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From Sensors to Socio-Technical Systems: A PRISMA-Based Systematic Review of IoT-Driven Landslide Early Warning Systems

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Systematic Review

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Abstract

Landslides are among the most recurrent and destructive natural hazards worldwide, generating severe impacts on human life, infrastructure, and ecosystems. Recent advances in Internet of Things (IoT) technologies, smart sensing, and data-driven architectures have significantly enhanced the capabilities of Early Warning Systems (EWS) for landslide risk mitigation. However, current implementations remain fragmented across technological layers and lack standardized validation and socio-technical integration.

This study presents a systematic literature review of IoT-based landslide EWS published between 2019 and 2025, following the PRISMA protocol. A total of 33 primary studies were selected from Scopus, Web of Science, and IEEE Xplore using predefined inclusion and exclusion criteria. The review analyzes key system dimensions, including sensing technologies, communication infrastructures, data processing architectures, validation approaches, and human-centered evaluation. The results reveal the predominance of Micro-Electro-Mechanical Systems (MEMS) and optical sensing technologies such as Fiber Bragg Grating (FBG) and Distributed Acoustic/Temperature Sensing (DAS/DTS), along with communication protocols such as Long Range (LoRa) and 5G. In addition, hybrid Edge–Cloud architectures are widely adopted to enable real-time monitoring and predictive analytics. Despite these advances, critical gaps persist in data validation standardization, system interoperability, and the integration of human-centered and participatory evaluation approaches. This study contributes by proposing an integrated socio-technical framework that unifies sensing, communication, data processing, validation, and human-centered dimensions in IoT-based EWS. The findings highlight the need for standardized validation protocols, AI-driven predictive integration, and user-centered design strategies to enhance the scalability, reliability, and social effectiveness of next-generation early warning systems.

1 Introduction

Landslides represent one of the most recurrent and destructive natural hazards worldwide, whose frequency and severity have intensified due to climate change, deforestation, and unplanned urban expansion into geologically unstable areas (Clague & Roberts, 2012; Highland & Bobrowsky, 2008). These processes generate significant human, economic, and environmental impacts, severely affecting infrastructure, ecosystems, and vulnerable communities (G¨oru¨m et al., 2025; L. Liu et al., 2025). Recent large-scale events, such as the more than 3,500 mass movements triggered by the 2023 Tu¨rkiye–Syria earthquake and recurrent landslides in Sub-Saharan Africa, highlight the increasing complexity and systemic nature of landslide risk.

Traditional mitigation approaches, primarily based on structural interventions such as retaining walls, drainage systems, and slope stabilization techniques, have proven to be costly, site-specific, and limited in scalability and long-term sustainability (Alc´antara-Ayala, 2025; Jelu˘si˘c, Vlastelica, & Zlender˘, 2024). In this context, a paradigm shift has emerged toward data-driven risk management strategies, where Early Warning Systems (EWS) integrate Internet of Things (IoT) technologies, realtime sensing, and

predictive analytics to enhance anticipatory capacity and disaster preparedness (Soegoto, Fauzi, & Luckyardi, 2021).

The Internet of Things has significantly strengthened EWS capabilities by enabling continuous monitoring of geotechnical, hydrological, and atmospheric variables, supporting near real-time decision-making and improving response effectiveness (Gupta & Satyam, 2024; Luong, 2024). However, despite these technological advances, current research reveals a critical fragmentation across system components, including sensing technologies, communication protocols, data architectures, validation methodologies,

Table 1
Research topics considered in the systematic review

Motivation	Research Topics
To identify which sensing technologies have been implemented in research on landslide early warning systems.	Sensor models, measured variables, and operating ranges.
To determine which communication protocols are used for data transmission in these systems.	Communication protocols between sensors,nodes,gateways,and servers.
To identify the databases and storage structures adopted for landslide early warning data management.	Types of databases, database platforms, and data schemas.
To analyze the software architectures implemented in IoT-based early warning systems.	Software architecture patterns and deployment approaches.
To determine which frameworks, programming languages, and libraries support these systems.	Frameworks, libraries, and programming languages.
To understand how IoT-based early warning systems validate sensor data and system outputs.	Data validation methodologies and validation workflows.
To identify the instruments and approaches used to evaluate human interaction with these systems.	Userexperienceandhumancentered evaluation instruments.

and human-centered evaluation mechanisms (Alc´antara-Ayala, 2025). This fragmentation limits interoperability, comparability, and large-scale implementation of EWS, particularly in resource-constrained and high-risk environments.

