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MCDM-Based Blockchain and Artificial Intelligence Integration for Earthquake Risk Recommendation System

Aditya Widianto[1], Ratih Titi Komala Sari[2]*, Djarot Hindarto[3], Asrul Sani[4]
[1)2)3)]Informatika, Fakultas Teknologi Komunikasi dan Informatika, Universitas Nasional, Indonesia
[4)]Magister Teknologi Informasi, Fakultas Teknologi Komunikasi dan Informatika, Universitas Nasional
[1)]adityawidianto2022@student.unas.ac.id,[2)]ratih.titi@civitas.unas.ac.id, [3)]djarot.hindarto@civitas.unas.ac.id,
[4)]asrul.sani@civitas.unas.ac.id

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Abstract: Indonesia is one of the countries with the highest earthquake vulnerability in the world because it is located at the meeting point of three major tectonic plates, namely Eurasia, Indo-Australia, and Pacific. The high risk of disaster requires a system that is capable of analyzing, predicting, and recommending earthquake-prone areas accurately, efficiently, and safely. This study aims to develop an earthquake risk recommendation system based on the integration of Artificial Intelligence (AI), Multi-Criteria Decision Making (MCDM), and Ethereum Blockchain. Earthquake data was obtained from Google Earth Engine (GEE) and geospatial data from the Geospatial Information Agency (BIG) and BMKG. The data is processed using AI algorithms for predictive analysis, then the MCDM methods of TOPSIS, and ELECTRE are applied to determine the priority of earthquake-prone areas based on a combination of seismic parameters, population density, infrastructure vulnerability, and distance to active faults. The analysis results are stored in a decentralized manner using the Ethereum Blockchain through smart contracts to ensure data integrity, security, and transparency. The research results show that the integration of AI–MCDM is capable of providing earthquake risk recommendations with high accuracy, while the application of blockchain ensures that the results cannot be manipulated. This system is expected to become a decision-making tool for disaster management agencies such as BMKG and BNPB in data-based earthquake risk mitigation.

Keywords: Blockchain, Artificial Intelligence, MCDM, Smart Contract, Earthquake Risk.

INTRODUCTION

Earthquakes are one of the most destructive and unpredictable geological hazards in the world. High seismic activity in regions located at tectonic plate boundaries, such as Indonesia, causes a high potential for damage to infrastructure and loss of life (Cremen & Galasso, 2021). According to the Meteorology, Climatology, and Geophysics Agency (BMKG), Indonesia experiences thousands of earthquakes every year, with increasing frequency in subduction zones such as Sumatra, Sulawesi, and Nusa Tenggara. This condition requires an analytical system that is intelligent, adaptive, and capable of comprehensively identifying, evaluating, and predicting risk levels. However, the current disaster mitigation system still faces various obstacles, such as limited spatial data integration, inaccurate predictions, and a lack of transparency and reliability in the decision-making process (Hindarto, Rachmadi, et al., 2025). In recent years, various studies have proposed the use of Artificial Intelligence (AI) to improve the effectiveness of natural disaster mitigation. AI has the ability to detect complex patterns from spatial and seismic data that are difficult to identify through conventional analysis, and can perform automatic and adaptive risk classification (KURNAZ, 2025).

Research by (NUGROHO et al., 2024) shows that the integration of AI and cloud computing can accelerate the spatial analysis process using satellite data, such as Landsat and MODIS, with high accuracy. Meanwhile, studies by (Alemdar, 2025) and (Jyothi et al., 2022) show that AI can be used to optimize community preparedness and support mitigation planning based on historical and spatial data. In addition to AI, the Multi-Criteria Decision Making (MCDM) method is one of the most widely used approaches in disaster risk assessment because it can

*name of corresponding author

systematically combine various criteria. Methods such as TOPSIS and ELECTRE have been proven effective in determining the priority of high-risk areas based on multidimensional parameters such as magnitude, hypocenter depth, distance to active faults, population density, and topography (Ruan et al., 2025) TOPSIS works by measuring the relative distance of each alternative to the ideal solution, while ELECTRE uses an outranking approach that is more suitable for uncertain data conditions. However, research (Tashatov et al., 2025) notes that MCDM calculation results are often influenced by weighting biases and data inconsistencies if not supported by a robust validation mechanism.

