G2M weighting: a new approach based on multi-objective assessment data (case study of MOORA method in determining supplier performance evaluation)

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ABSTRACT

Criteria weighting methods in decision support system (DSS) face various challenges and limitations that can affect their accuracy and reliability. One of the main challenges is subjectivity, this subjective assessment can reduce the objectivity and consistency of results. The main objective of the new weighting method grey geometric mean (G2M) weighting is to provide more objective and robust criteria weights under conditions of uncertainty and incomplete data. The new G2M weighting approach has a significant potential impact on the DSS field, it has the potential to generate more effective and efficient decisions, which can improve organizational performance, reduce risk and optimize outcomes. Pearson correlation test results of two sets of rankings generated by DSS methods namely grey relational analysis (GRA), simple additive weighting (SAW), multi-attributive ideal-real comparative analysis (MAIRCA), weighted product (WP), combined compromise solution (COCOSO), *vlsekriterijumska optimizacija i kompromisno resenje* (VIKOR), and a new additive ratio assessment (ARAS) that there is a strong positive correlation between the two methods using G2M weighting criteria. The high correlation value indicates that the rankings of the methods used tend to move together, giving confidence in the consistency and validity of the resulting ranking results. This gives confidence that both methods can be used simultaneously or interchangeably with consistent results. The use of G2M weighting in the DSS method used can support better decision-making by providing consistent information and validity of ranking results.

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1. INTRODUCTION

Decision support systems (DSS) are essential as they assist organizations and individuals in making more informative and timely decisions through complex data analysis [1], [2]. DSS utilizes information technology to collect, process, and analyze data, resulting in reliable recommendations. It is highly beneficial in various sectors, including business, healthcare, government, education, and finance. In the healthcare sector, human resources (HR) support the diagnosis and treatment planning of patients by analyzing medical data. Governments use DSS to formulate more effective policies based on social and economic data. By improving the accuracy, efficiency and speed of decision-making, DSS enables organizations to be more responsive to changes and challenges, and supports continuous innovation and development. With the ability to integrate multiple data sources and provide accurate analysis, DSS improves the efficiency, reliability and accuracy of decisions, making it an essential tool for operational and strategic success in various fields. The process of determining criteria weights in a DSS is an important step that ensures that each criterion in decision-making has the appropriate influence according to its level of importance. This process usually starts with the identification of relevant criteria based on the objective of the decision to be made. Next, various methods are used to determine the weight of each criterion, including subjective techniques such as expert interviews and the Delphi method, as well as objective techniques such as the analytic hierarchy process (AHP) and the entropy method. Subjective methods rely on expert judgment and experience to assign weights, while objective methods use quantitative data to assess the relative importance of each criterion. Accurate and fair determination of the weights is critical as they affect the final outcome of the DSS, ensuring that the decisions taken reflect the real priorities and needs of the situation at hand.

Criteria weighting methods in DSS face various challenges and limitations that can affect their accuracy and reliability [3], [4]. One of the main challenges is the subjectivity in weight determination when using expert-based methods, such as interviews or the Delphi method. These subjective judgments can be influenced by the personal preferences, experiences, or interests of the individuals involved, which can reduce the objectivity and consistency of the results [5]–[7]. These complex processes can require specialized skills in data analysis and an in-depth understanding of the methodology used, which can take significant time and resources. Furthermore, in dynamic contexts where criteria and priorities can change rapidly, traditional methods may lack the flexibility to adjust criteria weights in real-time or be responsive to changing situations. This could result in inappropriate or irrelevant decisions if the weights are not updated regularly. Grey number is a concept in grey systems theory that is used to handle uncertainty and incomplete information in decision making. Unlike exact numbers, grey numbers represent values that fall within a certain range, with upper and lower bounds that are not known with certainty. This allows for more flexible analyses in conditions where full or precise data is not available. In grey system applications, grey numbers are often used in methods such as grey relational analysis (GRA) to evaluate relationships between variables with partial or imperfect data, thus aiding decision-making in complex and ambiguous environments.

The main objective of the new weighting method, grey geometric mean weighting (G2M weighting) is to overcome the limitations and challenges that exist in traditional criteria weighting methods by combining the strengths of grey system analysis and geometric mean calculation [8]–[10]. G2M weighting is designed to provide more objective and robust criteria weights under conditions of uncertainty and incomplete data, often encountered in various DSS applications. This method aims to improve the accuracy and consistency of weighting by minimizing subjective perceptions and utilizing a quantitative approach that is more transparent, and easy to implement [11]. As such, G2M weighting seeks to improve the reliability and effectiveness of G2M in generating decisions that are more informative and adaptive to changing situations, supporting more informed and responsive decision-making in various sectors. G2M weighting aims to offer greater flexibility than traditional methods, allowing for dynamic adjustment of criteria weights according to changing contexts and priorities. By using grey system analysis, the method can better cope with data uncertainty, while the use of geometric mean ensures that the resulting criteria weights are more proportional and balanced. The method is also designed to reduce the analytical burden on non-technical users, making it more user-friendly and more efficiently implemented. By integrating these approaches, G2M weighting seeks to strengthen the ability of HR to provide more accurate and relevant recommendations, supporting more strategic and effective decision-making in a variety of diverse situations and environments.

