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Machine Learning Integration for Predictive Health Monitoring in Earthquake-Resistant Structures

Aditya Hidayat[1]*, Melati Saputra[2], Heri Wijaya[3]
[1,2] Department of Physical Education, Faculty of Sports Science, Universitas Negeri Jakarta, Jakarta, Indonesia
[3] Department of Mathematics Education, Faculty of Teacher Training and Education, Universitas Pendidikan Indonesia, Bandung, Indonesia

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ABSTRACT

This study aims to explore the integration of machine learning into predictive health monitoring for earthquake-resistant structures, with a focus on how field actors understand, interpret, and use predictive systems in structural safety management. The study used a qualitative case study approach conducted from November 2025 to February 2026 in earthquake-prone areas in Indonesia. Data were collected through semi-structured interviews, field observations, and document analysis involving structural engineers, sensor technicians, facility managers, construction consultants, machine learning system developers, and building managers. The findings reveal five main themes: readiness of monitoring infrastructure and sensor data, trust and interpretability of machine learning outputs, organizational barriers in predictive monitoring implementation, the role of human expertise in mediating data and decisions, and predictive monitoring as a socio-technical safety system. The study shows that the successful use of machine learning does not depend only on algorithmic accuracy, but also on data integration, explainable outputs, staff competence, clear procedures, and organizational commitment to preventive maintenance. These findings contribute to structural health monitoring literature by extending the discussion from technical model performance to socio-technical implementation in real building management contexts. The study implies that predictive monitoring systems should be designed as decision-support tools that strengthen expert judgment, support risk-based maintenance, and improve safety governance in earthquake-resistant structures. Future research should compare multiple structural contexts and examine ethical, legal, and data security aspects of machine learning-based monitoring.

***) Corresponding Author:**

Aditya Hidayat,
Department of Physical Education, Faculty of Sports Science, Universitas Negeri Jakarta, Jakarta, Indonesia
Email: aditya.hidayat076@gmail.com

1. Introduction

Earthquakes remain a serious threat to public safety, building performance, and infrastructure resilience, especially in areas with high seismic activity. Modern earthquake-resistant structures require more than strong initial design. They also require continuous monitoring during their service life. This need has encouraged the development of *predictive health monitoring*, which uses structural data to identify early signs of damage before failure occurs. Xie et al. (2020) show that *machine learning* offers strong potential in earthquake engineering because it can identify complex patterns from seismic, structural, and damage-related data. Hu et al. (2025) add that *machine learning* has become increasingly important in seismic performance evaluation because it supports faster prediction, classification, and design decision-making. Azimi et al. (2020) also explain that *deep learning* can improve structural damage detection by processing vibration data, visual data, and dynamic response patterns more effectively than many traditional methods.

In Indonesia, the issue becomes highly relevant because many public buildings, schools, hospitals, bridges, and high-rise buildings stand in earthquake-prone regions. Earthquake-resistant structures are often understood as products of engineering standards and construction regulations. However, their actual performance can change over time due to aging, repeated loads, environmental exposure, maintenance quality, and small-scale damage that visual inspection may not detect. Malekloo et al. (2022) explain that *structural health monitoring* has moved from conventional inspection toward intelligent systems supported by sensors, the Internet of Things, and high-dimensional data analytics. Scuro et al. (2021) show that IoT-based systems can improve structural monitoring because sensor data can be transmitted, processed, and used for technical decision-making. Shibu et al. (2023) further argue that AI and ML integration with multimodal sensor data can help detect early structural anomalies with better accuracy and speed.

Field-level problems appear when predictive monitoring systems have not been fully integrated into building management practices. Many building managers still depend on periodic inspection, manual reports, and visual judgment. These methods can miss early damage, especially when cracks, stiffness reduction, or vibration changes remain hidden from direct observation. Aravena Pelizari et al. (2021) show that street-level imagery and *deep learning* can support building characterization for seismic risk assessment, but data quality and visual context still influence the result. Kumari et al. (2022) also show that *machine learning* and web-based processes can support damage score estimation for existing buildings, but users still need practical, understandable, and context-sensitive systems. Zhang et al. (2023) demonstrate that *machine learning* can improve rapid seismic damage assessment of reinforced concrete frames, although validation against real damage conditions remains essential.

