QoS) parameters, pricing models, and security features [3]. The vast diversity and complexity of available cloud services make the selection of an optimal Cloud Service Provider (CSP) or specific service a challenging Multi-Criteria Decision Making (MCDM) problem [5]. Decision-makers must consider a multitude of often conflicting criteria, including both quantitative metrics (e.g., cost, response time and availability) and qualitative factors (e.g., security, reliability, vendor lock-in, and reputation) [21]. From a limited number of possibilities, MCDM approaches offer

formal frameworks for evaluating, ranking, and choosing the best option based on a number of criteria [6]. The abundance of service offerings has led to a critical and complex challenge: how to systematically choose the most suitable cloud service that aligns with the user's specific functional requirements and non-functional constraints such as availability, response time, security, and throughput [7].

Consequently, the selection of suitable cloud services involves the simultaneous assessment of several criteria and can therefore be formulated as a Multi-Criteria Decision-Making (MCDM) problem. The AHP, TOPSIS, VIKOR, BWM and their fuzzy versions have been broadly applied for ranking cloud service providers [8-13]. However, these methods are often plagued with scalability issues, increased computational complexity and vulnerability to human judgment errors when the number of evaluation criteria is large [14]. To overcome these issues, recent research trends have explored the hybridization of dimensionality reduction techniques such as Principal Component Analysis (PCA) with MCDM techniques [15].



Despite this progress, three specific gaps remain. First, weighting methods such as AHP and BWM treat QoS criteria as independent, although real QoS data are strongly correlated; in the widely used QWS benchmark data [30-32], availability and successability are correlated at up to 0.99. When such criteria are weighted separately, the same underlying quality dimension is counted several times, which distorts the ranking. Second, distance-based methods such as TOPSIS and VIKOR compute separation measures on the assumption of independent criteria, which does not hold in practice.

Third, the existing PCA-based selection methods, Weighted PCA [34] and the PCA-BWM framework OPTCLOUD [8], remove correlation but still rely on AHP ($n(n-1)/2 = 28$ comparisons for eight criteria) or BWM ($2n-3 = 13$ comparisons) to obtain the weights, whereas the BOM-TOPSIS framework [4] reduces the elicitation effort to $n-1$ comparisons but does not address correlation. No existing framework therefore removes inter-criteria correlation while keeping the decision maker's effort to a minimum of $n-1$ judgements. This is the research gap addressed in this paper.

Principal Component Analysis (PCA) offers a promising dimensionality reduction technique that can identify and retain the most significant components of the QoS criteria, thereby reducing redundancy and enhancing computational efficiency fulfilling the first requirement [16-18]. For the second requirement, the Best Only Method (BOM) - a novel pairwise comparison approach- provides a lightweight and consistent mechanism to capture user preferences. Unlike traditional methods that require extensive pairwise comparisons (e.g., AHP with $n(n-1)/2$ comparisons, BWM with $2n-3$ comparisons), BOM requires only $n-1$ comparisons, making it more scalable and suitable for large-scale cloud environments [19].

This paper is a disclosed extension of an earlier PCA-BOM study by the same authors [28]. That study introduced the combination of PCA-based decorrelation, BOM weighting and a variance-weighted utility, and it used two levels of elicitation: the decision maker weighted the criteria, and an expert then compared the twelve providers under each of the eight criteria, which required 95 judgements.

Three elements are carried over unchanged from [28]: the z-score standardisation and PCA of the QoS matrix, the BOM weighting of the criteria, and the utility that weights each component score by its share of the variance. The present paper changes the input to the projection. The BOM criterion weights are applied directly to the standardised QoS values, so that no provider-level judgement is needed. The effort falls from 95 to 7 judgments and, unlike the two-level form, it does not grow with the number of providers. This makes the method usable when nobody has first-hand knowledge of the individual providers, which is the usual situation when a

broker screens a long list of functionally equivalent services.

The contributions of this paper, beyond those of [28], are as follows:

- (i) A single-level PCA-BOM procedure in which the criterion weights act on the standardised QoS data, reducing the elicitation to $n-1$ judgements;
- (ii) A direct comparison of the single-level and two-level versions on the same decision matrix, under the same two preference profiles and the same two sensitivity designs, with an explanation of their ranking differences;
- (iii) A mathematical and numerical check of the correlation among the final component scores, which shows when the decorrelation achieved by PCA carries over to the weighted data and when it does not.
- (iv) New validation against PCA-BWM and Weighted PCA, a repeated computation-cost experiment, and the complete data, preference inputs and code needed to reproduce the results. Results reused from [28] are identified where they appear.

This paper's remaining sections are organized as follows: Section 2 reviews related work on MCDM approaches for cloud service selection, identifying specific limitations that motivate the proposed approach. Section 3 describes the proposed PCA-BOM integration methodology.

Section 4 presents the case study and experimental results using the QWS dataset. Section 5 discusses findings and implications. Finally, Section 6 concludes the paper with suggestions for future work.

2. Related Work

Various Multi-Criteria Decision Making (MCDM) models have been suggested to select Cloud Service Providers (CSPs) to cover different aspects such as uncertainty, scalability, sustainability, and computational efficiency.

The Analytical Hierarchy Process (AHP) is one of the commonly used MCDM methods, which is based on a sequence of paired comparisons to identify the relative weights of the criteria and rank the alternatives [20].

There have been a number of frameworks developed based on AHP to rank services using functional and non-functional QoS parameters, such as SMICloud [9]. A hybrid AHP-TOPSIS model was proposed for CSP selection with criteria weights based on expert judgement, and limitations in scalability and subjectivity were reported [11].

Entropy-based objective weighting and Single-Valued Neutrosophic Sets (SVNS) were later introduced to address decision ambiguity and the rank reversal problem [22]. [23] Proposed a CRITIC-O-TOPSIS method that reduced human bias by the objective weight derivation for Cloud Manufacturing environments. A fuzzy AHP-TOPSIS technique was used to prioritise software-testing parameters,

requiring expert calibration of the fuzzy parameters [24]. In a similar vein, ANP-VIKOR with Interval Type-2 Fuzzy Sets was applied to sustainable supplier selection to handle interdependence among criteria [25].

More recently, the Best-Worst Method has emerged as an attractive alternative. BWM has been demonstrated to produce more consistent results with substantially less pairwise comparisons than AHP, thus reducing the cognitive load on the user and simplifying the decision process [13]. BWM is also integrated with other methods, such as TOPSIS, to form hybrid frameworks [26].

However, BWM still requires $2n-3$ comparisons and does not directly eliminate correlation among QoS criteria. [19] proposed the Best-Only Method (BOM) and showed how it can be used to select CSPs effectively and consistently. [29] Propose an efficient selection middleware for heterogeneous, distributed systems that bakes reliability and performance interdependencies into runtime selection, reducing violations at deployment time. These works collectively argue that correlation must be modeled across both criteria and components to avoid optimistic bias.

Correlation-aware ranking has also received attention. OPTCLOUD combines PCA with BWM and shows that correlation reduction can improve service ranking stability [8]. Weighted PCA has been used to reduce the dimensionality of QoS-based service selection while preserving the major variance in the data [34].

More recent correlation-based TOPSIS models also show that dependency among criteria can influence ranking outcomes [27]. These studies confirm that correlation should not be ignored in QoS-based cloud selection.

However, existing models either retain a relatively high comparison burden or require more complex mathematical processing. The proposed PCA-BOM model is designed between these two approaches: it preserves the correlation-reduction benefit of PCA, but BOM has a lower comparison requirement. The relation between the present method and the earlier two-level PCA-BOM study [28], including the elements inherited from it, is set out in Section 5.6.

3. Proposed Method

The purpose of this research is to present a novel approach for choosing cloud services based on user requirements, among the several possibilities accessible.

The proposed framework is designed for situations where a user must rank several cloud service providers using multiple QoS criteria. PCA and BOM play different but complementary roles. PCA is used on the data side: it checks whether QoS criteria overlap and then summarizes the original criteria through a smaller number of independent principal

components. BOM is used on the preference side: it converts the user's view of the most important criterion into a complete weight vector.

The final ranking is obtained after projecting the weighted QoS matrix onto the retained principal components.

For example, if response time is selected as the best criterion and it is decided to be twice as important as availability and eight times as important as throughput, BOM directly converts these judgments into weight ratios.

At the same time, PCA identifies that availability and successability are highly correlated in the QWS case study.

Therefore, instead of counting both criteria as fully independent, PCA represents their shared contribution through principal components. This combination makes the model easier for users and more reliable for correlated QoS datasets.