To address issues of transparency and reliability of decision outcomes, Ethereum Blockchain has emerged as an innovative solution for storing and verifying risk analysis data. Blockchain technology enables decentralized and immutable storage of decision outcomes (immutable ledger), so that each recommendation can be digitally verified (Kushwaha et al., 2022). The implementation of smart contracts on the Ethereum network allows MCDM calculation results to be stored permanently with high security and transaction efficiency measured through Gas Used and Transactions Per Second (TPS) (Raut & Shevtekar, 2023;Hindarto et al., 2025). In addition, advances in Google Earth Engine (GEE) have also contributed greatly to the collection and processing of large-scale geospatial data. GEE enables fast and efficient satellite image processing to monitor environmental and spatial parameters relevant to earthquake risk analysis (Amani et al., 2020;NUGROHO et al., 2024) The integration of GEE, AI, MCDM, and Blockchain has the potential to produce a comprehensive risk recommendation system—from data extraction and predictive analysis to transparent and verified storage of decision results (Hindarto, Rachmadi, et al., 2025).

Based on this review, a similar research gap can be identified, namely the absence of research that comprehensively integrates AI, MCDM (TOPSIS & ELECTRE), and Ethereum Blockchain for earthquake risk recommendation systems based on seismic and spatial data. Therefore, this study aims to develop an AI–MCDM–Blockchain integrated earthquake risk recommendation system model to improve disaster mitigation effectiveness, decision reliability, and data transparency in the context of disasters in Indonesia. The main contribution of this research is to present an integrated earthquake risk recommendation system model based on AI–MCDM (TOPSIS and ELECTRE)–Ethereum Blockchain that can improve the accuracy of analysis, the validity of decisions, and the transparency of disaster mitigation data storage in a decentralized and digitally verifiable manner.

LITERATURE REVIEW

Advances in digital technology in the field of disaster mitigation have opened up a wide range of research opportunities, particularly through the integration of Artificial Intelligence (AI), Blockchain, and Multi-Criteria Decision Making (MCDM) methods. Several previous studies have shown that these approaches, although promising, are generally still being developed separately. (Pwavodi et al., 2024) argue that Artificial Intelligence has great potential in improving earthquake prediction capabilities by utilizing seismic, geospatial, and satellite data based on the Internet of Things (IoT). Machine learning models such as Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) are capable of detecting seismic vibration patterns and anomalies that are invisible to conventional methods. However, the study emphasizes that the biggest challenge in applying AI to disaster mitigation is the dependence on large, clean, and well-validated datasets. On the other hand, (Alemdar, 2025) integrated the Multi-Criteria Decision Making (MCDM) method with Geographic Information System (GIS) to assess seismic risk on the transportation network in Istanbul. The study uses the Analytic Hierarchy Process (AHP) method to determine the weight of criteria such as magnitude, depth, soil type, and distance to active faults, and combines it with TOPSIS to produce an accurate seismic risk map.

The results of the study show that MCDM is effective in prioritizing high-risk areas, but still requires validation from real-time seismic data to be more dynamic. (Hindarto, Rachmadi, et al., 2025) conducted innovative research by integrating MCDM and Blockchain in the context of landslide risk mitigation. Blockchain is used as a layer of security for geospatial data to ensure the immutability and transparency of the analysis process. The study succeeded in increasing the accuracy and reliability of data to 95%, proving that an integrated approach can reduce the potential for data manipulation in risk-based decision-making processes. Additionally, (Shevchuk et al., 2025) proposed a blockchain-based decision support system for disaster risk management.

They demonstrated that smart contracts in blockchain can automate data validation and risk assessment processes, thereby accelerating response and coordination between agencies in emergency situations. Similar results were obtained by (Astarita et al., 2025) who applied blockchain to improve risk management in public transportation systems by prioritizing transparency and speed of data transactions. Blockchain technology strengthens the integrity, auditability, and transparency of AI analysis results through the concept of immutable ledgers and smart contracts. A study by (Kumar et al., 2024) suggests that the blockchain-enabled eXplainable AI (XAI) model offers the ability to maintain the integrity of AI data and output, making decision support systems more trustworthy and secure against manipulation. This kind of convergent approach can produce adaptive and reliable systems. In line with this, emphasized that the synergy between AI and Blockchain can increase trust and

