

Identification of Factors Influencing the Seismic Vulnerability Assessment of Non-Engineered Buildings

Catur Singgih^{1✉}, Setya Winarno², Sri Kusumadewi³, Albani Musyafa⁴

^{1, 2, 4} Department of Civil Engineering, Universitas Islam Indonesia, Yogyakarta, Indonesia

³ Department of Informatics, Universitas Islam Indonesia, Yogyakarta, Indonesia

✉ Corresponding Author : Catur Singgih (e-mail: catur.singgih@students.uii.ac.id)

Article Information	ABSTRACT
Article History Received : February 14, 2026 Revised : March 06, 2026 Published : April 04, 2026	Non-engineered buildings remain prevalent in many developing countries and are disproportionately associated with earthquake damage and fatalities. However, comprehensive vulnerability assessment frameworks that simultaneously consider technical, socio-economic, and environmental determinants remain limited. This study aims to identify and prioritize the key factors influencing seismic vulnerability in non-engineered buildings through a structured expert-based evaluation. A questionnaire survey involving 30 decision-makers assessed the importance of 16 factors across three domains using a 1–5 Likert scale. The analysis applied a consensus-based weighting procedure consisting of: (i) aggregation of expert judgments using mean scores, (ii) normalization of mean values to derive relative weights ($\sum w_i = 1$), and (iii) a ratio test comparing each factor weight to the maximum weight ($r_i = w_i / w_{max}$) with a threshold of 0.1 to determine significant factors. The results show that the technical domain has the highest contribution (0.407), followed by socio-economic (0.372) and environmental factors (0.222). At the factor level, structural condition (T2), construction techniques (T5), material quality (T1), environmental and site conditions (E1), and socio-economic status (SE2) emerge as the most influential. The resulting framework provides a practical basis for vulnerability assessment and supports prioritization of mitigation and retrofitting strategies in earthquake-prone areas.
Keywords: <i>Consensus Method; Expert Judgment Analysis; Non-engineered Building; Risk Mitigation Strategy; Seismic Vulnerability Assessment.</i>	

INTRODUCTION

Over the last two decades, research on seismic building vulnerability has improved significantly, particularly in developing countries where non-engineered buildings continue to dominate the building stock. Numerous international studies have found that modest building constructed without sufficient structural engineering causes the most damage and loss of life during massive earthquakes in Asia, Africa, and Latin America. Finding from various developing countries show that national-scale seismic risk modelling indicated extremely high vulnerability levels in non-engineered, with low material quality and poor construction detailing (Giordano et al., 2021; Goda et al., 2024).

Non-engineered buildings often owned by low-income populations in Indonesia have been found to be extremely vulnerable to earthquake, because of insufficient material quality, a lack of structural planning, and poor construction technique. A case study conducted in Pacitan revealed significant structural damage in building featuring concrete block or clay brick masonry. These damages were attributed to a lacking adequate tie, weak joint detailing, and the absence of

established load-transfer paths. This proposed specific damage-level thresholds tailored for the seismic assessment of non-engineered buildings in Indonesia (Adamy et al., 2023; Kristiawan et al., 2024). According to research conducted in Java and Sumatra, houses in earthquake-prone areas are typically self-built without the guidance of engineering professionals, implying that construction methods are influenced more by local practices than by engineering standards and code-based principles (Fitria et al., 2024; Hidayat et al., 2023). Taken together, this evidence underscores the necessity for a more accurate and site-specific approach to evaluate the vulnerability of non-engineered buildings.

In the seismic performance assessment of buildings, two major groups can be easily distinguished: conventional and holistic approaches. Conventional approaches to evaluating the possibility of damage rely on physical and structural characteristic such as fragility curves, structural capacity analysis, and Rapid Visual Screening (RVS). Holistic approaches, on the other hand, integrate social, economic, physical, and environmental elements by a set of vulnerability indicators aimed at providing a more comprehensive overview. A systematic evaluation in Malaysia generated holistic indicators to explain seismic vulnerability at many levels of analysis, including exposure, response capacity, and recovery capacity. Nonetheless, most of these indicators continue to work at regional or urban scales and have not been detailed enough to assess non-engineered buildings on an individual level (Ansari et al., 2025; Sauti et al., 2023).

According to the literature on socio-economic vulnerability, earthquake impacts are significantly influenced by community's social, economic, and demographic characteristics. A study in India's National Capital Region indicated that locations with high illiteracy rates, high unemployment, and inadequate housing quality have higher vulnerability indices and exposure levels (Agrawal et al., 2021). Similar approaches have been used in multi-hazard studies to map urban vulnerability, integrating social, economic, and spatial factors (Ansari et al., 2025; Oz & Karalar, 2025). However, because most of these studies focus on aggregated spatial units, such as regions, districts, or cities. Direct linkage between a building's physical condition (including material quality, construction detailing, and maintenance patterns) and the socio-economic characteristic of its occupants is not sufficiently assessed at the individual-building scale.