The suggested workflow of the proposed system is displayed in Figure 1. Four crucial steps are involved in the selection process of cloud services overall:

- 1) Establish the evaluation standards and cloud service options that will be utilized during the service selection procedure.
- 2) Apply Principal Component Analysis (PCA) to reduce the effect of intercorrelations among QoS criteria by transforming them into mutually uncorrelated principal components.
- 3) To determine the evaluation criteria's weight, apply the best only method.
- 4) To assess and prioritize the cloud service options based on performance metrics, integrate BOM and PCA.

3.1. Algorithm

Step 1. – (Identify the Selected Criteria Set): Assume that $C = \{C_1, C_2, C_3, \dots, C_n\}$ is the chosen set of criteria, where n is the number of Quality of Service criteria.

Step 2. – (Identify the Chosen CSP Set): Assume that $CSP = \{CSP_1, CSP_2, CSP_3, \dots, CSP_m\}$ is the chosen collection of CSPs, where m is the number of CSPs.

Algorithm for the Proposed Methodology

Input: Decision Matrix (Say, $DM = (x_{ij})_{m \times n}$)

Where m is Number of cloud service providers (say, $CSP_i, i=1,2,\dots,m$) and
 n is Number of QoS Criteria (say, $C_i, i=1,2,\dots,n$)

Output: Ranked Cloud service Providers.

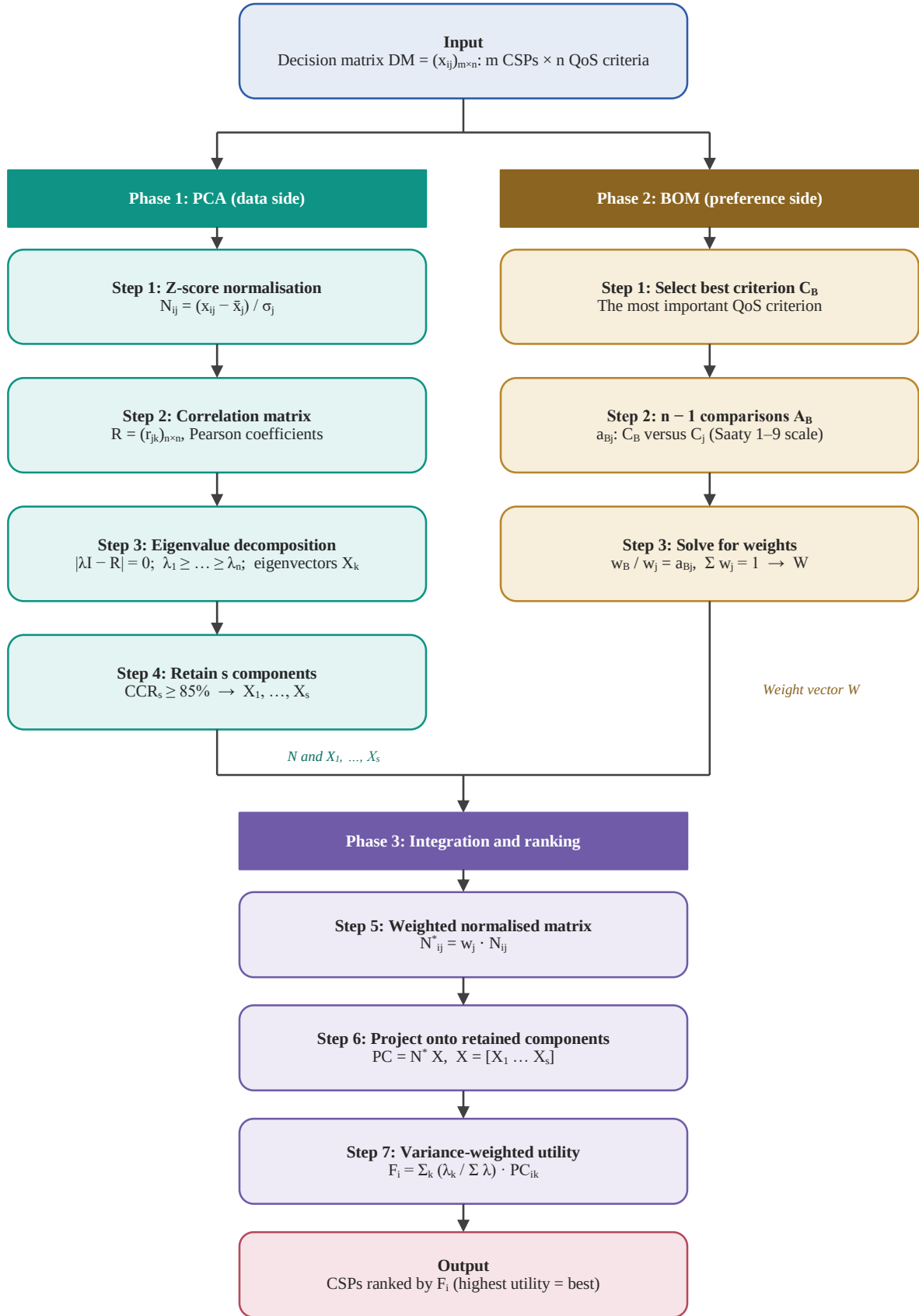


Fig. 1 Workflow of the proposed PCA-BOM cloud service ranking framework

3.1.1. Phase 1: Applying DRT Method to Eliminate Criteria Correlation - PCA

1. Normalization of the Decision Matrix: Various measuring units and ranges are used to estimate the values of QoS criteria due to their vast diversity. This could result in inconsistent results. Therefore, in order to achieve a consistent comparison, every value in the matrix DM's QoS criteria is normalized using Standard deviation method in this step.

For j = 1 to n Calculate

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

For i=1 to m do

For j=1 to n do

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

2. 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, the correlation matrix R = (rij)n×n of matrix N is computed using the Pearson correlation coefficient, where rij reflects the correlation coefficient between nxi and nxj for the QoS criteria.

For i=1 to n do

For j=1 to n do

$$R = r_{ij} \leftarrow \frac{\sum_{k=1}^m (N_{ki} - \overline{N_i})(N_{kj} - \overline{N_j})}{\sqrt{\sum_{k=1}^m (N_{ki} - \overline{N_i})^2} \times \sqrt{\sum_{k=1}^m (N_{kj} - \overline{N_j})^2}}$$

3. Extract principal components via eigenvalue decomposition: Eigenvalues show the data magnitude, and Eigenvectors indicate the data direction. Calculated the p eigenvalues (λ) of the correlation matrix R using the characteristic equation $|\lambda I - R|$. Sort the p eigenvalues (λ) as $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_p \geq 0$ (i.e., in Descending Order). Calculated the eigenvector X_j corresponding to the eigenvalues λ_j , $j=1,2,\dots,p$. Calculate the contribution ratio of each λ_j using,

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

and Calculate Cumulative Contribution ratio using

$$CCRM = \sum_{k=1}^m Tk \quad m = 1, 2, \dots, p$$

Contribution ratio is the term that indicates the amount of total variance that has been retained by selecting the principal

components instead of the original feature space.

4. Select the first s eigen vectors $X_1, X_2, \dots, X_s$ ($s \leq p$) whose Cumulative Contribution ratio is higher than 85% of the total variance, thereby reducing the dimensionality from n original criteria to s principal components without significant information loss.

3.1.2. Phase 2: Applying WEM Method (BOM) to Find Criteria Weight: Calculate_Weight (C,n)

Require: C = Set of the selected QoS criteria, n
= Number of elements in set C

Ensure: Criteria weight.

1. Choose the Best criteria: Assume that C_B , where $C_B \in C$, is the best criteria.
2. Obtain the Pairwise Comparison Values between the Best and Other Criteria (A_B) = { $a_{B1}, a_{B2}, \dots, a_{Bn}$ } using Saaty's scale of 1–9.
3. Compute the Optimal Weights of the Criteria by solving the system of linear equations.

$$\frac{w_B}{w_i} = a_{Bi}, \quad a_{Bi} \in A_B \quad (1)$$

$$\sum_{i=1}^n w_i = 1 \quad (2)$$

3.1.3. Phase 3: Integrating PCA with BOM

5. Obtain the Weight of Criteria (W) using the BOM method as describe in phase 2
Calculate the weighted normalized matrix

$$N^* = w_j * N_j \quad j = 1, 2, \dots, n$$

where w_j is the weight of jth QoS criteria obtain in phase 2.