More importantly, existing studies tend to focus on isolated technological dimensions, lacking an integrated perspective that connects physical sensing, data processing, system validation, and user interaction within a unified conceptual framework. This gap hinders the development of holistic, scalable, and socially sustainable early warning systems capable of addressing the multidimensional nature of landslide risk.

To address this limitation, this study conducts a systematic literature review of IoT-based landslide early warning systems published between 2019 and 2025, following the PRISMA methodology. Beyond identifying and classifying technological components, this research aims to provide an integrative analytical perspective of the field by examining the relationships among sensing, communication, data management, software architectures, validation approaches, and human-centered evaluation. The research topics considered in this review are summarized in Table 1.

By synthesizing these dimensions, this study contributes to advancing the conceptual understanding of intelligent early warning systems, highlighting key gaps and outlining directions toward more interoperable, scalable, and user-centered risk management solutions.

2 METHODS AND MATERIALS

This study was conducted following a Systematic Literature Review (SLR) approach, complemented by the PRISMA 2020 framework (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). The review adhered to the PRISMA 2020 checklist to ensure methodological transparency, reproducibility, and reporting completeness. This approach enabled the systematic identification, screening, classification, and analysis of relevant studies published between 2019 and 2025 on IoT-based EWS for landslide prevention.

Table 2 Research questions considered in the systematic review

RQ1 What types of sensors and indicators are used in IoT-based landslide early warning systems?

RQ2 What communication protocols are used between sensors and transmission nodes in these systems?

RQ3 What databases and storage structures are applied for managing the collected information?

RQ4 What frameworks, libraries, and programming languages support the reviewed systems?

RQ5 What software architectures are implemented in IoT-based EWS?

RQ6 What data validation methodologies are applied in the reviewed studies?

RQ7 What human-centered evaluation approaches have been used to assess IoT-based early warning systems?

The objective of this review is to synthesize the current state of technological and methodological developments in landslide monitoring and prediction systems, with particular emphasis on sensing technologies, communication infrastructures, software architectures, validation mechanisms, and human-centered evaluation approaches. Additionally, the study aims to identify research gaps and emerging trends to support future developments in intelligent and scalable early warning systems.

Following the guidelines proposed by Kitchenham and Charters (2007), a set of seven research questions (RQs) was defined to guide the data extraction and analysis process, as presented in Table 2.

Research Strategy

A comprehensive bibliographic search was conducted in July 2025 across three major scientific databases: Scopus, Web of Science (WoS), and IEEE Xplore. These sources were selected due to their high-quality indexing of Q1 and Q2 journals in engineering, geosciences, environmental science, and computer science.

The search strategy was designed through an iterative process involving pilot testing and refinement of keywords, Boolean operators, and controlled vocabulary. The final search string used was:

TITLE-ABS-KEY (landslide prevention AND (sensors OR indicator)) AND PUBYEAR

> 2019 AND PUBYEAR < 2026

Additional filters were applied to ensure relevance and quality, including:

- Language: English and Spanish
- Document type: Journal articles and conference papers
- Subject areas: Earth and Planetary Sciences, Computer Science, Engineering,

Environmental Science, and Decision Sciences

Table 3 Summary of the PRISMA literature selection process

Stage	Description	Records (#)
Identification	Records retrieved from Scopus, IEEE Xplore, and WoS	481
Screening	Records after duplicate removal and title/abstract screening	352
Eligibility	Full-text articles assessed for eligibility	197
Inclusion	Studies included in the final review	33

Adapted from the PRISMA 2020 statement (Page et al., 2021).

The inclusion criteria considered peer-reviewed studies focused on landslide early warning or monitoring systems that incorporated measurable indicators derived from sensors or monitoring technologies. Only studies providing sufficient technical detail to extract system components and indicators were included.

