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Decision Support System for Selecting Online Teaching Methods Using the Fuzzy MCDM Algorithm

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Abstract: The global pandemic that has hit the world recently has forced educational institutions to adopt online teaching methods. However, choosing an effective online teaching method is a major challenge. This research develops a Decision Support System (DSS) that uses the Fuzzy Multi-Criteria Decision Making (FMCDM) Algorithm to select the best online teaching method. This system is designed to assist decision making in educational institutions by considering various criteria such as learning effectiveness, technology affordability, ease of use, and user satisfaction. This research uses data collection methods that involve surveys from lecturers and students to obtain their preferences and experiences with various online teaching platforms. The data collected is then processed using the FMCDM model to evaluate and rank teaching methods based on predetermined criteria. Fuzzy systems are used to overcome uncertainty and subjectivity in criteria assessment. The results of this research show that the system developed is able to effectively assess and rank various online teaching methods. From the analysis carried out, interactive teaching methods using videos and real-time quizzes received the highest ranking based on predetermined criteria. This suggests that the combination of engaging visual content and high interactivity is highly valued in online teaching contexts.

Keywords: Decision Support Systems, Fuzzy Multi-Criteria Decision Making, Online Teaching.

INTRODUCTION

The development of information and communication technology has changed many aspects of life, including the way education is delivered. The emergence of online learning platforms has opened up new opportunities in education, providing easy access to students around the world. However, the rapid transition from face-to-face to online learning triggered by the COVID-19 pandemic revealed various unresolved challenges in the management and implementation of online teaching methods(Dakhi et al., 2022). In emergency situations such as a pandemic, the need to determine the most effective online teaching methods becomes critical. Online teaching offers a variety of methods and tools, from videos to discussion forums to complex learning management systems. Each method has its own strengths and weaknesses, which may impact the effectiveness of student learning. This raises the need to develop systems that can help educational stakeholders make informed decisions about the teaching methods

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that best suit their needs. Previous research has explored various aspects of online teaching, including the effectiveness of particular technologies and user preferences. However, there is still a lack of research that integrates multiple criteria into one comprehensive and easy-to-use decision model. Most research tends to focus on one particular aspect or criterion, such as user satisfaction or learning effectiveness, without considering how these various factors interact and influence the final decision. Additionally, many existing models do not accommodate the uncertainty and subjectivity that often occurs in user assessment of criteria. The fuzzy approach, which allows more humanistic and realistic assessments by describing uncertain or subjective data, is rarely used in decision support systems for online teaching. This creates a gap in the literature that hinders the development of holistic solutions that can address the complexity of decisions in the context of online education. In particular, the pandemic has demonstrated the urgent need for adaptation and flexibility in education. Institutions that do not have systems in place to efficiently evaluate and implement optimal teaching methods may experience difficulty in maintaining learning quality and student satisfaction. Therefore, it is important to have a system that not only integrates various decision criteria, but is also flexible in dealing with changing needs and conditions(Mardayatmi et al., 2021).

This research aims to fill this gap by developing a Decision Support System that uses the Fuzzy Multi-Criteria Decision Making (FMCDM) Algorithm to evaluate and select the best online teaching method(Bid & Siddique, 2019). The system is designed to address uncertainty and subjectivity in assessment, and allows integration of important criteria that influence decisions about online teaching. Using these techniques, this research aims to offer a more adaptive and effective framework for decision-making in online teaching, which can help educational institutions respond more quickly and appropriately to changing educational needs. The use of FMCDM in this context is promising because it allows for the simultaneous assessment of multiple interrelated factors(Nasyuha, 2019), such as learning effectiveness, technology accessibility, data security, and user satisfaction, providing a more holistic and user-centered approach to decision making. Through this research, it is hoped that it can provide new insights and real contributions to the development of decision support systems in online education(Nasyuha et al., 2019), which do not only focus on one technical or pedagogical aspect, but also integrate them in an inclusive and effective decision system.