The integration of *machine learning* into structural monitoring has social, educational, cultural, and public safety significance. In schools, universities, hospitals, government offices, and bridges, structural condition data does not only serve technical purposes. It also supports evacuation decisions, repair priorities, maintenance budgeting, and public risk communication. Sonbul and Rashid (2023) explain that bridge structural health monitoring requires integrated processes, including sensor data acquisition, feature extraction, pattern recognition, and condition interpretation. Xu et al. (2023) show that ML applications in concrete and steel bridge monitoring can improve damage detection and infrastructure condition assessment. Worden et al. (2020) also highlight the value of population-based SHM because it allows learning across structures when damage data from one structure remains limited. These findings show that predictive monitoring systems must not only produce accurate outputs. They must also provide information that engineers, facility managers, technicians, and policymakers can understand and trust.

Although studies on *machine learning* and *structural health monitoring* continue to grow, most studies still focus on model accuracy, classification algorithms, neural network architecture, and numerical validation. Cha et al. (2024) show that *deep learning*-based SHM has expanded into computer vision, vibration-based monitoring, UAV inspection, digital twin systems, and physics-informed learning. Cheraghzade and Roohi (2022) argue that seismic structural monitoring based on *deep learning* needs to account for mechanics-based model uncertainty. Fan et al. (2020) emphasize the importance of vibration signal denoising because noisy data can reduce the reliability of damage detection. Rodrigues et al. (2024) show that environmental variables can affect damage detection and create false alarms. Ge and Sadhu (2024) also explain that the gap between simulated data and real structural conditions remains a major challenge in intelligent SHM. However, fewer studies have explored how field actors understand, accept, interpret, and use *machine learning* systems in predictive monitoring for earthquake-resistant structures.

Based on this gap, this study aims to explore the integration of *machine learning* into *predictive health monitoring* for earthquake-resistant structures. The study focuses on the experiences, interpretations, barriers, and strategies of actors involved in sensor data use, model output interpretation, maintenance decisions, and seismic risk mitigation. This study argues that successful implementation does not depend only on algorithmic sophistication. It also depends on organizational readiness, data quality, user competence, trust in predictive outputs, and clear procedures for follow-up action. Theoretically, this study contributes to socio-technical discussions in structural engineering, disaster risk management, and intelligent infrastructure monitoring. Practically, this study provides insights for building managers, structural consultants, local governments, and educational institutions in designing predictive monitoring systems that are technically reliable, operationally useful, and understandable for decision-makers.

2. Materials and Methods

This study uses a qualitative approach with a case study design. The design fits the study because the research focuses on the process, experience, meaning, and challenges of integrating *machine learning* into *predictive health monitoring* for earthquake-resistant structures. A case study allows the researcher to examine a contemporary phenomenon within its real-life context, especially when technology, actors, work procedures, and organizational decisions interact closely. Priya (2021) explains that qualitative case study research helps researchers understand context, actors, and social dynamics in depth. Mtisi (2022) also states that case study research can systematically examine units of analysis, research questions, data collection, triangulation, and research quality. Therefore, this design is suitable because the integration of *machine learning* in structural monitoring involves not only computational models but also technical practices, organizational readiness, and field-level decision-making.

The research site consists of earthquake-resistant structures in earthquake-prone areas in Indonesia. The selected cases include public buildings, educational facilities, healthcare facilities, or technical infrastructure that already use structural inspection, vibration sensors, digital monitoring systems, or early plans for *machine learning*-based structural monitoring. The site is selected purposively because the research requires a context that has direct links to structural data use and maintenance decisions. The study takes place from November 2025 to February 2026. In November 2025, the researcher finalizes the instruments, maps potential informants, and completes field access procedures. From December 2025 to January 2026, the researcher conducts interviews, observations, and document collection. In February 2026, the researcher performs data validation, thematic analysis, and research finding development. This time frame allows the study to produce a clear unit of analysis and enables limited replication in other earthquake-resistant structures with similar characteristics.