Exclusion criteria comprised studies in which early warning systems were not the primary focus or where insufficient information was provided to identify relevant landslide indicators or system configurations see Table 3.

All phases of the PRISMA methodology were systematically applied. To ensure transparency and reproducibility, the complete dataset, including search strings, screening decisions, and extracted data, has been made publicly available in a Zenodo repository (Pinado, 2026).

3 THEORETICAL FRAMEWORK

Recent research on IoT-based landslide EWS reveals a progressive transition from isolated monitoring technologies toward integrated cyber-physical systems that combine sensing, communication, data processing, and human interaction. This evolution reflects a broader paradigm shift in disaster risk management, where traditional reactive approaches are being replaced by predictive, data-driven, and adaptive systems.

At the sensing level, current EWS architectures rely on the integration of heterogeneous sensor networks, including geotechnical, hydrological, and optical devices. Micro-Electro-Mechanical Systems (MEMS), such as dual-axis inclinometers and capacitive accelerometers, enable the detection of micro-scale ground deformation with high precision, directly correlating tilt variations with pore pressure dynamics and slope instability processes (J. Liu, Liu, Luo, Chen, & Wang, 2025; Najafabadi, Goto, Martins, Tsuzuki, & Barari, 2024). These systems are complemented by hydrological sensors, including piezometers and moisture probes, which characterize soil saturation under rainfall conditions (Mukhlisin et al., 2025), and optical technologies such as Fiber Bragg Gratings (FBG) and Distributed Acoustic/Temperature Sensing

(DAS/DTS), which provide continuous and high-resolution deformation monitoring (Xu, Zhu, Lalit, Fan, & Liu, 2021). The convergence of these sensing technologies enables multi-scale observation and reduces uncertainty in early warning signals.

From a communication perspective, the emergence of Low-Power Wide-Area Networks (LPWAN), particularly LoRa and LoRaWAN, has enabled long-range, energy-efficient data transmission in geographically complex environments (Guo, Meng, & Guo, 2024; Ragnoli, Leoni, Barile, Ferri, & Stornelli, 2022). These technologies are increasingly integrated with 5G IoT infrastructures, which provide higher bandwidth and support real-time data processing through edge computing (Z. Li, Fang, Sun, & Peng, 2021). Complementary protocols, such as Wi-Fi and nRF24L01, are used in localized or experimental environments, while wired interfaces (RS-485 and SPI) ensure reliability in deep sensing configurations (Y. Li, Li, Guo, Liu, & Zhang, 2024; Mukhlisin et al., 2025; Wedashwara, Yadnya, Sudiarta, Arimbawa, & Mulyana, 2023). At the application layer, MQTT and HTTP protocols facilitate scalable and persistent communication between field devices and cloud-based platforms (Bagwari, Roy, Singh, & Gehlot, 2022).

At the data and processing layer, there is a clear convergence between geospatial technologies, remote sensing, and machine learning. Satellite platforms such as Sentinel and Landsat provide multi-temporal

datasets for landslide susceptibility modeling and terrain analysis (Cerbelaud, Breil, Blanchet, Roupioz, & Briottet, 2022; Chen et al., 2023; Luo, Zhao, Li, Huang, & Zhao, 2025). Geographic Information Systems (GIS), including ArcGIS and QGIS, support spatial integration and visualization, while machine learning frameworks such as Scikit-learn and TensorFlow enable predictive modeling of slope failure dynamics. Additionally, explainability techniques such as SHAP contribute to improving model transparency and interpretability (Chen et al., 2023). These developments illustrate a transition toward hybrid Edge–Cloud architectures, where distributed processing enhances scalability, resilience, and real-time decision-making capabilities (Bai et al., 2020; Ragnoli et al., 2022).

Regarding data validation, current approaches emphasize multivariate consistency and cross-sensor verification. The integration of tilt measurements, pore pressure, moisture content, and three-dimensional morphological data enables the identification of precursor signals and improves predictive reliability (J. Liu et al., 2025). Experimental validation methods, such as tilt-rate analysis and geometric verification through laser scanning, have demonstrated strong performance under real-world conditions. However, the absence of standardized validation frameworks that integrate statistical, physical, and operational criteria remains a critical limitation, hindering comparability across studies and large-scale system deployment.