The new approach of G2M weighting has a significant potential impact on the DSS field. By overcoming the limitations of traditional methods, G2M weighting can improve the quality of decisions generated by a DSS, especially in terms of accuracy, consistency, and timeliness. This has the potential to generate more effective and efficient decisions, which in turn can improve organizational performance, reduce risks, and optimize outcomes. In addition, G2M weighting can also expand the scope of DSS applications, with its ability to manage uncertain and complex data, and integrate various relevant factors. This approach can pave the way for the development of more adaptive, responsive and highly competitive GIS, reinforcing the role of DSS as a vital tool in decision-making across sectors and scales. Another potential impact of the G2M weighting approach is increased transparency and accountability in the decision-making process. By providing a more robust basis for criteria weighting, G2M weighting can assist in explaining and justifying the decisions taken by the DSS. This can increase users' and stakeholders' confidence in the resulting decisions, as well as facilitate more effective communication between various stakeholders. In addition, by focusing on objectivity and fairness in weighting, G2M weighting can promote fairer and more sustainable decision-making, which complies with the principles of ethics and social responsibility [12], [13]. Therefore, this approach has the potential to create a positive impact in improving management and governance in various organizational contexts, as well as strengthening the role of PR as a tool that supports sustainable and impactful decision-making.

G2M weighting fills a gap in the literature by presenting a holistic and integrated approach to criteria weighting in DSS. It overcomes the limitations of traditional methods by incorporating grey system analysis and geometric mean calculations, which have not been widely explored in previous literature [14], [15]. The emphasis on managing data uncertainty and decision complexity makes G2M weighting a valuable contribution in developing more adaptive and responsive weighting methods. In addition, the focus on objectivity and transparency in weighting also fills a gap in the literature regarding the need for a more ethical and accountable approach to decision-making [16]–[18]. G2M Weighting makes a meaningful contribution in expanding our understanding of criteria weighting in HR, as well as identifying new directions for future research and development. G2M weighting also fills a gap in the literature by offering an approach that is easier for non-technical users to understand and apply. The method is designed to minimize the complexity of the analysis and calculations, thus allowing users from different backgrounds to use the method more efficiently. This creates room for more research on the application of DSS in various practical contexts, as G2M weighting can serve as a model for more user-friendly weighting methods. By broadening the scope of DSS accessibility, G2M weighting plays an important role in promoting the adoption of this technology across different sectors and organizations, as well as enriching the literature with a more inclusive and practical perspective.

G2M weighting overcomes the limitations of traditional weighting methods by integrating grey system analysis to handle uncertainty and incomplete data, and using geometric mean calculation to produce more proportional and balanced weights. Grey system analysis allows G2M weighting to better manage uncertain and partial data, providing flexibility in dealing with dynamic situations. In addition, the use of geometric averaging ensures that the extreme influence of outlier data is minimized, making the resulting criteria weights more stable and representative. The method is also designed to be easier to implement and understand by non-technical users, reducing complexity and analytical loads. As such, G2M weighting offers a more adaptive, accurate, and user-friendly approach, overcoming the subjective preferences and data limitations that often hamper conventional weighting methods, and improving the reliability and effectiveness of DSS. By overcoming these limitations, G2M weighting makes a significant contribution to improving the quality of decision-making in various contexts. For example, in industry, this method can assist companies in identifying more effective strategies by considering various factors proportionally. In healthcare, G2M weighting can be used to optimize resource allocation by taking into account a more balanced priority of criteria. In an academic setting, this method can assist researchers in determining the most influential variables in their research. Thus, G2M weighting makes a meaningful contribution in improving the decision quality and efficiency of decision-making processes in various sectors, making it one of the promising approaches in the development of more sophisticated and reliable DSS.

2. METHOD

The research conceptual framework is a theoretical structure that describes and explains the relationship between variables studied in a study. The conceptual framework provides a solid basis for hypothesis formulation, assists researchers in designing appropriate methodologies, and directs data analysis and interpretation of results. With a conceptual framework, research becomes more directed, systematic, and able to make a significant theoretical contribution to the field of science being studied. The conceptual framework is a key element in the research process that not only guides practical steps, but also directs the development of broader theory and knowledge. Figure 1 is the conceptual framework of the research conducted in G2M weighting.

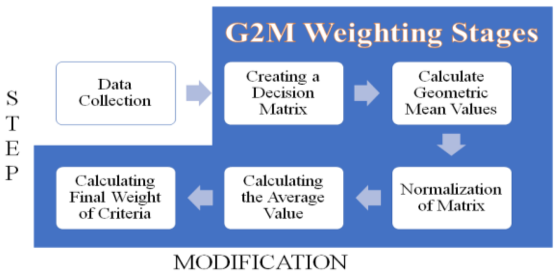

Figure 1. G2M weighting concept framework

The conceptual framework of Figure 1 is the process carried out in obtaining the weight of the criteria using G2M weighting, starting from collecting data based on the case study conducted. The assessment data obtained is then made in the form of a decision matrix and immediately calculates the geometric mean value. Next, normalize the matrix and calculate the grey value, finally calculating the weight value of each criterion.