Multi-factors approaches and soft computing methodologies have also become more prevalent for evaluating earthquake risk. Fuzzy Inference System (FIS) is often used to create earthquake risk indices by combining physical, socio-economic, and environmental characteristics while considering uncertainty and linguistic nature of the data. Several researches suggest that combining fuzzy logic and spatial data can result in more detailed seismic vulnerability maps than regular deterministic methods (Mohammadi et al., 2025; Yariyan et al., 2020). In addition, Likert-scale consensus methods combined with clustering approaches like Supervised Fuzzy C-Means have been found to be efficient for the synthesis of structural indicators and expert's opinions in order to expedite risk categorization for engineered reinforced concrete buildings. However, such methods have yet to be directly extended for assessing non-engineered buildings possessing traditional Indonesian construction characteristics.

A substantial gap is shown in the existing literature wherein most of the analytical works developed for non-engineered construction in developing countries concentrate on structural studies with fragility curves or strengthening details but have not fully included socio-economics drivers and institutional support in an integrated vulnerability assessment framework (Harirchian & Novelli, 2025; Purwanto et al., 2024). Nevertheless, socio-economic attributes at the individual building level can be comprehensively obtained by means of field surveys. Other multivariable fuzzy methodologies would be suitable as well, into the specific context of non-engineered housing in Indonesia's seismic regions, if they can be implemented through expert-based inquiries or Likert scales.

Research gaps are also visible in operational issues. Several field studies in Indonesia have begun to identify critical aspects influencing the vulnerability of modest housing, but none have established a systematic factor structure with well-defined domains and transparent weighting mechanisms. Existing assessment techniques are typically confined to checklists or basic scoring

systems that do not adequately capture factor interactions, local contextual heterogeneity, or the need to prioritize disaster-risk reduction interventions. Furthermore, building owner involvement, government role and support, and access to disaster-related technologies and information are rarely explicitly included in non-engineered building vulnerability models. As a result, policy suggestions based on these models are less sensitive to local socio-economic and environmental factors (Candra M et al., 2025).

Therefore, the aim of this study, in the light of this context and the limitations described above, is to identify and classify them and to provide a comprehensive review on how they have impact non-engineered building vulnerability for earthquakes. This work aims to bridge the gap that currently exists between these highly technical, structural vulnerability approaches and macro-level socio-economic vulnerability studies, adding up to a more comprehensive as well as feasible frame for assessing non-engineered building vulnerability in practical applications.

RESEARCH METHODS

This study adopts a quantitative approach using a structured expert survey to identify and prioritize factors influencing the seismic vulnerability of non-engineered buildings. The overall research process is illustrated in Figure 1, which summarizes the main stages from factor identification to vulnerability factor weighting.

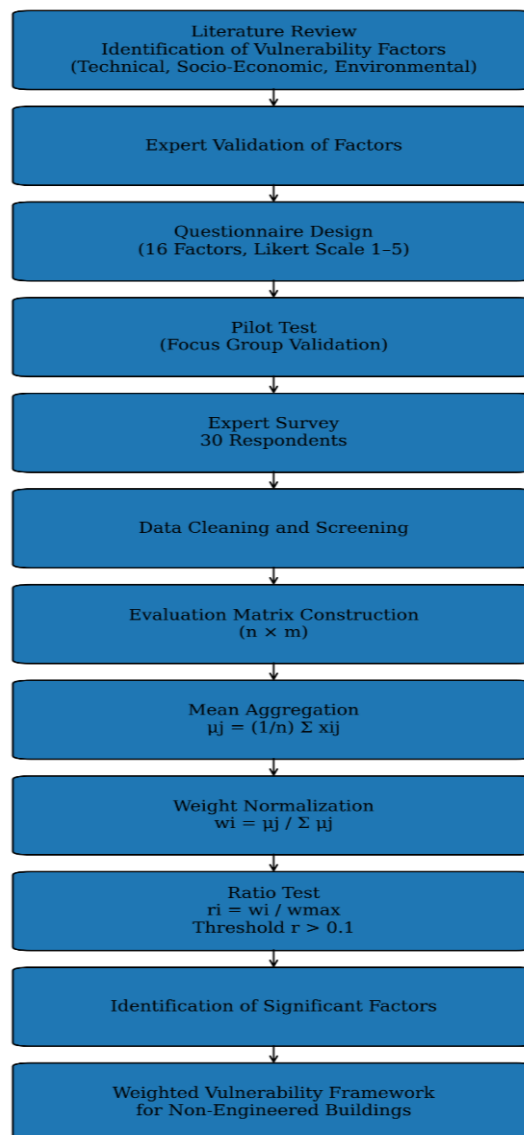


Figure 1. Research methodology flowchart

The research begins with a literature review to identify potential vulnerability indicators across technical, socio-economic, and environmental domains. The factors are validated by experts and translated into a structured questionnaire. After pilot testing and expert survey distribution, the collected responses are processed through mean aggregation and normalization to derive factor weights. A ratio test is then applied to identify significant factors. The final output is a weighted vulnerability framework that supports seismic vulnerability assessment of non-engineered buildings.