The human dimension constitutes a fundamental component of contemporary EWS, highlighting the transition toward socio-technical systems. Recent studies incorporate community-based evaluations through surveys, perception analysis, and participatory approaches to assess trust, usability, and system acceptance (Lin, Chao, & Lin, 2022; Pal & Karnjana, 2021). Nevertheless, the lack of standardized instruments, such as SUS, UEQ, and TAM, limits the reproducibility and comparability of user experience assessments, thereby constraining the evaluation of system effectiveness from a societal perspective.

Overall, the literature suggests that IoT-based landslide early warning systems are evolving toward integrated, intelligent, and adaptive platforms. However, this evolution is characterized by a structural fragmentation across sensing, communication, data processing, validation, and human interaction layers. This fragmentation limits interoperability, scalability, and the ability to establish unified performance standards.

To synthesize these interrelated components, Fig. 2 presents a compact conceptual framework that organizes IoT-based landslide early warning systems into five interconnected layers: sensing, communication, data processing, validation, and human-centered evaluation. This representation highlights both the technological integration required for effective early warning systems and the cross-cutting challenges that constrain their large-scale implementation.

Therefore, advancing toward holistic and interoperable frameworks that integrate technical, analytical, and human-centered dimensions is essential for the development of next-generation early warning systems capable of addressing the multi-dimensional nature of landslide risk.

4 RESULTS

4.1 General Overview

The analysis of the 33 selected studies reveals a consistent transition from isolated monitoring solutions toward integrated IoT-based early warning systems structured as cyber-physical platforms. This evolution reflects the progressive convergence of sensing technologies, communication infrastructures, data processing frameworks, and human-centered components within unified system architectures.

Three dominant patterns emerge from the reviewed literature. First, sensing strategies have evolved toward hybrid configurations that integrate geotechnical, hydrological, and optical sensors, enabling multi-scale monitoring of slope dynamics. Second, communication infrastructures have converged toward energy-efficient and long-range technologies, particularly LPWAN (e.g., LoRa/LoRaWAN), complemented by high-performance solutions such as 5G for real-time applications. Third, system architectures increasingly adopt distributed processing models based on Edge–Cloud integration, enhancing scalability, resilience, and responsiveness.

However, despite this technological convergence, the results reveal persistent structural gaps across the analyzed systems. These include the lack of standardized data validation frameworks, limited interoperability among heterogeneous platforms, and insufficient integration of human-centered evaluation mechanisms.

Figure 2 and Fig. 3 provide a complementary synthesis of these findings, illustrating both the architectural organization of IoT-based EWS and the distribution of indicators across domains. Together, these results highlight a critical imbalance between technological sophistication and socio-technical integration.

This overview establishes the analytical basis for the detailed examination of each system component, presented in the following subsections (RQ1–RQ7).

4.2 RQ1 – Sensors and Indicators

Analytical synthesis. The reviewed studies demonstrate that landslide early warning systems are predominantly grounded in the monitoring of geotechnical and hydrological indicators. MEMS-based sensors emerge as the dominant technology due to their high sensitivity, low cost, and energy efficiency, making them suitable for large-scale and long-term deployments. Optical and GNSS technologies complement these systems by providing high-resolution and large-scale deformation measurements, respectively.

Table 4
MEMS devices

Technology / Device	Key Performance Data	Reference
Capacitive accelerometer (PolyMUMPs)	Sensitivity 0.3 pF/g; cross-sensitivity 0.048%	Najafabadi et al. (2024)
HCA726S inclinometer	Accuracy ± 0.008°; resolution 0.0001°	J. Liu et al. (2025)
LoRa MEMS network	Long-range, low-power monitoring	Ragnoli et al. (2022)
Flexible MEMS array	Resolution 0.1°; full vertical profile	Y. Li et al. (2024)

This layered sensing paradigm enables multi-scale monitoring: MEMS sensors capture localized deformation processes, hydrological instrumentation tracks soil saturation and pore pressure dynamics, and remote sensing technologies provide regional-scale morphological and displacement information.

