



Intelligent decision support system for post-disaster damage assessment: integrating modified-topsis and neural networks for enhanced decision-making performance

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Article Information	Abstract
Submitted: Jan 17, 2026 Revised: March 23, 2026 Accepted: April 25, 2026 Keywords Intelligent Decision; Modified-TOPSIS; Neural Networks; Post Disaster; Multi Criteria.	Purpose: This study aims to develop an advanced Dynamic Intelligent Decision Support System (IDSS) for determining the damage level of sectors affected by natural disasters. Method: The research combines the Modified-TOPSIS method, a Multi-Criteria Decision-Making (MCDM) approach, with Neural Networks to improve post-disaster damage assessment. The method applies Pairwise Comparison for weighting criteria, and the Neural Network learns from historical data to enhance the accuracy of decisions. The system was tested with data from Blitar, East Java, and evaluated for accuracy using metrics such as precision, recall, and F-measure. Findings: The findings indicate that the Modified-TOPSIS method achieves 75% accuracy, while incorporating Neural Networks improves accuracy to 81%. The integration of Neural Networks provides more reliable and objective results compared to the Modified-TOPSIS method alone, particularly in managing complex data. Significance: This study contributes significantly to disaster management by offering a reliable, data-driven tool for assessing damage in affected sectors. The integration of AI with classical MCDM methods represents a major advancement in disaster recovery, providing more timely and efficient decision-making to aid rehabilitation efforts.

INTRODUCTION

Indonesia is frequently impacted by natural disasters such as earthquakes, floods, and volcanic eruptions, which cause extensive damage to critical sectors, including housing, infrastructure, economy, and social services. Post-disaster recovery efforts are heavily reliant on accurate damage assessments, which are essential for directing resources effectively (Mushtaha et al., 2025; Rouhanizadeh et al., 2020; Shafian & Hu, 2024). However, damage assessments conducted by surveyors often lack consistency due to the absence of clear, standardized criteria. This inconsistency in data reporting by local authorities such as the Regional Disaster Management Agency (BPBD) can delay response times and hinder timely assistance. Consequently, the need for an objective and reliable damage assessment system becomes evident. Artificial Intelligence (AI)-based Decision Support Systems (DSS) have emerged as a promising solution to enhance the accuracy and consistency of damage assessments (Kostopoulos et al., 2024; Ravi et al., 2025; Zabihi et al., 2023). One approach, Multi-Criteria Decision Making (MCDM), particularly the Modified-TOPSIS method, has demonstrated effectiveness in such assessments, yet it is still constrained by limitations in its accuracy and adaptability to the rapidly changing data encountered in post-disaster environments. Therefore, the integration of MCDM methods

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with Neural Networks could improve the quality and adaptability of post-disaster damage assessment systems. This research proposes the development of an advanced Intelligent Decision Support System Dynamic (IDSSD) that combines these two approaches to enhance damage assessment in the aftermath of natural disasters.

Traditional Decision Support Systems (DSS) are often inflexible when handling dynamic and complex data, especially in disaster contexts that require quick and precise action. Previous studies have demonstrated that incorporating Artificial Intelligence (AI) can significantly improve decision-making by enhancing accuracy and efficiency (Fonseca et al., 2024; Neiroukh et al., 2025). Specifically, Neural Networks, a method widely used in predictive analytics and classification tasks, offer substantial potential for improving the accuracy of damage assessments. These networks can learn from large datasets and adapt to new information, providing results that are more accurate in unpredictable scenarios. However, a major challenge in utilizing Neural Networks for post-disaster damage assessment is the presence of uncertain and incomplete data (Al Shafian & Hu, 2024; Jia & Ye, 2023; Zhang & Pan, 2022). This limitation can compromise the effectiveness of traditional methods, which often rely on structured data inputs. To address this challenge, this study suggests combining the Modified-TOPSIS method with Neural Networks. This hybrid approach will not only ensure that the decision-making process remains objective but also allow the system to better handle uncertainties and variability in the data, providing more reliable results in the field. The integration of these two methods is expected to offer a robust solution for faster and more consistent recovery efforts.

While the Modified-TOPSIS method is effective in evaluating post-disaster damage based on predefined criteria, it is primarily limited to processing structured data and does not easily accommodate the dynamic and multifaceted nature of real-time disaster scenarios. On the other hand, Neural Networks can manage both structured and unstructured data, learning from historical trends and detecting damage patterns that might not be immediately obvious through traditional methods (Goel et al., 2023; Rithani et al., 2023). The key challenge in applying Neural Networks in disaster recovery lies in the need for high-quality training data. Most data collected during disasters are inconsistent, incomplete, or unreliable, which can make it difficult for AI models to function effectively without large, comprehensive datasets (Rehan, 2022; Tan et al., 2021). However, combining these two methods Modified-TOPSIS for criteria-based decision-making and Neural Networks for handling data uncertainty could yield more adaptable and accurate results. This research aims to integrate these methods into a single Intelligent Decision Support System Dynamic (IDSSD), offering a system capable of assessing post-disaster damage more effectively. By combining the strengths of both methods, the system will be able to process complex, variable data and deliver reliable results that can assist recovery teams. The goal is to test and evaluate the performance of the IDSSD system in real-world post-disaster situations and to compare its efficacy with traditional assessment methods.