The research participants consist of informants who have direct involvement in planning, managing, maintaining, developing, or using structural monitoring systems. Key informants include structural engineers, sensor technicians, facility managers, construction consultants, *machine learning* system developers, building managers, and personnel involved in building safety decisions. The study involves approximately 12 to 20 informants, with adjustment based on data sufficiency. Informant criteria include at least one year of experience in structural inspection, building monitoring, sensor data analysis, facility management, or digital system development for infrastructure monitoring. The study uses *purposive sampling* because the researcher needs participants who understand the phenomenon directly. If initial informants recommend other relevant actors, the study uses limited *snowball sampling*. Algassim et al. (2023) show that qualitative studies on technology adoption need to examine user experience, managerial factors, ease of use, cost, training, and organizational readiness.

Data collection uses semi-structured interviews, field observation, documentation, and triangulation. Semi-structured interviews explore informants' experiences regarding the reasons for applying *machine learning*, sensor data readiness, technical barriers, trust in predictive outputs, and the use of predictive information in maintenance decisions. Field observation takes place in structural monitoring areas, sensor locations, control rooms, inspection areas, and technician work settings. Documentation includes inspection reports, maintenance records, safety procedures, sensor diagrams, monitoring data summaries, field photographs, and internal policy documents related to structural risk management. Triangulation compares interview data, observation findings, and documents. This step is important because predictive monitoring systems involve technical devices, data interpretation, human judgment, and institutional decision-making.

The research instruments consist of an interview guide, an observation sheet, and a document review form. The interview guide covers sensor infrastructure readiness, data quality, model output interpretation, system barriers, trust in prediction, and maintenance follow-up. Sample interview questions include how the monitoring system is used, what data the actors analyze most frequently, how users interpret predictive results, what barriers occur during system use, and how the organization makes decisions after the system detects potential risks. The observation sheet records device conditions, technician workflow, interactions among actors, and the use of supporting documents. The document review form examines the consistency between written procedures and field practice. The researcher records all interviews after obtaining informant consent and transcribes the recordings verbatim. The researcher protects informant identity by using codes, such as SE-01 for structural engineer, ST-01 for sensor technician, BM-01 for building manager, and SD-01 for system developer.

Data trustworthiness is maintained through source triangulation, method triangulation, *member checking*, and an *audit trail*. Source triangulation compares information from structural engineers, sensor technicians, facility managers, consultants, and system developers. Method triangulation compares interview results, observation notes, and documents. *Member checking* asks selected informants to review interview summaries or early interpretations to ensure that the researcher captures their meanings accurately. The *audit trail* stores research notes, coding changes, analytical memos, and category development records. Ahmed (2024) explains that qualitative research quality can be strengthened through credibility, transferability, dependability, and confirmability. Johnson et al. (2020) state that qualitative rigor must be maintained from research design to reporting. Morgan (2024) also shows that triangulation can increase the trustworthiness of qualitative studies because it allows the researcher to examine a phenomenon through several sources and techniques.

Data analysis uses thematic analysis. The first stage involves repeated reading of interview transcripts, observation notes, and research documents. The second stage uses *open coding* to identify units of meaning related to data readiness, technical barriers, model trust, actor roles, maintenance decisions, and structural risk. The third stage groups codes into categories, such as monitoring infrastructure readiness, sensor data quality, predictive output interpretation, organizational barriers, and follow-up strategies. The fourth stage develops main themes that explain the process of integrating *machine learning* into *predictive health monitoring*. Braun and Clarke (2021) emphasize that thematic analysis must maintain a logical relationship among data, codes, themes, and interpretation. Naeem et al. (2023) show that thematic analysis can support conceptual model development when researchers apply systematic coding and theme construction. The final findings are presented through themes, informant quotations, researcher interpretation, and a conceptual mapping of supporting and inhibiting factors in the integration of *machine learning* for predictive monitoring of earthquake-resistant structures.