Table 5
Hydrological and geotechnical devices

Device	Parameter	Reference
JSN-SR04T	Groundwater level	Mukhlisin et al. (2025)
METER EC-5	Water content	J. Liu et al. (2025)
TEROS 21	Matric suction	J. Liu et al. (2025)
HOBO RG3	Rainfall	Xi, Hua, Li, Wang, and Yang (2024)

MEMS-based devices, such as capacitive accelerometers and inclinometers, have demonstrated high performance in detecting micro-scale variations in ground tilt and deformation. As shown in Table 4, these sensors achieve high sensitivity and resolution, enabling the identification of early-stage instability processes. Their integration into LoRa-based networks further enhances their applicability in remote and mountainous environments.

Hydrological sensors play a critical complementary role by enabling the monitoring of soil moisture, pore water pressure, and groundwater levels. These parameters are essential for identifying hydromechanical thresholds associated with landslide triggering. Table 5 summarizes representative hydrological devices.

GNSS systems and crack meters provide macro-scale deformation monitoring, supporting the identification of displacement acceleration phases prior to slope failure (Table 6).

Table 6
GNSS and crack monitoring devices

Type	Measurement	Reference
GNSS receiver	Surface displacement	Wang, Wang, Lin, and Guo (2022)
Crack meter	Crack evolution	Guo et al. (2024)

Optical and fiber-based sensing technologies provide high-resolution and continuous monitoring capabilities, particularly in environments with electromagnetic interference (Table 7).

Table 7
Optical and fiber-based sensors

Type	Description	Reference
FARO X330	3D morphology (± 1 mm)	J. Liu et al. (2025)
FBG sensors	High-resolution deformation	Xu et al. (2021)
Fiber moisture sensor	Water content measurement	Leone et al. (2022)

Figure 3 presents the distribution of indicator domains identified across the reviewed studies. The figure shows that hydrological and geotechnical indicators dominate current landslide early warning research, confirming a strong emphasis on physically measurable variables directly associated with slope instability processes. By contrast, socio-human, environmental, and morphological domains remain less represented, which suggests that contemporary systems still prioritize instrumental monitoring over broader socio-technical integration.

In contrast, environmental and socio-economic indicators are significantly underrepresented, revealing a technological bias toward physical monitoring. This imbalance suggests that future systems should integrate socio-environmental dimensions to enhance risk assessment and community resilience.

4.3 RQ2 – Communication Protocols

Analytical synthesis. Communication technologies in landslide EWS reflect a trade-off between coverage, energy consumption, and latency. LPWAN technologies dominate large-scale deployments, while high-speed cellular networks enable real-time data transmission.

Figure 4 Trade-off between energy consumption and communication range in IoT protocols used in landslide early warning systems. LoRa is positioned as the most balanced alternative for remote deployments due to its low energy demand and long-range coverage, whereas 5G provides higher performance at the cost of greater energy consumption. Wired and short-range protocols remain suitable for local or embedded configurations.

LoRa and LoRaWAN technologies are widely adopted due to their long-range capabilities and low energy requirements. These features make them particularly suitable for remote monitoring in mountainous

environments. In contrast, 5G technologies enable high-bandwidth communication and support edge computing applications, enhancing system responsiveness.

Short-range communication protocols such as Wi-Fi and nRF24L01 are primarily used in laboratory and local configurations, while wired interfaces (SPI and RS-485) ensure reliable internal communication between sensors and microcontrollers.

Figure 4 illustrates the trade-off between communication range and energy consumption. Table 8 summarizes the main communication protocols identified in the reviewed studies, highlighting their key characteristics and application contexts.

Table 8
Communication protocols

Protocol	Characteristic	Reference
LoRa	Long-range, low power	Guo et al. (2024)
5G	High speed, real-time	Z. Li et al. (2021)
Wi-Fi	Local networks	Mukhlisin et al. (2025)
SPI/RS-485	Internal communication	Y. Li et al. (2024)

The results indicate that hybrid communication architectures, combining LPWAN and high-speed networks, provide optimal performance for large-scale EWS deployments.