A structured questionnaire was distributed online using Google Forms to 30 respondents, consisting of 20 decision-makers (local government officials, planners, and disaster-risk consultants) and 10 technical practitioners (engineers, construction supervisors, and contractors). Most respondents (89%) were located on Java Island, which has the highest population density and significant seismic exposure in Indonesia. This composition has been chosen to balance policy and technical perspectives in accordance with Multi Attribute Decision Making (MADM) recommendations and risk assessment studies that combine strategic and technical information (Mohammadi et al., 2025; Oz & Karalar, 2025).

The questionnaire was designed with a factor framework (Table 1) derived from the literature review, which covered technical (T1-T5), socio-economic (SE1-SE7), and environmental (E1-E4) domains, with each operationalized into clear and quantitative questions. The tool implemented a 1-5 Likert-scale, with 1 indicating very low important and 5 indicating very high importance. This approach is widely used in expert-based risk factor evaluation studies (Agrawal et al., 2021; Yariyan et al., 2020).

Table 1. Factors in Assessing the Vulnerability of Non-Engineered Buildings

No	Code	Factor Name	Domain
1	T1	Material Use and Quality (Cruz et al., 2025; Goda et al., 2024)	Technical
2	T2	Structural Condition (Jena et al., 2020)	
3	T3	Building Design and Layout (Alizadeh et al., 2021)	
4	T4	Damage, Age, and Maintenance (Yariyan et al., 2020)	
5	T5	Construction Techniques (Ismail et al., 2023)	
6	SE1	Owner Involvement (Adamy et al., 2023)	Socio-Economic
7	SE2	Social and Economic Factors (Wan et al., 2024)	
8	SE3	Construction Sustainability (Wan et al., 2024)	
9	SE4	Social Impact of Construction (Nursamsir et al., 2022)	
10	SE5	Risk-Management Capacity (Levy & Bodas, 2024; Niforatos et al., 2024)	
11	SE6	Government Role and Assistance (Wan et al., 2024)	
12	SE7	Access to Technology and Information (Febriani et al., 2025)	
13	E1	Environmental and Site Conditions (Jena et al., 2020)	Environmental
14	E2	Built-Form Arrangement and Environmental Density (Alizadeh et al., 2021)	
15	E3	Evacuation Access and Road Connectivity (El-Maissi et al., 2023; Zhang et al., 2023)	
16	E4	Secondary Hazards and Climate (Lessy et al., 2024)	

The initial step begins with identifying and validating key factors, such as technical, socio-economic, and environmental factors, that were compiled from the literature and then reviewed by experts to verify local contextual relevance and avoid indicator overlap. This approach is common practice when developing holistic vulnerability indices across seismic areas (Limboo et al., 2025). These identified key factors become the foundation for the development of the research questionnaire.

Before the survey distribution, a pilot test through a focus group discussion was conducted to ensure clarity of terminology, questionnaire structure, and completion time. After data collection, responses were exported to Microsoft Excel for data cleaning, including checking response completeness and identifying abnormal response patterns (Ranganathan & Caduff,

2024). During this phase, the completeness of responses was checked, anomalous response patterns (e.g., blanket responses) were identified, and standard practices for dealing with missing data were employed.

The collected responses were analyzed using a consensus-based weighting approach (which emphasizes working together and combining different stakeholder views rather than just counting the majority) to determine the relative importance of each vulnerability factor. This is particularly important for non-engineered housing where the three dimensions (technical, socio-economic and environmental) can be quite balanced with a coherent collectively agreed weight. The approach builds ownership and group commitment and improves credibility and sustainability of decisions. Although Hatefi (2019) remarks that using subjective weights only may result in lack of consistency, through expert Likert scores the research has tried to overcome these issues by framing consensus as a set of expert ratings in order to calculate collective factor weights. Such a hybrid approach is designed to provide for a consistent/transparent/inclusive/multi-faceted analysis, with the semi-objective weighting derived from the decision matrix serving as an aiding tool in cases where perfect consensus on attribute importance was inherently difficult.

First, the responses were organized into an Evaluation Matrix (M) of size $n \times m$, as described in Eq. (1).

$$M = \begin{bmatrix} w_{11} & w_{12} & \dots & w_{1m} \\ w_{21} & w_{22} & \dots & w_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \dots & w_{nm} \end{bmatrix} \quad (1)$$

Where:

n = number of respondents ($n=30$)

m = number of factors ($m=16$)

Each matrix element represents the Likert score supplied by a respondent to an identified factor. To obtain a representative value for each factor, an initial aggregation was performed by using the mean (μ_j) as a measure of central tendency, as shown in Eq. (2). The value μ_j indicated the importance of factor j as perceived by all respondents. This method has been widely applied in studies that depend on expert judgment to determine risk factor weights and mitigation priorities (Goda et al., 2024).

$$\mu_j = \frac{1}{n} \sum_{i=1}^n x_{ij}, \quad j = 1, 2, \dots, m \quad (2)$$

Where:

x_{ij} = Likert score assigned by respondent i to factor j , where $x_{ij} \in \{1, 2, 3, 4, 5\}$

The mean values were then normalized to obtain the relative weights of the factors, as presented in Eq. (3).

$$w_i = \frac{\mu_j}{\sum \mu_j} \quad (3)$$

This normalization ensures that the total weight of all factors equals one ($\sum w_i = 1$). This application the consensus is meant to consolidate expert opinions into a single weight, which would better express the notion of how people think something is important, the consensus, based Likert method used by Oz and Karalar (2025) in fast assessment of building seismic condition.