2.1. Data collection

Data collection is a critical stage in an effective and informative decision-making process. The primary objective of data collection is to gather relevant, accurate, and timely information required for decision analysis [19], [20]. The data collection process involves identifying relevant criteria for evaluation, developing appropriate collection methods, and acquiring data from a variety of sources that may include historical data, surveys, interviews, or other data sources. It is important to ensure that the data collected is complete, consistent and reliable, and that applicable privacy and ethical policies are observed. With good data, decision-makers can produce better analyses and make more informed and informed decisions. The data collection process also involves data validation and verification to ensure the accuracy and reliability of the information collected. This can involve techniques such as cross-checking data with other sources or conducting field trials to verify the veracity of the data. In addition, effective data collection also considers the methods of storing, managing and analyzing the data that will be used in the decision-making process. By paying attention to these aspects, data collection can provide a solid basis for accurate analysis and effective decision-making.

2.2. Creating a decision matrix

Creating a decision matrix is an important step in DSS development, a decision matrix is a table used to organize and compare various decision alternatives based on predetermined criteria [21]–[23]. The first step in creating a decision matrix is to identify all possible alternatives and the relevant criteria for evaluating those alternatives. After that, the matrix is filled with values that describe the extent to which each alternative meets each criterion. With this decision matrix, decision makers can clearly see and compare the values associated with each alternative, which can help in making informed and appropriate decisions. In (1) is the form of the decision matrix in the G2M weighting method.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

The main objective in creating a decision matrix is to simplify the decision-making process by organizing complex information into a format that is easier to understand [24], [25]. The decision matrix helps in identifying the best alternative based on predefined criteria, and provides a clear basis for comparing and evaluating each alternative. In addition, the decision matrix also helps in understanding the impact of each decision taken, as well as accounting for the different preferences and priorities of stakeholders. The decision matrix is an important tool in supporting a systematic, structured and informed decision-making process.

2.3. Calculate geometric mean values

Geometric mean values are the geometric mean values of a set of data used in various analysis contexts, including criteria weighting in DSS. Geometric mean values are calculated by multiplying all the data values, then multiplying the result by the total number of data [26], [27]. Geometric mean values are useful because they provide a better representation of unsymmetrical data distributions, especially when there are significant differences between data values. In the context of DSS, geometric mean values are used to calculate the relative weight of each criterion based on the given data, thus making an important contribution in producing more informed and precise decisions. In (2) is the calculation for geometric mean values in the G2M weighting method.

$$GM_i = \left(\prod_{i=1}^{j} x_i\right)^{1/n} \tag{2}$$

The main purpose of using geometric mean values is to provide a more accurate representation of data that has large differences in magnitude [28]–[30]. Geometric mean values give greater weight to smaller values, thus allowing unsymmetrical data to be interpreted in a more balanced manner. In the context of criteria weighting, geometric mean values are used to calculate the weights of criteria or factors in the decision-making process. By giving proportional attention to each value in the data set, geometric mean values help minimize distortions that can arise due to differences in scale or magnitude between values, thus improving accuracy and consistency in decision analysis.

2.4. Normalization of matrix

Matrix normalization is the process of transforming the values in a matrix onto a common scale to allow for fairer and more accurate comparisons between different elements [31], [32]. Matrix normalization is essential because different criteria may have different units of measurement or widely varying ranges of values. The normalization process usually involves converting the values into a proportional form. With normalization, each criterion in the decision matrix can be measured on the same scale, so that the relative influence of each criterion can be compared directly and fairly. This improves the accuracy and reliability of the analysis results, helping decision makers to make more informed and objective choices. In (3) is the form of matrix normalization in the G2M weighting method.

$$R_{ij} = \frac{x_{ij}}{GM_i} \tag{3}$$

The purpose of matrix normalization is to equalize the scale of values in a matrix, thus allowing fair and accurate comparisons between elements that may have different units or ranges of values [33]. Matrix normalization removes the preference that can arise from differences in scale, ensuring that each criterion or variable has proportionate influence in the decision analysis. By transforming values into a consistent scale, normalization facilitates the integration and analysis of data from multiple sources, increasing the reliability and validity of the results obtained. Matrix normalization plays a crucial role in producing more precise and informed recommendations, helping decision makers to make more objective choices based on balanced data analysis.

2.5. Calculating the grey value

Grey value is a concept used in grey system analysis to handle uncertainty and incomplete data [34], [35]. Grey values represent the level of certainty or information available about a variable or parameter. These grey values are in between exact values (black and white), reflecting uncertainty or lack of complete information. Grey values are often used in decision-making methods and data analysis where available data may be limited or not completely reliable. By incorporating grey values, grey systems can provide more flexible and realistic analysis, allowing decision makers to work with imperfect data and still produce informative and reliable decisions. In (4) is the form of grey value in the G2M weighting method.

$$GRG_i = \frac{1}{n} \sum_{j=1}^{n} R_{ij} \tag{4}$$

The main purpose of using grey value is to address and manage uncertainty and incomplete data in the decision-making and analysis process. Grey value provides a way to represent information that is partial or not fully known, allowing for more flexible and realistic analyses compared to traditional approaches that require complete and definitive data [36]. Using grey value, decision makers can consider different levels of certainty and integrate data of varying quality into the analysis model. This process helps in generating more accurate and adaptive decisions to complex and dynamic situations, where information is often incomplete or under conditions of uncertainty.