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efficiency in data-based systems, (KURNAZ, 2025) especially in the context of risk management and digital finance. The Multi-Criteria Decision Making (MCDM) method is an analytical approach used to evaluate various alternatives based on a number of conflicting criteria (Jyothi et al., 2022) In the context of disaster mitigation, MCDM is used to determine risk priorities based on variables such as magnitude, depth, distance from active faults, and population density (Alemdar, 2025) Research (Hindarto, Damastuti, et al., 2025) reinforces the relevance of this approach by integrating MCDM and Blockchain to ensure the validity of spatial data in landslide risk assessment, so that the results of decision calculations can be verified and not manipulated. Furthermore, (Tashatov et al., 2025) shows that the combination of MCDM and machine learning can produce more consistent decision-making in complex data conditions. This approach is important because disaster mitigation decisions often require assessments of various non-homogeneous factors. In this study, MCDM was adopted to determine the level of earthquake risk based on seven main parameters: magnitude, depth, population density, distance to active faults, spatial density, historical frequency, and composite risk score.

Artificial Intelligence (AI) technology plays a central role in disaster early warning systems due to its ability to detect complex patterns from big data. According to (Shevchuk et al., 2025), AI enables rapid decision-making based on historical learning to identify potential disaster threats in real-time. (KURNAZ, 2025) also emphasizes that the integration of AI with risk management systems can increase the speed of spatial analysis and assist communities in disaster preparedness. Meanwhile, (KURNAZ, 2025) shows that the use of AI algorithms in Internet of Things (IoT)-based early warning systems can minimize response time in detecting the early signs of an earthquake. In this study, AI functions as an analytical system to learn patterns from seismic and geospatial data to identify relationships between risk parameters. This model can function as a predictive layer before the MCDM evaluation stage to produce more objective and adaptive earthquake risk ratings. Blockchain technology presents a new paradigm in data storage and verification due to its decentralized and immutable ledger nature. (Hindarto, 2023) shows that Blockchain can be used to ensure the integrity of academic data and research results so that they cannot be manipulated. In the context of disasters, (Shevchuk et al., 2025) developed a Blockchain-based disaster management system that guarantees data authenticity and reduces the potential for human error in risk reporting. (KURNAZ, 2025) also emphasized that the convergence of Blockchain and AI can increase public trust in digital system results, especially in the context of open data-based risk assessment. (Hindarto, Rachmadi, et al., 2025) prove that the combination of Blockchain and MCDM can strengthen the security of geospatial data in landslide risk assessment, ensuring that each analysis result has a unique digital fingerprint. This concept is adapted in this study by using Blockchain (Ethereum) to store the hash of MCDM-AI calculation results, to ensure the transparency and auditability of the earthquake risk recommendation system.

The integration of AI, MCDM, and Blockchain offers a comprehensive solution in earthquake risk decision-making systems. According to (Hindarto & Hariadi, 2024), the integration of the Multi-Criteria Decision Making (MCDM) method with blockchain technology can improve accuracy and transparency in the decision-making process related to disaster mitigation. A study by (Javadpour et al., 2023) adds that the application of Blockchain in the Internet of Everything (IoE) network strengthens the reliability of data exchange in disaster management systems. This integration allows AI–MCDM decisions to be stored securely, with distributed verification ensuring the validity of the final results. A similar approach is also applied by (Tashatov et al., 2025), who combine reinforcement learning with MCDM to achieve a decision-making system that is consistent and adaptive to data dynamics. However, although various studies have shown positive results, most still focus on a specific technology, without an integrative approach that combines MCDM, AI, and Blockchain in a unified system for earthquake risk assessment and recommendations. This condition indicates a significant research gap and forms the basis for this study.