6. Obtain the final principal components PC = (PC1, PC2, ..., PCs) by multiplying weighted normalized matrix N^* with selected (s) eigenvectors.

$$PC_{ij} = c_{ij} = \sum_{k=1}^n N^*_{ik} \cdot X_{kj} \quad \text{where } i = 1, 2, \dots, m \text{ and } j = 1, 2, \dots, s.$$

7. Calculate the Final Utility Value using the following Equation to obtain the rank of CSP.

$$F_utility_j = \sum_{k=1}^s \frac{\lambda_k}{\sum_{i=1}^p \lambda_i} * PC_{kj}$$

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

Correlation of the final component scores. The eigenvectors $X_1, \dots, X_s$ are computed from the correlation

matrix R of the unweighted standardised data, so the unweighted scores $N X_k$ are mutually uncorrelated. The utility, however, is computed from the weighted matrix $N^* = N D$, where $D = \text{diag}(w_1, \dots, w_n)$. Because the columns of N have zero mean, the covariance matrix of the final scores $PC = N D X_s$ is given by Equation (3).

$$\text{Cov}(PC) = \frac{1}{m-1} PC^T PC = X_s^T D R D X_s \quad (3)$$

The off-diagonal elements of Equation (3) vanish for every pair of retained components only in special cases, for example, when all weights are equal, $D = (1/n) I$, in which case $\text{Cov}(PC) = n^{-2} \Lambda_s$. With unequal BOM weights, the final scores are, in general, correlated. For the case data of Section 4, the correlations between the final scores are $r(PC1, PC2) = 0.325$, $r(PC1, PC3) = 0.002$ and $r(PC2, PC3) = 0.079$ under the response-time-focused weights, and $r(PC1, PC3)$ reaches 0.721 under the reliability-focused weights of Section 5.6. The decorrelation achieved by PCA therefore applies to the projection directions, which are fixed by the data, and not to the final weighted scores. In the proposed method, PCA is used to define these directions and to discard the components with little variance; it is not claimed that the utility is computed on uncorrelated variables. Since the projection and the utility are both linear, the utility can also be written as in Equation (4), so that each criterion enters the ranking with its BOM weight scaled by a coefficient c_j that depends only on the correlation structure of the data.

$$F_i = \sum_{j=1}^n c_j w_j N_{ij}, \quad c_j = \sum_{k=1}^s T_k X_{jk} \quad (4)$$

4. Case Study with Experiments

A trial is conducted to evaluate the feasibility of the suggested approach. Using the QWS dataset [30-32], 12 distinct cloud services with the same functionality have been used for this case study. The cost values, which QWS does not provide, are adopted from [2]. Eight quality criteria—the response time (C1), availability (C2), throughput (C3), successability (C4), reliability (C5), best practices (C6), latency (C7), and Cost (C8)—are used to assess these services. Table 1 presents the decision matrix used for the case study.

1. Normalized the original Decision Matrix: Table 2 presents the normalized matrix.
2. Compute the matrix of correlation coefficients: The results are shown in Table 3.
3. Determine the matrix's eigenvalues and eigenvectors for the correlation coefficient: By using the characteristic equation $|\lambda I - R| = 0$, the p eigenvalues (λ) of the correlation matrix R were calculated and sorted as $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_p \geq 0$. The eigenvectors X_i corresponding to the eigenvalue λ_i , for $i = 1, 2, \dots, p$, the contribution ratio and the cumulative contribution ratio as shown in Table 4.
4. Choose $X_1, X_2, \dots, X_s$ ($s \leq p$) as the first s eigenvectors whose cumulative contribution ratio exceeds 85%.

From Table 4, the cumulative contribution ratio of the first three components reaches 94.13%, so $s = 3$. Table 5 shows the first three eigenvectors, also called Principal Component (PC) loadings.

Table 1. Decision matrix for 12 CSP (DM) $m \times n$

Cloud Service Provider	Response Time (ms)	Availability (%)	Throughput (invokes / second)	Successability (%)	Reliability (%)	Best Practices (%)	Latency (ms)	Cost (dollars/month)
CSP1	1069.5	71	3	72	83	91	744	10.1038
CSP2	1760.48	97	2.4	98	67	58	18.76	42.5356
CSP3	1558.07	97	2.6	98	67	58	13.14	43.9942
CSP4	1328.5	56	3.8	56	83	91	3.75	5.6308
CSP5	1734.34	97	2.5	98	67	58	14.65	42.8126
CSP6	621.2	85	8.3	95	73	80	10	21.2864
CSP7	392.5	46	5.6	47	73	75	1.5	3.6026
CSP8	146	93	5.9	98	67	72	24	37.4076
CSP9	302.75	89	7.1	90	73	80	187.75	29.9314
CSP10	411.12	39	6.2	39	73	84	24.87	2.6931
CSP11	70.75	56	8.3	56	83	91	7.5	5.5177
CSP12	74.5	92	8.4	97	73	80	23.5	34.2768

Table 2. Normalize decision matrix for 12 CSP

Cloud Service Provider	Response Time	Availability	Throughput	Successability	Reliability	Best Practices	Latency	Cost
CSP1	0.424275533	-0.2527445	-0.97716711	-0.288478512	1.5003779	1.142115	3.084245	-0.77931
CSP2	1.469961516	0.94204798	-1.22754445	0.836587684	-1.026574	-1.45718	-0.3331	1.133646
CSP3	1.163646861	0.94204798	-1.14408534	0.836587684	-1.026574	-1.45718	-0.35958	1.21968

CSP4	0.816229959	-0.9420479	-0.64333066	-0.98082694	1.5003779	1.142115	-0.40383	-1.04315
CSP5	1.430402872	0.94204798	-1.1858149	0.836587684	-1.026574	-1.45718	-0.35247	1.149985
CSP6	-0.25415369	0.39060526	1.234499379	0.706772354	-0.078967	0.275683	-0.37438	-0.11972
CSP7	-0.60025399	-1.4015835	0.107801354	-1.370272931	-0.078967	-0.11815	-0.41443	-1.16278
CSP8	-0.9732917	0.75823374	0.232990024	0.836587684	-1.026574	-0.35445	-0.30841	0.831176
CSP9	-0.73607604	0.5744195	0.733744701	0.49041347	-0.078967	0.275683	0.463184	0.3902
CSP10	-0.57207565	-1.7232585	0.358178693	-1.716447145	-0.078967	0.590749	-0.30431	-1.21642
CSP11	-1.08717035	-0.9420479	1.234499379	-0.98082694	1.5003779	1.142115	-0.38616	-1.04982
CSP12	-1.08149533	0.71228018	1.276228935	0.793315907	-0.078967	0.275683	-0.31077	0.646509

Table 3. Correlation coefficient matrix of 8 QoS criteria

	Response Time	Availability	Throughput	Successability	Reliability	Best Practices	Latency	Cost
Response Time	1	0.343021	-0.894928	0.284989	-0.244238	-0.567278	0.072714	0.392614
Availability	0.343021	1	-0.221833	0.992799	-0.615581	-0.656135	-0.022728	0.951179
Throughput	-0.894928	-0.221833	1	-0.145168	0.230968	0.523064	-0.248812	-0.310714
Successability	0.284989	0.992799	-0.145168	1	-0.611342	-0.620633	-0.040094	0.927701
Reliability	-0.244238	-0.615580	0.230968	-0.611341	1	0.899069	0.446006	-0.785791
Best Practices	-0.567278	-0.656135	0.523064	-0.620633	0.899069	1	0.369145	-0.818951
Latency	0.072714	-0.022728	-0.248812	-0.040094	0.446006	0.369145	1	-0.198009
Cost	0.392614	0.951179	-0.310714	0.927701	-0.785792	-0.818951	-0.198009	1

4.1. Phase 2: Applying WEM Method (BOM) to Find Criteria Weight

1. Choose the Best Criterion: Assume that Response Time is the best criteria CB. Thus, CB = C1 where CB ∈ C.
2. Determine the Pairwise Comparison Values of the Best Criterion to other criteria (A_B): Let the Pairwise comparison values be as shown in Table 6 using the Saaty's scale of 1–9 as (Table 7) [33].
3. Determine the Ideal Criteria Weights: Assume that the ideal weights of the criterion are represented by the vector W, which consists of n entries. To determine the ideal weight values, the following issue has to be resolved:

$$\frac{w_B}{w_i} = a_{Bi}, \quad a_{Bi} \in A_B$$

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

$$\frac{w_1}{w_2} = a_{12} = 2, \rightarrow \frac{w_1}{2} = w_2 \quad (5)$$

$$\frac{w_1}{w_3} = a_{13} = 8, \rightarrow \frac{w_1}{8} = w_3 \quad (6)$$

$$\frac{w_1}{1} + \frac{w_1}{2} + \frac{w_1}{8} + \frac{w_1}{3} + \frac{w_1}{5} + \frac{w_1}{3} + \frac{w_1}{2} + \frac{w_1}{3} = 1 \quad (7)$$

On solving linear equation ... (7), the weight of each criterion is obtained as shown in Table 8. In this case study,

response time is selected as the best criterion because low response time is critical in user-facing cloud services. The comparison vector is AB = {1, 2, 8, 3, 5, 3, 2, 3} as shown in Table 6.