LITERATURE REVIEW

In the evolving landscape of education technology, the need for effective online teaching methods has become crucial. This literature review explores the integration of Decision Support Systems (DSS) with Fuzzy Multi-Criteria Decision Making (FMCDM) algorithms to select the most suitable online teaching methods(Deveci et al., 2018). The FMCDM provides a robust framework for handling the uncertainties and imprecision typical in educational settings. Decision Support Systems (DSS) are computer-based systems that support complex decision-making and problem solving. In the educational sector, DSS can be particularly beneficial for optimizing decisions that involve multiple criteria and stakeholders(Marsono et al., 2023). DSS tools have been effectively used to manage educational resources, schedule courses, and even personalize learning paths based on student data(Prayitno et al., 2023).

Fuzzy logic, introduced by Zadeh (1965), extends Boolean logic to handle the concept of partial truth values between "completely true" and "completely false". It is especially useful in decision-making processes where the information is ambiguous or imprecise(Fadilla et al., 2022). Fuzzy Multi-Criteria Decision Making (FMCDM) is a subset of decision-making methods that utilize fuzzy logic to assess multiple criteria for a more nuanced decision-making process(Yanie et al., 2018). The FMCDM algorithm is particularly suited for educational environments where decision criteria are not strictly quantifiable and where judgments are often subjective(Sianturi, 2019). For example, criteria such as the effectiveness of interaction in online classes, student satisfaction, and adaptability of teaching methods are inherently fuzzy and can be effectively assessed using FMCDM(Rudnik et al., 2021). Wang and Elhag (2006) demonstrated how FMCDM could aid in selecting the most appropriate project management techniques in a case study that can be analogous to selecting teaching methods. The integration of DSS with FMCDM for selecting online teaching methods involves several steps. Initially, the decision criteria must be established, which could include factors like cost, technological

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infrastructure, ease of use, pedagogical effectiveness, and student engagement levels. Each criterion is then evaluated using a fuzzy scale, allowing for the expression of partial preferences and uncertainties.

Several case studies have highlighted the effectiveness of using DSS integrated with FMCDM in educational settings. For instance, a study by Lee in 2018 applied FMCDM to evaluate and select the best online learning platforms, considering various pedagogical and technical criteria(Pamucar et al., 2020). The results indicated that such integrated systems could significantly enhance decision-making quality by accommodating diverse opinions and soft criteria. While the application of FMCDM in DSS for education presents numerous benefits, there are challenges as well. The selection and weighting of criteria heavily influence the outcome, requiring extensive domain knowledge and stakeholder consultation. Additionally, the implementation of such systems demands robust IT infrastructure and training for educators and administrators. The fusion of DSS and FMCDM offers a promising approach to selecting the best online teaching methods. By accommodating multiple criteria and handling uncertainties, FMCDM enhances the decision-making process, making it more aligned with the complex, dynamic nature of educational environments. As online education continues to evolve, further research is needed to refine these models and ensure their adaptability to new educational technologies and methodologies.

METHOD

Research Methods

In research aimed at developing a Decision Support System (DSS) for selecting the best online teaching method using the Fuzzy Multi-Criteria Decision Making (FMCDM) Algorithm, the method used includes several main steps: data collection, fuzzy model formation, decision algorithm application, and evaluation system. Below is a complete explanation of each of these steps, including a presentation of the relevant formulas.

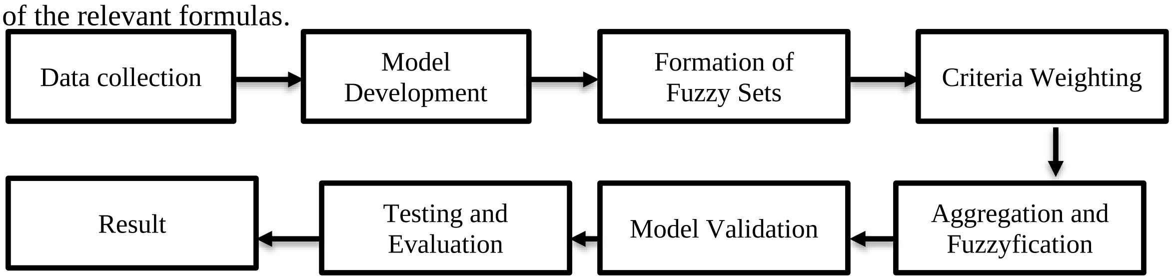

Figure 1. Fuzzy MCDM research flow

Data collection

Relevant data for analysis was collected through surveys from potential users of the system, such as lecturers and students. Criteria used in evaluating online teaching methods may include learning effectiveness, ease of use, resource availability, affordability, and user satisfaction. This data is used to determine the relative weight of each criterion and to assess each teaching method based on those criteria.