From this weight set, the maximum weight (w_{max}) was found. To identify the most influential factors, a ratio test was applied by comparing each factor weight with the maximum weight value and the ratio (r) as in Eq. (4) is obtained for all factors.

$$r_i = \frac{w_i}{w_{max}} \quad (4)$$

Threshold for the ratio test (r) is set at $r=0.1$. Variables with $r > 0.1$ were considered to be in the model as significant factors in vulnerability assessment of non-engineered buildings.

Whereas variables with $r \leq 0.1$ could be removed or considered to have a negligible contribution. This approach represents a simplified adaptation of consensus-based group decision-making framework in fuzzy-based method. Overall, the proposed methodology helps to compute consistent factor weights for the study and provides an analytical ground for extension of the method to fuzzy-based procedures.

Three main reasons guided the choice to perform an expert survey with a Likert scale and consensus analysis. First, expert judgment allows the integration of practical experience and contextual knowledge related to non-engineered housing. Second, the Likert aggregation and normalization procedure provides a transparent and replicable weighting system for multi-domain vulnerability indicators. Third, the purposively chosen expert-panel sample size was considered large enough for an exploratory study and complies with research practice regarding earthquake risk. Overall, this methodology provides a structured and practical approach to identifying and prioritizing vulnerability factors, which can serve as the basis for future development of more advanced models such as fuzzy inference systems for seismic vulnerability assessment.

RESULTS AND DISCUSSION

Mean Scores

The vulnerability factors were evaluated using a 1–5 Likert scale based on responses from 30 experts. The resulting mean scores ranged from 1.2 to 4.7, indicating different levels of perceived importance among the identified indicators. The results show that all proposed factors were considered relevant in assessing the seismic vulnerability of non-engineered buildings.

The distribution of scores indicates that vulnerability is influenced by a combination of structural, socio-economic, and environmental conditions rather than by a single dominant variable. This finding reflects the multidimensional nature of seismic vulnerability in low-income housing, where building quality, economic capacity, and environmental exposure collectively shape disaster risk. Similar patterns have been reported in previous studies, which highlight that earthquake damage in non-engineered buildings is often caused by the interaction between poor structural conditions, limited economic resources, and unfavorable environmental settings (Goda et al., 2024; Kristiawan et al., 2024). Therefore, the mean score analysis confirms the need for a holistic vulnerability assessment framework.

Domain-Level Weights

After aggregating and normalizing the expert scores, the technical domain obtained the highest relative weight (0.407), followed by the socio-economic domain (0.372) and the environmental domain (0.222), as illustrated in Figure 1.

The dominance of the technical domain suggests that experts still perceive structural characteristics—such as material quality, structural configuration, and construction practices—as the most critical determinants of earthquake vulnerability in non-engineered buildings. This finding is consistent with field observations in several earthquake events where structural deficiencies, weak masonry connections, and poor construction detailing have been identified as the primary causes of structural collapse.

This is corroborated by field observations in Pacitan, where extensive destruction and failures of non-engineered masonry were driven by poor quality of the materials, insufficient tying provision, and lack of appropriate bracing elements. At the national level in Malawi, studies have additionally shown that the structural configuration and construction quality of non-engineered masonry buildings are the primary determinants of collapse probability within probabilistic seismic risk assessment framework (Goda et al., 2024; Kristiawan et al., 2024).