2.6. Calculating final weight of criteria

Final weight of criteria is the final result of the criteria weighting process reflecting the importance of each criterion relative to the other criteria [37], [38]. These final weights play a crucial role in decision-making, as they are used to combine various criteria into one comprehensive scale that supports the evaluation and comparison of decision alternatives. The final weight of criteria ensures that each criterion is given the appropriate proportion of influence according to its importance, so that the decision taken is more precise, objective, and reflects true priorities. With accurate and fair final weights, DSS can provide more effective and relevant recommendations for various situations and contexts. In (5) is the form of the final weight of the criteria in the G2M weighting method.

$$w_j = \frac{GRG_i}{\sum_{i=1}^{j} GRG_i} \tag{5}$$

The main purpose of determining the final weight of criteria is to ensure that each criterion in the decision-making process is given an appropriate proportion of influence according to its level of importance [39], [40]. The final weight of criteria helps integrate various criteria that may have different units or scales, into one comprehensive scale that allows for objective and fair evaluation and comparison of decision alternatives. By assigning accurate final weights, decision makers can overcome subjective perceptions, ensuring that all important aspects are taken into account according to their true priority. This increases the reliability and validity of the decision results, supporting decision-making that is more informative, transparent, and responsive to various conditions and needs. The final weight of criteria is a key element in generating more precise and effective decision recommendations in various contexts and applications.

2.7. Grey geometric mean weighting

G2M weighting is a new approach as an innovative method in criteria weighting that combines grey system analysis and geometric mean calculation to produce more accurate and proportional weights under conditions of uncertainty and incomplete data. The method harnesses the power of grey systems to manage data uncertainty and provide more realistic estimates, while geometric averages are used to maintain a balance of relative weights between criteria, reducing the influence of extreme or outlier data. G2M weighting is designed to increase objectivity and consistency in the criteria weighting process, resulting in more informed and precise decisions in DSS. G2M weighting offers a more robust solution for a wide range of applications by virtue of its flexibility and adaptability, from business and management to scientific research and engineering in support of more responsive and reliable decision making.

With the G2M weighting approach, the process of determining criteria weights becomes more transparent and reliable, as it reduces subjective preferences that often occur in traditional methods. G2M weighting's ability to adapt to incomplete or uncertain data makes it particularly relevant in complex and dynamic contexts, where available information may not always be perfect. The end result is an improvement in the quality of decisions taken, by considering various factors more comprehensively and objectively. G2M weighting also facilitates integration in various DSS systems and applications, making it a very useful tool for professionals who rely on data to make strategic decisions. G2M weighting not only improves efficiency and accuracy in criteria weighting, but also contributes significantly to the development of more sophisticated and adaptive decision-making methods.

The main objective of G2M weighting is to provide a more objective and accurate approach to criteria weighting in DSS. It aims to overcome the limitations of traditional methods by combining grey system analysis and geometric mean calculation, resulting in more balanced and proportional criteria weights. The main advantage of G2M weighting is its ability to manage uncertainty and incomplete data, which often occur in complex decision environments. G2M weighting also allows decision makers to work with partial or uncertain data, thus increasing flexibility and responsiveness in decision making. The results of G2M weighting can help improve decision quality in a variety of contexts, from business and management to science and technology, making it a promising approach in the development of more sophisticated and reliable DSS.

2.8. Multi-objective optimization by ratio analysis method

The multi-objective optimization by ratio analysis (MOORA) method is one of the decision analysis methods used to select the best alternative from a set of available alternatives. This method allows decision makers to evaluate alternatives based on several different criteria, by considering the relative weight of each of these criteria. MOORA works by converting the absolute value of each criterion into a relative value, which is then used to calculate the relative preference value for each alternative. These relative preference values are then used to rank the alternatives, where the alternative with the highest relative preference value is considered the most desirable alternative. The first MOORA stage calculates matrix normalization using in (6).

$$x_{ij}^{*} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{j} x_{ij}^{2}}} \tag{6}$$

The last stage in MOORA calculates the optimization value based on the result of matrix normalization multiplied by the weight of the criteria. The maximum optimization value will be reduced by the minimum optimization value, where the maximum optimization value is for criteria that are benefits and the minimum optimization value is for criteria that are costs. The optimization value is calculated using in (7).

$$Y_j^{*} = \sum_{j=1}^{g} x_{ij}^{*} * w_j - \sum_{j=g+1}^{n} x_{ij}^{*} * w_j \tag{7}$$

The final result of the MOORA optimization score is the relative ranking of each evaluated alternative. Each alternative will have a relative preference value that indicates its relative degree of desirability or suitability in the context of the criteria being assessed. The alternative with the highest relative preference value is considered the most desirable or optimal alternative in that context.