The existing literature reveals several gaps in post-disaster damage assessment systems. While machine learning and remote sensing have been integrated into building damage assessment (Braik & Koliou, 2025; Shafian & Hu, 2024), challenges remain in real-time application and data processing, particularly in diverse disaster scenarios (Jung et al., 2020). Despite advancements in Intelligent Decision Support Systems (IDSS), there is

insufficient research on standardization and automation of data collection tools, which are essential for consistent and efficient decision-making (Lozano & Tien, 2023). Moreover, AI-based models like U-Net and Neural Networks) still struggle with black-box issues, limiting transparency in critical decision-making situations, while XAI approaches need further exploration to balance explainability and accuracy. Additionally, the integration of multi-criteria decision-making (MCDM) methods has been shown to aid in prioritizing post-disaster recovery efforts (Mohammadnazari et al., 2022), but they lack flexibility and adaptability to dynamic, changing conditions. These gaps point to the need for more robust, real-time, and adaptable systems that can handle evolving data and ensure faster, more objective decision-making across diverse post-disaster environments.

The purpose of this research is to develop and implement an Intelligent Decision Support System Dynamic (IDSSD) that integrates the Modified-TOPSIS method with Neural Networks to evaluate the extent of damage in sectors impacted by natural disasters. This system is expected to improve the accuracy, objectivity, and speed of post-disaster damage assessments, thereby facilitating more efficient decision-making for recovery operations. This study will also assess the system's ability to handle incomplete and conflicting data, providing a more efficient and adaptable solution for post-disaster recovery and decision-making.

LITERATURE REVIEW

Post-disaster damage assessment plays a critical role in the recovery process, as it provides the necessary data to allocate resources efficiently. Traditional methods of damage assessment often rely on subjective evaluations from surveyors, which can lead to inconsistencies in the data. In contrast, automated decision support systems (DSS) provide a more objective approach to evaluating damage by integrating multiple criteria to assess the severity of destruction (Aldeeb & Qasem, 2022; Zabihi et al., 2023). Previous studies have explored the potential of Multi-Criteria Decision Making (MCDM) methods, such as the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), in evaluating damage assessments across multiple sectors (Chaube et al., 2024; Potur et al., 2025). However, the main challenge with MCDM methods is their reliance on subjective weights for criteria, which can vary depending on the context of the disaster. More recent approaches have integrated AI techniques, such as Neural Networks, to refine the decision-making process by learning from historical data and making predictions based on new, unseen data. These AI-enhanced systems have the potential to improve accuracy by accounting for non-linear relationships in data that are often missed by traditional methods. However, the challenge remains to combine the strengths of AI with the structured decision-making frameworks of MCDM to create a system that is both accurate and interpretable. Several studies have identified this gap in integrating Neural Networks with MCDM methods for disaster damage assessment. This hybrid approach is expected to address the limitations of both techniques, offering a more robust solution to the assessment of post-disaster damage.

Decision support systems (DSS) are increasingly being recognized as valuable tools in disaster management, enabling faster and more accurate decision-making. These systems often integrate multiple sources of data and analytical models to support complex

decisions in dynamic environments. In disaster management, DSS can be particularly useful for determining priorities, allocating resources, and assessing the severity of damage (Jana et al., 2022; Khan et al., 2023; Rezvani et al., 2023). Traditional DSS, however, are often rigid and lack the flexibility needed to adapt to rapidly changing disaster scenarios. Research has shown that integrating AI and machine learning techniques can significantly enhance the capabilities of DSS by allowing these systems to process large amounts of unstructured data and provide real-time insights. For instance, Neural Networks have been widely used to model complex relationships and predict outcomes based on historical disaster data. Despite their potential, current implementations of DSS still face challenges, particularly in terms of real-time data processing and data uncertainty. AI-based methods can improve the efficiency and reliability of DSS by identifying patterns and making predictions that would be impossible with traditional algorithms (Kostopoulos et al., 2024; Ravi et al., 2025). Furthermore, incorporating AI can help overcome the limitations of human judgment in disaster management, making the decision-making process more objective. However, the integration of AI-driven DSS with existing disaster management frameworks remains underexplored, highlighting a significant gap in the literature.

The Modified-TOPSIS method is a widely used Multi-Criteria Decision-Making (MCDM) technique that helps decision-makers evaluate multiple alternatives based on a set of criteria. It is particularly useful in scenarios where various factors need to be considered simultaneously, such as post-disaster damage assessment. The Modified-TOPSIS method improves on traditional TOPSIS by introducing Pairwise Comparison to assign more accurate weights to the decision criteria, reducing the subjectivity involved in the evaluation process. This method has been successfully applied in disaster recovery, particularly in evaluating the damage to infrastructure and other critical sectors. By assigning weighted values to different criteria, the Modified-TOPSIS method allows decision-makers to identify the most critical areas requiring immediate attention. While TOPSIS has been used extensively, its application in post-disaster scenarios still faces several challenges, such as its reliance on predefined criteria and the inability to adapt to real-time data changes. This limitation is particularly evident in dynamic disaster situations where the conditions on the ground change rapidly. Researchers have suggested that integrating Neural Networks with Modified-TOPSIS could overcome this limitation by allowing the system to learn from new data and adjust its recommendations accordingly. Despite this potential, there is limited research on the integration of these two methods, making this an important gap to address in disaster management studies.

