Development of Multi-Attribute Utility Theory Methods in Dynamic Decision Models Using Change-Data Driven

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Development of Multi-Attribute Utility Theory Methods in Dynamic Decision Models Using Change-Data Driven

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Abstract: The determination of the weight of criteria is a crucial element in multi-criteria decision making because weights reflect the relative importance of each criterion to the decision maker's ultimate goal. Development of the Multi-Attribute Utility Theory (MAUT) method with change-driven objective weighting can significantly improve the accuracy and objectivity of decision making, with dynamically adjusting the weighting of criteria based on changes in environment or preferences, change-driven objective weighting allows for more precise evaluation of decision alternatives. The final utility ranking results of each vendor using the MAUT development show that Vendor 6 occupies the first position with the highest utility value of 0.646, indicating that this vendor has the best performance based on the given criteria. The results of the sensitivity analysis using Pearson's correlation for each weight change ranging from 0.1 to 0.5, obtained a high correlation coefficient of 1 which shows that the vendor rating is very sensitive to changes in criterion weights. Future research from the development of the MAUT method can be directed at several innovative aspects to increase its relevance and application. One of the focuses is integration with advanced weighting methods, such as machine learning-based approaches or hybrid entropy, to improve the objectivity and flexibility of decision analysis.

Keywords: Change-Driven; Decision; Development; Objectivity; Weighting

1. Introducing

An objective Decision Support System (DSS) is a tool or system designed to assist decision makers in overcoming subjectivity and increasing objectivity in the decision-making process[1,2)]. This DSS is based on clear criteria and data, and uses structured and measurable analysis methods to produce optimal recommendations or decisions[3)]. By utilizing information technology and computer systems, DSS can objectively integrate a variety of relevant information and produce reliable results[4–7)]. Objective DSS can assist managers in identifying opportunities, managing risk, and making better decisions based on available facts and evidence[8,9)]. By systematically considering various factors and criteria, objective DSS can provide valuable support for decision makers in dealing with complex and dynamic situations[10–12)].

Multi-Attribute Utility Theory (MAUT) is a decision-making method used to evaluate and select alternatives based on various criteria or attributes[13,14)]. In MAUT, each alternative is evaluated based on its contribution to various relevant criteria, and then assigned a utility score that reflects the decision maker's preferences. This process involves determining the weights for each criterion based on their importance, normalizing attribute values, and calculating the total utility for each alternative. MAUT is particularly useful in situations where decisions have to be taken taking into account a variety of conflicting factors, thus enabling decision makers to make more rational and informed choices[15,16)]. Using MAUT, decision makers can combine subjective preferences with objective data, enabling more comprehensive and transparent analysis. The main advantage of MAUT is its ability to decipher and manage the complexity of multi-criteria decision making, as well as provide a logical and systematic basis for making optimal decisions[17,18)].

The determination of the weight of criteria is a crucial element in multi-criteria decision making because weights reflect the relative importance of each criterion to the decision maker's ultimate goal[19–21)]. Proper weighting ensures that more important criteria have greater influence in the evaluation process and selection of alternatives. By determining weighting accurately, decision makers can avoid unwanted inconsistence and ensure that decisions reflect true priorities and values[22,23]. The weighting process also helps in clarifying and aligning goals, reduces subjectivity, as well as increases transparency and consistency in decision making. Without proper weighting, decision outcomes may not reflect actual preferences and needs, which can lead to suboptimal or unsatisfactory choices.

One of the main weaknesses of MAUT in the context of weighting criteria is its dependence on the subjectivity of decision makers. The weighting process often relies on subjective judgments, which can be influenced by personal opinions, experiences, and perceptions of individuals. This can reduce the objectivity and consistency of decision results. In addition, precise weighting requires a deep understanding of each criterion and its impact on the overall goal, which can be challenging in complex situations or where information is limited. Errors or inaccuracies in weight determination can lead to unrepresentative and suboptimal results, reducing the reliability and validity of decisions resulting through MAUT.