3. RESULTS AND DISCUSSION

The implementation of G2M weighting in criteria weighting introduces an innovative and effective approach in DSS. This method utilizes a combination of grey system analysis and geometric mean calculation to overcome data uncertainty and produce more balanced and proportional criteria weights. By using grey system analysis, G2M weighting can provide more accurate and realistic estimates, while geometric mean calculation helps maintain the balance of relative weights between criteria, reducing the impact of extreme or outlier data. The implementation of G2M weighting in determining criteria weights can help improve the quality of decision-making by providing a more solid and measurable basis, and minimizing perceptions that may arise in subjective judgements. G2M weighting becomes a very useful tool in improving the effectiveness and accuracy of DSS in various contexts and applications.

The implementation of G2M weighting also paves the way for increased efficiency and effectiveness in multi-criteria decision making. By integrating various aspects of uncertainty and complexity in decision analysis, this method helps decision makers to understand and evaluate the impact of each criterion more holistically. In addition, the implementation of G2M weighting can strengthen the basis of decision analysis by producing more measurable and objective criteria weights, which can be used as guidelines in choosing the most suitable alternative. The implementation of G2M weighting in determining criteria weights can bring significant benefits in improving decision quality and optimizing results in a variety of complex and dynamic decision-making situations.

3.1. Data collection (case study determining supplier performance evaluation using MOORA)

Data collection in determining supplier performance evaluation is an important step in measuring and understanding the extent to which suppliers fulfil the set requirements and expectations. This process involves collecting information related to various aspects of supplier performance namely average cost (CR-1), delivery time (CR-2), product quality (CR-3), flexibility (CR-4), and availability of goods (CR-5). The data is obtained from the company's judgement in evaluating supplier performance. Comprehensive and accurate data collection enables companies to identify suppliers' strengths and weaknesses, and take necessary actions to improve overall supply chain performance. Table 1 is the result of the performance assessment of existing suppliers.

Table 1. Supplier performance assessment results

Supplier name	Performance rating of each criterion				
	CR-1	CR-2	CR-3	CR-4	CR-5
Supplier YA	800	3	5	4	4
Supplier FT	750	5	4	5	4
Supplier HE	860	2	5	3	3
Supplier TW	900	3	3	4	3
Supplier AS	940	3	4	4	4
Supplier BR	920	4	3	4	4
Supplier OR	780	2	4	4	5
Supplier NW	880	3	3	3	5
Supplier DS	940	2	4	4	4
Supplier CH	830	4	5	3	5

The supplier assessment data Table 1 obtained from the company is very valuable information in measuring supplier performance and contribution to business operations. This data includes an evaluation of various aspects of supplier performance, namely average cost, delivery time, product quality, flexibility, and availability. By analyzing this supplier assessment data, the company can identify suppliers that add the most value, as well as identify areas where suppliers can improve their performance. This enables companies to take appropriate actions to improve the efficiency, quality, and sustainability of their supply chain. The data source in the case study was obtained from the results of an internal survey conducted on the company's procurement team. The assessment was conducted based on work experience with 10 suppliers who were assessed using five main criteria: product quality, price, delivery accuracy, after-sales service, and flexibility. The data was collected from the company's historical record of supplier performance over the past year, as well as the results of interviews with procurement managers and logistics teams.

3.2. Implementation of the G2M weighting method

The implementation of the G2M weighting method involves a systematic series of steps to determine the weights of criteria in a DSS. The implementation of the G2M weighting method can help improve the objectivity and accuracy of determining criteria weights, thereby supporting better and informed decision making. The implementation of G2M weighting can be a very effective tool in overcoming uncertainty and complexity in decision making, as well as improving the quality and objectivity in the process of determining the weight of criteria in DSS. The first stage in G2M weighting creates a decision matrix based on the assessment data in Table 1. The decision matrix X for each column is the criteria and for the rows are the alternative values for each criterion. After the decision matrix is made, then calculate the geometric mean value for each criterion using in (2).

$$GM_1 = (800 * 750 * 860 * 900 * 940 * 920 * 780 * 880 * 940 * 930)^{1/10} = 857.5493$$
$$GM_2 = (3 * 5 * 2 * 3 * 3 * 4 * 2 * 3 * 2 * 4)^{1/10} = 2.9612$$
$$GM_3 = (5 * 4 * 5 * 3 * 4 * 3 * 4 * 3 * 4 * 5)^{1/10} = 3.9233$$
$$GM_4 = (4 * 5 * 3 * 4 * 4 * 4 * 4 * 3 * 4 * 3)^{1/10} = 3.7521$$
$$GM_5 = (4 * 4 * 3 * 3 * 4 * 4 * 5 * 5 * 4 * 5)^{1/10} = 4.0378$$

The final result of the calculation from (2) for existing criteria is the result of the geometric mean calculation based on the values of all existing alternatives. The next stage calculates the normalization value using in (3).

$$R_{11} = \frac{x_{11}}{GM_1} = \frac{800}{857.5493} = 0.9329$$

Table 2 is the overall result of matrix normalization calculations for each alternative based on existing criteria.