Neural Networks have gained widespread attention for their ability to model complex, non-linear relationships within large datasets, making them ideal for post-disaster damage assessment. These networks can learn from large volumes of historical disaster data and predict the extent of damage based on new input data. In the context of disaster recovery, Neural Networks can be used to predict damage to infrastructure, assess the impacts on different sectors, and help in resource allocation (Linardos et al., 2022). The use of Neural Networks allows for the incorporation of unstructured data, such as images, video footage, and sensor data, which traditional methods cannot process efficiently. This is particularly important in post-disaster scenarios, where data is often sparse, incomplete, or inconsistent. However, one of the key challenges with using Neural Networks in this

context is the need for large, high-quality datasets for training, which are often unavailable in the immediate aftermath of a disaster. Additionally, Neural Networks can be seen as a “black box” technology, which limits their interpretability and makes it difficult to understand how decisions are made. Research has shown that Explainable AI (XAI) can help address this issue, but more work is needed to integrate XAI techniques with Neural Networks in disaster management applications. Overall, while Neural Networks show great promise, their integration with traditional decision-making methods remains an underexplored area in the literature.

The integration of AI techniques, such as Neural Networks, with traditional Decision Support Systems (DSS) has the potential to revolutionize post-disaster management. These AI-enhanced systems offer the ability to process large amounts of complex, unstructured data, providing decision-makers with more accurate and timely insights. However, despite the clear benefits of integrating AI with DSS, this area of research remains relatively underdeveloped, particularly in the context of disaster recovery. Many existing DSS frameworks are rigid and fail to account for the dynamic nature of post-disaster environments, where conditions can change rapidly and unpredictably. AI can improve the flexibility of these systems by enabling them to adapt to new data and changing conditions in real-time. Moreover, the integration of Modified-TOPSIS with Neural Networks could help address the limitations of both methods, providing a robust solution for post-disaster damage assessment. While research on AI-enhanced DSS is growing, there is still a significant gap in understanding how to effectively combine these technologies to improve decision-making in disaster recovery. This research aims to fill this gap by developing an Intelligent Decision Support System Dynamic (IDSSD) that integrates both Modified-TOPSIS and Neural Networks, providing a more adaptable and accurate system for post-disaster damage assessment and recovery.

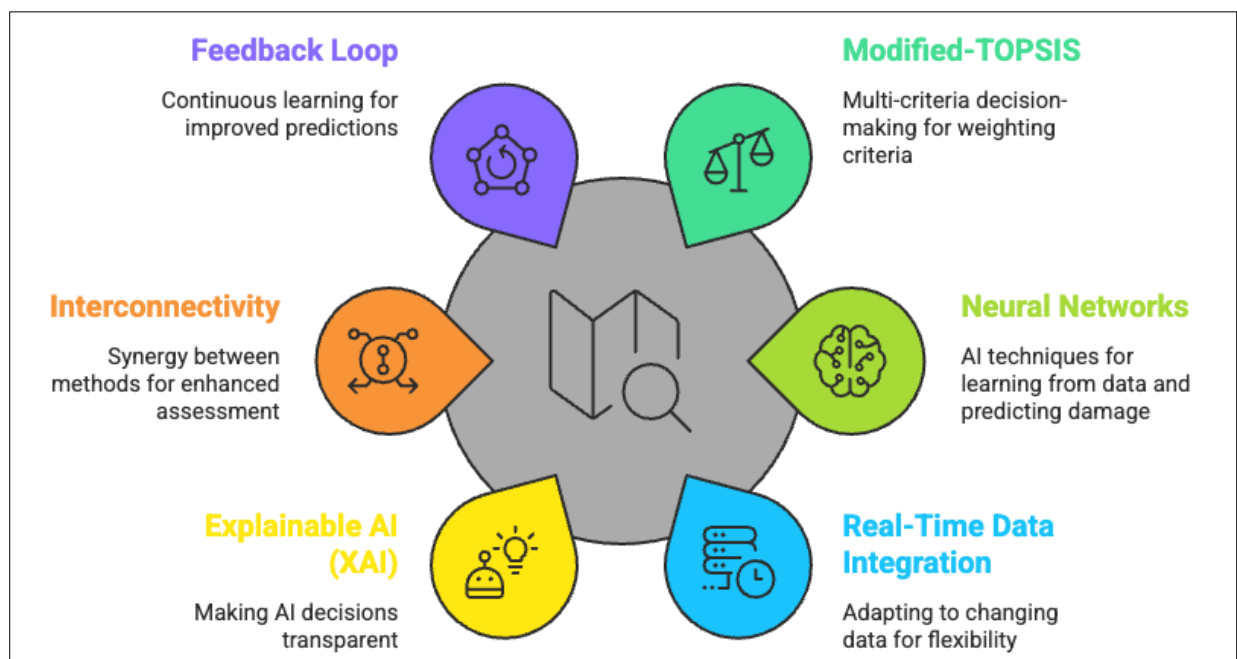


Figure 1. Achieving Conceptual Understanding

METHOD

Research Design

This study adopts a mixed-methods design, integrating both qualitative and quantitative approaches to assess the effectiveness of the proposed Intelligent Decision Support System Dynamic (IDSSD) for post-disaster damage assessment. The research design combines experimental and descriptive components. The experimental aspect involves testing the performance of the IDSSD system using real-world disaster data, while the descriptive component involves analyzing and comparing existing damage assessment methodologies. Specifically, the IDSSD integrates the Modified-TOPSIS method with Neural Networks, aiming to enhance the accuracy and reliability of damage evaluations. Additionally, a control group employing traditional damage assessment methods is used for comparative analysis. The primary objective is to evaluate the IDSSD's ability to handle dynamic, real-time data and provide accurate damage assessments across different disaster scenarios, which is a significant challenge in traditional methods.