METHOD

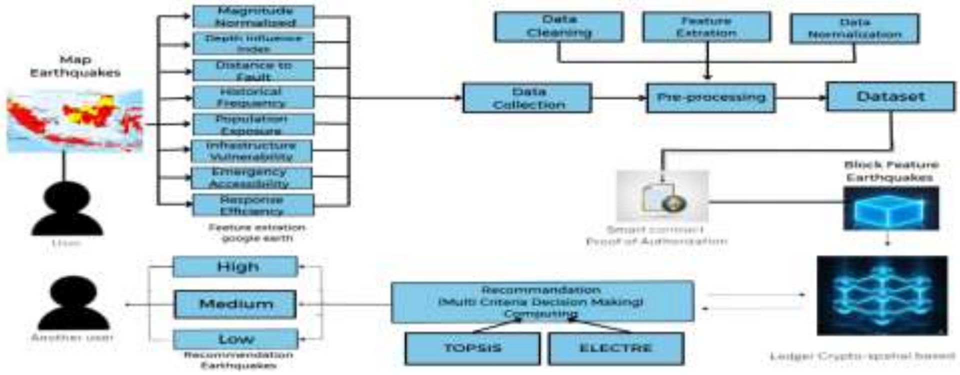

Fig.1 A proposed framework for earthquake hazard risk MCDM topsis and electre

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Figure 1. This research design describes the systematic flow of the data collection, processing, analysis, and storage of earthquake risk recommendations based on the integration of Artificial Intelligence (AI), Multi-Criteria Decision Making (MCDM), and Ethereum Blockchain. The main objective of this design is to produce a recommendation system that is capable of identifying earthquake-prone areas accurately, transparently, and verifiably. This research utilizes a main dataset, namely geospatial data processed through Google Earth Engine (GEE), which contains earthquake data in Indonesia. This dataset consists of 250 earthquake event entries with 8 main features relevant to risk analysis, including magnitude, depth, distance to fault, historical frequency, population exposure, infrastructure vulnerability, emergency accessibility, and response efficiency.

The research flow begins with the data collection process, in which all spatial and seismic data are compiled from various sources, BMKG, and Google Earth Engine (GEE). The data includes the location of the earthquake, magnitude, hypocenter depth, historical frequency, and additional parameters such as population density and infrastructure vulnerability. The combination of this data aims to produce an integrated database that is ready for spatial analysis and risk calculation. The next stage is data pre-processing, which consists of three main activities, namely data cleaning, feature extraction, and data normalization. In the data cleaning stage, the data is checked to remove empty values, duplicates, and anomalies that could affect the accuracy of the analysis results. The feature extraction stage is carried out to select relevant columns that are directly related to earthquake risk parameters. Meanwhile, data normalization is used to standardize the data scale so that each feature has a proportional weight in the analysis process. Normalization is carried out using the following formula:

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

The final result is a clean and standardized dataset that is ready to be used in the MCDM method. The next stage is risk analysis using the Multi-Criteria Decision Making (MCDM) method, namely TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) and ELECTRE (Elimination and Choice Expressing Reality). These two methods are used to assess the risk level of each region based on eight main criteria extracted from the dataset. The TOPSIS method calculates the relative distance of each alternative to the positive and negative ideal solutions to determine risk priority. The closer a region is to the positive ideal solution, the higher the risk level. The calculation is performed using the following formula:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (2)$$

with D_i⁺ and D_i⁻ representing the distance to the positive and negative ideal solutions, respectively.

Meanwhile, the ELECTRE method is used to compare alternatives based on outranking relationships, which is the degree of dominance of one alternative over another. This method calculates the concordance (consistency) and discordance (inconsistency) values between regions to determine the most risky areas. The advantage of ELECTRE is its ability to handle uncertainty and data inconsistency, especially in dynamic spatial and seismic data. The results of these two methods produce earthquake risk priority values, which are then classified into three categories: High Risk, Medium Risk, and Low Risk. High-risk areas are typically characterized by large magnitudes, shallow depths, and high population densities, while low-risk areas have infrequent earthquakes and limited impacts.

The next step is the integration of Ethereum Blockchain as a mechanism for storing and verifying risk analysis results. At this stage, the calculation results from TOPSIS and ELECTRE are converted into block feature earthquakes containing regional data, coordinates, risk values, analysis times, and hash marks. This data is then sent to the Ethereum network via a smart contract that functions as Proof of Authorization. The smart contract ensures that every decision result comes from a legitimate system, is immutable, and can be publicly verified. Every transaction on the Ethereum network is measured using the Gas Used parameter to determine computational consumption and Transaction Per Second (TPS) to assess system efficiency.

The final stage is storing the recommendation results in a Crypto-Spatial Based Ledger. In this stage, each risk analysis result stored in the Blockchain serves as a permanent digital archive that can be audited and accessed by various related parties, such as government agencies, researchers, and the general public. This system not only improves data transparency and security but also strengthens trust in the analysis results because all data is stored in an immutable ledger. Overall, this research design demonstrates the synergistic relationship between spatial data processing (via Google Earth Engine), multi-criteria analysis (via TOPSIS and ELECTRE), and Blockchain Ethereum-based result storage. This combination enables the system to generate accurate, efficient, and transparently verifiable earthquake risk recommendations. Thus, this research not only contributes to the development of AI and Blockchain-based disaster mitigation technology but also provides a strong scientific basis to support national policies in earthquake risk management in Indonesia.

