Journal Publication of International Research for Engineering and Management (JOIREM)
Volume: 04 Issue: 03 | Mar-2026
ISSN (O) 3107-6696

AI-Based Multi-Criteria Decision-Making (MCDM) Models

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Abstract- Complex environments tend to compel decision-making to consider a number of conflicting criteria at the same time. Multi-Criteria Decision-Making (MCDM) tools have been extensively applied to assist in facilitating structure decision-making in business management, engineering, healthcare, and the public policy arena. As the field of artificial intelligence (AI) is evolving rapidly, the conventional MCDM models are gradually being combined with machine learning, fuzzy logic, and evolutionary algorithms to enhance the accuracy and flexibility of decisions. MCDM models that utilize AI can help companies process large volumes of data, model uncertainty, and make complicated decisions through automation. In this paper, AI-based MCDM models and their uses in business and management decision-making are reviewed. The research points to the significant methods of artificial neural networks, fuzzy systems, evolutionary algorithms, and hybrid AI models. These results indicate that AI-based MCDM models can help to improve the quality and efficiency of the decisions considerably, but issues of model transparency, computational complexity, and data quality are also not negligible. The ways forward in future research involve creating explainable AI systems and hybrid intelligent decision support systems.

***Keywords*:** Artificial Intelligence, Multi-Criteria Decision-Making, Decision Sciences, Machine Learning, Decision Support Systems

1. Introduction

In contemporary organizations, decision-making is becoming highly complicated as it has to deal with a number of, often competing criteria. Cost, quality, risk, sustainability, and efficiency are some of the factors that managers should put into consideration when making an evaluation (Saaty, 1980). The Multi-Criteria Decision-Making (MCDM) techniques offer a logical way of evaluating such options and finding the best ones (Triantaphyllou, 2000).

The MCDM techniques of the traditional type such as the Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) have been extensively applied to decision sciences (Hwang and Yoon, 1981). Nevertheless, they can be limited in cases where dealing with big data, uncertainty, and dynamic environments (Zavadskas and Turskis, 2011).

Artificial Intelligence (AI) has become a potent instrument in improving the decision-making process since it allows predictive analysis and data modeling (Russell and Norvig, 2021). MCDM methods can be enhanced with AI methods including machine learning, neural networks, and fuzzy systems to enhance their performance and flexibility (Goodfellow, Bengio, and Courville, 2016).

AI-based MCDM models also enable the decision-makers to work with complex datasets, use uncertainty, and create optimal decisions in real-time settings (Davenport and Harris, 2007). Such models are also more and more used in the field of supply chain management, financial analysis, healthcare planning, and environmental management (Choi, Wallace, and Wang, 2018).

This paper will analyze the significance of AI-based MCDM models in the contemporary decision-making and review their methods, applications, and issues.

2. Literature Review

2.1 Multi-Criteria Decision-Making Models

MCDM is a term which is employed to refer to a group of techniques applied to compare alternatives in terms of various criteria (Triantaphyllou, 2000). The techniques help decision-makers to make the most appropriate choice when there exists a trade-off between criteria (Belton and Stewart, 2002).

The Analytic Hierarchy Process (AHP) is one of the most popular MCDM approaches that organizes decision issues into hierarchical steps and uses the weight of criteria in terms of pair-to-pair comparison (Saaty, 1980). The other technique that is widely employed is the TOPSIS which ranks the alternatives depending on their proximity to ideal and negative ideal solutions (Hwang and Yoon, 1981).

The other MCDM methods are ELECTRE, PROMETHEE and VIKOR methods, which offer alternative mechanisms of comparing the decision alternatives (Zavadskas and Turskis, 2011). The techniques have been extensively used in the engineering design, project selection and also in policy evaluation.

Nevertheless, conventional MCDM approaches might not have the capacity to work with big data and ambiguous data, which is why scientists combine them with AI algorithms (Velasquez and Hester, 2013).

2.2 Artificial Intelligence in Decision Sciences

Artificial Intelligence is defined as computational systems that can perform tasks that would be performed using human intelligence like reasoning, learning, and problem-solving (Russell and Norvig, 2021). The advancement of AI technologies has made the use of such technologies in decision sciences more significant because it can interpret big data and provide predictive information (Jordan and Mitchell, 2015).

The machine learning algorithms enable systems to recognize data patterns and enhance accuracy in decision-making as time goes by (Mitchell, 1997). Such algorithms are common in predictive analytics, classification and optimization (Hastie, Tibshirani, and Friedman, 2009).

AI can also be used to improve decision-making processes by automating the data analysis process and finding some complicated relationships among variables that can be missed by traditional models (Domingos, 2012).

2.3 AI-Based MCDM Techniques

MCDM models based on AI are the models that include both artificial intelligence and traditional decision-making models.

ANNs are often employed to estimate the complicated interconnection between decision criteria (Goodfellow et al., 2016). Such networks are capable of learning nonlinear tendencies as well as being capable of multi-criteria assessments.

The other common approach that is applicable in MCDM is fuzzy logic especially where the criteria of decision making are uncertain or linguistic in nature (Zadeh, 1965). Fuzzy MCDM models can help decision-makers manage inaccurate information (Zimmermann, 2001).

Genetic algorithms are evolutionary algorithms which are usually combined with MCDM techniques to determine the optimal solution to complex optimization problems (Goldberg, 1989). The algorithms imitate the natural selection patterns in order to produce better solutions with time (Deb, 2001).

Artificial intelligence has also been used to create hybrids via neural networks, fuzzy logic, and optimization algorithms that can be used to improve decision support systems (Chen, Chiang, and Storey, 2012).

2.4 Applications of AI-Based MCDM Models

MCDM models that are AI-based have found extensive application in various industries.