Using the BOM closed-form equation, the final weights are obtained as shown in Table 8. The highest weight is assigned to response time, followed by availability and latency. This reflects a user preference for fast and responsive services.

4.2. Phase 3: Calculation of the Final Utility Value to Select Best CSP

5. Calculate weighted normalized matrix: Here weighted normalized matrix, as shown in Table 9, is obtained by multiplying the criteria weight obtained in phase 2 with the respective column of criteria in the normalized matrix using the equation.

$$N^* = w_j \times N_j$$

Where j = 1, 2, ..., n and w_j is the weight of the jth QoS criteria determined using the BOM method in Phase 2.

6. Obtain the final principal components: Here final principal components as shown in (Table 10) PC = (PC1, PC2, ..., PC_s) is obtained by multiplying the weighted normalized matrix N* (Table 9) with selected (s) eigenvectors (Table 5).

Table 4. Eigenvalues, contribution ratio, cumulative contribution ratio and Eigenvectors

j	Eigenvalue (λ _j)	Contribution ratio (%)	Cumulative contribution ratio (%)	Eigen Vector (X _j)
1	4.60425	57.553205	57.553205	[-0.26778006, -0.41303028, 0.22668036, -0.40029979,

				0.38844859, 0.42845681, 0.1025927, -0.44842292]
2	1.74994	21.874276	79.427481	[-0.55586133, 0.11375467, 0.63202612, 0.16245688, -0.22126337, 0.01357738, -0.43331396, 0.12379816]
3	1.17643	14.705424	94.132905	[-0.18908326, 0.38510877, 0.17226365, 0.40289978, 0.2657619, 0.29918873, 0.66349813, 0.15350149]
4	0.35578	4.447316	98.580221	[0.43225691, 0.21544395, 0.10766713, 0.22592613, 0.58485625, 0.27351596, -0.53430203, 0.04191146]
5	0.06348	0.793556	99.373777	[-0.54476336, 0.07221759, -0.59130146, -0.17062461, 0.25552567, 0.15287455, -0.21110622, 0.43132063]
6	0.03455	0.431931	99.805708	[-0.11992052, 0.03980733, 0.20224028, -0.16506293, 0.55370319, -0.77182262, 0.10495868, 0.05073294]
7	0.01486	0.185773	99.991481	[0.29251104, -0.08496415, 0.34252948, -0.51360437, -0.05381786, 0.17527127, 0.13900526, 0.68786892]
8	0.00068	0.008519	100	[-0.00165375, -0.77956532, 0.0051979, 0.52900758, 0.11263672, -0.0459863, 0.03317683, 0.31063912]

Table 5. Selected top Eigenvectors(X)

X_1	X_2	X_3
-0.26778006	-0.55586133	-0.18908326
-0.41303028	0.11375467	0.38510877
0.22668036	0.63202612	0.17226365
-0.40029979	0.16245688	0.40289978
0.38844859	-0.22126337	0.2657619
0.42845681	0.01357738	0.29918873
0.1025927	-0.43331396	0.66349813
-0.44842292	0.12379816	0.15350149

Table 6. The (C_B - to - others) comparison values A_B

C_B - to - others	Pairwise Comparison Values
C_1 - to - C_1	1
C_1 - to - C_2	2
C_1 - to - C_3	8
C_1 - to - C_4	3
C_1 - to - C_5	5
C_1 - to - C_6	3
C_1 - to - C_7	2
C_1 - to - C_8	3

7. Determine the Final Utility Value in order to rank the CSP. The results are displayed in Table 10 and are computed using the evaluation function that is described in the procedure. The

cloud service options that were chosen as the top ones had a higher final utility value score.

Table 7. Saaty's scale of relative importance levels [33]

Importance (Preference)	Definition
1	Equal Importance
3	Moderate Importance
5	Strong Importance
7	Very strong or demonstrated Importance
9	Extreme Importance
2,4,6,8	Intermediate Values
Reciprocals	If activity i has one of the above numbers assigned to it when compared with activity j then j has the reciprocal value when compared with i
Rationales	Ratios arising from the scale

Table 8. Criterion weight using the BOM method

Criterion	Weight
Response Time	0.30075
Availability	0.150375
Throughput	0.037593
Successability	0.10025
Reliability	0.0601503
Best Practices	0.10025
Latency	0.1503759
Cost	0.10025

Table 9. Weighted normalized matrix

Cloud Service Provider	Response Time	Availability	Throughput	Successability	Reliability	Best Practices	Latency	Cost
CSP1	0.127601	-0.038006	-0.0367356	-0.0289201	0.0902482	0.11449	0.4637963	-0.0781264
CSP2	0.442093	0.141661	-0.0461482	0.08386843	-0.0617488	-0.14608	-0.0500903	0.1136487
CSP3	0.349968	0.141661	-0.0430107	0.08386843	-0.0617488	-0.14608	-0.0540725	0.1222737
CSP4	0.245482	-0.141661	-0.0241853	-0.0983285	0.0902482	0.11449	-0.0607260	-0.1045761
CSP5	0.430196	0.141661	-0.0445795	0.08386843	-0.0617488	-0.14608	-0.0530025	0.1152867
CSP6	-0.07643	0.058737	0.0464097	0.07085437	-0.0047499	0.02763	-0.0562974	-0.0120017
CSP7	-0.18052	-0.210764	0.0040526	-0.1373707	-0.0047499	-0.01184	-0.0623203	-0.1165692
CSP8	-0.29271	0.114020	0.0087590	0.08386843	-0.0617488	-0.03553	-0.0463773	0.0833259
CSP9	-0.22137	0.086378	0.0275843	0.04916425	-0.0047499	0.02763	0.0696516	0.0391177
CSP10	-0.17205	-0.259136	0.0134653	-0.1720749	-0.0047499	0.05922	-0.0457609	-0.1219473
CSP11	-0.32696	-0.141661	0.0464097	-0.0983285	0.0902482	0.11449	-0.0580688	-0.1052449
CSP12	-0.32526	0.107109	0.0479785	0.07953041	-0.0047499	0.02763	-0.0467316	0.0648129

Table 10. Utility values and ranking of cloud services

Cloud Service Provider	PC1	PC2	PC3	F_Utility	Ranking
CSP1	0.151508	-0.3322238	0.297232267	0.058228782	6
CSP2	-0.36361	-0.197716398	-0.079103149	-0.264123995	12
CSP3	-0.3425	-0.141731521	-0.06246165	-0.237288332	10
CSP4	0.151432	-0.188875867	-0.142857687	0.024841925	7
CSP5	-0.3611	-0.188646928	-0.078264156	-0.260573695	11
CSP6	-0.01203	0.114348018	0.041426231	0.024172916	8
CSP7	0.230261	0.07008077	-0.165730095	0.123479336	3
CSP8	-0.08163	0.238434467	0.089535453	0.018328935	9
CSP9	0.009776	0.134389504	0.158908724	0.058376787	5
CSP10	0.298556	0.053302291	-0.166897701	0.158942286	2
CSP11	0.321298	0.172711409	-0.020795414	0.219622128	1
CSP12	-0.00196	0.265928054	0.129007179	0.075992928	4

5. Result and Discussion

This section examines how well the suggested technique performs while taking into account sensitivity analysis, computation cost, reduced dimensionality of the selection criteria, comparative analysis, and rank conformance analysis.

5.1. Rank Conformance Analysis

To evaluate the conformity of the proposed methodology with other modern MCDM approaches, ranks obtained using the proposed approach were compared with those of other cloud service selection methodologies, such as Weighted PCA [34] and PCA BWM [8]. For this comparison, the identical

datasets utilised in the case studies were taken into account. Following the comparison, it has been noted that the rankings of the suggested approach closely resemble those of the PCA BWM [8] and Weighted PCA [34] methodologies.

For instance, as Figure 2 illustrates, all approaches fully agree that CSP 11 is the ideal substitute for cloud services. Similarly, as Figure 2 illustrates, all methodologies that were taken into consideration agreed on the second, third, eighth, ninth, tenth, eleventh, and twelfth ranks. The results show that the performance of the proposed methodology is on par with existing MCDM methods.