4.4 RQ3 – Databases and Datasets

Analytical synthesis. The reviewed studies reveal a clear transition toward multisource data ecosystems that integrate heterogeneous datasets, including instrumental sensor data, geospatial information, and socio-environmental records. This integration enables multi-scale modeling and enhances predictive capabilities; however, it also introduces challenges related to data heterogeneity, storage scalability, and real-time processing. Table 9 presents the main types of databases employed in IoT-based landslide early warning systems, including geospatial, instrumental, and socio-environmental data sources.

Table 9
Types of databases employed in landslide early warning systems

Database Type	Examples	Reference
Geospatial	Sentinel, Landsat, InSAR	Chen et al. (2023)
Meteorological	Radar data, rain gauges	Cerbelaud et al. (2022)
Instrumental	Sensordatabases (SQL/NoSQL)	Ragnoli et al. (2022)
Socioenvironmental	Surveys, resilience data	Lin et al. (2022)

Three main categories of databases were identified. First, instrumental databases store real-time sensor data using relational and non-relational systems such as MySQL, PostgreSQL, and MongoDB. Second, geospatial databases rely on satellite platforms such as Sentinel and Landsat, as well as InSAR-derived deformation datasets, which are widely used for susceptibility modeling and terrain analysis. Third, socio-environmental datasets capture community-level information, including risk perception and resilience indicators.

The integration of these data sources supports more comprehensive modeling approaches; however, the lack of standardized data schemas and metadata frameworks limits interoperability and reproducibility across studies. Furthermore, the increasing volume and velocity of data generated by IoT systems necessitate distributed storage architectures and real-time processing mechanisms to ensure system scalability.

4.5 RQ4 – Frameworks, Libraries, and Languages

Analytical synthesis. The technological ecosystem supporting landslide early warning systems demonstrates a convergence between geospatial analysis tools, machine learning frameworks, and embedded system technologies. This convergence enables the development of modular and scalable systems capable of integrating data acquisition, processing, and visualization functionalities.

Python is the dominant programming language due to its flexibility in data analysis and machine learning applications. Libraries such as Scikit-learn and TensorFlow are widely used for predictive modeling, while SHAP is employed to enhance model interpretability. GIS platforms, including ArcGIS and QGIS, remain essential for spatial data integration and visualization.

In IoT implementations, frameworks such as LoRaWAN and The Things Network (TTN) support communication between distributed sensor nodes and cloud platforms. Embedded systems rely on microcontroller environments such as STM32, which enable efficient data acquisition and processing in resource-constrained environments. Table 10 summarizes the main frameworks, platforms, and technologies supporting the development of IoT-based early warning systems.

Table 10
Frameworks and technologies employed in landslide early warning systems

Category	Technology	Reference
GIS	ArcGIS, QGIS	Chen et al. (2023)
Machine Learning	TensorFlow, Scikit-learn	Chen et al. (2023)
IoT Platforms	LoRaWAN, TTN	Ragnoli et al. (2022)
Embedded Systems	STM32	Y. Li et al. (2024)

This technological convergence supports the implementation of distributed and microservice-based architectures, facilitating system scalability and adaptability.

4.6 RQ5 – Software Architectures

Analytical synthesis. Landslide early warning systems are predominantly structured using layered and distributed architectures that integrate sensing, communication, processing, and visualization components. These architectures reflect a transition toward scalable and resilient systems capable of supporting real-time monitoring and prediction.

The most common configuration is a three-layer architecture consisting of sensing, transmission, and application layers. This structure is often complemented by Edge–Cloud architectures that distribute processing tasks between local nodes and centralized servers, reducing latency and improving system responsiveness.

Microservice-based architectures are increasingly adopted, allowing system components to operate as independent services interconnected through message queues and APIs. This approach enables efficient management of large volumes of sensor data and enhances system scalability. Table 11 presents the dominant architectural patterns identified in the reviewed systems, highlighting their structural characteristics and deployment approaches.

These architectures highlight a shift toward decentralized and adaptive systems that can operate under variable connectivity conditions and support large-scale deployments.