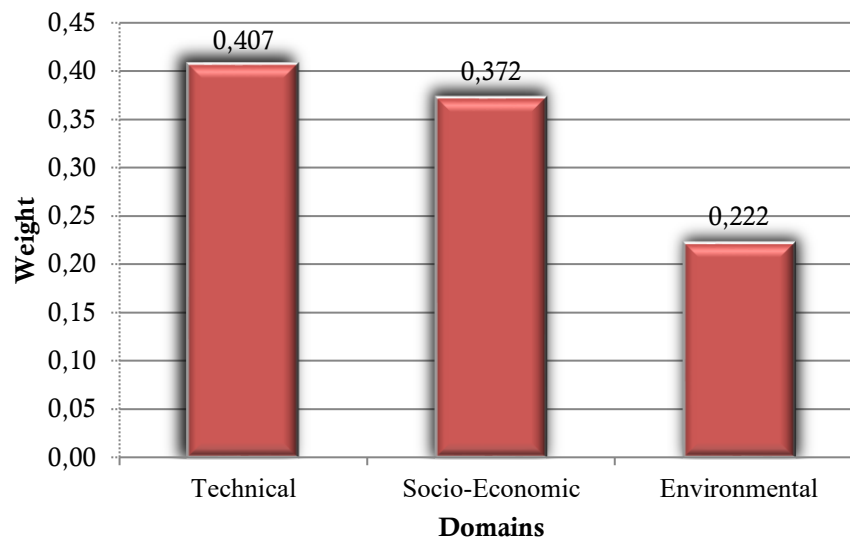


Figure 2. Relative Weights Across Vulnerability Domains

Prior research indicates that the socio-economic domain is a primary determinant of vulnerability in non-engineered structures during seismic events. The high weighting attributed to socio-economic factors, roughly equivalent to technical parameters, suggests that stakeholders do not view vulnerability as a purely structural concern. Rather, there is an implicit understanding that a household's capacity to finance repairs, access critical information, and secure external assistance directly dictates the efficacy of technical mitigation. This observation mirrors the findings of Agrawal et al. (2021) in India's National Capital Region, where regions with comparable hazard exposure exhibited significantly higher seismic vulnerability indices due to diminished socio-economic and housing conditions.

The environmental domain also contributes significantly to vulnerability. Site conditions such as unstable slopes, flood-prone areas, and locations exposed to cascading hazards can amplify structural risk even when buildings share similar construction characteristics. Previous studies have also emphasized that environmental exposure and secondary hazards play an important role in shaping disaster risk patterns (Yariyan et al., 2020). Consequently, these findings suggest that risk-reduction strategies for non-engineered construction must integrate three concurrent dimensions: structural retrofitting, socio-economic capacity building, and environmental site management.

Factor-Level Weights

At the individual factor level, the normalized weights indicate that Structural Condition (T2) has the highest importance ($w = 0.095$). Other influential factors include Construction Techniques (T5), Material Use and Quality (T1), Environmental and Site Conditions (E1), and Socio-economic Factors (SE2). The ratio test results presented in Table 2 show that all sixteen factors exceeded the threshold value of $r > 0.1$, indicating that each factor contributes meaningfully to the vulnerability assessment framework.

Tabel 2. Ratio Test Result for Vulnerability Factors

Factors	Ranking	Weight	Weight Normalization (w)	Ratio Test ($r > 0,1$)	
				Ratio	Test Results
T1	3	0.972	0.092	0.972	Significant
T2	1	1.000	0.095	1.000	Significant
T3	10	0.517	0.049	0.517	Significant
T4	9	0.797	0.076	0.797	Significant
T5	2	0.986	0.094	0.986	Significant
SE1	11	0.441	0.042	0.441	Significant
SE2	5	0.881	0.084	0.881	Significant

SE3	14	0.259	0.025	0.259	Significant
SE4	16	0.245	0.023	0.245	Significant
SE5	7	0.832	0.079	0.832	Significant
SE6	6	0.853	0.081	0.853	Significant
SE7	12	0.399	0.038	0.399	Significant
E1	4	0.944	0.090	0.944	Significant
E2	15	0.252	0.024	0.252	Significant
E3	13	0.322	0.031	0.322	Significant
E4	8	0.811	0.077	0.811	Significant

Based on Table 2, these results indicate the presence of significant factors consisting of critical structural weaknesses (T2, T5, T1), socio-economic capacity and institutional support (SE2, SE6, SE5), and site context and cascade hazard (E1, E4). Figure 2 displays an overall distribution of weighted factors.