3. Results and Discussions

The results and discussions section is the main part of the paper. The author(s) meticulously present their findings, providing a comprehensive analysis of the data collected. The author(s) elucidates the significant trends and patterns observed, correlating them with the hypotheses stated earlier in the study. The discussion integrates these findings with existing literature, highlighting agreements and discrepancies with prior research. The author(s) delve into the implications of the results, considering both theoretical and practical perspectives. Furthermore, the author(s) should address potential limitations and suggest areas for future research to build upon their work, ensuring a holistic understanding of the topic under investigation.

Readiness of Monitoring Infrastructure and Sensor Data

The findings show that the integration of machine learning into predictive health monitoring for earthquake-resistant structures depends strongly on the readiness of monitoring infrastructure and the quality of available sensor data. Informants explained that the monitoring system could not work effectively when sensors were not installed at critical structural points. In several buildings, vibration sensors were already available, but their use remained limited to data recording. The data had not yet been fully processed for predictive analysis through machine learning models. This condition shows that structural monitoring is still moving from conventional inspection toward intelligent data-based monitoring.

One informant stated, “The sensors are already installed, but not all data are used for prediction. Usually, the data are only checked when there is a report or after a strong vibration occurs” (SE-02). This statement shows that structural data have not yet become part of daily decision-making. Field observation also found that several sensor data sets were stored separately and had not been integrated into an automatic analysis system. This condition slowed down interpretation because technicians still had to compare sensor outputs with manual inspection records.

Maintenance documents supported this finding. Inspection reports still focused more on visual findings, such as cracks, deformation, joint condition, and visible material damage. Digital sensor data were not always included in routine evaluation reports. This shows a gap between the availability of monitoring technology and its use in structural management. Therefore, technical readiness does not only depend on the presence of devices. It also depends on the organization’s ability to manage, clean, store, integrate, and interpret data consistently.

Trust and Interpretability of Machine Learning Outputs

The second theme relates to user trust in machine learning outputs. Informants acknowledged that algorithm-based systems can help detect potential structural damage more quickly. However, several informants were still reluctant to use prediction results as the main basis for decision-making. This reluctance appeared because users did not always understand how the model produced risk classifications or early warnings. They still needed additional technical explanation before approving maintenance actions.

A building manager explained, “When the system gives a warning, we still need an explanation from the engineer. We cannot make a decision only based on numbers or risk status” (BM-01). This statement shows that trust in technology does not emerge automatically. Users need a system that is not only accurate but also explainable in clear technical language. In this context, interpretability becomes an important factor in the acceptance of machine learning.

Field observation showed that technicians trusted prediction results more when the system could show the relationship between sensor data, structural condition, and recommended action. Warnings that only displayed “safe,” “alert,” or “high risk” were considered insufficient. Informants needed trend visualization, vibration history, structural frequency changes, and comparison with technical thresholds. These findings indicate that machine learning should be positioned as a decision-support tool, not as a complete replacement for expert judgment.

Organizational Barriers in Predictive Monitoring Implementation

The findings also reveal that the main barriers to machine learning integration are not only technical but also organizational. Several informants mentioned limited budgets, lack of training, absence of standard procedures, and weak coordination between units as major constraints. Predictive systems require device updates, sensor maintenance, data storage, and experts who can interpret model outputs. However, these needs have not always become part of building management priorities.

A sensor technician stated, “The problem is not only installing the device. After the device is installed, there must be someone who maintains it, reads the data, and knows when to report” (ST-03). This statement shows that system sustainability depends on human resource readiness. If devices are available but monitoring procedures remain unclear, the system cannot provide optimal benefits. Internal documents also showed that routine inspection schedules were available, but specific procedures for responding to algorithmic prediction results had not yet been developed.