Table 11
Architectural patterns in landslide early warning systems

Architecture	Description	Reference
Three-layer IoT	Sensing–Transmission–Application	Y. Liu, Huang, Xiao, Ma, and Zhou (2022)
LoRaWAN WSN	Distributed sensor network	Ragnoli et al. (2022)
Microservices	Scalable distributed architecture	Bai et al. (2020)

4.7 RQ6 – Data Validation

Analytical synthesis. Data validation in landslide early warning systems is primarily based on multivariate consistency and cross-sensor verification. These approaches ensure that sensor measurements are physically and temporally coherent, thereby enhancing the reliability of predictive models.

Table 12
Validation approaches applied in landslide early warning systems

Method	Description	Reference
Cross-sensor validation	Multivariate consist. analysis	J. Liu et al. (2025)
AE/MS analysis	Acoustic precursor detection	Zhu et al. (2024)
KPI frameworks	Performance eval metrics	Gonzalez-Ollauri, Munro, Mickovski, Thomson, and Emmanuel (2021)

Validation methods include the integration of geotechnical, hydrological, and morphological data, as well as experimental approaches involving acoustic emission (AE) and microseismic (MS) signals. These techniques enable the identification of precursor signals associated with slope instability. Table 12 summarizes the main data validation approaches applied in landslide early warning systems, emphasizing multivariate and cross-sensor methodologies.

Despite these advances, the absence of standardized validation frameworks remains a critical limitation, restricting comparability across studies and hindering large-scale system implementation.

4.8 RQ7 – Human-Centered and Participatory Evaluation

Analytical synthesis. Human-centered evaluation remains significantly underrepresented in landslide early warning systems. Only a limited number of studies incorporate participatory approaches, highlighting a gap between technological development and social adoption.

Existing approaches rely on surveys, focus groups, and expert-based methods to assess risk perception and community resilience. Participatory methods, including cocreation processes, are increasingly being explored to improve system usability and acceptance. Table 13 presents the human-centered evaluation approaches identified in the literature, including perception, resilience, and performance assessment methods.

Table 13
Human-centered evaluation approaches

Approach	Focus	Reference
Surveys	Risk perception	Pal and Karnjana (2021)
AHP/FDM	Resilience indicators	Lin et al. (2022)
KPI frameworks	System performance	Gonzalez-Ollauri et al. (2021)

The limited use of standardized instruments such as SUS, UEQ, and TAM restricts the reproducibility and comparability of user experience assessments.

4.9 Integrated Synthesis and Key Findings

The results of this review reveal a clear transition from isolated monitoring approaches toward integrated and intelligent early warning systems based on IoT and distributed analytics. This evolution is characterized by the convergence of sensing technologies, communication infrastructures, and data processing frameworks into cohesive architectures capable of real-time monitoring and prediction.

Across the analyzed studies, geotechnical and hydrological indicators dominate system design, reflecting a strong emphasis on physically measurable parameters directly associated with slope instability processes. Communication technologies show a clear preference for LPWAN solutions, particularly LoRa, due to their suitability for remote and energy-constrained environments. In parallel, system architectures increasingly adopt Edge–Cloud and microservice-based configurations to enhance scalability and operational resilience.

Table 14
Global synthesis of findings

Dimension	Trend	Gap
Sensors	High precision	Scalability
Communication	Low power	Interoperability
Data	Integration	Standardization
Validation	Multimodal	Lack of standards
UX	Emerging	Lack of metrics

However, despite these advances, the results highlight persistent structural limitations. The absence of standardized validation frameworks restricts comparability across studies, while interoperability challenges hinder the integration of heterogeneous system components. Additionally, the limited incorporation of human-centered evaluation reveals a gap between technological development and real-world usability. The overall synthesis of the findings across dimensions is summarized in Table 14.

These findings indicate that the future of landslide early warning systems depends not only on technological innovation but also on the development of holistic and interoperable frameworks that integrate sensing, communication, analytical, and human-centered dimensions. Addressing these gaps is essential to ensure the scalability, reliability, and social effectiveness of next-generation early warning systems.