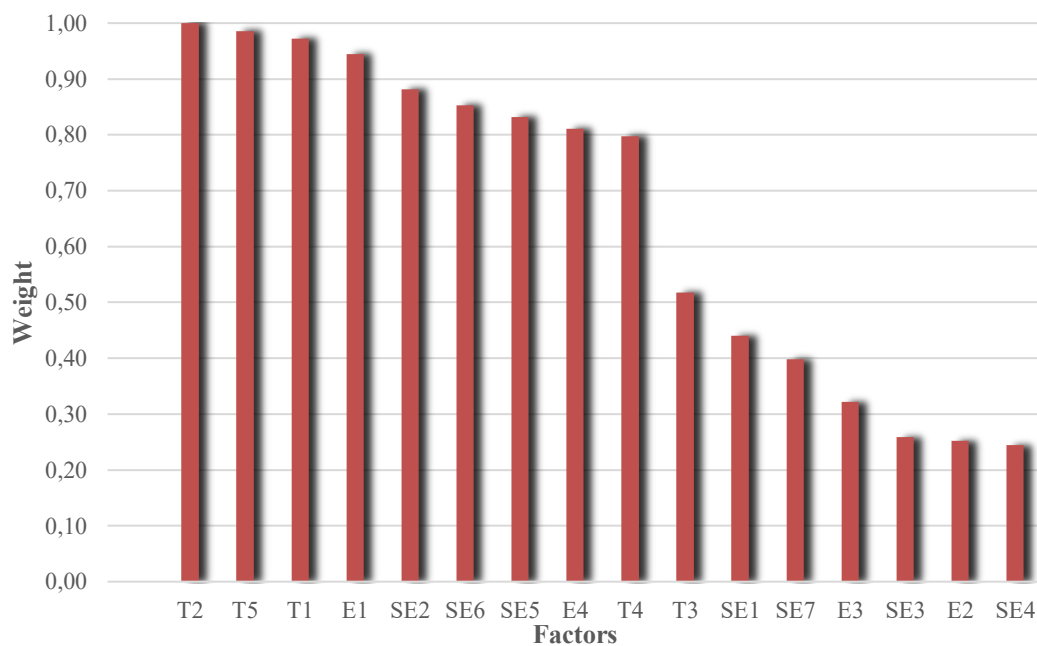


Figure 3. Distribution of Weighted Factors

Consistency and Comparison with Literature Study

From a technical perspective, the high weights assigned to T2, T5, and T1 are consistent with the research finding of Purwanto et al. (2024), who prove that strengthening connections and improving construction detailing can significantly improve the seismic performance of non-engineered buildings. In other words, respondents agreed that the most effective treatments for reducing structural vulnerability are to improve the quality of load-bearing wall systems and on-site construction practices. Focusing on the structural fragility and damage modeling of non-engineered buildings, Giordano et al., (2021) emphasized the importance of field observations to calibrate fragility curves and damage-state threshold, with the main focus on technical aspects such material quality, structural configuration, and connection detailing.

Within the environmental domain, the high weight of E1 and E4 indicates that building location in landslide-prone slopes, riverbanks, or areas with high site amplification, as well as the presence of cascading hazard, have significant impacts on overall vulnerability, even when buildings are technically identical. These findings complement risk-assessment paradigms that include exposure and secondary hazard in vulnerability indices (Yariyan et al., 2020).

Whereas socio-economic factors are distributed evenly from high, fair, and less important level. The three least important of Socio-Economic Factors are SE4: Social Impact of

Construction, SE3: Construction Sustainability , and SE7: Access to Technology and Information that are often less priority during the vulnerability reduction of non-engineered buildings (Ansari et al., 2025; Oz & Karalar, 2025).

Practical Implication and Overall Impact

This study focuses on such technical aspects of the seismic vulnerability assessment of non-engineered buildings with a holistic view that integrates socio-economic and environmental considerations in a comprehensive and systematic framework. This is consistent in acknowledging that economic conditions, access to services, and environmental factors contribute to vulnerability. From a methodological perspective, the Likert scale + consensus + ratio-test approach adopted for this study offers an obvious advantage in terms of simplicity. The method can be easily implemented in field applications without requiring complicated computational resources, and its framework design is sufficient to be further developed into FIS models.

The weighted factors identified in this study provide a practical framework for assessing the seismic vulnerability of non-engineered buildings at the building level. The framework can be translated into structured inspection checklists or field survey instruments that evaluate structural condition, construction practices, socio-economic capacity, and environmental exposure. By combining these indicators into a composite vulnerability index, local governments and practitioners can identify buildings with the highest risk levels and prioritize them for retrofitting programs or targeted risk reduction interventions. This approach supports more efficient allocation of resources in disaster risk management.

Furthermore, the proposed framework bridges the gap between structural engineering approaches that primarily focus on physical damage modelling and broader vulnerability frameworks that emphasize socio-economic conditions. As such, it offers a more comprehensive basis for future development of advanced vulnerability assessment models, including fuzzy inference systems or other multi-criteria decision-making approaches.

CONCLUSION

This study identifies and prioritizes the key determinants of seismic vulnerability in non-engineered buildings through an expert-based consensus evaluation. The results indicate that technical factors dominate the vulnerability structure (0.407), followed by socio-economic (0.372) and environmental domains (0.222). At the factor level, “Structural Condition” (T2), Construction Techniques (T5), and “Material Quality” (T1) emerge as the most critical determinants, highlighting the central role of structural integrity and construction practices in reducing earthquake risk. At the same time, socio-economic capacity and environmental exposure significantly influence the level of vulnerability by shaping households’ ability to prepare for and recover from seismic events.

The proposed framework of 16 weighted factors provides a practical foundation for building-level vulnerability assessment and can support the development of inspection tools and prioritization of retrofitting programs. Future research should integrate empirical post-earthquake damage data and advanced analytical approaches, such as fuzzy inference systems, to enhance the predictive capability and operational applicability of vulnerability assessment models.