Table 2. Results of matrix normalization

Supplier name	Normalization of matrix				
	CR-1	CR-2	CR-3	CR-4	CR-5
Supplier YA	0.9329	1.0131	1.2744	1.0661	0.9906
Supplier FT	0.8746	1.6885	1.0196	1.3326	0.9906
Supplier HE	1.0029	0.6754	1.2744	0.7996	0.7430
Supplier TW	1.0495	1.0131	0.7647	1.0661	0.7430
Supplier AS	1.0961	1.0131	1.0196	1.0661	0.9906
Supplier BR	1.0728	1.3508	0.7647	1.0661	0.9906
Supplier OR	0.9096	0.6754	1.0196	1.0661	1.2383
Supplier NW	1.0262	1.0131	0.7647	0.7996	1.2383
Supplier DS	1.0961	0.6754	1.0196	1.0661	0.9906
Supplier CH	0.9679	1.3508	1.2744	0.7996	1.2383

The results of matrix normalization in Table 2 are the results of the calculation of the overall normalization value of each alternative for the criteria used, the next step is to calculate the grey value using (4).

$$GRG_1 = \frac{1}{10}(0.9329 + 0.8746 + 1.0029 + 1.0495 + 1.0961 + 1.0728 + 0.9096 + 1.0262 + 1.0961 + 0.9679) = 1.0029$$
$$GRG_2 = \frac{1}{10}(1.0131 + 1.6885 + 0.6754 + 1.0131 + 1.0131 + 1.3508 + 0.6754 + 1.0131 + 0.6754 + 1.3508) = 1.0469$$
$$GRG_3 = \frac{1}{10}(1.2744 + 1.0196 + 1.2744 + 0.7647 + 1.0196 + 0.7647 + 1.0196 + 0.7647 + 1.0196 + 1.2744) = 1.0196$$
$$GRG_4 = \frac{1}{10}(1.0661 + 1.3326 + 0.7996 + 1.0661 + 1.0661 + 1.0661 + 1.0661 + 0.7996 + 1.0661 + 0.7996) = 1.0128$$
$$GRG_5 = \frac{1}{10}(0.9906 + 0.9906 + 0.7430 + 0.7430 + 0.9906 + 0.9906 + 1.2383 + 1.2383 + 0.9906 + 1.2383) = 1.0154$$

The last stage calculates the final weight of the G2M weighting method using (5).

$$w_1 = \frac{GRG_1}{GRG_1+GRG_2+GRG_3+GRG_4+GRG_5} = \frac{1.0029}{1.0029+1.0469+1.0196+1.0128+1.0154} = 0.197$$
$$w_2 = \frac{GRG_2}{GRG_1+GRG_2+GRG_3+GRG_4+GRG_5} = \frac{1.0469}{1.0029+1.0469+1.0196+1.0128+1.0154} = 0.205$$
$$w_3 = \frac{GRG_3}{GRG_1+GRG_2+GRG_3+GRG_4+GRG_5} = \frac{1.0196}{1.0029+1.0469+1.0196+1.0128+1.0154} = 0.2$$
$$w_4 = \frac{GRG_4}{GRG_1+GRG_2+GRG_3+GRG_4+GRG_5} = \frac{1.0128}{1.0029+1.0469+1.0196+1.0128+1.0154} = 0.198$$
$$w_5 = \frac{GRG_5}{GRG_1+GRG_2+GRG_3+GRG_4+GRG_5} = \frac{1.0154}{1.0029+1.0469+1.0196+1.0128+1.0154} = 0.2$$

The final result of determining criteria weights using the G2M weighting method is a set of weights that reflect the relative importance of each criterion. These weights are generated through a combination of geometric mean of normalized data and grey system analysis to manage uncertainty and incomplete data. These weights provide a more objective and measurable guide to decision-making that allows decision-makers to give each criterion the right priority based on its contribution to the end goal. The final result of criteria weighting using G2M weighting helps to improve quality, reliability and effectiveness in the decision-making process.

3.3. Case study of MOORA method in determining supplier performance evaluation

The MOORA method can be used in supplier performance evaluation to assist companies in selecting the best supplier based on predetermined criteria. The use of the MOORA method can help companies evaluate supplier performance holistically and objectively, so that they can choose the supplier that best suits their needs. The first stage of MOORA calculates matrix normalization using in (6), Table 3 is the result of matrix normalization from supplier performance evaluation. The last stage in MOORA calculates the optimization value based on the results of matrix normalization multiplied by the weight of the criteria (using G2M weighting). The optimization value is calculated using in (7), Table 4 is the result of the MOORA method optimization value.

