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RESEARCH ARTICLE

A Group Multi-Criteria Decision-Making Approach Based on the Best-Only Method for Cloud Service Selection

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ABSTRACT The evaluation of cloud services from various providers involves assessing multiple criteria, creating a multi-criteria decision-making (MCDM) problem. Group decision-making among experts adds complexity to this process. Traditional methods like AHP and BWM are effective but burdensome due to extensive pairwise comparisons, computational demands, and inconsistency. Thus, there is a clear need for a more efficient and reliable approach that reduces comparison efforts, ensures consistency, and improves overall decision-making efficiency, crucial for enhancing cloud service selection tailored to user needs. The best-only method (BOM) simplifies decision-making by considering a single decision-maker's preferences, but it fails to address group decision-making complexities. This paper introduces the group BOM (GBOM), which aggregates criteria/alternative weights using probability and statistical techniques across multiple decision-makers (DMs). The GBOM method was validated with three numerical examples, demonstrating consistent criteria rankings compared to existing AHP and BWM group-based MCDM methods, with a constant consistency ratio (CR) of zero and lower computational complexity requiring only $n-1$ comparisons compared to BWM's $2n-3$ and AHP's $n\times(n-1)/2$. Furthermore, GBOM was applied to a real-world cloud service selection case study, showcasing improved consistency (CR $=0$), reduced expert comparisons, and a novel approach to ranking cloud services based on group preferences using the best-only method. The proposed GBOM method offers a robust and efficient solution for MCDM in cloud service selection, addressing critical limitations of existing methodologies.

INDEX TERMS Multi-criteria decision-making (MCDM), best-only method (BOM), group decision-making, cloud service providers (CSPs), cloud service ranking.

I. INTRODUCTION

Multicriteria decision-making (MCDM) approach contributes significantly to improving real-life decisions through the sorting and ranking of criteria/alternatives. They provide useful assistance when faced with difficult decision-making situations. It has been shown that MCDM methods are effective in addressing practical decision-making issues in a wide range of fields, including social sciences, engineering, management, and economics [1], [2], [3], [4], [5], [6], [7], [8]. Utilizing certain approaches and existing decision information while considering a variety of criteria, MCDM involves sorting all the alternatives in order to determine the most optimal. In order to rank alternatives, it is necessary to establish the set of criteria for decision making and the weight assigned to each criterion before ranking them. Following this, the alternatives' performance in relation to the criteria can be calculated. Finally, the problem can be solved by applying different techniques [9]. Analytic hierarchy processes (AHP) [10] have been applied to solve various decision-making problems over the past several decades and are widely considered to be one of the most important decision-making tools. According to AHP, goals, criteria, sub-criteria, and alternatives are identified for solving a problem. Starting with the first level and moving downwards, a pairwise comparison is performed between elements at each level with respect to

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elements at the next higher level. Based on the comparison of elements at each level, preference matrices are generated. Decision makers use Saaty's scale of relative preference as a basis for their assessment. According to this scale, criteria and alternatives are ranked from 1 to 9 in order of importance. There are nine levels of importance on the scale from 1 to 9, where 1 represents equal importance and 9 represents extreme importance. In order to determine the optimal solution, pairwise comparisons are used to determine the comparative importance of the criteria and alternatives.

Consider a problem in which n criteria $c_1, c_2, \cdots, c_n$ are given, and we are required to calculate their weights. The pairwise comparison matrix A will represent the relative preferences for each given criterion over the others. It shows the following relative preferences [11]:

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix} \tag{1}$$

where:

$a_{ij} = 1$, in the case where criteria i and j are of equal importance.

$a_{ij} > 1$, in the case where the weight of criterion i is greater than the weight of criterion j.

$a_{ij} < 1$, in the case where the weight of criterion i is lower than the weight of criterion j.

In addition, for the purpose of consistency in the decisions made by the DM, we should have $a_{ij} = 1/a_{ji}$ (the reciprocal property) and $a_{ii} = 1$. Therefore, matrix A can be created only by making $n \times (n-1)/2$ comparisons.

A recent multi-criteria decision-making approach, the best-worst method (BWM), was proposed by Rezaei in 2015 [12]. This method begins with determining the worst and best criteria at the beginning of the process. According to the DM, the best criterion is of the highest importance, while the worst criterion is of the lowest importance. In contrast to AHP, BWM employs fewer pairwise comparisons and consists of only two vectors for comparison, the first containing the preference of the best criterion over all others and the second containing the preference of all criteria over the worst criteria. The optimal weights of the criteria were determined based on pairwise comparisons using a min-max mathematical model. While both AHP and BWM use pairwise comparisons to calculate the optimal weights of criteria, BWM requires only $2n - 3$ pairwise comparisons. This makes it a more efficient method for data collection. In spite of the fact that AHP and BWM have been rigorously evaluated, they still suffer from certain deficiencies, including low consistency of comparison and complex computation.

A novel method of MCDM, the best-only method (BOM), was introduced in 2021 as an innovative method for MCDM [6]. BOM requires the decision maker to identify only the best criterion before conducting the pairwise comparisons of that criterion with other criteria. This ensures the full consistency of the resulted pairwise comparison vector. Moreover, the BOM approach only requires one vector, versus two vectors for the BWM approach. Consequently, BOM requires only $n - 1$ pairwise comparisons, resulting in a reduced computational burden.

A cloud computing environment provides users with access to a wide range of resources and applications, including storage, computing, and networking, and is highly efficient and cost-effective [13]. Additionally, cloud computing enables users to quickly deploy resources as needed as it provides scalability and disaster recovery. Cloud service providers (CSPs) compete based on price, performance, and features. Customers should thoroughly investigate the different options and select a provider that meets their specific needs [14]. Considering that there are many different cloud computing service providers available, cloud users may find it difficult to evaluate and select the one that meets their specific needs [15]. Consequently, cloud service selection becomes a multi-criteria decision-making problem. This requires an expert decision maker to analyze the available criteria pairwise and determine the optimal weights for each. Also, CSPs are evaluated against each criterion by the DM. Finally, CSPs are ranked based on their weights and optimal criteria weights. When a group of experts participates in the decision-making process and must decide on a common multi-criteria problem, complexity increases [9]. This is a group decision-making process that requires a group decision-making method for aggregating individual preferences and presenting the most acceptable outcome [16]. This heightened complexity underscores a critical challenge: how to effectively aggregate individual preferences in a group decision-making context to arrive at the most acceptable outcome. Traditional methods, like AHP and BWM, while useful, often involve extensive pairwise comparisons and can be computationally intensive and inconsistent. The need for a more efficient and reliable group decision-making method becomes apparent. Such a method should reduce the burden of comparisons, enhance consistency, and improve overall decision-making efficiency. Addressing this challenge is essential for facilitating better cloud service selection and ensuring that cloud users can make well-informed, optimal choices that meet their specific requirements.