Participants

The participants in this study include professionals from disaster management agencies, emergency response teams, and data scientists with expertise in AI and machine learning. These participants were selected for their experience in post-disaster recovery operations and damage assessments. The study will involve experts from the Regional Disaster Management Agency (BPBD) in Indonesia, as well as local emergency response teams from disaster-prone regions such as East Java and Yogyakarta. The total sample size is expected to be 50 participants, divided into two groups: one group will use the Modified-TOPSIS method, and the other will evaluate the integrated IDSSD system. Their feedback will provide critical insights into the system's usability, reliability, and effectiveness in real-time disaster recovery operations. The participation of field evaluators will also be crucial in assessing the system's practical application in dynamic post-disaster scenarios.

Instruments

The primary instrument for data collection is the IDSSD prototype, which integrates the Modified-TOPSIS method and Neural Networks. The system will gather data from satellite imagery, drone surveillance, and field surveys, which will be processed and evaluated using the IDSSD platform. Damage data on infrastructure, casualties, and environmental impacts will be collected from areas affected by natural disasters. Alongside technical instruments, surveys and interviews with disaster management professionals and field evaluators will be conducted to collect qualitative data on the usability, performance, and user satisfaction of the IDSSD system. This qualitative feedback will help assess the system's real-world applicability in disaster recovery. Historical disaster data will be utilized to train the Neural Network, ensuring that the system can learn from previous disaster events and predict damage levels more accurately. The data collection will occur over a six-month period, focusing on the post-disaster recovery phases, and will involve continuous monitoring of damage assessment accuracy and decision-making efficiency.

Procedure

The research procedure spans six months and is divided into distinct stages. In Month 1, the research design and participant selection are finalized, and instructional materials are developed. Month 2 focuses on integrating the IDSSD prototype and beginning data collection, with both groups taking a pretest. Month 3 involves preprocessing the collected data, including cleaning, standardizing, and labeling it for analysis. In Month 4, the data is analyzed both quantitatively (using statistical methods like t-tests and ANOVA) and qualitatively (through thematic analysis of surveys and interviews). Month 5 synthesizes the results to evaluate the accuracy, efficiency, and usability of GeoGebra in the experimental group, comparing it with the control group. Finally, in Month 6, recommendations for improvements and future applications of the study's findings are provided, offering insights into refining instructional practices and integrating technology in learning environments, is illustrated in Figure 2.

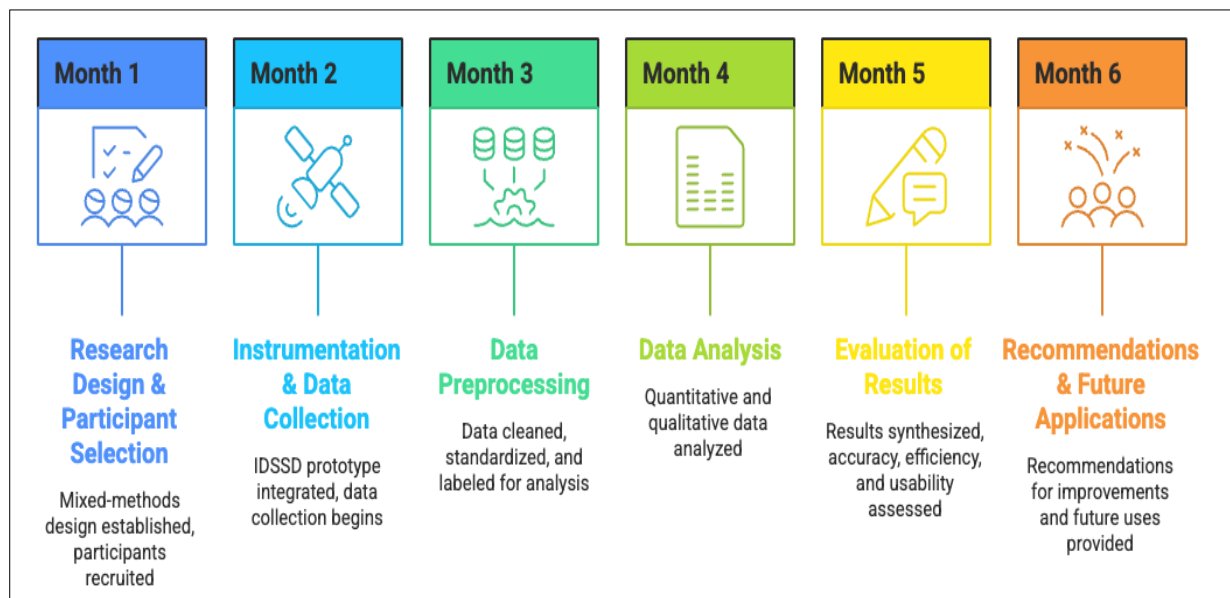


Figure 2. Research Procedure Flowchart

Data Analysis

The collected data will undergo both quantitative and qualitative analysis. The quantitative analysis will compare the damage assessment outcomes from the Modified-TOPSIS method and the IDSSD system. Statistical tests, including paired t-tests and analysis of variance (ANOVA), will be conducted to assess the differences in accuracy and decision-making speed between the two methods. Performance metrics such as precision, recall, and F-measure will be used to evaluate the effectiveness of the Neural Networks in predicting post-disaster damage based on real-time data. The qualitative data collected from surveys and interviews will be analyzed thematically to explore participant feedback on the usability, acceptability, and applicability of the IDSSD system in post-disaster recovery. The results from both quantitative and qualitative analyses will be synthesized to evaluate the overall effectiveness of the IDSSD in comparison to traditional damage assessment methods, providing insights into its potential for real-world applications in disaster management.