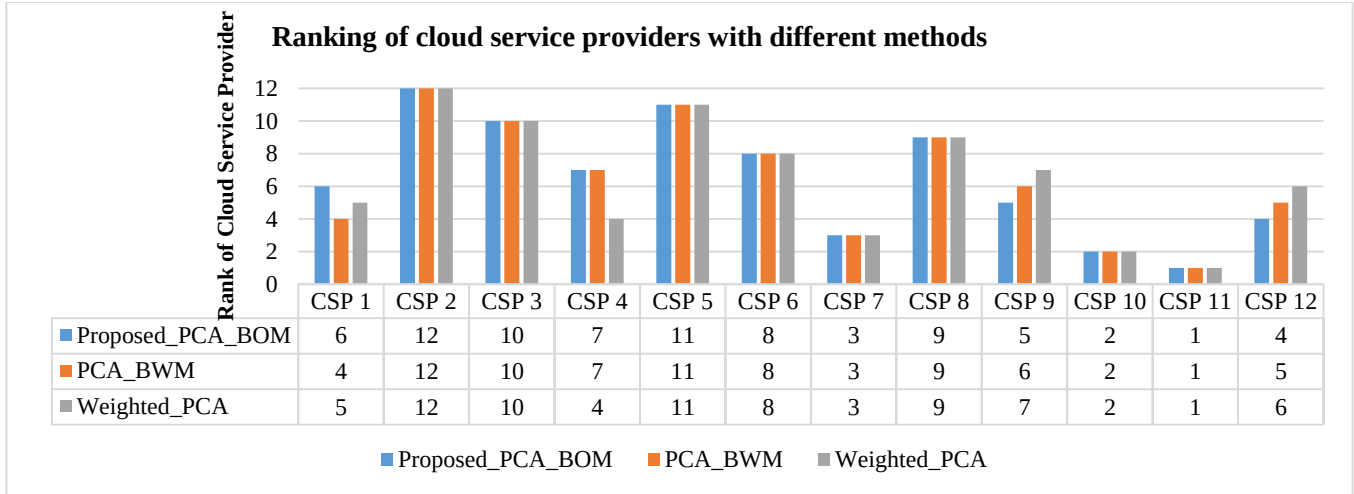


Fig. 2 Ranking of cloud service providers

Table 11. Rank correlation with existing methods

Method Pair	Spearman's ρ	Kendall's τ
Proposed vs. PCA-BWM [8]	0.979	0.939
Proposed vs. Weighted PCA [34]	0.937	0.848

To quantify the degree of agreement between the proposed method and existing approaches, Spearman's rank correlation coefficient (ρ) and Kendall's Tau (τ) were computed between the rankings produced by the proposed method and those yielded by Weighted PCA [34] and PCA-BWM [8]. The results, shown in Table 11, confirm a high degree of rank conformance: $\rho = 0.979$ with PCA-BWM and $\rho = 0.937$ with Weighted PCA, indicating that the proposed method produces consistent rankings while requiring significantly fewer pairwise comparisons.

5.2. Comparative Analysis

In order to assess the degree of improvement in the criteria weight calculation, BOM, BWM, and AHP are compared in this subsection. To distinguish among BOM, AHP, and BWM, the identical QoS dataset as presented in the case study is utilised. Many methods currently used for pairwise comparison in the cloud service selection problem employ the AHP and BWM.

In contrast, as shown in Figure 3 the proposed method uses the Best Only Method (BOM), which demonstrates superior performance compared to AHP and BWM. BOM requires only $n-1$ comparisons, while AHP necessitates $n(n-1)/2$ comparisons, and BWM requires $(2n-3)$ comparisons. Moreover, the proposed method requires fewer pairwise comparisons compared to both AHP and BWM.

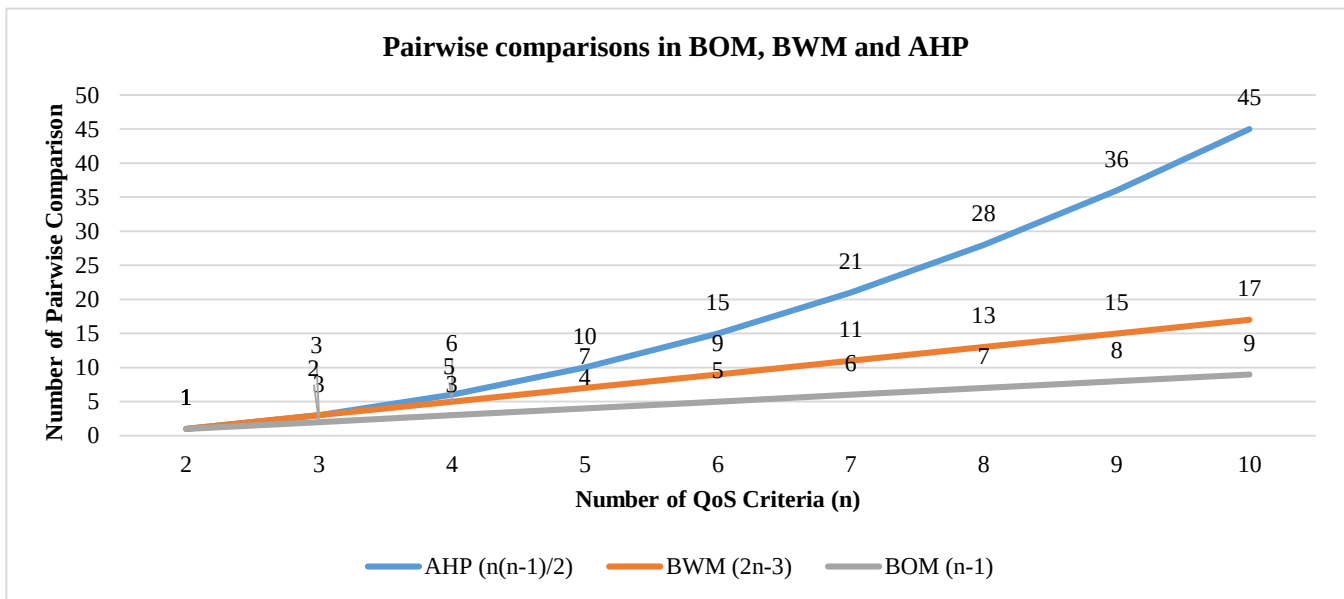


Fig. 3 Pairwise comparisons in BOM, BWM and AHP

Table 12. Comparative summary of MCDM methods

Criterion	PCA-BOM (Proposed)	AHP-TOPSIS [11]	BWM [13]	Weighted PCA [34]
Pairwise Comparisons	$n-1 = 7$	$n(n-1)/2 = 28$	$2n-3 = 13$	$n(n-1)/2 = 28$
Handles Correlation	Yes (PCA)	No	No	Yes (PCA)
Computational Complexity	$O(mn^2 + n^3)$	$O(mn^2 + n^2)$	$O(mn^2 + n)$	$O(mn^2 + n^3 + n^2)$
Consistency Guarantee	High (linear system)	Moderate (CR check)	High (min-max)	Moderate (CR check)
Scalability ($n > 10$)	Excellent	Poor	Good	Moderate

The comparative analysis, as shown in Table 12, reveals that the proposed PCA-BOM method offers the best balance between computational efficiency and methodological rigor.