Subjectivity weighting is an evaluation method in which judgments are given based on the personal views or opinions of the evaluator, rather than through objective data or algorithms[24]. This process is often influenced by the preferences, experiences, and knowledge of the judging individual, which can lead to variations in assessment results due to differences in perception and bias. While subjectivity can provide flexibility and more contextual judgment in complex and multifaceted situations, subjectivity can also introduce uncertainty and inconsistency if not managed properly. The main drawbacks of subjectivity weighting are the potential for user assumptions and inconsistencies in assessments. Because these assessments are based on individual opinions and perceptions, the results can vary greatly depending on who is performing the assessment. Therefore, it is important to combine subjectivity with other, more objective assessment techniques to achieve more balanced and reliable results.

MAUT development involves adjusting and developing techniques to address specific limitations or needs in multi-criteria decision making. One common development is the integration of more dynamic and adaptive weighting methods, such as the use of weights that can change according to different contexts or decision preferences. Development of MAUT with change-driven objective weighting is an innovative approach to multi-criteria decision making. Change-driven objective weighting introduces a weighting adjustment mechanism based on changes in the environment or decision makers' preferences[25,26]. The weight of each criterion is not fixed, but can be adjusted dynamically based on changes in relevant external or internal conditions[27]. This approach allows decision makers to be more responsive to changing situations, increasing the flexibility and relevance of decisions taken[28,29]. By combining an established MAUT with the flexibility of change-based weighting, it can provide a more adaptive and contextual framework for complex decision making[30,31]. With adjustable weights, Change-driven objective weighting enables a more thorough and comprehensive evaluation of alternatives, resulting in higher quality and purposeful decisions[32,33].

The development of the MAUT method with objective weighting based on changes called development MAUT change-data driven (D-MAUT) can significantly increase the accuracy and objectivity of decision making. By allowing dynamic adjustment of criteria weights based on changes in environment or preference, change-driven objective weighting enables more precise evaluation of decision alternatives. This reduces the risks that may arise from the fixed weight setting in conventional MAUT. Change-driven objective weighting helps ensure that decisions taken are not only more responsive to change, but also more objective and accurate according to existing circumstances[34,35]. The implementation of change-driven objective weighting in MAUT can also contribute significantly to the improvement of decision-making processes. With an integrated weight adjustment mechanism, decision makers can effectively monitor and evaluate the performance of decisions that have been taken, as well as make the necessary changes to improve results. In addition, change-driven objective weighting can also increase transparency in the decision-making process by providing a better understanding of how the weight of criteria changes and why those changes are needed.

Development of MAUT with change-driven objective weighting can also help overcome the problem of sensitivity to extreme data or outliers in the determination of criteria weighting. In conventional MAUT, extreme data or outliers can have a disproportionate impact on the weighting of criteria, which can lead to suboptimal decisions. However, with a change-driven objective weighting approach that allows dynamic weight adjustments[36,37], the influence of extreme data or outliers can be muted. Change-driven objective weighting can respond more wisely to extreme data, reducing the potential for making unbalanced or unrealistic decisions due to unrepresentative data. Change-driven objective weighting not only improves accuracy and objectivity, but also helps improve resilience to unusual data in the decision-making process. Adjustment of criteria weights can be done by considering significant changes in data, including extreme data or outliers[26]. Change-driven objective weighting helps reduce the risk of overfitting extreme data and improves reliability and consistency in criteria weighting, thus strengthening the integrity of the overall decision-making process[38,39].

1.1 Motivation for Conducting Research

The motivation to conduct this research was driven by the need to improve the effectiveness and accuracy of the AUT method in multi-criteria decision-making, especially in the face of dynamic and complex data challenges. In the application of conventional MAUT methods, the determination of the weight of the criteria is often subjective, so it is susceptible to bias and does not reflect the actual conditions of the data. This can reduce the validity of the results and the relevance of the method in a real-world context. Along with technological developments and the availability of increasingly abundant data, there is an opportunity to integrate data-driven and change-driven approaches into the MAUT framework. This approach allows the method to adaptively capture significant changes in the data and objectively update the criteria weights, resulting in more transparent, responsive, and reliable results.

This research is also motivated by the desire to contribute to academic literature by expanding the use of the MAUT method which is more modern, versatile, and applicable. In addition, this research aims to support decision-makers in various fields, such as performance evaluation, supplier selection, and strategic planning, with more robust and data-driven tools. Thus, this research is not only theoretically relevant but also has a significant practical impact.