In this paper, we propose a novel approach to the group MCDM, GBOM, that applies best-only method and statistical inference to cloud service selection problem. This study is aimed at helping cloud customers rank service providers. GBOM, based on the best-only method and statistical inference, is the first to base group MCDM on the Best-Only Method (BOM) and offers significant advantages over traditional methods like BWM and AHP. Inputs to the GBOM are identical to those in the original BOM, which are pairwise comparisons that are modeled based upon a multinomial distribution. Meanwhile, the output of this model is the optimal aggregated final weights of all DMs based on Dirichlet distribution modeling. GBOM simplifies pairwise comparisons, requiring only $n - 1$ comparisons compared to BWM's $2n - 3$ and AHP's $n\times(n-1)/2$, reducing data collection and analysis time. GBOM ensures fully consistent results with a consistency ratio (CR) of zero and uses integer values for comparisons, as opposed to AHP's fractional numbers, making it easier to understand and interpret. This approach is more data-efficient and consistently achieves a CR of 0, highlighting its reliability and efficiency over AHP and BWM. As a means of testing and validating the proposed method, three numerical examples were used to demonstrate its efficiency and consistency. The developed approach was also compared to the existing methods presented in [16] (Group BWM and Group AHP), and [17]. Based on their aggregated optimal weights, all approaches ranked the criteria in the same order, but the developed model exhibited a superior consistency ratio (CR) and lower computational complexity. Finally, we apply the GBOM to a real dataset for selecting cloud services. One drawback of the proposed method, similar to AHP and BWM, is that when dealing with qualitative criteria, the ultimate ranking of the CSPs, and consequently the reliability of the decision, hinges on the decision maker's judgments of the pairwise comparison values.

The rest of the paper is arranged as follows. A review of related work was given in Section II. In Section III, a background is provided for the best-only method. The proposed GBOM method is given in Section IV. In Section V, an experimental study is presented utilizing three numerical examples. In Section VI, the GBOM is applied to a real case study based on a real dataset to select cloud service providers. Section VII is about discussion of results. Finally, Section VIII concludes our study and discusses its limitations and future work.

II. RELATED WORK

There are many MCDM methods available to derive the weights of the decision criteria based on preferences of a single decision maker. These methods include ELECTRE (Elimination and Choice Translation Reality) [18], TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) [19], AHP (the Analytic Hierarchy Process) [10], ANP (the Analytic Network Process) [1], PROMETHEE (preference ranking organization method for enrichment evaluations) [20], BWM (best-worst method) [12], and recently, BOM (best-only method) [6]. Nevertheless, due to the increasing complexity of the decision-making problems, many businesses are now switching from a single decision maker to a team of experts who collaborate to resolve a specific multi-criteria decision problem [9]. This helps to ensure that the decision is based on a more comprehensive view of the problem. It takes into account the different perspectives of experts. As the first research on a group MCDM, group-AHP was developed based on AHP in order to obtain optimal weights based on the individual preferences [21]. The researchers further extended AHP-based models to solve group-based decision-making problems [22]. Since these approaches rely on AHP, they necessitate pairwise comparisons of all criteria and alternatives to determine the weights. This results in increased computational complexity and potential inconsistencies in the pairwise comparisons.

Considering how ambiguity in decision-making plays an important role, fuzzy theory has recently been applied to decision-making problems in an imprecise environment in which uncertain information and flexibility in human judgment play a crucial role. Guo and Zhao [23] proposed a fuzzy BWM in which fuzzy numbers represent pairwise reference comparisons with linguistic terms. In this approach, the weights of criteria and alternatives with regard to various criteria were determined using the graded mean integration representation (GMIR) method. However, as the number of criteria and alternatives increases, the method may become less efficient and more cumbersome to apply, impacting its scalability. In addition, While GMIR aims to provide a more accurate representation in a fuzzy environment, it might not adequately address inconsistencies that arise during the fuzzification and defuzzification processes. Ahmed et al. [24] used group BWM in a different application to identify and prioritize strategies to combat the Covid-19 outbreak.

Sarfarzadeh et al. [16] presented GBWM as a new approach that incorporated two different mathematical models, based on BWM, to facilitate the process of decision-making among group of DMs.

A new extension of the BWM method called the multi-choice best-worst method (MCBWM) has recently been proposed by Hasan et al. [25] to manipulate multiple preference values for each pairwise comparison. In this method, many choices are associated with parameters, and the method is based on multichoice mathematical model [26]. They demonstrated an improvement over the BWM by demonstrating that the MCBWM proposed could handle numerous pairwise comparison options provided by the decision maker. By accommodating multiple models of BWM, MCBWM can provide a single model through multiple choice. In this process, all selected pairwise comparison values are inserted into a choice set. The optimal pairwise comparison value can be determined from a choice set of values while minimizing inconsistencies and finding the optimum weight for the criteria. The MCBWM provides the decision maker with the flexibility to select multiple preference values according to human perception and cognition. In an extension of the MCBWM, Ahmad et al. [17] developed a method for solving group MCDM problems using the model.

For these BWM-based models, solving them becomes computationally challenging, particularly when there are a large number of decision-makers, as each one must identify the best and worst alternatives for each criterion. Moreover, the results still exhibit inconsistency since the consistency ratio (CR) is not equal to 0.

Regarding the application of MCDM methods to cloud service selection, some studies utilized AHP-based approaches for the selection of cloud services to help cloud users in ranking cloud service providers using Saaty's basic 1–9 scale. Garg et al. [27] proposed the SMICLOUD framework for evaluating and ranking three IaaS cloud services based on the cloud service measurement index (SMI). This study presents a number of key performance indicators (KPIs) for quality-of-service criteria derived from the cloud service measurement initiative consortium (CSMIC), with various cloud service providers being compared based on these KPIs. Based on DM preferences, the authors calculated the weights for SMI criteria using the AHP approach and then compared the three IaaS cloud services using the calculated weights. In selecting CSPs, they only considered quantifiable CSMIC criteria and did not take into account the non-quantifiable QoS trustworthiness criteria. Based on the AHP approach, Godse and Mulik [28] assessed various QoS criteria of SaaS services, including usability, architecture, functionality, vendor reputation, and pricing.