Table 3. Results of MOORA method matrix normalization

Supplier name	Normalization of matrix				
	CR-1	CR-2	CR-3	CR-4	CR-5
Supplier YA	0.0798	0.1500	0.1250	0.1370	0.0914
Supplier FT	0.0858	0.1000	0.1250	0.1027	0.0686
Supplier HE	0.1029	0.0600	0.0938	0.0822	0.0514
Supplier TW	0.1125	0.0900	0.0750	0.1096	0.0686
Supplier AS	0.1150	0.1200	0.0750	0.1096	0.0914
Supplier BR	0.0954	0.0800	0.0750	0.1096	0.1143
Supplier OR	0.0913	0.0600	0.0750	0.0822	0.1429
Supplier NW	0.1100	0.0600	0.0750	0.0822	0.1143
Supplier DS	0.1037	0.0800	0.1250	0.0822	0.1143
Supplier CH	0.1037	0.2000	0.1563	0.1027	0.1429

Table 4. MOORA optimization value calculation result

Supplier name	MOORA optimization score
Supplier YA	0.0854
Supplier FT	0.0627
Supplier HE	0.0373
Supplier TW	0.0467
Supplier AS	0.0569
Supplier BR	0.0572
Supplier OR	0.0542
Supplier NW	0.0448
Supplier DS	0.0601
Supplier CH	0.1007

The implementation of the MOORA method helps companies systematically and objectively determine the best suppliers, the final result in the form of supplier rankings provides clear guidance for decision making, helping companies choose suppliers that provide optimal value based on various important criteria. Figure 2 is the result of ranking based on the optimization value of the MOORA method. The results of ranking alternatives using the MOORA method provide a relative ranking of each alternative based on several relevant evaluation criteria. The supplier ranking results from Figure 2 show that the first best ranking is obtained on behalf of supplier CH with an optimization value of 0.1007. This result ensures that the selection of alternatives is based on a comprehensive and objective analysis, thus helping decision makers choose the best alternative based on various important criteria.

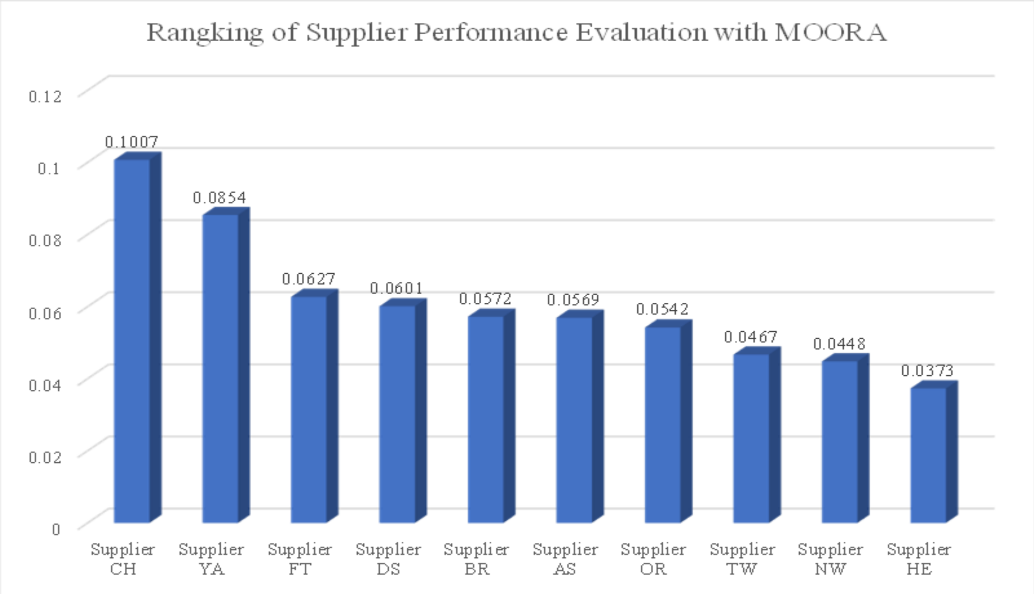

Figure 2. Ranking of supplier performance evaluation with MOORA

3.4. Discussion

The introduction of the G2M weighting method represents a significant advancement in the field of multi-objective decision making by overcoming some of the major limitations of existing weighting methods. Traditional methods such as AHP have been widely used to evaluate criteria weights in the decision-making process. However, these methods often struggle in handling incomplete or uncertain data and may introduce subjective preferences during the weighting process. The G2M weighting method, which integrates geometric mean calculation with grey system theory, offers a more robust and objective approach. By incorporating grey system theory, G2M weighting can effectively manage uncertainty in data, making it particularly suitable for real-world applications where perfect information is rarely available. The geometric mean component ensures that the influence of extreme values is minimized, providing a more balanced representation of criteria importance. In our case study on supplier performance evaluation, G2M weighting demonstrated its effectiveness by producing consistent and reliable ratings even with incomplete data. The method's ability to produce stable weights amidst data gaps highlights its strengths compared to conventional methods. To test the G2M weighting method we performed with several other DSS methods including GRA, simple additive weighting (SAW), multi-attributive ideal-real comparative analysis (MAIRCA), weighted product (WP), combined compromise solution (COCOSO), *vlsekriterijumska optimizacija i kompromisno resenje* (VIKOR), and a new additive ratio assessment (ARAS). Table 5 shows the ranking results of the tested methods by applying G2M weighting in the case of supplier performance evaluation.