The MAUT method was chosen for evaluation in this study because it has a superior ability to capture decision-maker preferences explicitly through utility functions. MAUT allows for clear quantitative measurement of the level of satisfaction or benefit obtained from each alternative, thus providing flexibility to accommodate different types of criteria, both qualitative and quantitative. The main reason for the selection of MAUT in this study is that this study aims to develop a framework that integrates objective weighting to overcome subjectivity bias, thereby reducing one of the main limitations of MAUT. With MAUT deep capabilities in measuring absolute utility, coupled with the improvement of data-driven weighting, this method provides a solid foundation for more transparent, accurate, and adaptive evaluations in complex decision-making scenarios.

1.2 The Contributions of the Study

This study makes a significant contribution to the development of the MAUT method by integrating objective weighting mechanisms in a change-driven and data-driven framework. This study ensures that the weighting process can dynamically adapt to changes in data patterns and variability between criteria. This minimizes subjective bias and improves decision-making accuracy, especially in complex scenarios in the real world where the importance of criteria can change. The proposed framework leverages data-driven insights to adjust weights, making the method more responsive and reflecting the actual decision-making context. In addition, the change-driven aspect of the study ensures that the modified MAUT method is able to adapt to the ever-evolving dataset, thereby improving its scalability and applicability in various areas such as supplier selection, performance evaluation, and strategic planning.

2. Materials and Method

2.1 Case Study and Data

Case study of internet provider vendor selection, a manufacturing company plans to improve their network connectivity across branch offices. A vendor is a party or company that provides goods or services to other organizations as part of a supply chain or business process[40,41]. They have to choose between several different internet service vendors. Assessment criteria include speed and reliability of service (C01), available technical support (C02), monthly subscription fee (C03), geographic reach (C04), and contract flexibility (C05).

The service speed and reliability criteria (C01) are a major factor, as stable and fast connectivity is essential to support the needs of users, both individuals and businesses. The available technical support criteria (C02) are a crucial aspect, as responsive customer service can ensure that technical glitches can be resolved immediately. The monthly subscription fee criterion (C03) is also a significant consideration, as users tend to look for solutions that offer a balance between quality of service and affordable costs. The geographic coverage criterion (C04) is an important factor to ensure services are accessible in the user's location, especially in hard-to-reach areas. The contractual flexibility criterion (C05) plays a role in making it easy for users to change plans or cancel services without burdensome consequences.

Table 1 is the result of assessment data on internet provider vendors.

Table 1. The Result of Assessment Data.

Vendor Name	Criteria and Value					Rank
	C01	C02	C03	C04	C05	
Vendor 1	5	4	3	4	3	6
Vendor 2	4	4	4	4	3	7
Vendor 3	3	3	5	5	4	3
Vendor 4	4	3	3	5	4	4
Vendor 5	3	3	4	4	3	9
Vendor 6	5	3	5	4	5	1
Vendor 7	4	4	5	5	3	2
Vendor 8	4	5	4	4	4	5
Vendor 9	3	4	4	3	4	8

The results of the assessment table 1 are the data to be used in this study, where the data is obtained from the company and the vendor ranking of the company in the selection of vendors. The ranking results of the company will be compared with the development of the MAUT method in this study. The data used in this study was obtained from the company's internal documents containing an assessment of the performance of internet provider vendors. The document includes regular evaluations carried out by the company's procurement team based on various criteria that have been determined. This data source is relevant primary data and supports the research objective, which is to evaluate the performance of internet provider vendors. Data is collected through an internal assessment by the procurement team using an evaluation form that includes several criteria. The assessment was carried out in a structured manner using a Likert scale of 1-9, where 1 indicates very poor performance and 9 indicates excellent performance. The data used in this study was collected during the period January 2023 to June 2024 which included an annual assessment of vendor performance in that year. This period is chosen to ensure that the data used is up-to-date and reflects the current conditions related to the cooperation relationship with internet provider vendors.

2.2 MAUT Development Concept Framework

The MAUT development concept framework is an approach that extends the conventional MAUT model by integrating change-driven objectivity. With this approach, decision makers can consider more complex aspects in the multi-criteria decision-making process[42,43]. The development allow for a more comprehensive evaluation of diverse alternatives, thus enabling decision makers to cope with the uncertainty and complexity associated with dynamic decision-making environments. Using this conceptual framework, decision makers can make more informed and adaptive decisions in the face of complex and changing challenges. Figure 1 is a framework for the concept of modifying the MAUT method with change-driven objectivity. Figure 1 is a framework for the concept of modifying the MAUT method with change-driven objectivity.