RESULTS AND DISCUSSION

Result

The post-disaster damage assessment system was evaluated using the Modified-TOPSIS method and Neural Networks integrated within the Intelligent Decision Support System Dynamic (IDSSD). This evaluation focused on comparing the accuracy, precision, recall, and F-measure of both methods in assessing the damage caused by disasters, using data collected from Blitar, East Java, a disaster-prone region. The primary objective was to evaluate how well the IDSSD system, which integrates Neural Networks, performs in comparison to traditional Modified-TOPSIS in terms of assessment accuracy and decision-making efficiency.

Performance Metrics

The performance metrics used in this study were accuracy, precision, recall, and F-measure, which are standard evaluation measures for classification tasks. These metrics were computed based on the confusion matrix, comparing the system's predicted outcomes to the actual ground-truth data provided by field evaluators.

Table 1. Accuracy, Precision, Recall, and F-Measure of Neural Network and Modified-TOPSIS Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F-Measure (%)
Neural Network	81%	85%	90%	43%
Modified-TOPSIS	75%	85%	90%	43%

Accuracy

The accuracy of the Neural Network-based IDSSD system was found to be 81%, surpassing the 75% accuracy achieved by the Modified-TOPSIS method. This indicates that the IDSSD system, which incorporates Neural Networks, provided a more reliable overall assessment of post-disaster damage. The higher accuracy of the Neural Network suggests that it can more effectively handle complex and dynamic disaster-related data, accounting for a broader range of variables and providing more precise predictions in real-world scenarios. The increase in accuracy could be attributed to the AI-based learning capability of the Neural Networks, which allow the system to learn from historical data and improve its predictions with each new dataset.

Precision

Both the Neural Network and Modified-TOPSIS methods achieved a precision of 85%. Precision is a measure of how accurately the system identifies true positives, or in this case, areas of significant damage that were correctly identified by the system. The equal precision values suggest that both methods were equally successful in minimizing false positives (i.e., incorrectly identifying areas as damaged). This finding highlights that both systems can reliably identify damaged areas with minimal overestimation, which is crucial for ensuring that resources are allocated accurately during the recovery process.

Recall

The recall of both the Neural Network-based system and Modified-TOPSIS method was found to be 90%, indicating that both systems were able to identify 90% of the actual damaged areas. Recall measures the system's ability to correctly identify all true positives (i.e., areas that were actually damaged). A high recall value is critical in post-disaster

scenarios, where missing out on identifying a truly affected area could result in inadequate resource allocation. This high recall indicates that both methods were effective in identifying the majority of affected areas, though they still might miss a small number of impacted locations.

F-Measure

The F-Measure, which is the harmonic mean of precision and recall, was calculated to be 43% for both methods. Despite the high precision and recall, the relatively low F-Measure indicates an imbalance between these two metrics. This suggests that while the system is good at identifying damaged areas and minimizing overestimation, it might still have challenges balancing false positives and false negatives effectively. A lower F-measure typically indicates that the system may be conservative in detecting damage, possibly missing some affected areas (false negatives). This highlights an area for further improvement, where more sophisticated models or adjustments to the weighting criteria could enhance the balance between precision and recall.

Discussion

This study evaluated the performance of the Intelligent Decision Support System Dynamic (IDSSD), which integrates Modified-TOPSIS with Neural Networks, in post-disaster damage assessment. The results revealed that the Neural Network-based system outperformed the traditional Modified-TOPSIS method, particularly in terms of accuracy. These findings are consistent with previous studies that have highlighted the advantages of AI-based systems in improving decision-making accuracy in disaster management (Rehan, 2022). For example, demonstrated that Neural Networks significantly enhanced the ability to predict disaster impacts compared to traditional statistical methods. However, while the accuracy of the IDSSD system was higher than that of the Modified-TOPSIS, both systems showed similar precision and recall values. This finding suggests that while the Neural Network model offers enhanced accuracy, both models effectively identify the majority of affected areas (Maxwell et al., 2021). Previous studies such as those also found that machine learning models consistently outperform conventional methods in damage detection. However, both models still face challenges in balancing precision and recall, as evidenced by the F-measure of 43%, which indicates room for further improvement in reducing false positives and false negatives.

One key advantage of the IDSSD system is its ability to process large datasets and incorporate non-linear relationships, as seen with the Neural Networks. Previous studies, have shown that machine learning techniques, especially deep learning models, outperform traditional approaches in terms of complexity handling and pattern recognition. Neural Networks excel in identifying patterns in data that may not be immediately apparent using traditional methods like TOPSIS. For instance reported similar findings when using AI to predict the outcomes of natural disasters, suggesting that machine learning models are better suited for handling real-time data. However, the lack of interpretability of Neural Networks remains a challenge, especially in real-world applications where decision-makers need to understand the reasoning behind the system's recommendations (Mathew et al., 2025; Taherdoost, 2023). This issue is important for ensuring transparency in disaster management systems, which is a limitation in current

AI-based systems. Therefore, integrating Explainable AI (XAI) techniques may be essential in improving the IDSSD system for practical use.