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TOPSIS

The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method was used in this study to determine the priority level of earthquake risk in each region based on eight parameters (F1–F8), namely normalized magnitude, depth, distance to active faults, historical seismic frequency, population density, infrastructure vulnerability, emergency accessibility, and response efficiency. This approach was chosen because it is capable of producing objective decision rankings by considering the distance of each alternative from the best ideal solution (highest risk condition) and the worst ideal solution (lowest risk condition).

Formation of the Decision Matrix.
Each region A_i is assessed against each criterion C_j:

$$X = [x_{ij}], \quad i = 1,2,\dots,m; \quad j = 1,2,\dots,n \tag{3}$$

where x_{ij} represents the performance value of region -i against criterion j.

Normalization of Decision Matrix.

To standardize values between criteria with different units, normalization is performed using the following formula:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{4}$$

(Cremen & Galasso, 2021) emphasize that normalization is necessary so that each risk variable, such as magnitude, depth, and population density, can be compared proportionally.

Formation of a Weighted Decision Matrix
Each criterion is given a weight w_j according to its level of importance to earthquake risk, with:

$$v_{ij} = w_j \times r_{ij}, \quad \text{dan} \quad \sum_{j=1}^{n} w_j = 1 \tag{5}$$

This weight is determined based on an objective assessment of the contribution of each parameter, such as magnitude (F1), depth (F2), distance to the fault (F3), and so on.

Determining Positive and Negative Ideal Solutions.

$$A^+ = \{v_1^+, v_2^+, \dots, v_n^+\} = \{\max(v_{ij}) \mid j \in K_b; \min(v_{ij}) \mid j \in K_c\} \tag{6}$$
$$A^- = \{v_1^-, v_2^-, \dots, v_n^-\} = \{\min(v_{ij}) \mid j \in K_b; \max(v_{ij}) \mid j \in K_c\}$$

Where:

- K_b: benefit criteria, such as response efficiency (F8).
- K_c: cost criteria, such as magnitude (F1) and population density (F5).

Calculating the Distance to the Ideal Solution.

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}, D_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \tag{7}$$

(Hindarto, Rachmadi, et al., 2025) explains that Euclidean distance calculations in the Blockchain–MCDM system are computationally efficient and suitable for large geospatial data.

Determining Preference Values (Closeness Coefficient).

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{8}$$

The C_i value value indicates the level of risk of the area the higher the C_i value, the greater the potential risk of earthquakes. (Astarita et al., 2025)

Ranking.
All alternatives are sorted based on C_i values in descending order, resulting in a list of earthquake risk priorities that will be validated using the ELECTRE method.

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ELECTRE

The ELECTRE (Elimination and Choice Expressing Reality) method is used as a validation and dominance selection stage for TOPSIS ranking results.
Unlike compensatory methods such as TOPSIS, ELECTRE uses the concept of outranking, which assesses the dominance of alternatives in pairs (Ruan et al., 2025)
This approach ensures that areas with high risk values remain identified even if there are relatively strong criteria in other aspects.

Forming the Decision Matrix and Normalization.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \quad v_{ij} = w_j \times r_{ij} \qquad (9)$$

Matriks Concordance dan Discordance.
The Concordance value (C) describes the weight of the superiority of alternative A_i relative to A_k:

$$C_{ik} = \sum_{j \in J_{ik}} w_j, \quad J_{ik} = \{j \mid v_{ij} \geq v_{kj}\} \qquad (10)$$

The Discordance Value (D) indicates the maximum difference ratio between criteria:

$$D_{ik} = \frac{\max_j |v_{ij} - v_{kj}|}{\max_j |v_{ij} - v_{kj}|} \qquad (11)$$

(Battisti, 2022) state that in the ELECTRE III variant, a discrimination threshold s(δ) must first be determined, representing the minimum difference between credibility values to be considered significant in ranking alternatives.
Determining the Threshold (Threshold).

$$C^* = \frac{1}{m(m-1)} \sum_{i=1}^{m} \sum_{k=1, k \neq i}^{m} C_{ik}, D^* = \frac{1}{m(m-1)} \sum_{i=1}^{m} \sum_{k=1, k \neq i}^{m} D_{ik} \qquad (12)$$

This threshold is used as a benchmark in determining the dominance relationship between alternatives.