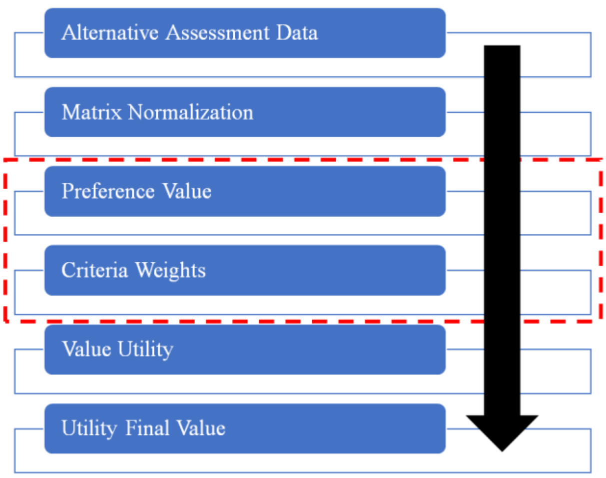

Fig. 1: framework for the concept of development the MAUT method with change-driven objectivity.

The MAUT method development concept framework is an approach that extends conventional MAUT methods by incorporating additional elements that improve the accuracy and relevance of multi-criteria decision evaluations. The first step in the development of the MAUT method is the collection of assessment data against alternatives, this data will be used in the assessment of alternatives that will result in ranking of existing alternatives. The internet service provider assessment data is obtained from reports owned by the company. These data sources include information on speed and reliability of service, available technical support, monthly subscription fee, geographic reach, and contract flexibility as key assessment criteria. The pre-processing step begins with the collection of data in a structured format in the form of a spreadsheet. From the data, data is cleaned to remove duplicates, handle missing values with interpolation or averaging methods, and identify and handle outliers.

The second step in modifying the MAUT method is to make a decision matrix based on alternative assessment data that has been carried out using equation (1).

$$X = \begin{bmatrix} x_{i1} & \cdots & x_{in} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

A decision matrix is a tool used in multi-criteria decision analysis to compile, analyze, and compare alternatives based on a number of specific criteria. This matrix is usually a table in which the rows represent the alternative under consideration, and the columns represent the evaluation criteria. The values in the cells of the matrix reflect the performance or score of each alternative against each criterion.

The third step in modifying the MAUT method is to calculate the matrix normalization value from the decision matrix data that has been made using equations (2) and (3).

$$r_{ij}^{*} = \frac{x_{ij} - min(x_{ij})}{max(x_{ij}) - min(x_{ij})} \quad (2)$$

$$r_{ij}^{*} = 1 + \frac{min(x_{ij}) - (x_{ij})}{max(x_{ij}) - min(x_{ij})} \quad (3)$$

Matrix normalization is the process of converting the values in a decision matrix into a uniform scale between 0 and 1, making it easier to compare between criteria that may have different scales. The normalization process helps in eliminating the effects of different scales on the evaluation of criteria. Normalization equation (2) is used to calculate criteria with benefit type, while equation (3) is used to calculate criteria with cost type.

The fourth step in modifying the MAUT method is to calculate the preference value of the criterion from the results of matrix normalization that has been calculated using equation (4). The calculation of this preference value is an addition to this study in the development of the MAUT method.

$$PV_i = 100 * \left| \frac{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}{\ln \frac{m}{\sigma_1}} \right| \quad (4)$$

The preference value of change-driven objective is a technique used in decision making to determine the priority of alternatives based on changes or significant differences between these alternatives. It is often used in multi-criteria methods to ensure that alternatives with significant changes or improvements get appropriate attention.

The fifth step in the development of the MAUT method is to calculate the weight of the criteria from the preference value using equation (5). The calculation of the weight value of this criterion is an addition to this study in the development of the MAUT method.

$$w_j = \frac{PV_i}{\sum PV_i} \quad (5)$$

The criterion weighted value is a value or factor used to indicate the relative importance of each criterion in a multi-criteria decision-making process. This weighting helps in allocating different priorities on different criteria, so that the more important criteria gain greater influence in the final evaluation compared to the less important criteria.