These models are used in the supply chain management process to assist organizations to appraise the suppliers according to a variety of parameters including cost, reliability, and sustainability (Choi et al., 2018).

AI-based MCDM methods are used to help investors in choosing the best portfolios in terms of risk, returns, and the market conditions in financial decision-making (Bertsimas and Kallus, 2020).

The AI-MCDM models can assist medical decision-making in healthcare by evaluating treatment options in terms of patient outcomes and available resources (Topol, 2019).

Likewise in the case of environmental management, MCDM models can assist policy makers to assess sustainability policies by taking into consideration economic, social, and environmental policies (Keeney and Raiffa, 1993).

2.5 Challenges of AI-Based MCDM Models

Although AI-based MCDM models have their benefits, they have a number of challenges. Model interpretability is among the key problems because complicated AI models can serve as black boxes, and it can be hard to determine the rationale behind recommendations by the decision-maker (Rudin, 2019).

The other issue is the quality of data, as inaccurate or incomplete data sets may have harmful implications on the performance of models (Kelleher, Mac Namee, and D'Arcy, 2015).

Also, adopting AI-driven decision support systems can be very costly in terms of computational power and technical skills (Brynjolfsson and McAfee, 2014).

These issues need to be addressed to make sure that AI-based MCDM models can be adopted successfully in the decision sciences.

3. Research Methodology

The paper employs a conceptual and literature based research approach. The secondary data sources were comprised of academic journals, books and conference publications on artificial intelligence and multi-criteria decision making.

The systematic literature review aimed at analyzing the progress of AI-based MCDM models, determining the most important techniques, and discussing their usage in various industries.

4. Discussion

The combination of artificial intelligence and MCDM models helps to improve the level of decision-making greatly. Artificial intelligence methods provide companies with an opportunity to process intricate data set and find the most efficient solutions based on various criteria.

Such hybrid models involving the application of machine learning algorithms with conventional MCDM techniques are especially useful in the context of complex decision environments. These models enable organizations to come up with more precise and flexible decisions.

Nevertheless, organizations need to be transparent and ethical in their decision systems that are based on AI. One of the ways to enhance the trust and accountability of AI-supported decision-making processes is through explainable AI models.

5. Conclusion

Multi-Criteria Decision-Making models based on AI is an effective model to tackle the problem of decisions with several goals. Once combined with conventional MCDM approaches, machine learning, fuzzy logic, and optimization, the organizations can considerably improve the accuracy and efficacy of their decision.

Although all these will be an advantage, issues like model interpretability, data quality, and computational complexity should be addressed. Further studies ought to be conducted on the creation of explainable AI-MCDM models as well as hybrid AI-MCDM models, which enhance transparency and scalability.

In general, AI-based MCDM models are likely to be instrumental in the development of decision sciences and to assist the process of strategic decision-making at data-driven organizations.

References

- Belton, V., & Stewart, T. (2002). *Multiple criteria decision analysis*. Springer.
- Bertsimas, D., & Kallus, N. (2020). From predictive to prescriptive analytics. *Management Science*, 66(3), 1025–1044.
- Brynjolfsson, E., & McAfee, A. (2014). *The second machine age*. W.W. Norton.
- Chen, H., Chiang, R., & Storey, V. (2012). Business intelligence and analytics. *MIS Quarterly*, 36(4), 1165–1188.
- Choi, T., Wallace, S., & Wang, Y. (2018). Big data analytics in operations management. *Production and Operations Management*, 27(10), 1868–1883.
- Davenport, T., & Harris, J. (2007). *Competing on analytics*. Harvard Business School Press.
- Deb, K. (2001). *Multi-objective optimization using evolutionary algorithms*. Wiley.
- Domingos, P. (2012). A few useful things to know about machine learning. *Communications of the ACM*, 55(10), 78–87.
- Goldberg, D. (1989). *Genetic algorithms in search, optimization and machine learning*. Addison-Wesley.
- Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.
- Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning*. Springer.
- Hwang, C., & Yoon, K. (1981). *Multiple attribute decision making*. Springer.
- Jordan, M., & Mitchell, T. (2015). Machine learning: Trends and prospects. *Science*, 349(6245), 255–260.
- Keeney, R., & Raiffa, H. (1993). *Decisions with multiple objectives*. Cambridge University Press.

- Kelleher, J., Mac Namee, B., & D'Arcy, A. (2015). *Fundamentals of machine learning for predictive data analytics*. MIT Press.
- Mitchell, T. (1997). *Machine learning*. McGraw-Hill.
- Provost, F., & Fawcett, T. (2013). *Data science for business*. O'Reilly.
- Rudin, C. (2019). Stop explaining black box machine learning models. *Nature Machine Intelligence*, 1(5), 206–215.
- Russell, S., & Norvig, P. (2021). *Artificial intelligence: A modern approach* (4th ed.). Pearson.
- Saaty, T. (1980). *The analytic hierarchy process*. McGraw-Hill.
- Shmueli, G., & Koppius, O. (2011). Predictive analytics in information systems research. *MIS Quarterly*, 35(3), 553–572.
- Topol, E. (2019). *Deep medicine*. Basic Books.
- Triantaphyllou, E. (2000). *Multi-criteria decision making methods*. Springer.
- Velasquez, M., & Hester, P. (2013). An analysis of multi-criteria decision making methods. *International Journal of Operations Research*, 10(2), 56–66.
- Zadeh, L. (1965). Fuzzy sets. *Information and Control*, 8(3), 338–353.
- Zimmermann, H. (2001). *Fuzzy set theory and its applications*. Springer.
- Zavadskas, E., & Turskis, Z. (2011). Multiple criteria decision making methods. *Technological and Economic Development of Economy*, 17(2), 397–427.