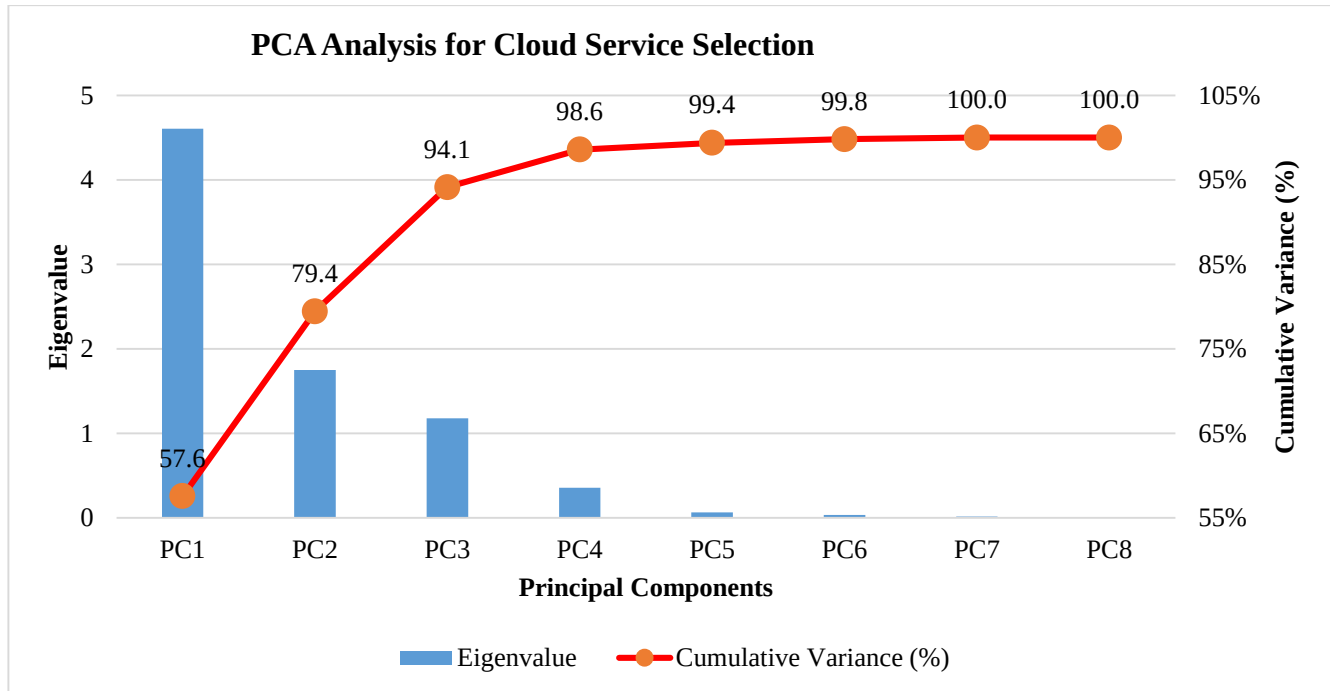
While AHP-TOPSIS requires 28 pairwise comparisons for 8 criteria and is known to suffer from consistency issues as n grows, BOM requires only 7 comparisons and guarantees consistency through a deterministic linear system.

Thus, BOM reduces the comparison burden by 75.0% compared with AHP and 46.2% compared with BWM. Compared to BWM, which also reduces comparisons (13 for 8 criteria), the proposed method further addresses inter-criteria correlation through PCA — a feature that BWM lacks. Weighted PCA handles correlation but relies on AHP for weighting, inheriting its scalability limitations.

5.3. Dimensionality Reduction Effectiveness

Higher correlation between criteria often leads to larger eigenvalues for the first few principal components, indicating that those components capture more of the variance in the data, which is why they are considered more significant. By identifying the primary elements that account for the majority of the variation, the number of main components and their association with QoS criteria lower the complexity of the selection criteria. Figure 4 shows PCA analysis of the number of principal components and their correlation with QoS criteria reduce the dimensionality of the selection criteria.

The first three principal components preserve 94.13% of the variance, which is greater than the 85% threshold. Hence, only three transformed components are sufficient to represent the original eight QoS criteria for ranking. This reduces dimensionality while retaining most of the useful information.

**Fig. 4 PCA Analysis for cloud service selection**

5.4. Computation Cost

The computation cost of the procedure was measured on synthetic decision problems with $m = 10, 20, 30, 40$ and 50 providers and $n = 8, 10, 12, 14$ and 16 criteria. Since the QWS dataset contains only nine QoS attributes, the decision matrices were generated as independent random numbers uniformly distributed on $[0, 1]$, with a fixed random seed. The range of the generated values does not affect the computation, because every criterion is standardised before PCA. For each matrix, a random Best-to-Others vector with values from 1 to 9 was drawn, and the complete procedure was timed, from standardisation to the final ranking. Each configuration was run 200 times after one warm-up run; nothing was printed inside the timed code, and the median time is reported. The experiment was carried out for this revision in Python 3.13 with NumPy 2.5 on a two-core Intel Xeon virtual machine at

2.10 GHz; the script is part of the supplementary material. Figure 5 shows the results. For all twenty-five combinations, the median time lies between 0.07 and 0.12 ms, and it rises only slightly with m and n , because at this size the fixed overhead of the library calls is larger than the arithmetic. A second run with $n = 16$ and larger candidate sets gave median times of 0.10, 0.20, 0.30, 1.84 and 3.34 ms for $m = 100, 500, 1,000, 5,000$ and $10,000$, which grow roughly in proportion to m . The theoretical complexity is $O(mn^2 + n^3)$ for the standardisation, the correlation matrix and the eigen-decomposition, $O(n)$ for the BOM weights and $O(mns)$ for the projection. Since n is small compared with m in practice, the cost grows linearly with the number of providers, which agrees with the measurements. In every case, the computation time is negligible compared with the time a decision maker needs to give the $n - 1$ judgments.

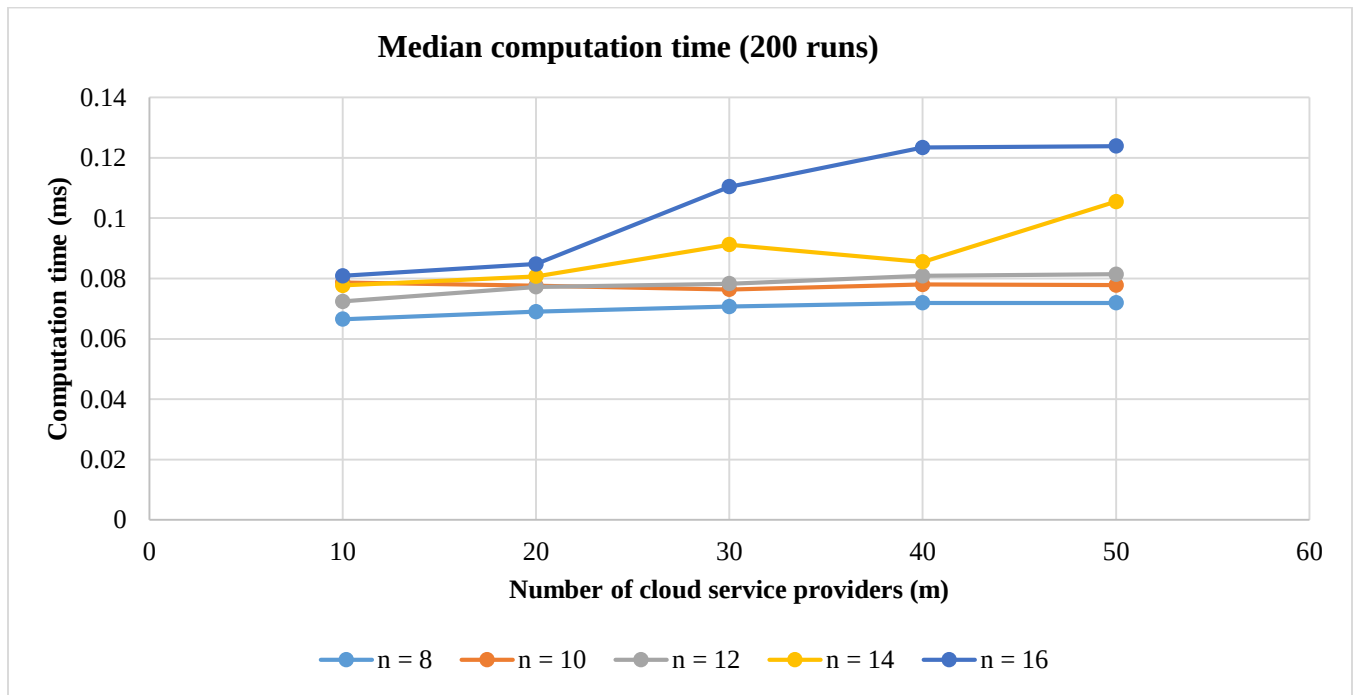


Fig. 5 Median computation time of the single-level PCA-BOM procedure for m providers and n QoS criteria (200 runs per configuration)

5.5. Sensitivity Analysis

Using sensitivity analysis, this portion confirms the proposed scheme's effectiveness and resilience. In order to conduct the sensitivity analysis, potential changes in the cloud service provider ranking are examined under various weight values. The entire procedure is carried out in each case so that changes under different conditions may be tracked. A variety of scenarios are produced by sequentially switching the weights of each QoS criterion. For example, the exchange of the weight of criteria C1 and C3 is indicated by C1–C3. By assessing the impact of modifications in criterion weight, the rankings of cloud service providers are established for every scenario. In Total, nine weight-swap scenarios were carried out. The suggested methodology is considered robust if the

rankings of cloud service alternatives remain consistent across all scenarios. The results show that the suggested method is reliable and capable of identifying the top cloud service providers. Figure 6 displays the specifics of the sensitivity assessment test. According to Figure 6, CSP 11 is the top cloud service provider in all nine scenarios, while CSP 10 is the second-best option. It has been observed that CSP11, CSP10, and CSP7 frequently appear in the leading group, and Middle-ranked services show higher variation when closely scored. To quantify ranking stability, the average Spearman's rank correlation coefficient has been computed across the nine weight-swap scenarios. The average $\rho = 0.96$, indicating that the proposed method is generally stable and infrequently affected by shifts in the criterion weights.