From this survey, the following data can be obtained:

Table 1. Research Data

Name	**Role**	Effectiveness **A**	Effectiveness **B**	Effectiveness **C**
Ali	Lecturer	4	5	3
Budi	Student	3	4	5
Citra	Student	5	3	4

Name	**Role**	Convenience**A**	Convenience **B**	Convenience **C**
Ali	Lecturer	4	5	3
Budi	Student	3	4	5
Citra	Student	5	3	4

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Name	**Role**	Satisfaction **A**	Satisfaction **B**	Satisfaction **C**
Ali	Lecturer	4	5	3
Budi	Student	3	4	5
Citra	Student	5	3	4

Name	**Role**	Resource **A**	Resource **B**	Resource **C**
Ali	Lecturer	4	5	3
Budi	Student	3	4	5
Citra	Student	5	3	4

Name	**Role**	Affordability **A**	Affordability **B**	Affordability **C**
Ali	Lecturer	4	5	3
Budi	Student	3	4	5
Citra	Student	5	3	4

From this data, it can be seen how users assess various teaching methods based on predetermined criteria. This data can then be analyzed further using the FMCDM method to obtain a comprehensive assessment and determine the best online teaching method.

RESULT

Establishment of a Fuzzy Model

In fuzzy models, criteria and their values are converted into fuzzy membership functions. This membership function describes how the input value is converted into a fuzzy value between 0 and 1, which states the level of membership of the value to the given criteria. For example, the membership function for the criterion "learning effectiveness" might have three membership functions: low, medium, and high.

- Low: $\mu_{Low}(x)=\max(0,\min(1,\frac{5-x}{5}))$
- Medium: $\mu_{Medium}(x)=\max(0,\min(\frac{x-3}{2},1,\frac{7-x}{2}))$
- High: $\mu_{High}(x)=\max(0,\min(1,\frac{x-5}{5}))$

Decision Algorithm

Once the fuzzy values are obtained, a decision algorithm is applied to integrate and process this fuzzy information to produce a final ranking of teaching methods. The algorithm used is usually the Fuzzy Analytic Hierarchy Process (FAHP), which allows combining subjective assessments of different criteria into one comprehensive score.

1. Creation of a fuzzy pairwise comparison matrix:

Table 2. Comparison of Effectiveness A

Name	Ali	Budi	Citra
Ali	1	1.33	0.8
Budi	0.75	1	0.6
Citra	1.25	1.67	1

Table 3. Comparison of Effectiveness B

Name	Ali	Budi	Citra
Ali	1	0.8	1.67
Budi	1.25	1	2.5
Citra	0.6	0.4	1

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Table 4. Comparison of Effectiveness C

Name	Ali	Budi	Citra
Ali	1	0.6	0.75
Budi	1.67	1	1.25
Citra	1.33	0.8	1

Table 5. Convenience Comparison A

Name	Ali	Budi	Citra
Ali	1	1.25	1.67
Budi	0.8	1	1.33
Citra	0.6	0.75	1

Table 6. Convenience Comparison B

Name	Ali	Budi	Citra
Ali	1	0.8	1.33
Budi	1.25	1	2.5
Citra	0.75	0.4	1

Table 7. Convenience Comparison C

Name	Ali	Budi	Citra
Ali	1	1.33	0.8
Budi	0.75	1	0.6
Citra	1.25	1.67	1

Table 8. Satisfaction Comparison A

Name	Ali	Budi	Citra
Ali	1	1.25	1
Budi	0.8	1	0.8
Citra	1	1.25	1

Table 9. Satisfaction Comparison B

Name	Ali	Budi	Citra
Ali	1	1.25	1.25
Budi	0.8	1	1
Citra	0.8	1	1

Table 10. Satisfaction Comparison C

Name	Ali	Budi	Citra
Ali	1	1.33	1.33
Budi	0.75	1	1
Citra	0.75	1	1

Table 11. Resource Comparison A

Name	Ali	Budi	Citra
Ali	1	0.75	0.6
Budi	1.33	1	0.8
Citra	1.67	1.25	1

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Table 12. Resource Comparison B