The sixth step in the development of the MAUT method is to calculate the utility value using equation (6).

$$u_{ij} = \frac{e\left(\left(r_{ij}^*\right)^2\right)-1}{1.71} \quad (6)$$

Utility value is a number that describes the level of satisfaction or benefit obtained from an alternative in multi-criteria decision making. Utility values are used to gauge a decision maker's preference for different alternatives based on predetermined criteria.

The final step in modifying the MAUT method is to calculate the final value of the utility using equation (7).

$$u_{(x)} = \sum_{j=1}^{n} u_{ij} . w_j \quad (7)$$

The final utility score is the total score obtained by each alternative after multiplying the utility value of each criterion by the corresponding criteria weighted and summing the results. This final score reflects the level of preference or overall satisfaction provided by the alternative.

The MAUT method development concept framework is a decision-making approach that combines the weight of criteria with utility values for each alternative to provide a more comprehensive and objective assessment. These-development can involve various aspects, such as weight adjustment based on dynamic importance, integration of more sophisticated normalization methods, or more efficient application of algorithms for utility calculations. The main objective of these development is to improve the accuracy and relevance of decision outcomes by taking into account changes in the environment or preferences of decision makers, thus generating the best alternative that best suits specific needs and contexts.

3. Result and Discussion

The development of the MAUT method and objective weighting for dynamic decision models aims to improve the decision-making process by incorporating flexible and context-sensitive criteria weighting and more sophisticated utility calculations. This development overcomes the limitations of static weight determination by allowing real-time adjustments based on changing priorities and environmental factors. This improved MAUT method integrates more advanced normalization techniques and adaptive algorithms to provide a more accurate and relevant evaluation of alternatives. Ultimately, this approach ensures that decision models are robust, responsive, and capable of making optimal choices in dynamic and complex situations. Development of MAUT and objective weighting for dynamic decision models provide the flexibility needed to deal with changing environments and decision-maker preferences. Taking these dynamics into account, the method can provide more adaptive and relevant solutions. The integration of these new techniques also reduces the potential for irregularities in weight determination and increases the accuracy and accuracy in selecting the best alternative. Thus, development of MAUT becomes a stronger approach in supporting decision making in a changing context.

3.1 Implementations of MAUT Development in Case Studies

The implementation of MAUT development in internet vendor selection case studies is used to determine the best vendor based on predetermined criteria. By applying MAUT development, the weight of criteria can be adjusted dynamically based on decision makers' preferences and changing market conditions. This allows decision makers to make decisions that are more informed and responsive to environmental changes, thereby increasing efficiency and effectiveness in the decision-making process.

The first step in modifying the MAUT method is to make a decision matrix based on alternative assessment data that has been carried out using equation (1).

$$X = \begin{bmatrix} 5 & 4 & 3 & 4 & 3 \\ 4 & 4 & 4 & 4 & 3 \\ 3 & 3 & 5 & 5 & 4 \\ 4 & 3 & 3 & 5 & 4 \\ 3 & 3 & 4 & 4 & 3 \\ 5 & 3 & 5 & 4 & 5 \\ 4 & 4 & 5 & 5 & 3 \\ 4 & 5 & 4 & 4 & 4 \\ 3 & 4 & 4 & 3 & 4 \end{bmatrix}$$

After the decision matrix is created, the next step is to calculate the normalized value of the matrix from the decision matrix data that has been made using equation (2) because all the criteria used are beneficial.

$$r_{11}^* = \frac{x_{11} - \min x_{11,19}}{\max x_{11,19} - \min x_{11,19}}$$

$$r_{11}^* = \frac{5-3}{5-3} = \frac{2}{2} = 1$$

Table 2 is the result of the calculation of the matrix normalization value.

Table 2. The Result of Assessment Data.