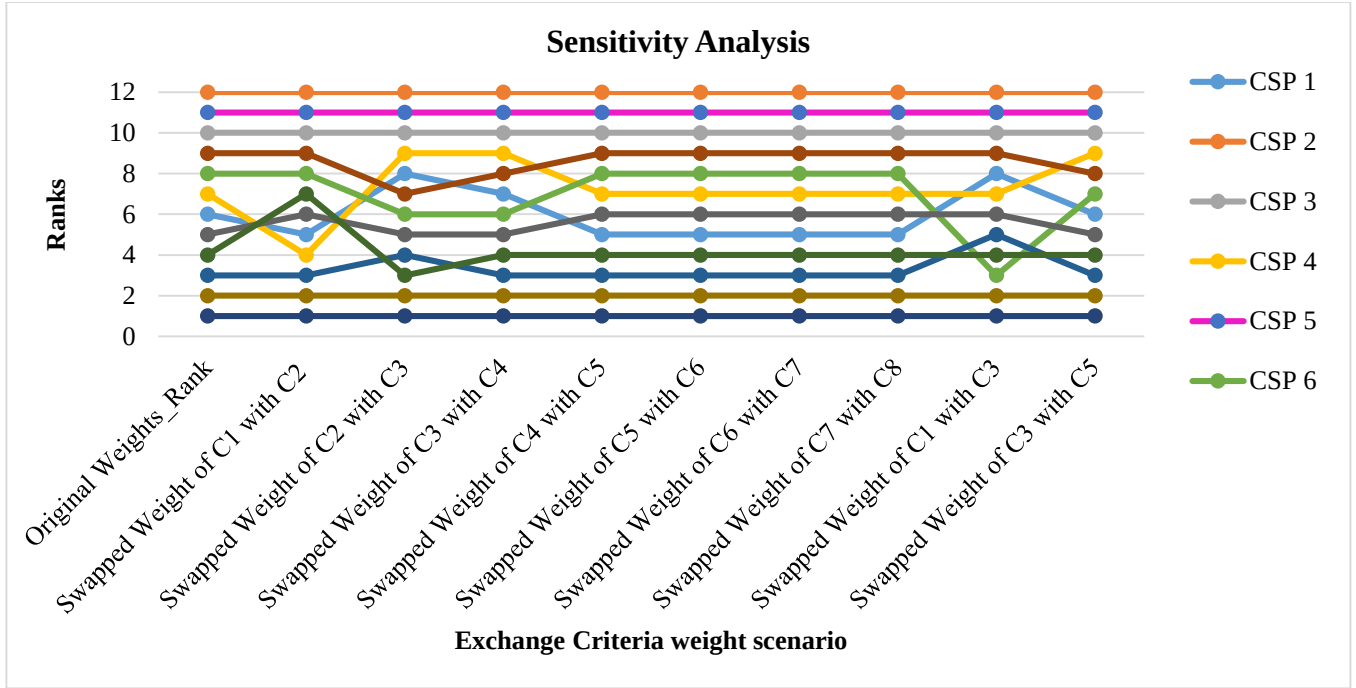


Fig. 6 Sensitivity of ranking to weight changes

5.6. Comparison with the Earlier Two-Level PCA-BOM Study

Table 13 lists the elements that the present method shares with the two-level PCA-BOM study [28] and those that are

new. The data side, the BOM weighting of the criteria and the utility function are inherited. The input to the projection, the number of judgments, and the evaluation reported here differ.

Table 13. Elements inherited from the two-level PCA-BOM study [28] and elements new in this paper

Element	Two-level PCA-BOM [28]	This paper
Decision matrix	12 QWS services, 8 criteria (Table 1)	Same
Standardisation and PCA	z-score; eigen-decomposition of R; $s = 3$ (94.13%)	Same (inherited)
Criterion weighting	BOM, $n - 1 = 7$ judgements	Same (inherited)
Provider-level judgements	BOM under each criterion, $n(m - 1) = 88$	None
Input to the projection	Expert service weights $\times$ criterion weights	Standardised QoS values $\times$ criterion weights
Utility	$F_i = \sum_k T_k PC_{ik}$	Same (inherited)
Total judgements ($n = 8, m = 12$)	95	7
Growth of the effort	$(n - 1) + n(m - 1)$	$n - 1$, independent of m
Preference profile reported	Reliability-focused (W2)	Response-time-focused (W1)
Evaluation	Agreement with BOM and PCA-BWM; 10 swaps; RSI	Comparison with [28] under W1 and W2; PCA-BWM and Weighted PCA; ρ and τ ; 9 and 10 swaps; correlation check; new timing experiment

To check whether removing the provider-level judgements preserves the quality of the decision, both versions were run on the same decision matrix under both criterion weight vectors: W1, the response-time-focused weights of Table 8, and W2, the reliability-focused weights used in [28].

W2 follows from the Best-to-Others vector (2, 8, 3, 5, 1, 3, 2, 4) with reliability as the best criterion, which gives $w = (0.1542, 0.0386, 0.1028, 0.0617, 0.3085, 0.1028, 0.1542, 0.0771)$. The two-level version used the expert's provider-level vectors of [28], which are listed in Appendix A.

Recomputing the two-level version with W2 reproduces the ranking published in [28] exactly. Table 14 lists the four rankings.

Table 14. Ranks of the twelve services under the two versions and the two weight vectors

Service	W2 two-level [28]	W2 single-level	W1 two-level	W1 single-level
CSP1	2	2	9	6
CSP2	11	12	12	12
CSP3	12	10	11	10
CSP4	1	3	1	7
CSP5	5	11	7	11
CSP6	10	8	10	8
CSP7	8	6	2	3
CSP8	9	9	5	9
CSP9	7	7	4	5
CSP10	4	4	3	2
CSP11	3	1	6	1

CSP12	6	5	8	4
Spearman's ρ between versions	0.797		0.559	

Under W2, both versions place CSP4, CSP1 and CSP11 in the first three positions, although in a different order, and the two rankings are significantly correlated (Spearman's $\rho = 0.797$, $p = 0.002$; Kendall's $\tau = 0.636$, $p = 0.004$). Under W1, the correlation falls to 0.559 ($p = 0.059$), which is not significant at the 5% level. The two versions therefore agree closely when the consumer's priorities match those for which the expert's judgements were given, and they diverge when the priorities change. No reference ranking exists for these services, so neither ranking can be called correct. Decision quality was therefore judged by stability, with the measures of Section 5.5. Both versions were evaluated under both weight vectors and under both swap designs, the nine swaps of Section 5.5 and the ten swaps used in [28]. Table 15 gives the results.

Table 15. Stability of the two versions under the same weights and the same swap designs

Weights, design	Version	Mean ρ	Min ρ	Mean RSI	Leader kept
W1, 9 swaps	Two-level [28]	0.831	0.357	0.869	8 of 9
W1, 9 swaps	Single-level	0.963	0.881	0.948	9 of 9
W1, 10 swaps	Two-level [28]	0.822	0.357	0.862	9 of 10
W1, 10 swaps	Single-level	0.957	0.881	0.942	10 of 10
W2, 9 swaps	Two-level [28]	0.871	0.678	0.882	9 of 9
W2, 9 swaps	Single-level	0.934	0.601	0.925	9 of 9
W2, 10 swaps	Two-level [28]	0.939	0.741	0.925	10 of 10
W2, 10 swaps	Single-level	0.979	0.923	0.963	10 of 10

In all four settings, the single-level version has the higher mean correlation with its baseline and the higher average Ranking Stability Index, and in three of the four settings, it also has the higher minimum correlation. Its leading service did not change in any of the 38 swap scenarios, whereas the two-level version changed its leader in two scenarios, both under W1 when the weights of response time and throughput were exchanged. On these data, therefore, removing the provider-level judgements did not reduce stability; it increased it.

The reason lies in the input to the projection. In the two-level version, a single service holds about a quarter of the weight in each column of the service-weight matrix, so moving a large criterion weight onto that column shifts the service by several places. Standardised QoS values are spread more evenly across the services.