Pairwise comparisons were conducted for estimating weight values of criteria and alternatives based on AHP, while TOPSIS was used to finally rank alternatives. In order to assess the trustworthiness of 15 CSPs from various perspectives, nine Quality of Service criteria were used (customer service, cost, response time, storage, speed, ease of use, capacity, features, technical support, and availability). Youssef [29] proposed a method of ranking CSPs based on evaluation criteria describing their service offerings using an MCDM approach that incorporates TOPSIS and the BWM.

Based on the analysis of these research papers, it can be concluded that a large number of criteria were used to rank CSPs. Consequently, pairwise comparisons became significantly more complex. Furthermore, many of these criteria are qualitative, making pairwise comparisons less reliable due to decreased consistency.

While AHP is an effective tool for making decisions, it does not consider uncertainty in decision making when making pairwise comparisons. The fuzzy AHP was developed in response to this issue, which provides decision makers with an opportunity to use fuzzy ranking in place of exact ranking [40].

Mun et al. [30] proposed a method that replaces the traditional fuzzy AHP for determining criterion weights with a direct estimation method using triangular fuzzy numbers, which is simpler and more flexible. It normalizes the fuzzy decision matrix using a nonlinear method with a threshold. Instead of using the traditional Euclidean distance, it calculates distances from positive and negative ideal solutions using the fuzzy weighted average method based on the centroid of the fuzzy number. Finally, it evaluates alternatives using a relative closeness coefficient weighted by these distances. This method has been validated through its application to selecting talent with high intelligence. While this approach offered simplicity and flexibility, it has several potential disadvantages: The use of triangular fuzzy numbers and the centroid method for calculating distances can be mathematically complex and computationally intensive compared to traditional methods. Direct estimation of weights using triangular fuzzy numbers introduces subjectivity and bias, as it heavily depends on the decision-maker's judgment. In addition, much information is lost when DMs' judgments/weights are aggregated. Furthermore, averages can be significantly impacted by outliers, which can also have an impact on the results.

Barasin et al. [31] propose a novel MCDM approach to enhance warehouse management and operational efficiency. The proposed method integrates the Group Best-Worst Method (G-BWM) and the Ranking Alternatives based on Trace-to-Median Index (RATMI). G-BWM is used to determine the relative importance of performance criteria by aggregating the preferences of decision-makers. RATMI is then employed to rank the warehouses based on their performance scores relative to these weighted criteria. The study considers five key performance criteria: cost, quality, time, productivity, and safety. Data were collected from four mega retail warehouses in the western region of Saudi Arabia. The findings reveal each warehouse's strengths and weaknesses, offering insights for strategic improvements. However, employing RATMI, a linear additive model, to combine criterion scores might not fully capture the complex, non-linear interactions between variables in real-world warehouse settings. Additionally, the G-BWM method for weighting criteria is not fully consistent and requires more computations compared to the proposed approach.

The best-only method (BOM) has been proposed by Ahmed [6] for solving the problem of cloud services selection, which is fully consistent and computationally efficient. In BOM, the expert needs only to select the best criterion/alternative and decides the pairwise comparison values for it over the remaining criteria/alternatives. Compared with AHP and BWM, BOM is more efficient and reliable due to its lower computing complexity and full consistency. For selecting cloud service providers based on the best-only method (BOM) and the order of preference by similarity to an ideal solution (TOPSIS), Ahmed [11] proposed an integrated MCDM framework for cloud service selection. A pairwise comparison is conducted by BOM for each criterion and among alternatives with respect to each criterion in order to obtain the weights of criteria and the relative weights of alternatives related to criteria. TOPSIS uses these weights to determine the final ranking of CSPs. Ahmed [32] presented a hybrid model to detect and record transition patterns in the priorities of user requirements. This model is based on a Markov chain which is applied to calculate the priorities of user requirements. Afterwards, the BOM method is used to calculate the weights of all criteria relative to each user requirement. Then, the aggregated weights of the criteria are calculated using the BOM method and based on the priorities of user requirements. In the final stage of the process, we obtained a ranked list of CSPs, and the best one can be selected.

For group decision making, two classes of techniques are commonly employed [33]. One technique which is called aggregation of individual judgment (AIJ) [34]. AIJ is used for integrating pairwise comparisons from various DMs into a single set. This set is then evaluated in accordance with the same method as a single DM approach. The other technique is called aggregation of individual priorities (AIP) [35], [36]. AIP begins by calculating a weight for each DM input, and then combining those weights, usually using arithmetic means. Despite the fact that both techniques are practically simple, aggregation results in the loss of much information. Additionally, averages are susceptible to outliers, which can have a significant impact on the results.

A novel approach to the group MCDM, called a group BOM (GBOM), is presented in this study based on the best-only method and statistical inference in order to assist cloud customers in ranking cloud services. To the best of our knowledge, this is the first study to present a group MCDM based on the BOM method. There are many advantages of GBOM over BWM and AHP group-based MCDM methods. Following are the reasons of preferring GBOM over BWM and AHP group-based MCDM methods.

1. The BOM delivers more reliable results compared to the AHP and BWM methods. While all these methods use pairwise comparisons to determine criteria weights and rankings, AHP is matrix-based and requires pairwise comparisons among all criteria. BWM involves two vectors for comparing the best to other criteria and others to the worst criteria. In contrast, BOM uses only one vector for comparing the best to other criteria, resulting in significantly fewer comparisons. This reduces the need for extensive data collection, calculation, and analysis time.
2. In BOM, there is only $n-1$ comparisons which is much lesser than comparisons in BWM i.e. $2n-3$ and in AHP i.e. $n \times (n-1)/2$.
3. The BOM yields fully consistent results with a consistency ratio (CR) of zero, indicating greater consistency compared to BWM and AHP based methods. This improvement is achieved by eliminating redundant comparisons.
4. In BOM, pairwise comparisons are conducted using integer values on a scale of 1 to 9. In contrast, AHP utilizes fractional numbers ranging from 1/9 to 9. This gives BOM an advantage over AHP in terms of easier analytical evaluation, understanding, and interpretation of comparisons, aligning better with human perception and cognition.
5. BOM is more data-efficient compared to AHP and BWM-based methods. In AHP and BWM, the solution can become inconsistent if the consistency ratio (CR) exceeds 0.1, necessitating revisions to improve consistency in comparisons. In contrast, BOM consistently achieves a CR of 0.