Vendor Name	Criteria				
	C01	**C02**	**C03**	**C04**	**C05**
Vendor 1	1	0.5	0	0.5	0
Vendor 2	0.5	0.5	0.5	0.5	0
Vendor 3	0	0	1	1	0.5
Vendor 4	0.5	0	0	1	0.5
Vendor 5	0	0	0.5	0.5	0
Vendor 6	1	0	1	0.5	1
Vendor 7	0.5	0.5	1	1	0
Vendor 8	0.5	1	0.5	0.5	0.5
Vendor 9	0	0.5	0.5	0	0.5

After the normalization value is calculated, the next step is to calculate the preference value of the criterion using equation (4).

$$PV_1 = 100 * \left| \frac{\sqrt{\sum_{i=1}^{m} x_{11,19}{}^2}}{\ln \frac{9}{\sigma_1}} \right|$$

$$PV_1 = 100 * \left| \frac{\sqrt{3}}{\ln \frac{9}{0.3333}} \right| = 100 * \left| \frac{1.7321}{\ln \frac{9}{1.1180}} \right|$$

$$PV_1 = 100 * \left| \frac{1.7321}{2.0857} \right| = 100 * |0.8305| = 83{,}05$$

Table 3 is the result of the calculation of the preference value of the criterion.

Table 3. The Result of Preference Value.

	Criteria				
	C01	**C02**	**C03**	**C04**	**C05**
PV	83.05	61.35	99.81	99.89	61.35

After the criteria preference value is calculated, the next step is to calculate the weight of the criterion by using equation (5).

$$w_1 = \frac{PV_1}{\sum PV_{1,5}}$$

$$w_1 = \frac{83.05}{83.05 + 61.35 + 99.81 + 99.89 + 61.35}$$

$$w_1 = \frac{83.05}{405.43} = 0.2048$$

Table 4 is the result of the calculation of the criteria weight value.

Table 4. The Result of Criteria Weight Value.

	Criteria				
	C01	**C02**	**C03**	**C04**	**C05**
W	0.2048	0.1513	0.2462	0.2464	0.1513

After the criterion weight value is calculated, the next step is calculating the criterion utility value by using equation (6).

$$u_{11} = \frac{e((r_{11}^*)^2) - 1}{1.71}$$

$$u_{11} = \frac{e((1)^2) - 1}{1.71}$$

$$u_{11} = \frac{2.718 - 1}{1.71} = \frac{1.718}{1.71} = 1.005$$

Table 5 is the result of the calculation of the utility value of the criterion.

Table 5. The Result of the Calculation of the Utility Value of the Criterion.

Vendor Name	Criteria				
	C01	**C02**	**C03**	**C04**	**C05**
Vendor 1	1.005	0.166	0	0.166	0
Vendor 2	0.166	0.166	0.166	0.166	0
Vendor 3	0	0	1.005	1.005	0.166
Vendor 4	0.166	0	0.000	1.005	0.166
Vendor 5	0	0	0.166	0.166	0.000
Vendor 6	1.005	0	1.005	0.166	1.005

Vendor 7	0.166	0.166	1.005	1.005	0
Vendor 8	0.166	1.005	0.166	0.166	0.166
Vendor 9	0	0.166	0.166	0	0.166

After the criterion utility value is calculated, the next step is calculating the final utility value by using equation (7).

$$u_{(1)} = \sum_{j=1}^{n} u_{11,51} . w_{1,5}$$

$$u_{(1)} = (1.005 * 0.2048) + (0.166 * 0.1513) + (0 * 0.2462) + (0.166 * 0.2464) + (0 * 0.1513)$$

$$u_{(1)} = 0.272$$

Table 6 is the result of the calculation of the final value of the utility.

Table 6. The Result of the Final Value Utility.

Vendor Name	Final Value Utility
Vendor 1	0.272
Vendor 2	0.141
Vendor 3	0.520
Vendor 4	0.307
Vendor 5	0.082
Vendor 6	0.646
Vendor 7	0.554
Vendor 8	0.293
Vendor 9	0.091

From the data in Table 6, you can see the final utility rating of each vendor. Vendor 6 occupies the first position with the highest utility value of 0.646, indicating that this vendor has the best performance based on the given criteria. In second place is Vendor 7 with a utility value of 0.554, followed by Vendor 3 in third place with a utility value of 0.52, showing good performance but not as good as Vendor 6. Vendor 4 is in fourth position with a utility value of 0.307, followed by Vendor 8 in fifth position with a utility value of 0.293, showing quite good performance. Vendor 1 occupies the sixth position with a utility value of 0.272, followed by Vendor 2 in seventh position with a utility value of 0.141, and Vendor 9 in eighth position with a utility value of 0.091, indicating lower performance. Lastly, Vendor 5 occupies the ninth position with the lowest utility value of 0.082, indicating the weakest performance among all vendors. These rankings help in understanding how well each vendor meets the set criteria.