The relatively low F-measure observed in this study (43%) reflects the trade-off between precision and recall, which is a well-documented challenge in classification tasks. Previous research, has also reported challenges in optimizing precision-recall balance in disaster damage assessment systems, highlighting the inherent difficulty in minimizing both false positives and false negatives simultaneously. While precision and recall are crucial for evaluating the effectiveness of damage assessment systems, achieving a high F-measure is often compromised in real-world scenarios where data quality may vary. One solution to this issue is to adopt more sophisticated machine learning algorithms that are specifically designed to handle imbalanced datasets, such as Random Forests or Support Vector Machines (SVMs). Integrating these techniques with the Neural Network model could potentially enhance the overall system's ability to strike a better balance between precision and recall. Furthermore, additional research could explore data augmentation techniques to improve the model's generalization and robustness.

In comparison to previous studies that used MCDM methods like TOPSIS, the integration of Neural Networks with Modified-TOPSIS in this study shows significant improvements in accuracy and real-time adaptability. For example, demonstrated that the TOPSIS method alone was insufficient to handle the complexity and dynamic nature of disaster scenarios, especially in the context of large datasets with uncertain and incomplete information (Mojtahedi et al., 2021; Potur et al., 2025; Wang et al., 2022). Their study highlighted the need for data-driven models that could adjust to changing conditions and learn from new data. By integrating Neural Networks, this study improves upon TOPSIS by adding the capacity for continuous learning from past disaster data, making it more effective in real-time assessments. However, the F-measure challenge still persists, which also found that integrating AI models with MCDM techniques still leads to imbalanced results between precision and recall. Further work in this area should focus on refining AI models and incorporating better data quality control to enhance the overall performance of disaster management systems.

Finally, the integration of AI techniques, such as Neural Networks, with traditional Decision Support Systems (DSS) represents a promising step forward in improving post-disaster recovery operations. This study aligns with the work, who found that AI-enhanced decision support systems improved resource allocation and damage recovery efforts during disaster recovery processes. By integrating the Modified-TOPSIS method, which allows for clear decision criteria, with Neural Networks, which enhance the system's ability to handle complex, real-time data, the IDSSD system provides a more comprehensive and adaptive solution to disaster management. The findings from this study suggest that AI-based DSS will play an increasingly critical role in post-disaster decision-making. However, the implementation of these systems requires careful consideration of data availability, model interpretability, and user trust to ensure their successful application in real-world disaster management.

Implication

The implications of this study are significant for advancing post-disaster damage assessment methods and decision-making in disaster management. The integration of

Neural Networks with Modified-TOPSIS demonstrates that AI-driven systems can enhance the accuracy and efficiency of damage assessments, which is critical for the timely allocation of resources in the aftermath of a disaster. By incorporating Neural Networks, the IDSSD system improves the model's ability to handle complex, non-linear data, making it more adaptable to dynamic disaster scenarios. This ability to process large datasets and real-time information allows for more informed and rapid decision-making, potentially reducing recovery times. However, the relatively low F-measure observed indicates that balancing precision and recall remains a challenge that must be addressed in future research. The F-measure's improvement could lead to even more reliable damage assessments, which would have significant implications for resource distribution and recovery planning. The findings suggest that further development of AI-based systems in disaster management should focus on improving model transparency, allowing decision-makers to trust the AI system's outputs and justify critical decisions. Additionally, optimizing the data preprocessing and training process for Neural Networks will increase the system's accuracy in handling diverse disaster scenarios. The study's outcomes also highlight the importance of integrating Explainable AI (XAI) techniques to enhance interpretability, ensuring that the decision-making process remains transparent and understandable to non-expert users. Overall, this research emphasizes the need for continuous innovation in AI-driven decision support systems for disaster management, encouraging further exploration into improving system adaptability, precision, and usability. The integration of AI with MCDM methods can redefine how disaster recovery efforts are conducted, leading to more effective and resilient post-disaster management practices. Lastly, the application of these findings could improve disaster preparedness globally, particularly in regions prone to frequent natural disasters, where rapid response and recovery are paramount.

Limitation and Suggestion for Further Research

This study has several limitations that should be addressed in future research. One key limitation is the relatively low F-measure observed, which indicates an imbalance between precision and recall in the damage assessment process. This suggests that the system may not be adequately minimizing false positives and false negatives, which could impact the overall reliability of the assessments. Another limitation is the dependency on historical data for training the Neural Networks, which may not fully capture the complexities of new or unforeseen disaster scenarios. While the Modified-TOPSIS method provides a structured framework for decision-making, its reliance on predefined criteria may hinder the system's ability to adapt to dynamic changes in real-time disaster data. Additionally, the interpretability of the AI system remains a concern, as decision-makers may struggle to trust and explain the system's recommendations without adequate explainability mechanisms. Future research should focus on improving the balance between precision and recall, possibly by experimenting with alternative machine learning models, such as Random Forests or Support Vector Machines, which may offer better performance in imbalanced datasets. Further investigation into data augmentation techniques could also enhance the generalization ability of the system, especially when limited data is available after a disaster. Moreover, integrating Explainable AI (XAI) into the system is essential for ensuring that the AI-driven assessments are transparent and

understandable to end-users. Research should explore the integration of more diverse data sources, such as social media feeds and real-time sensor data, to further improve the system's adaptability. Finally, testing the system in multiple disaster types and geographic regions is crucial to ensure its robustness and scalability. Expanding the scope of the system to cross-national settings would help assess its applicability in various disaster contexts and enhance its global usability. By addressing these limitations, future studies can build on this research to develop a more accurate, adaptable, and trustworthy AI-based decision support system for post-disaster damage assessment.