III. THE BEST-ONLY METHOD

Among the many MCDM models, the best-only method (BOM) is a recent model that is robust, cost-effective, and entirely consistent. There is only one criterion that needs to be identified by the decision maker in accordance with the BOM: the best criterion. It calculates criteria weights based only on a pairwise comparison of the best criterion to the other criteria. Thereby, the derived weights are based on fully consistent pairwise comparison vector.

BOM is more efficient than AHP [10] and BWM [12], two widely known MCDM methods. BWM and BOM are vector-based MCDM approaches, so a lower number of comparisons are required compared to matrix-based MCDM approaches like AHP. Furthermore, BOM requires only one comparison vector for the best criterion, whereas BWM requires two comparison vectors for the best and worst criteria [6]. For AHP, $n \times (n-1)/2$ pairwise comparisons are conducted. For BWM, $2n-3$ pairwise comparisons are conducted. For BOM, only $n-1$ pairwise comparisons are conducted. Therefore, it is evident that BOM needs fewer pairwise comparisons than AHP or BWM, which implies that it is more computationally efficient.

The BOM method produces a constant consistency ratio (CR) equal to 0. Therefore, it is more reliable and fully consistent than AHP and BWM. Following is a summary of the BOM method steps:

Step 1: Identify the set of n criteria $C = (c_1, c_2, \cdots, c_n)$.

Step 2: The DM chooses C_B, where $C_B \in C$, is the best criterion.

Step 3: The DM provides the pairwise comparison vector PC_B which contains the preference values made by the DM for the best criterion over other criteria in C.

$$PC_B=(PC_{\mathrm{B}1}, PC_{\mathrm{B}2}, \cdots, PC_{Bn}) \tag{2}$$

Step 4: Calculate the optimal criteria weights by solving the following equations:

$$\frac{w_B}{w_j} = PC_{Bj} \forall j \neq B \text{ and } PC_{Bj} \in PC_B, j = 1, 2, \ldots, n. \tag{3}$$

$$\sum_{j=1}^{n} w_j = 1 \tag{4}$$

IV. THE PROPOSED APPROACH

This section presents a statistical inference model based on the preferences of a group of decision makers to find the optimal weights of a set of criteria using the best-only method. The proposed model will be referred to as the group best-only method (GBOM). Initially, we need to specify the given inputs to the model and the expected output.

Let us suppose that we have m decision makers need to determine the weights for n criteria. According to BOM, each DM will only provide one comparison vector for the best criterion over other criteria. So, we will have m vectors as follows:

$$PC_B^x = \left(PC_{B1}^x, PC_{B2}^x, \ldots, PC_{Bn}^x\right), x = 1, 3, \ldots, m. \tag{5}$$

where PC_B^x represents the pairwise comparison vector for decision maker x for all $x = 1, 2, 3, \ldots, m$.

The expected output of the proposed model is the aggregated weight of the set of criteria $w^a = \{w_1^a, w_2^a, \cdots, w_n^a\}$.

In order to compute the aggregated weight, w^a, given the set of pairwise comparison vectors for DMs, PC_B^x, based on statistical inference, we need to formulate both the inputs and the output of the model as a probability distribution function. This means that for the inputs, which are the pairwise comparisons of DMs, we need to represent them using appropriate probability distribution (multinomial distribution) that capture the variability inherent in these assessments. Similarly, the outputs, which are the aggregated final weights of criteria, must also be modeled as probability distributions (Dirichlet distribution). This probabilistic approach allows for a more rigorous and nuanced handling of the data, enabling us to derive more reliable and robust conclusions. By treating both inputs and outputs probabilistically, we can apply advanced statistical techniques, such as Bayesian inference.

The input pairwise comparison vector for each DM can be formulated using the multinomial distribution as follows:

$$Prob(PC_B^x|w^x) = \frac{(\sum_{j=1}^{n} PC_{Bj}^x)!}{\prod_{j=1}^{n} (PC_{Bj}^x)!} * \prod\nolimits_{j=1}^{n} \frac{1}{w_j^x} \tag{6}$$

where:

n: The number of criteria.

m: The number of decision makers.

j: $1, 2, 3, \ldots, n$.

x: $1, 2, 3, \ldots, m$.

PC_B^x: Pairwise comparison vector for decision maker x.

w^x: Criteria weight vector for decision maker x.

PC_{Bj}^x: Pairwise comparison value of the best criterion over criterion j set by the decision maker x.

w_j^x: Weight of criterion j according to PC_B^x.

In this context, each pairwise comparison can be seen as an event with multiple possible outcomes, where each outcome corresponds to a particular preference expressed by the DM. By using the multinomial distribution, we can effectively model the probability of each possible pairwise comparison outcome across multiple decision-makers. This statistical approach allows us to capture the variability in the comparisons provided by different DMs.

As the weight vector must satisfy both the properties of sum-to-one and non-negativity, the Dirichlet distribution appears to be an appropriate choice for modeling the weights of the criteria. The Dirichlet distribution is a family of continuous multivariate probability distributions parameterized by a vector of positive reals. It is particularly well-suited for modeling probabilities that must sum to one and remain within the interval [0, 1], which aligns perfectly with the requirements for the weight vector of the criteria. Using the Dirichlet distribution allows us to model the variability in the criteria weights. It provides a flexible and mathematically sound approach to representing the distribution of weights across different decision-makers. The use of the Dirichlet distribution facilitates the application of Bayesian inference techniques. This enables us to refine the estimated weights iteratively, improving the robustness and reliability of the final decision-making model.

$$Dirichlet\left(w^x \mid \alpha\right) = \frac{1}{B(\alpha)} * \prod\nolimits_{j=1}^{n} (w_j^x)^{\alpha_j - 1} \tag{7}$$

where $\alpha = (\alpha_1, \alpha_2, \cdots, \alpha_n)$ is the concentration vector that determine the shape and concentration of the distribution and $B(\alpha)$ is the multivariate Beta function.

Dirichlet distributions are used in Bayesian statistical inference as a prior to the multinomial distribution. The posterior distribution would also be a Dirichlet distribution if Dirichlet were used as the prior distribution. During initialization, α will equal 1, then its value will be updated by PC_B^x values. This choice of parameter α equal to 1 result in a uniform distribution over the simplex, indicating that initially, we assume all criteria are equally important, reflecting a state of no prior preference or information bias. The Dirichlet distribution with this parameter serves as a non-informative prior, providing a neutral starting point for further analysis. To refine this initial distribution and incorporate the data obtained from decision-makers, we will compute the posterior distribution using Markov-chain Monte Carlo (MCMC) techniques. MCMC methods are powerful statistical tools used to approximate the posterior distribution of complex models by generating samples from the distribution.