3.2 Sensitivity Analysis

Sensitivity analysis in criterion weighting is a method to evaluate how changes in criterion weighting affect decision outcomes in decision support systems. The goal is to understand the extent to which a change in one or more weights can affect the ranking or final decision. By conducting a sensitivity analysis, it is possible to identify the criteria that most affect the outcome of the decision, as well as explore whether the outcome of the decision will remain stable or susceptible to changes in weight. This helps ensure that the resulting decisions are more robust and reliable, even if there are changes in priorities or views regarding different criteria.

The sensitivity analysis in this study by increasing the weight by 0.1 to 0.5 is a way to test how changes in the criteria weights can affect the outcome of the decision. By gradually increasing the weight of one criterion, ranging from 0.1 to 0.5, it is possible to see how the rating or score of the vendor or alternative changes. This makes it possible to identify the criteria that are most sensitive to weight changes, as well as evaluate the impact of those changes on the final decision. This sensitivity analysis helps in understanding how variability in criterion weights can affect decisions, and ensures that decisions remain consistent despite changes in criterion priorities. Table 7 is the result of a sensitive analysis of the final value and ranking of each vendor.

Table 7. Results of Sensitivity Analysis of Each Alternative.

Vendor Name	Original		Test 1 ($w_i + 0.1$)		Test 2 ($w_i + 0.2$)		Test 3 ($w_i + 0.3$)		Test 4 ($w_i + 0.4$)		Test 5 ($w_i + 0.5$)	
	Final Value	Rank	Final Value	Rank	Final Value	Rank	Final Value	Rank	Final Value	Rank	Final Value	Rank
Vendor 6	0.646	1	0.964	1	1.282	1	1.600	1	1.918	1	2.236	1
Vendor 7	0.554	2	0.788	2	1.022	2	1.257	2	1.491	2	1.725	2
Vendor 3	0.52	3	0.738	3	0.955	3	1.173	3	1.390	3	1.608	3
Vendor 4	0.307	4	0.46	4	0.627	4	0.794	4	0.961	4	1.128	4
Vendor 8	0.293	5	0.44	5	0.574	5	0.708	5	0.842	5	0.975	5
Vendor 1	0.272	6	0.406	6	0.539	6	0.673	6	0.807	6	0.94	6
Vendor 2	0.141	7	0.207	7	0.274	7	0.34	7	0.407	7	0.473	7

Vendor 9	0.091	8	0.141	8	0.191	8	0.241	8	0.29	8	0.34	8
Vendor 5	0.082	9	0.115	9	0.148	9	0.181	9	0.215	9	0.248	9

From the data available in Table 7, sensitivity analysis using Pearson correlation is used to measure the extent to which vendor ratings change when the criteria weights change. Based on Pearson's correlation calculation for each weight change ($\boldsymbol{w_i}$ + 0.1, $\boldsymbol{w_i}$+ 0.2, $\boldsymbol{w_i}$+ 0.3, $\boldsymbol{w_i}$+ 0.4, $\boldsymbol{w_i}$+ 0.5), a high correlation coefficient of 1 is obtained, which indicates that the vendor rating is very sensitive to changes in the criterion weight. This indicates that if there is a change in the weight of the criteria, the vendor rating may change significantly. The results of Vendor 6 retained the first rank in any weight change, indicating good performance stability. Pearson correlation provides insight into how well or badly weight changes affect rankings, aiding in understanding the stability of vendor performance against criteria changes.

3.3 Discussion

The results of the MAUT ranking method provide a deeper understanding of the preferences and priorities given by decision makers to the alternatives evaluated. Using MAUT, alternatives can be sorted by total utility value calculated from predefined criteria and weighted given criteria. These rankings provide a clear view of which alternatives best suit their preferences and desired goals, allowing decision makers to make more informed and informed decisions. In addition, the results of the MAUT ranking can also provide insight into which criteria are most influential in the final decision, so as to help in strategic planning and future development. Figure 2 is a comparison of rankings from the MAUT method.