Determining Dominance Relations.

$$E_{ik} = \begin{cases} 1, & If C_{ik} \geq C * and D_{ik} \leq D * \\ 0, & \end{cases} \qquad (13)$$

The alternative with the highest dominance is considered the most risky and becomes the top priority for mitigation.

RESULT

This section presents the results of the implementation of an earthquake risk recommendation system developed by integrating Artificial Intelligence (AI), Multi-Criteria Decision Making (MCDM), and Ethereum Blockchain technologies. The test results focused on the performance of the AI algorithm in analyzing seismic data to identify risk levels in various regions, as well as the application of two MCDM methods, namely TOPSIS and ELECTRE, in determining the priority and dominance of earthquake-prone areas based on eight risk parameters (F1–F8). The analysis was conducted to evaluate the accuracy of the model in classifying hazard levels and the consistency of results between the two methods. In addition, the final results of the system were integrated with an Ethereum-based smart contract that ensures the transparency, authenticity, and security of the recommendation data. All calculation results, including preference values, dominance matrices, and regional risk data, are recorded in a decentralized manner through transaction processes on the blockchain network to ensure the integrity and accountability of the analysis results.

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Fig 2. User interface input block store to ledger

Figure 2 shows the interface of the earthquake risk recommendation system that has been integrated with the Ethereum Blockchain through the implementation of smart contracts. This system allows users to enter eight key risk parameters (Normalized Magnitude, Depth Influence, Distance to Fault, Historical Frequency, Population Exposure, Infrastructure Vulnerability, Emergency Accessibility, and Response Efficiency), then select the analysis model to be used, namely TOPSIS or ELECTRE. After the data is entered, the calculation results are stored on the blockchain using the Save to Blockchain button, which records transactions permanently and transparently. The bottom of the interface displays a Complete Data Records table containing all stored risk data along with the transaction time (timestamp). Each entry includes the calculation results from each MCDM model, which are verified in a decentralized manner on the Ethereum network, ensuring the authenticity and immutability of the earthquake risk analysis results.

Fig 3. Ganache for storage ledger

The Ganache interface in this image functions as a local Ethereum blockchain used to store the transaction ledger of the “Earthquake” smart contract, which handles the recording of earthquake risk recommendation system analysis results. At the top of the interface, network information is displayed—such as the current block, gas price, gas limit, hard fork version, network ID, and RPC connection to the local server—indicating that the active test network is running locally. In the CONTRACTS panel, the Earthquake contract is shown to have been successfully deployed at a specific address on the network. In addition, the “PredictionAdded” event is decoded and displays the execution result parameters in the form of entry ID, model used (TOPSIS), and transaction time (timestamp) which is automatically recorded on the blockchain. The RETURN VALUES section displays the results of the data storage, confirming that each model calculation result is stored permanently, transparently, and immutably. Ganache makes it easy for developers to verify smart contract implementation, monitor event logs in real-time, and test blockchain functions without incurring gas fees, making it an essential tool before the system is implemented on the public Ethereum network.

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A. Manual Calculation Topsis (Technique for Order Preference by Similarity to Ideal Solution)

Table 1. Decision Matrix

No	Region	Feature							
		F1	F2	F3	F4	F5	F6	F7	F8
1	Banten (R1)	7.9	39.9	3.39	5	1977	0.173	91	1.89
2	Kalimantan Tengah (R2)	8.23	53.0	55.04	2	2,379	0.583	51	6.18
3	Jawa timur (R3)	8.33	31.5	16.41	4	10	0.140	43	0.10
4	Sumatra Selatan (R4)	7.46	57.2	9.65	5	250	0.322	68	4.34
5	Kalimantan timur (R5)	7.07	62.9	4.17	4	872	0.142	34	0.47
6	Lampung (R6)	6.98	39.7	1.50	1	295	0.369	69	8.59
7	Jawa Tengah (R7)	5.93	45.7	1.51	7	10	0.602	8	3.25
8	Bali (R8)	5.76	43.1	3.30	6	3,715	0.806	89	0.63
9	Criteria Type	Cost	Benefit	Benefit	Cost	Cost	Cost	Cost	Benefit