Table 5. Ranking results of several DSS methods

Supplier name	MOORA rankings	GRA rankings	SAW rankings	MAIRCA rankings	WP rankings	COCOSO rankings	VIKOR rankings	MOORA rankings
Supplier CH	1	3	2	3	3	3	4	3
Supplier YA	2	4	3	4	5	2	2	1
Supplier FT	3	2	1	2	2	1	3	2
Supplier DS	4	1	5	1	1	5	1	4
Supplier BR	5	6	8	6	6	8	6	8
Supplier AS	6	5	6	5	4	6	5	5
Supplier OR	7	7	4	7	8	4	7	6
Supplier TW	8	10	10	10	9	10	10	10
Supplier NW	9	8	7	8	7	7	8	7
Supplier HE	10	9	9	9	10	9	9	9

Testing the ranking results of DSS methods using Pearson correlation for the purpose of evaluating the extent to which the ranking results of two different methods are linearly correlated, by calculating the Pearson correlation coefficient, we can determine the strength and direction of the relationship between two sets of rankings. Pearson correlation provides valuable insights in testing and validating the ranking results of different DSS methods by offering a quantitative way to measure the alignment between the resulting rankings. Testing using Pearson correlation not only aids in the validation of the methods used but also in better decision-making by providing a deeper understanding of the reliability and consistency of the DSS methods applied [41]–[43]. Table 6 is the result of testing the DSS method using Pearson correlation.

Table 6. Testing results using Pearson correlation

Name of method	Testing	Correlation values	Correlation results
MOORA	Original	1	Perfect correlation
GRA	Testing 1	0.8424	Strong correlations
SAW	Testing 2	0.7939	Strong correlations
MAIRCA	Testing 3	0.8424	Strong correlations
WP	Testing 4	0.7939	Strong correlations
COCOSO	Testing 5	0.7818	Strong correlations
VIKOR	Testing 6	0.8424	Strong correlations
ARAS	Testing 7	0.8424	Strong correlations
MOORA	Testing 8	0.8424	Strong correlations

Based on the results of testing the Pearson correlation of the two sets of rankings generated by the DSS method, it can be concluded that there is a strong positive correlation between the two methods using the G2M weighting criteria. A high correlation value indicates that the rankings from both methods tend to move together, giving confidence in the consistency and validity of the resulting ranking results. This gives decision makers confidence that the two methods can be used simultaneously or interchangeably with consistent results. The use of G2M weighting in the DSS method used can support better decision making by providing consistent and reliable information and providing consistency and validity of the ranking results. G2M weighting has a number of advantages that allow it to overcome the limitations often encountered in existing criteria weighting methods. One of the main advantages is its ability to handle uncertainty and vagueness in data, which is often difficult for traditional methods to handle. By integrating grey system theory, G2M weighting can process incomplete or uncertain data to provide more accurate and consistent results. In addition, by using geometric averages, this method is able to reduce the influence of extreme values that can ruin the whole weighting process. This makes G2M weighting a more stable and reliable approach in determining criteria weights, especially in the context of multi-criteria decision making in complex environments.

4. CONCLUSION

Criteria weighting methods in DSS face various challenges and limitations that can affect their accuracy and reliability. One of the main challenges is subjectivity; these subjective judgments can be influenced by the personal preferences, experiences, or interests of the individuals involved, which can reduce the objectivity and consistency of the results. The main objective of the new weighting method G2M weighting is to overcome the limitations and challenges present in traditional criteria weighting methods by combining the power of grey system analysis and geometric mean calculation. G2M weighting is designed to provide more objective and robust criteria weights under conditions of uncertainty and incomplete data. The new approach of G2M weighting has a significant potential impact on the DSS field, it has the potential to generate more effective and efficient decisions, which in turn can improve organizational performance, reduce risk, and optimize outcomes.

G2M weighting as an innovative step in the development of DSS, this method not only offers a solution to the limitations of traditional weighting methods, but also makes a meaningful contribution in improving the accuracy, consistency and flexibility of DSS in dealing with the complexity of decisions in various sectors. The Pearson correlation test results of two sets of rankings generated by DSS methods namely GRA, SAW, MAIRCA, WP, COCOSO, VIKOR, and ARAS can be concluded that there is a strong positive correlation between the two methods using G2M weighting criteria. The high correlation value indicates that the rankings of the methods used tend to move together, giving confidence in the consistency and validity of the resulting ranking results. This gives confidence that both methods can be used simultaneously or interchangeably with consistent results. The use of G2M weighting in the DSS methods used can support better decision making by providing consistent and reliable information and providing consistency and validity of the ranking results. The proposed G2M weighting approach offers significant innovations in supplier performance assessment by utilizing multi-objective data more effectively, as demonstrated in the MOORA method case study. This approach not only improves the accuracy of evaluation, but also provides flexibility in dealing with the complexity of diverse criteria. Further research can explore the implementation of G2M weighting in various industries to expand its applications, as well as explore the integration of machine learning techniques for deeper predictive analysis.

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