Reasons for the different rankings. The rankings of [28] (CSP4, CSP1 and CSP11 at the top) and of Section 4 (CSP11, CSP10 and CSP7) refer to the same twelve QWS services, with the same identities, and to the same decision matrix

(Table 1). Two inputs differ. First, [28] used the reliability-focused weights W2, whereas Section 4 uses the response-time-focused weights W1. Changing only the weights moves the single-level ranking from CSP11, CSP10, CSP7 to CSP11, CSP1, CSP4 (Table 14). Second, [28] projected the expert's service weights instead of the standardised QoS values. With the weights held at W2, this second change moves CSP4 from third to first and CSP11 from first to third, because the expert named CSP4 the best service under reliability, the criterion with the largest weight (0.3085), which gave CSP4 the largest entry of the whole weighted matrix. The other changes occur in the middle of the ranking, where the utilities are close.

What is omitted by the single-level version. The 95 judgements of [28] consist of 7 criterion-level judgements and 88 provider-level judgements, 11 for each of the eight criteria. The single-level version keeps the 7 criterion-level judgements and drops the 88. What is lost is the expert's own assessment of each provider under each criterion. Such knowledge is valuable when it goes beyond the recorded data, for example, on support quality or on the long-term dependability of a provider. In [28], however, the expert's best

service under every criterion was the service with the largest recorded value in Table 1, so the provider-level judgements largely restated the decision matrix on the coarser 1 to 9 scale. Their effect on the ranking is the one described above: a clearer lead for the expert's preferred provider under the dominant criterion, a separation of services with almost identical QoS values (CSP2, CSP3 and CSP5), and larger movements of the ranking when the priorities change. When an expert does have provider knowledge that the QoS data do not record, the two-level version remains the better choice. The two versions can also be used in sequence, with the single-level version shortening a long list before an expert compares the remaining few providers.

5.7. Why the Proposed Method Performs Well

Three structural properties of the PCA-BOM framework account for its performance relative to existing methods.

5.7.1. Elimination of Redundancy before Aggregation

Among The eight QoS criteria in the dataset, availability, successability and cost share a pairwise correlation of $r \geq 0.93$ and consequently represent a single underlying quality dimension. Under the BOM weighting scheme, these three criteria collectively attract 35.09% of the total weight — a share that exceeds the weight assigned to response time (30.08%) — yet they contribute no additional discriminating information beyond what one of them already encodes.

Frameworks that aggregate the original criterion scores directly, including AHP-weighted TOPSIS and entropy-weighted MCDM variants, implicitly count this dimension three times. In the proposed method, these three criteria load together on the first principal component, so their shared variation enters the utility mainly through one direction rather than as three separate terms. After weighting, the component scores are not exactly uncorrelated (Equation (3)), but the directions onto which the data are projected are fixed by the decorrelated structure of the data.

5.7.2. Consistent Preference Elicitation with Minimal Evaluator Burden

BOM derives the full weight vector from a single comparison series of length $n - 1 = 7$. Because every weight ratio follows directly from that one sequence, the elicited preferences are reproduced exactly and internal inconsistency is structurally precluded. AHP and BWM, by contrast, must reconcile 28 and 13 separate judgements respectively, and discrepancies among those judgements introduce the possibility of rank instability even after consistency correction. The high rank agreement with PCA-BWM (Spearman $\rho = 0.979$) confirms that the reduction in elicitation effort does not degrade ranking quality: the two methods diverge only for CSP1, CSP9 and CSP12; CSP1 and CSP9 differ by only 0.0002 in utility, and CSP12 lies 0.018 above them, so small weight differences reorder them without affecting the top or bottom of the ranking.

5.7.3. Separation of the Data-Processing and Preference-Elicitation Stages

The more pronounced difference from Weighted PCA — CSP4 is placed fourth by that method and seventh by the proposed framework — originates in the weighting stage, not in the PCA transformation. CSP4 attains high scores on reliability and best practices, two criteria that receive weights of 0.0602 and 0.1003 under the response-time-centred preference profile used in this study. Because BOM elicits weights on the original, named QoS attributes, such rank differences can be traced directly to documented user priorities rather than to opaque numerical adjustments, which strengthens the auditability and transparency of the final ranking.

Taken together, these three properties position the proposed framework relative to its closest antecedents as follows. Against the two-level PCA-BOM study [28], the single-level design reduces the number of judgments from 95 to 7 while keeping the same data side, and Section 5.6 shows that it is also the more stable of the two on the same data. Against BOM-TOPSIS, it adds explicit handling of inter-criterion correlation at no additional elicitation cost.

The net contribution is therefore not an alternative ranking — no ground-truth ordering of cloud service providers exists against which correctness can be established — but a ranking of equivalent quality to established correlation-aware methods ($\rho \geq 0.937$), achieved with 46–75% fewer elicited judgements, zero consistency error by construction, and demonstrated ordinal stability across nine weight-perturbation scenarios (mean $\rho = 0.963$).

5.8. Practical Implications and Limitations

The proposed method is practical for cloud brokers, enterprise users, and decision-support systems that must rank multiple services under QoS constraints. The user only needs to identify the best criterion and compare it with the remaining criteria. This is simpler than completing a full AHP matrix. The PCA stage is also useful for cloud datasets because QoS indicators are often correlated. By using independent principal components, the model reduces the risk of overemphasizing duplicate information.

The study has limitations. The case study uses twelve QWS services, and the computation-cost experiment uses synthetic uniform data, so it measures computation time and not ranking quality. Because no provider-level judgements are used, the method cannot take account of knowledge about individual providers that the QoS data do not record; in that situation, the two-level version of [28] remains preferable. The final component scores are correlated when the criterion weights are unequal (Equation (3)), so the utility should be read as a weighted combination of the original criteria along data-derived directions, not as a sum of independent effects. The ranking also depends on the selected best criterion and on

the comparison values given by the decision maker, and dynamic behaviour such as workload changes, regional pricing and SLA violations is not modelled.

6. Conclusion and Future Work

This paper presented a single-level PCA-BOM procedure for ranking cloud services. It extends an earlier two-level PCA-BOM study [28], from which it inherits the PCA of the standardised QoS data, the BOM weighting of the criteria and the variance-weighted utility. The new element is that the criterion weights act directly on the standardised QoS values, so no provider-level comparison is needed. For eight criteria and twelve providers, the effort falls from 95 judgments to 7, and it no longer depends on the number of providers. On the same QWS data and under the same reliability-focused weights, the two versions selected the same three leading services and their rankings were significantly correlated ($\rho = 0.80$); under the response-time-focused weights, they agreed less ($\rho = 0.56$), which reflects the provider-level information that the two-level version adds. In all four common-basis sensitivity settings, the single-level version was the more stable and kept its leading service in every scenario. Its ranking also agreed with PCA-BWM ($\rho = 0.98$) and Weighted PCA ($\rho = 0.94$). The analysis of the final component scores showed that they are uncorrelated only when the weights are equal, and the claims about decorrelation were limited to the projection directions. Future work will test the method on larger real monitoring datasets from several regions and service categories, extend it to fuzzy or interval-valued

judgements, integrate it into a cloud broker with monitoring APIs, study weights that change with the workload type, and generate explanations of why one provider is preferred over another.

Data and Code Availability

The decision matrix is given in Table 1, the criterion-level preference vectors in Table 6 and Section 5.6, and the provider-level vectors of [28] in Appendix A. Two Python scripts are provided as supplementary material: one reproduces every ranking, correlation and stability value of Sections 4 and 5, including the comparison with [28], and the other runs the computation-cost experiment of Section 5.4. A workbook with all inputs and intermediate results is also provided. The PCA results (Tables 2 to 5) are the same as those underlying [28], since the data side is shared, and the two-level ranking under W2 reproduces the published ranking of [28]. The single-level analyses, the comparison of the two versions under both weight vectors, the correlation check and the computation-cost experiment were carried out for this paper.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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Appendix A

Table A1 lists the provider-level Best-to-Others vectors used in the two-level study [28]. Under each criterion, the expert named the best service, which has the value 1, and compared it with the other services on a 1 to 9 scale. BOM converts each column into service weights that sum to one.

Table A1. Provider-level Best-to-Others judgements of the two-level study [28]

Service	C1	C2	C3	C4	C5	C6	C7	C8
CSP1	2	6	3	2	2	8	1	7
CSP2	1	8	4	7	3	5	8	9
CSP3	3	2	6	3	8	9	2	1
CSP4	7	4	2	7	1	2	4	8
CSP5	8	1	3	8	4	3	3	2
CSP6	2	3	9	2	3	8	7	4
CSP7	5	5	7	5	9	2	8	3
CSP8	9	9	8	1	7	4	6	4
CSP9	4	3	4	8	6	3	4	6
CSP10	6	2	3	4	4	4	5	8
CSP11	2	4	5	3	5	1	2	3
CSP12	3	6	1	9	9	7	9	2
Best CSP	2	5	12	8	4	11	1	3