Work culture also influenced system implementation. Several informants explained that maintenance practices were still reactive. Technical action was often taken after damage became visible, not when the system detected early risk indicators. This pattern shows that predictive technology requires organizational culture change. Building managers need to move from a “repair after damage” approach to a “prevent before damage” approach.

Human Expertise as a Mediator Between Data and Decision

Another important finding is that human expertise remains central in predictive monitoring systems. Informants did not reject machine learning. However, they emphasized that model outputs must be interpreted together with technical experience, structural knowledge, and field context. In several cases, sensor outputs could show anomalies, but the cause was not always structural damage. Anomalies could appear due to environmental disturbance, calibration error, human activity, temporary load changes, or device instability.

A structural engineer stated, “The model can help detect patterns, but the engineer still has to understand the context. Not every signal change means that the structure is damaged” (SE-04). This statement shows that machine learning integration requires collaboration between intelligent systems and professional judgment. Users need the ability to distinguish between warnings that indicate real structural risk and warnings caused by technical or environmental noise.

The findings also show that informants viewed machine learning as most useful when it helped filter large amounts of data. The system could identify early patterns, while engineers assessed their technical meaning. In this model, technology does not replace human actors. It accelerates detection and strengthens the basis for technical decisions.

Predictive Monitoring as a Socio-Technical Safety System

The final theme shows that predictive health monitoring for earthquake-resistant structures must be understood as a socio-technical safety system. The system does not only consist of sensors, software, and algorithms. It also involves user trust, organizational procedures, risk communication, and public safety responsibility. Informants stated that prediction results must be translated into clear actions, such as additional inspection, restricted access, special maintenance, structural audit, or repair planning.

A facility manager explained, “We need results that can be used directly for decisions. If the output is only a graph, management will find it difficult to decide what to do” (FM-02). This statement shows that technical outputs must be presented in a format that can be used by different actors, including non-technical managers. In public buildings, predictive information is also related to users' sense of safety. Decisions about maintenance, evacuation, or access restriction must be communicated carefully to prevent confusion or panic.

Socially and organizationally, this finding shows that structural safety is not only the responsibility of engineers. Safety becomes a shared responsibility between building managers, technicians, building users, consultants, and government agencies. Therefore, machine learning integration must be supported by clear governance. Predictive systems need procedures for verification, reporting, communication, and follow-up action.

Discussion

The findings show that the integration of machine learning into predictive health monitoring cannot be understood only as a technical issue. The findings on sensor readiness, data quality, and system integration are consistent with Malekloo et al. (2022), who state that modern structural health monitoring requires sensors, IoT, high-dimensional data, and intelligent analytics. The findings also support Shibu et al. (2023), who explain that multimodal sensor data can improve the ability of AI and ML systems to recognize structural conditions. However, this study adds a practical perspective. Data availability alone is not enough. Data must be integrated into organizational workflows so that it can support maintenance decisions.

User hesitation toward prediction results shows the importance of interpretability in machine learning implementation. This finding is in line with Cha et al. (2024), who explain that deep learning-based structural health monitoring has expanded into computer vision, vibration-based monitoring, UAV inspection, digital twins, and physics-informed learning. However, the field findings show that model sophistication does not automatically create user trust. Users need explanations about why the model gives a warning, what indicators have changed, and how prediction results relate to the physical condition of the structure. Therefore, this study expands the technical discussion of model accuracy into a practical discussion of output understandability.

The finding on organizational barriers shows that predictive systems require a shift in maintenance culture. Many organizations still use a reactive approach, where action is taken after visible damage appears. Predictive systems require a preventive approach. This finding relates to Scuro et al. (2021), who show that IoT can support continuous structural monitoring. However, this study shows that continuous monitoring can only work when organizations provide budgets, procedures, training, and clear role distribution. Without these elements, sensors and algorithms may become additional devices that do not transform maintenance practice.