In GBOM, to compute the aggregated weight, w^a, we need to solve the following joint probability based on the Bayes theorem:

$$\begin{aligned} &Prob(w^a, w^{x=1..m}|PC_B^{x=1..m} \\ &= Prob\left(PC_B^{x=1..m}|w^a, w^{x=1..m}\right) * Prob\left(w^a, w^{x=1..m}\right) \\ &= Prob\left(w^a\right) * \prod\nolimits_{x=1}^{m} Prob\left(PC_B^x|w^x\right) * Prob\left(w^x|w^a\right) \end{aligned} \tag{8}$$

where $Prob\left(w^x|w^a\right)$ is modeled as a Dirichlet distribution with w^a represents its mean. The initial distribution for w^a uses a Dirichlet distribution with the parameter α equal to 1. The posterior distribution will be computed using MCMC techniques [37].

The MCMC sampling is performed using the "just another Gibbs sampler" (JAGS) [38], one of the most powerful probabilistic languages available. In this process, JAGS handles the computationally intensive task of sampling from the posterior distribution of the model parameters. It iteratively generates samples from the distributions of the criteria weights w^a, gradually building up an accurate approximation of the full posterior distribution. This iterative process ensures that the sampled weights accurately reflect the underlying probabilistic structure of the data and the initial Dirichlet prior. The overall procedure for the proposed GBOM is presented in Fig. 1.

V. EXPERIMENTAL STUDIES

We present three numerical examples to demonstrate the application of the proposed GBOM method to a variety of group decision-making problems and provide an evaluation of the results based on the comparison of the three numerical examples. These examples are derived from [16] and [17].

The optimal weights for the proposed model of the examples were determined by solving the model using Python. The proposed method, GBOM, is validated by comparing its results for the three numerical examples to those obtained by GBWM [16] (Model 1 and Model 2), MCBWM-GDM [17], and the arithmetic mean of the calculated weights by applying BOM separately to each DM's preferences (AIP_BOM). The third numerical example, which is a real-world case study of a piping selection method, is also compared with the results obtained using Group-AHP in [16]. To perform the analysis and validate the proposed GBOM method, we implemented the model using Python. The key libraries involved: *numpy* for numerical computations and handling arrays, *jags*(Just Another Gibbs Sampler) for MCMC sampling, and *pyjags* for interfacing with JAGS from Python.

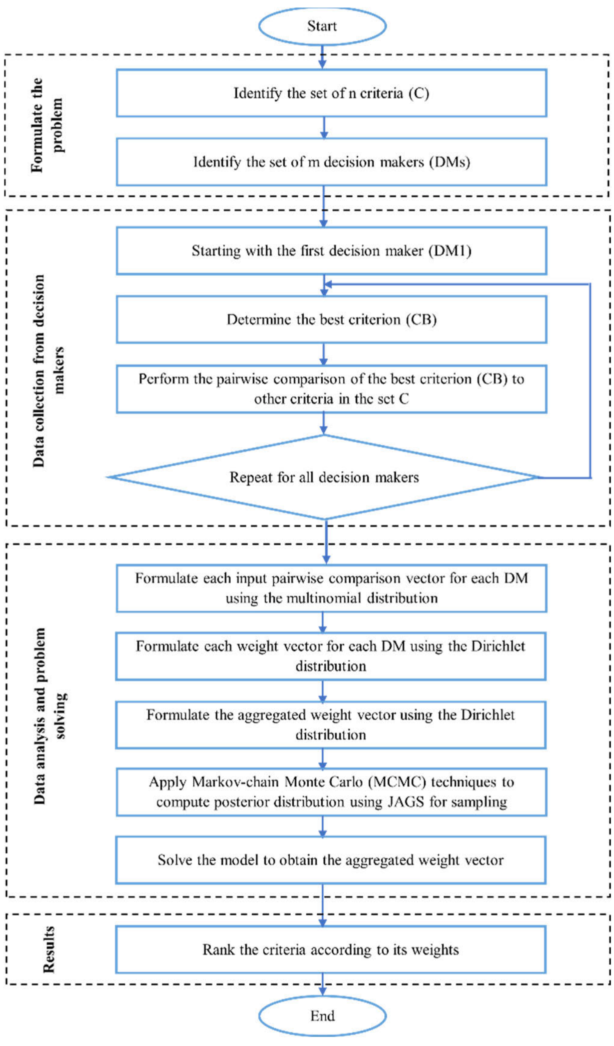

FIGURE 1. Flow chart of research methodology.

A. EXAMPLE 1

This example demonstrates the responses provided by two DMs in response to four criteria. It was determined that the best criterion is the first while the worst is the third one. Note that for our proposed GBOM method, only the best criterion needs to be determined. According to Table 1, the two DMs have developed pairwise comparison vectors for the best and the worst criteria.

For the proposed method, we need only the pairwise comparison values P_{12}, P_{13}, and P_{14}. Table 2 provides results regarding the optimal weights and ranking of the criteria. These weights were obtained by using our model as well as other existing models. Fig. 2 shows the optimal weights obtained and the consistency ratio (CR) of these weights for the different models.

TABLE 1. Pairwise comparison values for Example 1.

	P_{12}	P_{13}	P_{14}	P_{23}	P_{43}
DM_1	2	9	3	4	2
DM_2	2	8	2	4	2

TABLE 2. Criteria weights and CR values FOR Example 1.

Model	W_1	W_2	W_3	W_4	CR
Safarzadeh et al. [16] Model-1	0.5280	0.2220	0.0650	0.1850	0.0960
Safarzadeh et al. [16] Model-2	0.5120	0.2460	0.0630	0.1790	0.0960
Ahmad et al. [17] MCBWM-GDM	0.5067	0.2667	0.0667	0.1600	0.0270
AIP_BOM	0.4924	0.2462	0.0580	0.2034	0
Proposed approach	0.4474	0.2577	0.0675	0.2274	0

The optimal weight values obtained by the five models differ slightly from each other, however, the order of the criteria based on the weight values remains the same ($C_1 \rightarrow C_2 \rightarrow C_4 \rightarrow C_3$). Further, the proposed GBOM method always guarantees a CR value of zero, which makes it superior to other models. Additionally, GBOM utilizes fewer computational resources because it relies on only one pairwise comparison vector.