REFERENCES

- Adamy, A., Meillyta, Maharani, L., Aidina, F., & Aini, Q. (2023). Disaster Vulnerability Assessment of Low-Cost Houses in Java Island. *Journal of Contemporary Urban Affairs*, 7(2), 20–37. <https://doi.org/10.25034/ijcua.2023.v7n2-2>
- Agrawal, N., Gupta, L., & Dixit, J. (2021). Assessment of the Socioeconomic Vulnerability to Seismic Hazards in the National Capital Region of India Using Factor Analysis. *Sustainability*, 13, 9652. <https://doi.org/10.3390/su13179652>

- Alizadeh, M., Zabihi, H., Rezaie, F., Asadzadeh, A., Wolf, I. D., Langat, P. K., Khosravi, I., Pour, A. B., Nataj, M. M., & Pradhan, B. (2021). Earthquake Vulnerability Assessment for Urban Areas Using an ANN and Hybrid SWOT-QSPM Model. *Remote Sensing*, 13, 4519. <https://doi.org/10.3390/rs13224519>
- Ansari, A., El-Hussain, I., Deif, A., Mohamed, A. M. E., Al-Shijbi, Y., Al-Jabri, K., Mandhaniya, P., Lee, J. H., Alluqmani, A. E., Mutaz, E., Al-Qayoudhi, H., Al-Abdulsalam, W., Al-Kharusi, A. A., Al-Musalhi, M., & Al-Balushi, S. (2025). Integrated GIS-AHP Based Assessment of Earthquake Vulnerability and Risk for Urban Residential Buildings in Muscat, Sultanate of Oman. *Scientific Reports*, 15, 31995. <https://doi.org/10.1038/s41598-025-17618-6>
- Candra M, A., Wulandari, E., & Witjaksana, B. (2025). Identification of Dominant Factors of Simple House Building Vulnerability in Earthquake-Prone Areas Using RVS and FTA Methods. *Enrichment: Journal of Multidisciplinary Research and Development*, 3(6), 2933–2943. <https://doi.org/10.55324/enrichment.v3i6.488>
- Cruz, A., Chieffo, N., Karimzadeh, S., Ortiz, A., Sandoval, E., & Lourenço, P. B. (2025). Earthquake Vulnerability Assessment of Non-Engineered URM Residential Buildings. *International Journal of Disaster Risk Reduction*, 122, 105476. <https://doi.org/10.1016/j.ijdr.2025.105476>
- El-Maissi, A. M., Argyroudis, S. A., Kassem, M. M., & Nazri, F. M. (2023). Integrated Seismic Vulnerability Assessment of Road Network in Complex Built Environment Toward More Resilient Cities. *Sustainable Cities and Society*, 89, 104363. <https://doi.org/10.1016/j.scs.2022.104363>
- Febriani, R. A., Ophiyandri, T., & Hidayat, B. (2025). Public Knowledge of Simple Earthquake-Resistant Houses after the 2022 Pasaman Earthquake. *Journal of Civil Engineering and Vocational Education*, 12(1), 230–240. <https://doi.org/10.24036/cived.v12i1.712>
- Fitria, W., Guspari, O., Afriyani, S., Putra, R. T., & Misriani, M. (2024). Design of Non-Engineered Earthquake Resistant Housing in West Sumatera. *Journal of Civil Engineering and Planning*, 5(2), 226–237. <https://doi.org/10.37253/jcep.v5i2.10008>
- Giordano, N., Risi, R. De, Voyagaki, E., Kloukinas, P., Novelli, V., Kafodya, I., Ngoma, I., Goda, K., & Macdonald, J. (2021). Seismic Fragility Models for Typical Non-Engineered URM Residential Buildings in Malawi. *Structures*, 32, 2266–2278. <https://doi.org/10.1016/j.istruc.2021.03.118>
- Goda, K., Williams, J., De Risi, R., & Ngoma, I. (2024). Probabilistic Seismic Collapse Risk Assessment of Non-Engineered Masonry Buildings in Malawi. *Frontiers in Built Environment*, 10, 1333576. <https://doi.org/10.3389/fbuil.2024.1333576>
- Harirchian, E., & Novelli, V. I. (2025). Leveraging Transformer Models for Seismic Fragility Assessment of Non-Engineered Masonry Structures in Malawi. *Infrastructures*, 10, 279. <https://doi.org/10.3390/infrastructures10110279>
- Hatefi, M. A. (2019). Indifference Threshold-based Attribute Ratio Analysis: A Method for Assigning the Weights to the Attributes in Multiple Attribute Decision Making. *Applied Soft Computing Journal*, 74, 643–651. <https://doi.org/10.1016/j.asoc.2018.10.050>
- Hidayat, M. R., Habieb, A. B., & Sutrisno, W. (2023). Numerical Study of Using Multi-Direction Angle Wire Mesh As a Confinement System for Confined Masonry Under Horizontal Cyclic Loads. *Journal of Civil Engineering*, 38(2), 99–110. <https://doi.org/10.12962/j20861206.v38i2.17405>
- Ismail, F. A., Fauzan, Hakam, A., & Alfajri, A. (2023). Study on the Behavior of a Simple House Partially Retrofitted Using Ferrocement Layers due to Earthquake Loads. *International Journal on Advanced Science, Engineering and Information Technology*, 13(2), 501–513. <https://doi.org/10.18517/ijaseit.13.2.16987>
- Jena, R., Pradhan, B., & Beydoun, G. (2020). Earthquake Vulnerability Assessment in Northern Sumatra Province by Using a Multi-Criteria Decision-Making Model. *International Journal*