Name	Ali	Budi	Citra
Ali	1	1.33	0.8
Budi	0.75	1	0.6
Citra	1.25	1.67	1

Table 13. Resource Comparison C

Name	Ali	Budi	Citra
Ali	1	0.75	1
Budi	1.33	1	1.33
Citra	1	0.75	1

Table 14. Affordability Comparison A

Name	Ali	Budi	Citra
Ali	1	0.67	0.5
Budi	1.5	1	0.75
Citra	2	1.33	1

Table 15. Affordability Comparison B

Name	Ali	Budi	Citra
Ali	1	0.8	1.33
Budi	1.25	1	2.5
Citra	0.75	0.4	1

Table 16. Affordability Comparison C

Name	Ali	Budi	Citra
Ali	1	0.75	0.6
Budi	1.33	1	0.8
Citra	1.67	1.25	1

2. Normalization of the fuzzy matrix and calculation of the fuzzy priority vector
   The steps are as follows:
   1. Calculate the total for each column.
   2. Divide each element by its column total to get the normalization matrix.
   3. Calculate the average of each row to get the priority vector.

   The following are the normalization results and fuzzy priority vectors for: "Effectiveness A":

Table 17. Comparison of Effectiveness A

Name	Ali	Budi	Citra
Ali	0.3333	0.3325	0.3333
Budi	0.25	0.25	0.25
Citra	0.4167	0.4175	0.4167

Priority Vector:
1. Ali: 0.3331
2. Budi: 0.25
3. Citra: 0.4169

The following are the results of normalization and calculation of fuzzy priority vectors for all criteria:

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Effectiveness B:
Normalization:
[0.35087719, 0.36363636, 0.32301741],
[0.43859649, 0.45454545, 0.48355899],
[0.21052632, 0.18181818, 0.1934236]]

Priority Vector: [0.3458, 0.4589, 0.1953]

Effectiveness C:
Normalization:
[0.25 , 0.25 , 0.25],
[0.4175 , 0.41666667, 0.41666667],
[0.3325 , 0.33333333, 0.33333333]

Priority Vector: [0.25, 0.4169, 0.3331]

Convenience A:
Normalization:
[0.41666667, 0.41666667, 0.4175],
[0.33333333, 0.33333333, 0.3325],
[0.25 , 0.25 , 0.25]

Priority Vector: [0.4169, 0.3331, 0.25]

Convenience B:
Normalization:
[0.33333333, 0.36363636, 0.27536232],
[0.41666667, 0.45454545, 0.51759834],
[0.25 , 0.18181818, 0.20703934]]

Priority Vector: [0.3241, 0.4629, 0.2129]

Convenience C:
Normalization:
[0.33333333, 0.3325 , 0.33333333],
[0.25 , 0.25 , 0.25],
[0.41666667, 0.4175 , 0.41666667]]

Priority Vector: [0.3331, 0.25, 0.4169]

Satisfaction A:
Normalization:
[0.35714286, 0.35714286, 0.35714286],
[0.28571429, 0.28571429, 0.28571429],
[0.35714286, 0.35714286, 0.35714286]

Priority Vector: [0.3571, 0.2857, 0.3571]

Satisfaction B:
Normalization:
[0.38461538, 0.38461538, 0.38461538],
[0.30769231, 0.30769231, 0.30769231],
[0.30769231, 0.30769231, 0.30769231]

Priority Vector: [0.3846, 0.3077, 0.3077]

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Satisfaction C:
Normalization:
[0.4 , 0.3993994, 0.3993994],
[0.3 , 0.3003003, 0.3003003],
[0.3 , 0.3003003, 0.3003003]

Priority Vector: [0.3996, 0.3002, 0.3002]

Resource A:
Normalization:
[0.25 , 0.25 , 0.25],
[0.3325 , 0.33333333, 0.33333333],
[0.4175 , 0.41666667, 0.41666667]