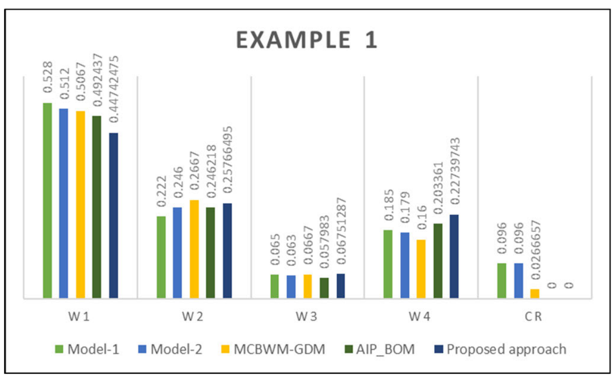

FIGURE 2. The optimal weights and CR values for Example 1.

B. EXAMPLE 2

This example demonstrates the responses provided by three DMs in response to four criteria. Similar to the previous example, the best and worst criteria were determined to be the first and third criteria. The values of pairwise comparisons for the best and the worst criteria are shown in Table 3.

Table 4 provides the optimal weights and ranking of the criteria obtained by using our model as well as other existing models. For the proposed method, we only require the pairwise comparison values P_{12}, P_{13}, and P_{14}. Fig. 3 displays the optimal weights obtained and the consistency ratio (CR) of these weights.

TABLE 3. Pairwise comparison values for Example 2.

	P_{12}	P_{13}	P_{14}	P_{23}	P_{43}
DM_1	2	9	3	4	2
DM_2	2	8	4	4	2
DM_3	2	8	4	3	2

TABLE 4. Criteria weights and CR values for Example 2.

Model	W_1	W_2	W_3	W_4	CR
Safarzadeh et al. [16] Model-1	0.5530	0.2260	0.0660	0.1550	0.0400
Safarzadeh et al. [16] Model-2	0.5510	0.2270	0.0650	0.1570	0.0450
Ahmad et al. [17] MCBWM-GDM	0.5340	0.2670	0.0670	0.1340	0
AIP_BOM	0.5270	0.2635	0.0635	0.1460	0
Proposed approach	0.4932	0.2758	0.0712	0.1598	0

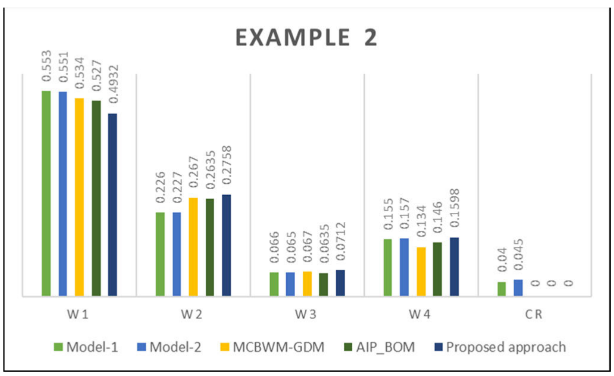

FIGURE 3. The optimal weights and CR values for Example 2.

Although the weights obtained by the five models differ slightly, the order of the criteria based on the weights remains the same ($C_1 \rightarrow C_2 \rightarrow C_4 \rightarrow C_3$). GBOM is also superior to other methods because it guarantees a CR value of zero and uses fewer computational resources since it relies on pairwise comparisons of only the best criterion.

C. EXAMPLE 3

This example demonstrates a real-world case study [16] involving the selection of piping. Ten decision makers analyzed four categories of costs: total costs (C_1), security costs (C_2), social costs (C_3), and environmental costs (C_4). The total cost (C_1) was the best criterion, whereas an environmental cost (C_4) was the worst. The pairwise comparison values for the case study are shown in Table 5.

Table 6 provides results regarding the optimal weights and ranking of the criteria obtained using our proposed model compared with other existing models including the Group-AHP model. Fig. 4 shows the optimal weights obtained and the consistency ratio (CR) of these weights for the different models.

TABLE 5. Pairwise comparison values for Example 3.

	Other models data					Group-AHP model data					
	P_{12}	P_{13}	P_{14}	P_{24}	P_{34}	P_{12}	P_{13}	P_{14}	P_{24}	P_{34}	P_{23}
DM_1	6	6	7	4	3	6	5	9	3	1	3
DM_2	7	7	7	6	5	7	7	6	6	5	6
DM_3	7	7	9	8	8	7	6	9	8	8	8
DM_4	2	4	6	4	3	2	4	6	3	4	2
DM_5	3	4	8	3	5	3	5	8	3	5	4
DM_6	5	7	7	5	3	5	8	7	5	3	6
DM_7	9	4	9	9	8	9	4	7	9	8	9
DM_8	9	9	9	8	2	9	9	9	8	2	8
DM_9	8	9	9	3	1	8	9	8	3	1	2
DM_{10}	9	9	9	3	1	9	9	9	3	1	3

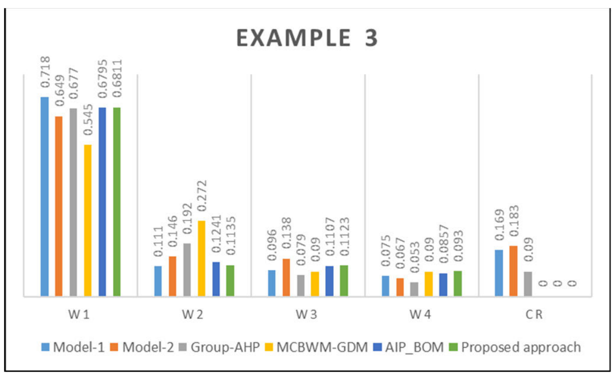

FIGURE 4. The optimal weights and CR values for Example 3.

The optimal weight values obtained by the six models is the same ($C_1 \rightarrow C_2 \rightarrow C_3 \rightarrow C_4$). Although MCBWM-GDM resulted in a CR value of 0, it assigns the same weight to C_3 and C_4, which results in an ambiguous situation for these two criteria.

VI. A REAL CASE STUDY FOR CLOUD SERVICE SELECTION

In this section, we present a real dataset which is used through an experimental case study to clarify how GBOM can be used in real-world cloud service selection problems.

TABLE 6. Criteria weights and CR values for Example 3.