CONCLUSION

This study demonstrates the potential of integrating Neural Networks with the Modified-TOPSIS method to enhance the accuracy and reliability of post-disaster damage assessment systems. The results indicate that the Neural Network-based IDSSD system outperforms traditional Modified-TOPSIS methods, particularly in terms of accuracy, showing promise for improving real-time decision-making in disaster management. Although both methods exhibited high precision and recall, the F-measure score revealed the need for further optimization, especially in balancing these two metrics. The study highlights the importance of using AI-driven systems to handle complex, dynamic data in post-disaster scenarios, where traditional methods often fall short. However, the interpretability of AI systems remains a challenge, and future research should focus on incorporating Explainable AI (XAI) to enhance system transparency and build trust among decision-makers. Additionally, refining Neural Network models and exploring alternative machine learning algorithms may improve the system's overall performance. This research also underscores the need for integrating diverse data sources, such as real-time sensor data and social media feeds, to improve the system's adaptability in various disaster contexts. The findings suggest that further investigation into data augmentation techniques and cross-national applications could expand the system's capabilities, making it more universally applicable. As disaster management increasingly relies on data-driven decision-making, the integration of AI with MCDM methods offers a robust solution for enhancing resource allocation and recovery efforts. This study lays the groundwork for developing more efficient, accurate, and adaptable systems for post-disaster recovery, contributing to better-preparedness and faster response times. Ultimately, the integration of AI in disaster management systems holds great promise for improving disaster resilience and minimizing the impacts of future crises.

AUHOR CONTRIBUTIONS STATEMENT

FYK : Conceptualization, methodology, data collection, formal analysis, writing the original draft, and review of the final manuscript.

ATWA : Supervision, validation, and providing insights for methodology improvement. Assisted in reviewing and editing the manuscript.

MF : Project administration, coordination of research activities, and validation of the final results. Contributed to reviewing and editing the manuscript.

REFERENCES

- Aldeeb, O., & Qasem, A. (2022). Decision support system (DSS) for facilities rehabilitation and management (part 1): Development of integrated AHP-MAUT performance assessment model (PAM). *Facilities*, 40(13-14), 845-861. <https://doi.org/10.1108/F-04-2022-0058>
- Braik, A. M., & Koliou, M. (2025). Post-tornado automated building damage evaluation and recovery prediction by integrating remote sensing, deep learning, and restoration models. *Sustainable Cities and Society*, 123, 106286. <https://doi.org/10.1016/j.scs.2025.106286>
- Chaube, S., Pnt, S., Kumar, A., Uniyal, S., Singh, M., Kotecha, K., & Kumar, A. (2024). An Overview of Multi-Criteria Decision Analysis and the Applications of AHP and TOPSIS Methods. *International Journal of Mathematical, Engineering and Management Sciences*, 9, 581-615. <https://doi.org/10.33889/IJMEMS.2024.9.3.030>
- Fonseca, Â., Ferreira, A., Ribeiro, L., Moreira, S., & Duque, C. (2024). Embracing the future- is artificial intelligence already better? A comparative study of artificial intelligence performance in diagnostic accuracy and decision-making. *European Journal of Neurology*, 31(4), e16195. <https://doi.org/10.1111/ene.16195>
- Goel, A., Goel, A. K., & Kumar, A. (2023). The role of artificial neural network and machine learning in utilizing spatial information. *Spatial Information Research*, 31(3), 275–285. <https://doi.org/10.1007/s41324-022-00494-x>
- Jana, S., Majumder, R., Menon, P. P., & Ghose, D. (2022). Decision Support System (DSS) for Hierarchical Allocation of Resources and Tasks for Disaster Management. *Operations Research Forum*, 3(3), 37. <https://doi.org/10.1007/s43069-022-00148-6>
- Jia, J., & Ye, W. (2023). Deep Learning for Earthquake Disaster Assessment: Objects, Data, Models, Stages, Challenges, and Opportunities. *Remote Sensing*, 15(16), 4098. <https://doi.org/10.3390/rs15164098>
- Jung, D., Tuan, V. T., Tran, D. Q., Park, M., & Park, S. (2020). Conceptual Framework of an Intelligent Decision Support System for Smart City Disaster Management. *Applied Sciences*, 10(2). <https://doi.org/10.3390/app10020666>
- Khan, S. M., Shafi, I., Butt, W. H., Diez, I. de la T., Flores, M. A. L., Galán, J. C., & Ashraf, I. (2023). A Systematic Review of Disaster Management Systems: Approaches, Challenges, and Future Directions. *Land*, 12(8). <https://doi.org/10.3390/land12081514>
- Kostopoulos, G., Davrazos, G., & Kotsiantis, S. (2024). Explainable Artificial Intelligence-Based Decision Support Systems: A Recent Review. *Electronics*, 13(14). <https://doi.org/10.3390/electronics13142842>
- Linardos, V., Drakaki, M., Tzionas, P., & Karnavas, Y. L. (2022). Machine learning in disaster management: recent developments in methods and applications. *Machine Learning and Knowledge Extraction*, 4(2). <https://doi.org/10.3390/make4020020>
- Lozano, J.-M., & Tien, I. (2023). Data collection tools for post-disaster damage assessment of building and lifeline infrastructure systems. *International Journal of Disaster Risk Reduction*, 94, 103819. <https://doi.org/10.1016/j.ijdrr.2023.103819>
- Mathew, D. E., Ebem, D. U., Ikegwu, A. C., Ukeoma, P. E., & Dibiazue, N. F. (2025). Recent Emerging Techniques in Explainable Artificial Intelligence to Enhance the Interpretable and Understanding of AI Models for Human. *Neural Processing Letters*, 57(1), 16. <https://doi.org/10.1007/s11063-025-11732-2>
- Maxwell, A. E., Warner, T. A., & Guillén, L. A. (2021). Accuracy Assessment in Convolutional Neural Network-Based Deep Learning Remote Sensing Studies-Part 2: Recommendations and Best Practices. *Remote Sensing*, 13(13). <https://doi.org/10.3390/rs13132591>