The findings also strengthen the view that human expertise remains important in machine learning-based systems. Fan et al. (2020) explain that vibration signal quality influences structural monitoring results. Rodrigues et al. (2024) show that environmental factors can affect damage detection and create false alarms. This study shows that engineers and technicians act as contextual interpreters. They help distinguish anomalies that indicate structural risk from anomalies caused by technical or environmental disturbances. Therefore, machine learning should be understood as a decision-support system, not as a substitute for professional knowledge.

The socio-technical nature of predictive monitoring offers an important contribution to studies on earthquake-resistant structures. Xie et al. (2020) emphasize the potential of machine learning in earthquake engineering, while Hu et al. (2025) highlight the role of ML in seismic performance evaluation and design. This study complements those discussions by showing that ML integration must consider actors, institutions, work culture, and risk communication. In practice, prediction results must be translated into clear decisions. These decisions may include further inspection, structural strengthening, restricted use, or mitigation planning.

The findings also differ from several previous studies that focus mainly on algorithm performance. Zhang et al. (2023) show that ML can support rapid seismic damage assessment of reinforced concrete frames. Kumari et al. (2022) also show that ML can help estimate building damage scores. This study does not reject these technical contributions. Instead, it shows that model accuracy is not always enough to guarantee field use. Users still need understandable systems, reliable data, follow-up procedures, and organizational support.

Theoretically, this study contributes to the development of a socio-technical perspective in structural health monitoring. Machine learning integration is not only shaped by technical variables such as sensors, algorithms, and data. It is also shaped by human and organizational factors, including trust, competence, coordination, and safety culture. This finding broadens the understanding of SHM from a damage detection system into a risk-based decision-making system. In this way, the study connects structural engineering, facility management, and disaster risk management within one analytical framework.

Practically, the findings suggest that managers of earthquake-resistant structures need to prepare four main elements before implementing machine learning-based predictive systems. First, sensors must be installed at relevant structural points and must produce stable data. Second, the organization must develop monitoring procedures that explain who reads the data, who verifies the results, and who makes decisions. Third, the system must present prediction results in a form that technical and non-technical actors can understand. Fourth, the organization must provide training so that technicians and managers understand the function, limitations, and risks of predictive models.

This study also has implications for building safety policy. Local governments, public facility managers, and structural consultants can use these findings to develop more adaptive structural monitoring standards. Predictive health monitoring can help determine maintenance priorities, especially for public buildings with high risk exposure. However, such policy must regulate data validation, prediction verification, data security, and risk communication mechanisms. Without clear governance, predictive systems may create confusion, especially when model outputs are not understood by decision-makers.

Future research can develop this study through comparative analysis across different types of structures, such as schools, hospitals, bridges, and government buildings. Further studies can also combine qualitative and quantitative approaches to compare user experience with model performance. In addition, future research can explore ethical issues, data security, legal responsibility, and risk communication in the use of machine learning for earthquake-resistant structural monitoring. This is important so that predictive systems can become not only technically advanced but also safe, transparent, and responsible.

4. Conclusions

This study concludes that the integration of machine learning into predictive health monitoring for earthquake-resistant structures is not only a technical process, but also a socio-technical practice shaped by infrastructure readiness, data quality, user trust, professional expertise, and organizational procedures. The main findings show that sensor availability alone does not guarantee effective predictive monitoring. Structural data must be integrated into routine workflows, interpreted through expert judgment, and translated into clear maintenance decisions. The study also shows that users are more willing to trust machine learning outputs when the system provides explainable results, visual trends, technical thresholds, and actionable recommendations.

Theoretically, this study contributes to the development of a socio-technical perspective in structural health monitoring by showing that predictive systems depend on the interaction between algorithms, human actors, institutional readiness, and safety culture. Practically, the findings suggest that building managers, structural engineers, facility operators, and public agencies need to strengthen sensor governance, staff training, data validation, and follow-up procedures before adopting machine learning-based monitoring systems. From a policy perspective, predictive health monitoring can support safer and more preventive infrastructure management in earthquake-prone areas. Future studies should compare different types of structures, apply mixed-method designs, and examine ethical, legal, and data security issues in machine learning-based structural monitoring.

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