- of Disaster Risk Reduction*, 46, 101518. <https://doi.org/10.1016/j.ijdrr.2020.101518>
- Kristiawan, S. A., Safarizki, H. A., Purwanto, E., Sangadji, S., Trisnawan, A. D., & Nugroho, T. S. (2024). Damage State of Non-Engineered Residential Buildings Owing To Earthquakes: a Case Study in Pacitan Regency, Indonesia. *Civil and Environmental Engineering*, 20(1), 426–439. <https://doi.org/10.2478/cee-2024-0033>
- Lessy, M. R., Lassa, J., & Zander, K. K. (2024). Understanding Multi-Hazard Interactions and Impacts on Small-Island Communities: Insights from the Active Volcano Island of Ternate, Indonesia. *Sustainability*, 16, 6894. <https://doi.org/10.3390/su16166894>
- Levy, L., & Bodas, M. (2024). Risk Messaging Style and Its Effect on Public Preparedness for Earthquakes: Longitudinal Intervention-Based Study. *Journal of Public Health Policy*, 46, 87–109. <https://doi.org/10.1057/s41271-024-00534-w>
- Limboo, S., Guite, L. T. S., Haq, A. U., & Bharti, S. (2025). Evaluating Determinants of Inherent Vulnerability and Risk Index (IVRI) Assessment of Gangtok City Using PCA (Principal Component Analysis) Approach. *Discover Environment*, 3, 224. <https://doi.org/10.1007/s44274-025-00398-1>
- Mohammadi, S., Balouei, F., Amini, S., & Rabiei-Dastjerdi, H. (2025). Beyond the Richter Scale: a Fuzzy Inference System Approach for Measuring Objective Earthquake Risk. *Natural Hazards*, 121, 245–268. <https://doi.org/10.1007/s11069-024-06786-9>
- Niforatos, S., Panagiotakos, D., & Delladetsimas, P. M. (2024). Socio-Demographic Determinants of Earthquake Risk Perception: the Case of the Corinthiakos Gulf, in Greece. *Natural Hazards*, 120, 3847–3864. <https://doi.org/10.1007/s11069-023-06356-5>
- Nursamsir, Jamaluddin, I. I., Iqbal, M., & Ismanto. (2022). The Social and Political Aspects of Permanent Housing Provision for Earthquake Tsunami and Liquefaction Casualties in Palu City, Central Sulawesi. *JKAP (Jurnal Kebijakan dan Administrasi Publik)*, 26(2), 85–101. <https://doi.org/10.22146/jkap.54013>
- Oz, B., & Karalar, M. (2025). An Approach to Rapid Assessment of Building Seismic Conditions Utilizing Supervised Fuzzy C-means with Consensus-Based Likert Analysis. *Journal of Building Engineering*, 116, 114715. <https://doi.org/10.1016/j.jobe.2025.114715>
- Purwanto, E., Kristiawan, S. A., Sangadji, S., & Saifullah, H. A. (2024). Influence of Joint Strengthening on the Seismic Performance of Non-Engineered Buildings. *Buildings*, 14, 488. <https://doi.org/10.3390/buildings14020488>
- Ranganathan, P., & Caduff, C. (2024). Designing and Validating a Research Questionnaire - Part 1. *Perspectives in Clinical Research*, 15(1), 42–45. https://doi.org/10.4103/picr.picr_318_23
- Sauti, N. S., Daud, M. E., Kaamin, M., & Sahat, S. (2023). A Comprehensive Review of Holistic Indicators for Seismic Vulnerability Assessment of Malaysia. *International Journal of Design and Nature and Ecodynamics*, 18(3), 631–642. <https://doi.org/10.18280/ijdne.180315>
- Wan, J., Dou, R., & Ma, T. (2024). Seismic Risk Assessment and Analysis of Influencing Factors in the Sichuan–Yunnan Region. *Sustainability*, 16, 5968. <https://doi.org/10.3390/su16145968>
- Yariyan, P., Zabihi, H., Wolf, I. D., Karami, M., & Amirian, S. (2020). Earthquake Risk Assessment Using an Integrated Fuzzy Analytic Hierarchy Process with Artificial Neural Networks Based on GIS: A Case Study of Sanandaj in Iran. *International Journal of Disaster Risk Reduction*, 50, 101705. <https://doi.org/10.1016/j.ijdrr.2020.101705>
- Zhang, Z., Hu, Y., Lu, W., Cao, W., & Gao, X. (2023). Spatial Accessibility Analysis and Location Optimization of Emergency Shelters in Deyang. *Geomatics, Natural Hazards and Risk*, 14(1), 2213809. <https://doi.org/10.1080/19475705.2023.2213809>