Table 1 shows the results of the TOPSIS method decision matrix for eight regions, namely Banten, Central Kalimantan, East Java, South Sumatra, East Kalimantan, Lampung, Central Java, and Bali. Each region was evaluated based on eight main criteria (F1–F8) covering geophysical and socio-infrastructural factors, such as maximum magnitude, hypocenter depth, distance to active faults, earthquake frequency, population density, infrastructure vulnerability, emergency response time, and response efficiency. Criteria F2 (Depth Influence Index) and F3 (Distance to Fault) are benefit criteria, while F1, F4, F5, F6, F7, and F8 are cost criteria because an increase in their values increases risk. The table shows that East Java has the highest magnitude (8.33) and the closest fault distance (16.41 km), indicating the highest seismic risk. Central Kalimantan is also at high risk due to infrastructure vulnerability (0.583) and high population density, while Bali shows a lower risk despite its dense population. This matrix forms the basis for normalization and weighting calculations in TOPSIS to determine the proximity of each region to positive and negative ideal solutions, thereby producing objective earthquake risk preference values.

Final Topsis Score Calculation Results

Table 2. Topsis Calculation Results

No	Region	Preference	Rank
1	Banten (R1)	0.4226	7
2	Kalimantan Tengah (R2)	0.5690	2
3	Jawa timur (R3)	0.6148	1
4	Sumatra Selatan (R4)	0.4856	4
5	Kalimantan timur (R5)	0.5480	3
6	Lampung (R6)	0.4251	6
7	Jawa Tengah (R7)	0.4754	5
8	Bali (R8)	0.3259	8

The decision matrix in Table 2 Based on the results of calculations using the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method for the eight regions tested (Table 2), it was found that East Java (R3) had the highest preference value ($C_i = 0.6148$). This value indicates that East Java is the region with the highest earthquake risk among all the alternatives analyzed. The results indicate that the seismic characteristics in this region—such as a maximum magnitude of 8.33, a relatively close distance to the fault (16.41 km), and significant infrastructure vulnerability (0.140)—cause this region to have the closest proximity to the positive ideal solution (A^+), which is the maximum risk condition in the TOPSIS model. Meanwhile, Bali (R8) shows the lowest preference value ($C_i = 0.3259$), which means that this region has a relatively low risk level compared to other

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regions. A small preference value indicates that the characteristics of the Bali region are closer to the negative ideal solution (A^{-}), which is the safest condition or has minimal risk of earthquakes. Factors supporting this include a higher hypocenter depth (43.1 km) and a fairly good level of emergency response efficiency (distance to health facilities is only 0.63 km), which significantly reduces the potential seismic impact.

B.Preference Ranking Organization Method Electre

Table 3. Determining Preference Values

No	Region	Feature							
		F1	F2	F3	F4	F5	F6	F7	F8
1	Banten (R1)	7.9	39.9	3.39	5	1977	0.173	91	1.89
2	Kalimantan Tengah (R2)	8.23	53.0	55.04	2	2,379	0.583	51	6.18
3	Jawa timur (R3)	8.33	31.5	16.41	4	10	0.140	43	0.10
4	Sumatra Selatan (R4)	7.46	57.2	9.65	5	250	0.322	68	4.34
5	Kalimantan timur (R5)	7.07	62.9	4.17	4	872	0.142	34	0.47
6	Lampung (R6)	6.98	39.7	1.50	1	295	0.369	69	8.59
7	Jawa Tengah (R7)	5.93	45.7	1.51	7	10	0.602	8	3.25
8	Bali (R8)	5.76	43.1	3.30	6	3,715	0.806	89	0.63

Table 3 shows the baseline data used in the ELECTRE method calculation process to assess earthquake risk levels in eight study areas: Banten, Central Kalimantan, East Java, South Sumatra, East Kalimantan, Lampung, Central Java, and Bali. Each region is assessed based on eight key parameters (F1–F8) covering geophysical and socio-infrastructure factors, such as magnitude, earthquake depth, distance to active faults, frequency of occurrence, population density, infrastructure vulnerability, emergency access, and response efficiency. The values in this table represent the actual conditions of each region before normalization and weighting in the ELECTRE method. The data are used to compare dominance between regions, where high values for magnitude and population density indicate greater risk, while high values for fault depth and distance indicate safer conditions. Based on this data, the ELECTRE method determines the relationship between the strengths and weaknesses of each region relative to others to produce an objective earthquake risk priority order.

Result Electre.