Priority Vector: [0.25, 0.3331, 0.4169]

Resource B:
Normalization:
[0.33333333, 0.3325 , 0.33333333],
[0.25 , 0.25 , 0.25],
[0.41666667, 0.4175 , 0.41666667]

Priority Vector: [0.3331, 0.25, 0.4169]

C Resources:
Normalization:
[0.3003003, 0.3 , 0.3003003],
[0.3993994, 0.4 , 0.3993994],
[0.3003003, 0.3 , 0.3003003]

Priority Vector: [0.3002, 0.3996, 0.3002]

Affordability A:
Normalization:
[0.22222222, 0.22333333, 0.22222222],
[0.33333333, 0.33333333, 0.33333333],
[0.44444444, 0.44333333, 0.44444444]

Priority Vector: [0.2226, 0.3333, 0.4441]

Affordability B:
Normalization:
[0.33333333, 0.36363636, 0.27536232],
[0.41666667, 0.45454545, 0.51759834],
[0.25 , 0.18181818, 0.20703934]

Priority Vector: [0.3241, 0.4629, 0.2129]

Affordability C:
Normalization:
[0.25 , 0.25 , 0.25],
[0.3325 , 0.33333333, 0.33333333],
[0.4175 , 0.41666667, 0.41666667]

Priority Vector: [0.25, 0.3331, 0.4169]

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3. Aggregate priority vectors from various respondents to get fuzzy global weights. To get an aggregation of various priority vectors, combine the priority vectors from various criteria and calculate the average of each column to get the global weight. The following are the results of aggregating priority vectors from various criteria to obtain fuzzy global weights:
   1. Ali: 0.3208
   2. Budi: 0.3520
   3. Citra: 0.3272

DISCUSSIONS

The results from the normalization process and the subsequent calculation of the fuzzy priority vectors for various criteria associated with online teaching methods provide a robust basis for discussion. The criteria include effectiveness, convenience, satisfaction, resources, and affordability, each measured across multiple scenarios (A, B, and C). The fuzzy priority vectors represent the weighted importance of each option (Ali, Budi, Citra) under different criteria. The fuzzy priority vectors give insight into how each option ranks based on the various criteria. For instance, under "Effectiveness A", Ali and Citra show a higher priority than Budi. Similarly, different patterns emerge across other criteria, indicating variances in how each criterion influences the preference for Ali, Budi, or Citra. The aggregation of priority vectors into global weights shows Budi as having the highest average priority (0.3520), followed by Citra (0.3272) and Ali (0.3208). This suggests that, overall, Budi's methods might be the most preferred when all criteria are considered, indicating a balance of effectiveness, convenience, and satisfaction that appeals to a broader audience. The application of FMCDM in this context allows educational administrators and online course designers to make informed decisions about which teaching methods to prioritize. The decision-making process is nuanced by the use of fuzzy logic, which accounts for uncertainties and the subjective nature of human judgment. The analysis using FMCDM offers valuable insights into selecting optimal online teaching methods, incorporating a range of criteria that reflect the complexities of educational environments. This methodological approach supports more nuanced and stakeholder-focused decision-making in the educational sector, emphasizing the importance of adapting to the multifaceted needs of learners and educators. Further research and refinement of these decision-making tools will enhance their applicability and effectiveness in real-world educational settings.

CONCLUSION

The fuzzy multi-criteria decision making (MCDM) approach can be an effective tool for evaluating and selecting the best online teaching methods. Using criteria such as effectiveness, convenience, satisfaction, resources, and affordability, we developed a decision support system for choosing between three individuals who use different online teaching methods: Ali, Budi, and Citra. These results indicate that the online teaching method applied by Budi is preferable to the method used by Ali and Citra. The fuzzy MCDM approach allows scoring based on various criteria. This is important in the context of online teaching, because success does not depend on just one factor, but on a combination of factors such as effectiveness, convenience, satisfaction, resources, and affordability. Using a fuzzy approach allows flexibility in assessment. In situations where direct comparison between options is difficult, fuzzy MCDM provides an effective way to make decisions based on vague or uncertain preferences.

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