Model	W_1	W_2	W_3	W_4	CR
Safarzadeh et al. [16] Model-1	0.7180	0.1110	0.0960	0.0750	0.1690
Safarzadeh et al. [16] Model-2	0.6490	0.1460	0.1380	0.0670	0.1830
Safarzadeh et al. [16] Group-AHP	0.6770	0.1920	0.0790	0.0530	0.0900
Ahmad et al. [17] MCBWM-GDM	0.5450	0.2720	0.0900	0.0900	0
AIP_BOM	0.6795	0.1241	0.1107	0.0857	0
Proposed approach	0.6811	0.1135	0.1123	0.0930	0

A. DATASET

Based on the real-world dataset (CloudHarmony) [39], we conducted our analyses. In order to record the performance of several cloud services dynamically, the CloudHarmony dataset utilizes a number of benchmark applications that run on different virtual machines over a predetermined period of time. CloudHarmony periodically assesses the quality of service (QoS) metrics for leading CSPs such as Amazon AWS, Microsoft Azure, IBM Bluemix, Alibaba Cloud, and others. In addition to evaluations, CloudHarmony offers cloud service profiling and consulting services. Cloud service profiling entails detailed information on features, pricing policies, SLAs, and uptime commitments provided by various service providers. Table 7 provides a summary of the dataset used. For each of the 10 real-world Cloud Service Providers in the dataset, five QoS criteria values have been collected. These QoS criteria are CPU Performance (C1), Memory Performance (C2), Disk Performance (C3), Disk Consistency (in ms) (C4), and Price (in \$) (C5).

B. CASE STUDY

It was assumed that there would be five decision-makers. The pairwise comparison values for the criteria are generated at random. The profiles of the DMs may include cloud architects or engineers, IT managers, business strategists, and end users or application developers. Each DM's unique perspective and expertise contribute to a comprehensive evaluation process aimed at selecting the best criterion and the pairwise comparison values that meet both technical requirements and strategic business goals. Initially, decision makers select the best QoS criterion. Suppose that CPU Performance (C1) is the best criterion selected. DMs provide pairwise comparison values of the best criterion over other criteria. Table 8 presents pairwise comparison values. Afterwards, GBOM is used to calculate the weights of the criteria based on the pairwise comparison values set by the DMs. Table 9 shows the optimum weights of the criteria using the proposed method (GBOM).

In Table 10, we present the normalized values of the criteria for the CSPs calculated from the dataset as presented in our previous study [32].

In order to determine the final CSPs' scores (priorities), the following formula was applied:

$$R_i = \sum_{k=1}^{n} w_k QoS_{ik}$$

where:

n: The number of criteria.

k: $1, 2, 3, \ldots, n$.

i: $1, 2, 3, \ldots, 10$ (number of CSPs).

w_k: Optimal weight of criteria k.

QoS_{ik}: The normalized value of the QoS_k relative to CSP_i.

Table 11 summarizes our rankings of cloud service providers in the case study. The results of this case study indicated that HP ranked highest among the cloud service providers, due to its high CPU performance, which was previously selected as the best criterion by the DMs.

It is interesting to note that the obtained CSP rankings differ slightly from those in [32], since the priorities of user requirements were not taken into account when determining the weights of the criteria.

VII. DISCUSSION

The experimental studies presented in this paper highlight the practical applicability and effectiveness of the proposed GBOM Method for group decision-making. By comparing GBOM with several existing methods, including the Group Best-Worst Method (GBWM) [16], MCBWM-GDM [17], and AIP_BOM, the results demonstrate GBOM's capability to consistently produce optimal weights and rankings with improved consistency and reduced computational complexity. Unlike AHP and BWM-based group decision-making methods, which require a large number of pairwise comparisons, GBOM significantly reduces this burden. Specifically, GBOM requires only $n - 1$ comparisons compared to BWM's $2n - 3$ and AHP's $n \times (n - 1)/2$. This reduction not only minimizes the effort required from DMs but also enhances the feasibility of the decision-making process in scenarios involving numerous criteria. The consistency ratio (CR) in GBOM is consistently zero, indicating a high level of reliability and robustness in the final weight estimates. This improvement in consistency is crucial for ensuring that the decision outcomes are logically sound and free from internal contradictions. In addition, by using the multinomial distribution to model input pairwise comparisons and the Dirichlet distribution for the criteria weights, GBOM incorporates a rigorous probabilistic framework. This allows us to quantify variability in the DMs' inputs, leading to more robust and reliable aggregated weights. Furthermore, the application of Bayesian inference using Markov-chain Monte Carlo techniques via JAGS enables the continuous update of the criteria weights as new data becomes available. This dynamic updating mechanism ensures that the decision-making model remains relevant and accurate over time.

The validation of GBOM through numerical examples and a real-world cloud service selection case study demonstrates

TABLE 7. Cloud services dataset summary.

Cloud Service Providers (CSPs)	Virtual Machine Configurations		QoS Metrics				
	Virtual Processors	Memory (in GB)	CPU Performance (C1)	Memory Performance (C2)	Disk Performance (C3)	Disk Consistency (in ms) (C4)	Price (in $) (C5)
Amazon (CSP1)	4	7.5	63.44	91	56.82	66	0.17
HP (CSP2)	4	15	111.95	131.81	100.5	119.63	0.42
Microsoft Azure (CSP3)	2	4	77.49	80.67	40.23	23.43	0.12
Rackspace (CSP4)	2	4	5.45	84.2	109.2	78.56	0.12
Google (CSP5)	4	7	82.2	61.8	78.49	67.97	0.24
Century Link (CSP6)	4	4	41.85	63.44	63.1	70.29	0.24
City-Cloud (CSP7)	8	16	58.42	78.15	68.45	31.22	1.05
Linode (CSP8)	8	64	37.05	132.87	102.74	36.15	1.65
GoGrid (CSP9)	4	8	42.05	97.16	174.5	59.63	0.21
SoftLayer (CSP10)	2	2	4.87	83.74	82.01	133.61	0.12

its practical applicability and effectiveness. In Examples 1 and 2, the GBOM method yielded optimal weights and criterion rankings that were slightly different from those generated by GBWM (both Model-1 and Model-2), MCBWM-GDM, and AIP_BOM. Despite these differences, the ranking order of the criteria remained consistent across all methods (C1 $\rightarrow$ C2 $\rightarrow$ C4 $\rightarrow$ C3). This consistency underscores the robustness of the proposed GBOM method in preserving the relative importance of criteria while ensuring a zero Consistency Ratio (CR).

TABLE 8. Pairwise comparison values for the case study.

	P_{12}	P_{13}	P_{14}	P_{15}
DM_1	2	3	5	7
DM_2	3	5	7	3
DM_3	3	5	7	3
DM_4	5	7	5	3
DM_5	2	5	4	3

TABLE 9. The optimum weights of the criteria for the case study.