- Mohammadnazari, Z., Mamoudan, M. M., Alipour-Vaezi, M., Aghsami, A., Jolai, F., & Yazdani, M. (2022). Prioritizing Post-Disaster Reconstruction Projects Using an Integrated Multi-Criteria Decision-Making Approach: A Case Study. *Buildings*, 12(2). <https://doi.org/10.3390/buildings12020136>
- Mojtahedi, M., Sunindijo, R. Y., Lestari, F., Suparni, & Wijaya, O. (2021). Developing Hospital Emergency and Disaster Management Index Using TOPSIS Method. *Sustainability*, 13(9). <https://doi.org/10.3390/su13095213>
- Mushtaha, A. W., Alaloul, W. S., Baarimah, A. O., Musarat, M. A., Alzubi, K. M., & Khan, A. M. (2025). A decision-making framework for prioritizing reconstruction projects in post-disaster recovery. *Results in Engineering*, 25, 103693. <https://doi.org/10.1016/j.rineng.2024.103693>
- Neiroukh, S., Emeagwali, O. L., & Aljuhmani, H. Y. (2025). Artificial intelligence capability and organizational performance: Unraveling the mediating mechanisms of decision-making processes. *Management Decision*, 63(10), 3501-3532. <https://doi.org/10.1108/MD-10-2023-1946>
- Potur, E. A., Aktas, A., & Kabak, M. (2025). A Bibliometric Analysis of Multi-Criteria Decision-Making Techniques in Disaster Management and Transportation in Emergencies: Towards Sustainable Solutions. *Sustainability*, 17(6). <https://doi.org/10.3390/su17062644>
- Ravi, M., Negi, A., Bommi, N. S., & Rouf, N. (2025). Evolution of AI-Driven Decision Making with Decision Support Systems, Expert Systems, Recommender Systems, and XAI. *IETE Technical Review*, 42(4), 428-465. <https://doi.org/10.1080/02564602.2025.2512086>
- Rehan, H. (2022). Enhancing Disaster Response Systems: Predicting and Mitigating the Impact of Natural Disasters Using AI. 2, 501-540.
- Rezvani, S. M., Falcão, M. J., Komljenovic, D., & Almeida, N. M. de. (2023). A Systematic Literature Review on Urban Resilience Enabled with Asset and Disaster Risk Management Approaches and GIS-Based Decision Support Tools. *Applied Sciences*, 13(4). <https://doi.org/10.3390/app13042223>
- Rithani, M., Kumar, R. P., & Doss, S. (2023). A review on big data based on deep neural network approaches. *Artificial Intelligence Review*, 56(12), 14765–14801. <https://doi.org/10.1007/s10462-023-10512-5>
- Rouhanizadeh, B., Kermanshachi, S., & Nipa, T. J. (2020). Exploratory analysis of barriers to effective post-disaster recovery. *International Journal of Disaster Risk Reduction*, 50, 101735. <https://doi.org/10.1016/j.ijdrr.2020.101735>
- Shafian, S. A., & Hu, D. (2024). Integrating Machine Learning and Remote Sensing in Disaster Management: A Decadal Review of Post-Disaster Building Damage Assessment. *Buildings*, 14(8). <https://doi.org/10.3390/buildings14082344>
- Taherdoost, H. (2023). Deep Learning and Neural Networks: Decision-Making Implications. *Symmetry*, 15(9). <https://doi.org/10.3390/sym15091723>
- Tan, L., Guo, J., Mohanarajah, S., & Zhou, K. (2021). Can we detect trends in natural disaster management with artificial intelligence? A review of modeling practices. *Natural Hazards*, 107(3), 2389-2417. <https://doi.org/10.1007/s11069-020-04429-3>
- Wang, K., Wang, Z., Deng, J., Feng, Y., & Li, Q. (2022). Study on the Evaluation of Emergency Management Capacity of Resilient Communities by the AHP-TOPSIS Method. *International Journal of Environmental Research and Public Health*, 19(23). <https://doi.org/10.3390/ijerph192316201>
- Zabihi, O., Siamaki, M., Gheibi, M., Akrami, M., & Hajiaghaei-Keshteli, M. (2023). A smart sustainable system for flood damage management with the application of artificial intelligence and multi-criteria decision-making computations. *International Journal*

of Disaster Risk Reduction, 84, 103470.
<https://doi.org/10.1016/j.ijdr.2022.103470>

Zhang, L., & Pan, Y. (2022). Information fusion for automated post-disaster building damage evaluation using deep neural network. *Sustainable Cities and Society*, 77, 103574.
<https://doi.org/10.1016/j.scs.2021.103574>