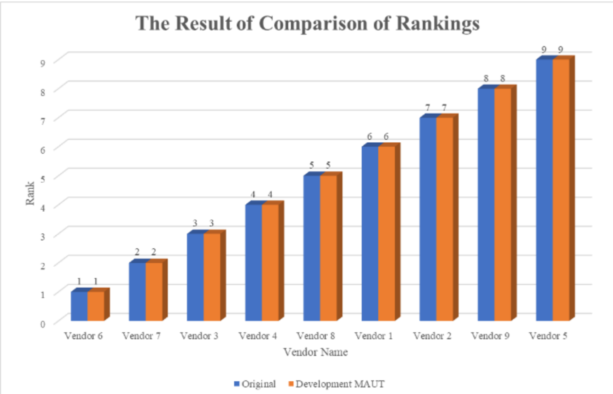

Fig. 2: The result of comparison of rankings.

The results of the development MAUT ranking method and the original ranking results of the case study showed the same value and there was no significant difference in terms of objectivity and accuracy. MAUT development, using change-driven objectives, tend to produce more consistent and reliable rankings compared to conventional MAUT. This is due to a more transparent and data-driven approach in determining the weight of criteria, which reduces subjectivity in decision making. MAUT development ratings are also better able to accommodate dynamic changes in preferences and market conditions, providing more relevant and adaptive results in changing environments.

The results of the development MAUT ranking method and the original ranking resulted in a Spearman correlation value that was both 1, indicating that both methods gave identical ratings to the evaluated alternatives. A Spearman correlation value of 1 indicates a perfectly positive monotonic relationship between the two sets of ratings, meaning the alternate sequences of both methods are exactly the same. The ranking results of both methods can be considered consistent and equal in determining the best alternative based on given preferences and criteria.

The development of the MAUT method in decision support systems offers significant improvements compared to previous research, especially in terms of flexibility, accuracy, and relevance in complex decision environments. Previous research generally relied on weighting methods that tended to be subjective or less sensitive to the dynamics of changing criteria preferences. With the new development by adding objective weighting methods, MAUT can reduce subjective bias, improve the reliability of results, and provide a more adaptive solution to data variations and user priorities. In addition, these new findings often leverage modern computing technologies to process larger, more complex data, allowing for application to real-time decision scenarios.

The implications of these findings for future research include opportunities to integrate MAUT with other methods, in order to improve predictive and automation capacity. The resulting system from the development of the MAUT method can also be applied to multi-stakeholder scenarios, where the consolidation of individual preferences is a major challenge. These innovations not only improve the efficiency of today's decision-making but also build the foundation for more responsive and sustainable decision-making in the future.

The limitation of the developed MAUT model is the potential difficulty in dealing with the problems of non-linearity and complexity associated with attributes or criteria that cannot be easily quantified in numerical form. These models often require data transformation or proper utility scaling, which can add to the computational load and affect results.

4. Conclusion

The development of the MAUT method and objective weighting for dynamic decision models has proven to be a powerful approach in improving the accuracy and sustainability of multi-criteria decision-making. The ranking results in the development of MAUT based on the original ranking results from the case studies showed the same values and there was no significant difference in terms of objectivity and accuracy. MAUT development ratings are also better able to accommodate dynamic changes in preferences and market conditions, providing more relevant and adaptive results in a changing environment. The results of the development of the MAUT rating method and the original ranking result in a Spearman correlation value of both 1, which shows that both methods provide identical ratings for the evaluated alternatives. A Spearman correlation value of 1 indicates a perfect positive monotonic relationship between the two sets of ratings, meaning that the alternate order of the two methods is exactly the same. The ranking results of both methods can be considered consistent and the same in determining the best alternative based on the given preferences and criteria.

The results of the sensitivity analysis using Pearson's correlation for each weight change ranging from 0.1 to 0.5, obtained a high correlation coefficient of 1 which shows that the vendor rating is very sensitive to changes in criterion weights. This indicates that if there is a change in the weight of the criteria, the vendor's rating may change significantly. The results of Vendor 6 retained the first rank in any weight change, indicating good performance stability. Future research from the development of the MAUT method can be directed at several innovative aspects to increase its relevance and application. One of the focuses is integration with advanced weighting methods, such as machine learning-based approaches or hybrid entropy, to improve the objectivity and flexibility of decision analysis. Computing efficiency can be a priority to ensure the implementation of MAUT on resource-constrained devices or large-scale scenarios, thus driving the use of this method in a variety of increasingly complex decision contexts.

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