Criteria	C_1	C_2	C_3	C_4	C_5
Weight	0.4722	0.1787	0.1110	0.0989	0.1392

The zero CR is particularly noteworthy, as it demonstrates GBOM's superior ability to maintain internal consistency without the computational overhead associated with existing methods. In Example 3, a real-world case study on piping selection, the GBOM method's rankings aligned closely with those from GBWM and MCBWM-GDM. The Group-AHP model, although producing a similar ranking, showed higher CR values (>0.1), indicating potential inconsistencies.

The slight variations in weight values across methods are attributed to the inherent differences in how each

TABLE 10. The normalized values of the QoS criteria relative to the CSPs in the case study.

	C_1	C_2	C_3	C_4	C_5
Amazon (CSP1)	0.7371	0.8186	0.7151	0.50006	0.5234
HP (CSP2)	0.8685	0.9063	0.8426	0.50003	0.5095
Microsoft Azure (CSP3)	0.7808	0.7901	0.6563	0.50017	0.5332
Rackspace (CSP4)	0.5217	0.8001	0.8626	0.50005	0.5332
Google (CSP5)	0.7945	0.7317	0.7837	0.50006	0.5166
Century Link (CSP6)	0.6622	0.7371	0.7360	0.50006	0.5166
City-Cloud (CSP7)	0.7205	0.7827	0.7532	0.50013	0.5038
Linode (CSP8)	0.6445	0.9080	0.8479	0.50011	0.5024
GoGrid (CSP9)	0.6629	0.8343	0.9595	0.50007	0.5190
SoftLayer (CSP10)	0.5194	0.7988	0.7939	0.50003	0.5332

method handles pairwise comparisons and aggregates group preferences. The weighting differences observed in the experimental examples have significant implications for decision-making outcomes. For instance, in Example 1, the optimal weight assigned to the best criterion (C1) by GBOM (0.4474) was lower than those assigned by GBWM (0.5280 and 0.5120 for Model-1 and Model-2, respectively), MCBWM-GDM (0.5067), and AIP_BOM (0.4924). This suggests that GBOM provides a more balanced consideration of criteria, preventing the overemphasis of the best criterion and potentially leading to more nuanced and holistic decision-making. Similarly, in Example 2, the GBOM method assigned weights that were more evenly distributed among the criteria, further emphasizing its ability to balance the decision-making

TABLE 11. CSPs ranking scores in the case study.

CSP	Score	Rank
Amazon (CSP1)	0.6960	4
HP (CSP2)	0.7860	1
Microsoft Azure (CSP3)	0.7064	3
Rackspace (CSP4)	0.6087	9
Google (CSP5)	0.7143	2
Century Link (CSP6)	0.6475	8
City-Cloud (CSP7)	0.6833	6
Linode (CSP8)	0.6801	7
GoGrid (CSP9)	0.6903	5
SoftLayer (CSP10)	0.5998	10

process. However, in Example 3, it appears that most decision-makers assign higher pairwise comparison values to the best criterion compared to the others, which emphasizes a greater weight for the best criterion relative to the other criteria.

In the real-world case study of cloud service selection, GBOM's optimal weights resulted in the ranking of cloud service providers (CSPs). HP, ranked highest by GBOM, demonstrated superior CPU performance (C1), the best criterion selected by the decision-makers. However, the slight differences in weights assigned to other criteria (C2, C3, C4, C5) influenced the final rankings of other CSPs. This highlights the importance of considering user requirements in determining the final rankings [32].

The differences in weightings and final rankings have practical implications for decision-makers in various contexts. For example, in strategic decision-making scenarios, such as selecting a cloud service provider, the nuanced differences in weights can impact long-term outcomes, cost efficiency, and overall satisfaction with the chosen service. The GBOM method, with its balanced weighting approach and zero CR, provides a more reliable and consistent framework for such critical decisions. Furthermore, the computational efficiency of GBOM, achieved by requiring only the best criterion for pairwise comparisons, simplifies the decision-making process. This reduction in computational resource requirements makes GBOM particularly suitable for scenarios involving a large number of decision-makers or criteria, where traditional methods may become cumbersome and resource-intensive.

VIII. CONCLUSION

The evaluation of cloud services involves navigating complex multi-criteria decision-making (MCDM) challenges, particularly when incorporating group decision-making among experts. While traditional methods like AHP and BWM have proven effective, their reliance on extensive pairwise comparisons, computational demands, and inconsistency underscore the need for more efficient and reliable approaches. This paper introduces the group BOM (GBOM) method, which expands the BOM method and addresses these challenges by aggregating criteria and alternative weights using probabilistic and statistical techniques across multiple decision-makers (DMs). A multinomial distribution is used to model the inputs, which are pairwise comparisons collected from a group of experts. While the output of the method is the optimal aggregated final weights of all DMs, it is formulated according to Dirichlet distribution modeling. For estimating the aggregated final weights for the criteria, Bayes theorem was applied. Our validation with two numerical examples and a case study for a piping selection method demonstrates GBOM's ability to consistently rank criteria compared to established AHP and BWM group-based MCDM methods, achieving a consistent ratio (CR) of zero and requiring significantly fewer comparisons. Specifically, GBOM necessitates only $n - 1$ comparisons, contrasting sharply with BWM's $2n - 3$ and AHP's $n \times (n - 1)/2$. By relying only on the best criterion for pairwise comparisons, we eliminate redundancy and inconsistency. Moreover, our application of GBOM to a real-world cloud service selection case study reaffirms its advantages, showcasing improved consistency and offering a streamlined approach to ranking cloud services based on group preferences using the best-only method. This underscores GBOM's potential as a robust and efficient solution for MCDM in cloud service selection, effectively overcoming key limitations of existing methodologies. There are also limitations to the proposed approach. Experts' confidence levels for their pairwise comparison values were not taken into account. Furthermore, the formulating and programming of the probability distribution models requires some level of technical expertise. These limitations can be addressed in a future study.

Future research could investigate hybrid approaches that combine GBOM with other methodologies like fuzzy logic or grey systems theory. This would enable the handling of complex decision scenarios where criteria weights and alternatives' rankings need to be assessed under uncertain or ambiguous conditions. Additionally, developing interactive decision support systems centered on GBOM could foster real-time collaboration among decision-makers. This could involve user-friendly interfaces, visualization tools, and feedback mechanisms to enhance transparency and consensus-building in group decision-making processes. Furthermore, conducting case studies across diverse application domains beyond cloud service selection would be instrumental in verifying and enhancing the applicability and effectiveness of GBOM.

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