Table 4. Electre Results

No	Region	Concordance Avg	Discordance Avg	Outranked	Outranking By Others	Net Flow	Rank
1	Banten (R1)	0.486	0.549	1	6	-5	7
2	Kalimantan Tengah (R2)	0.492	0.492	5	2	+3	2
3	Jawa timur (R3)	0.564	0.481	6	1	+5	1
4	Sumatra Selatan (R4)	0.519	0.517	3	4	-1	4
5	Kalimantan timur (R5)	0.542	0.505	4	3	+1	3
6	Lampung (R6)	0.497	0.534	2	5	-3	6
7	Jawa Tengah (R7)	0.503	0.522	3	4	-1	5
8	Bali (R8)	0.471	0.561	0	7	-7	8

Table 4 shows the results of the analysis using the ELECTRE method, which illustrates the dominance relationship between regions based on Concordance, Discordance, and Net Flow values resulting from a

*name of corresponding author

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comparison of earthquake risk criteria. The Concordance value indicates the level of superiority of a region over other regions, while Discordance describes the level of discrepancy or difference between regions. Based on the calculation results, East Java (R3) has the highest Net Flow (+5) and is ranked first, indicating that this region is the most dominant in terms of earthquake risk. Central Kalimantan (R2) and East Kalimantan (R5) are ranked second and third with positive values, indicating a high risk level but below East Java. Conversely, Bali (R8) has the lowest Net Flow (-7), indicating that this region is the least dominant over other regions and is classified as low risk. Overall, these ELECTRE results are in line with the previous TOPSIS analysis, which confirmed that East Java is the most vulnerable region to earthquake potential among the eight study areas.

DISCUSSIONS

This study shows that the integration of Artificial Intelligence (AI), Multi-Criteria Decision Making (MCDM), and Ethereum Blockchain is capable of producing an accurate, transparent, and reliable earthquake risk recommendation system. This system utilizes eight main parameters (F1–F8) covering geophysical and socio-infrastructural factors as the basis for risk assessment. Based on the calculation results, the TOPSIS method produced the highest preference value in East Java (C_i = 0.6148), followed by Central Kalimantan (0.5690) and East Kalimantan (0.5480), indicating that these three regions have the highest risk levels. The ELECTRE method produced the same regional dominance order, thereby strengthening the validity of the results and showing that both methods provide consistency in multi-criteria decision making.

These results are in line with the research by (Hindarto, Damastuti, et al., 2025) which proves the effectiveness of the MCDM method for determining priority disaster areas based on a combination of geophysical and social indicators. However, this study develops this approach by adding a layer of blockchain integration, which ensures the transparency and security of the calculation results, something that has not been implemented in Hindarto's research. Compared to (NUGROHO et al., 2024) who only used TOPSIS for forest fire risk assessment, this model utilizes two MCDM methods simultaneously, TOPSIS and ELECTRE, which validate each other's results and improve the reliability of the system. This approach is also consistent with (Alemdar, 2025) findings, which highlight the effectiveness of MCDM-based decision-making for geohazard mitigation, but this study expands on it by applying AI and blockchain to strengthen the predictive and verifiable aspects.

CONCLUSION

This study successfully developed an earthquake risk recommendation system based on the integration of Artificial Intelligence (AI), Multi-Criteria Decision Making (MCDM), and Ethereum Blockchain as an innovative approach to disaster mitigation. This system is capable of objectively processing eight main risk parameters (F1–F8) through the TOPSIS and ELECTRE methods, which consistently produce earthquake-prone area priorities with high accuracy and validity. The analysis results show that East Java has the highest risk level, followed by Central Kalimantan and East Kalimantan, while Bali has the lowest risk level. The consistency of the results between TOPSIS and ELECTRE proves the effectiveness of combining the two methods in supporting multi-criteria decision making. Additionally, the implementation of Ethereum smart contracts successfully integrated the analysis results into a decentralized storage system that ensures the transparency, authenticity, and immutability of the recommendation data. Through testing using Ganache, all transactions and calculation results can be publicly verified without the need for a single authority, thereby increasing the trust and security of the system. This integration confirms the potential of blockchain as a secure and transparent decision-making infrastructure in the context of disasters. Overall, the integrative AI–MCDM–Blockchain model developed in this study proves its effectiveness in producing an earthquake risk recommendation system that is not only analytically accurate but also structurally and ethically reliable in data management. This research contributes to the development of decentralized technology-based smart disaster mitigation systems in Indonesia. For further research, it is recommended to develop further integration with real-time data from seismic sensors and the Internet of Things (IoT) network, as well as evaluate blockchain performance on public networks to enhance the scalability and transaction speed of the recommendation system.

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*name of corresponding author