5 DISCUSSION

The findings of this study provide an integrated perspective on the current state and evolution of IoT-based landslide EWS, revealing both substantial technological progress and persistent structural limitations. By synthesizing evidence across sensing, communication, data processing, validation, and human-centered dimensions, this study contributes to a more comprehensive understanding of the socio-technical nature of contemporary EWS.

The results confirm a clear transition from isolated monitoring solutions toward integrated cyber-physical systems, in which multiple technological layers operate in a coordinated and interdependent manner. As illustrated in Fig. 2, these systems are increasingly structured as multi-layered architectures that combine heterogeneous sensing technologies, energy-efficient communication infrastructures, and distributed processing frameworks. This convergence reflects broader trends in disaster risk management, where real-time monitoring and predictive analytics are central to proactive risk mitigation.

To further interpret these relationships, Fig. 5 presents an analytical representation of IoT-based EWS, highlighting both system integration and structural limitations. The figure shows that, while significant progress has been achieved in integrating sensing, communication, and processing layers, important gaps persist in interoperability, validation standardization, and human-centered integration. These limitations indicate that technological maturity has not yet been matched by equivalent advances in methodological consistency and socio-technical alignment.

From a sensing perspective, the predominance of geotechnical and hydrological indicators reflects a strong reliance on physically measurable parameters directly associated with slope instability processes. MEMS-based sensors, complemented by hydrological instrumentation and optical technologies, enable multi-scale monitoring and enhance the detection of early warning signals. However, this technological emphasis also reveals a critical limitation: the underrepresentation of environmental and socio-economic indicators. As shown in Fig. 3, current systems prioritize physical monitoring while largely neglecting broader contextual factors that influence vulnerability and risk exposure. This imbalance suggests the need for more comprehensive approaches that integrate socio-environmental dimensions into risk assessment.

Communication infrastructures further highlight the inherent trade-offs in EWS design. LPWAN technologies, particularly LoRa, dominate due to their ability to provide long-range communication with low energy consumption, making them suitable for remote and resource-constrained environments. In contrast, high-performance technologies such as 5G enable real-time data processing and advanced analytics but require greater energy consumption and infrastructure investment. As illustrated in Fig. 4, these trade-offs emphasize the importance of hybrid communication architectures that balance coverage, latency, and energy efficiency according to deployment conditions.

At the data and processing level, the integration of geospatial technologies, remote sensing, and machine learning represents a major advancement in predictive modeling capabilities. The use of satellite data (e.g., Sentinel, Landsat), combined with GIS platforms and machine learning frameworks, enables multi-scale analysis of landslide susceptibility and dynamics. Additionally, the adoption of Edge–Cloud architectures enhances scalability and reduces latency, supporting near real-time decision-making. Nevertheless, this increasing complexity introduces challenges related to data heterogeneity, interoperability, and computational scalability.

A key limitation identified across the reviewed studies is the absence of standardized data validation frameworks. Although multivariate validation approaches and cross-sensor verification methods are

commonly employed, there is no unified methodology that ensures consistency, comparability, and reliability across different systems. This lack of standardization represents a major barrier to large-scale deployment and cross-institutional integration of EWS.

Equally significant is the limited incorporation of human-centered evaluation approaches. While some studies include participatory methods and community-based assessments, the use of standardized usability and acceptance frameworks remains limited. This gap highlights a disconnect between technological development and realworld application, as the effectiveness of early warning systems ultimately depends on user trust, comprehension, and response behavior. Therefore, integrating humancentered design principles and standardized evaluation instruments is essential to enhance system adoption and effectiveness.

The conceptual framework proposed in this study synthesizes these findings by organizing EWS into five interconnected layers: sensing, communication, data processing, validation, and human-centered evaluation. This framework provides a structured basis for both future research and system design, emphasizing the need for integration across technical and social dimensions.

From a practical perspective, the results suggest that next-generation EWS should prioritize interoperability, scalability, and user-centered design. This includes the development of standardized validation protocols, the integration of heterogeneous data sources, and the incorporation of socio-environmental indicators into predictive models. Furthermore, hybrid communication architectures and distributed processing frameworks should be optimized to support diverse environmental and operational contexts.

Overall, this study contributes to the advancement of disaster risk management by highlighting that effective early warning systems require not only technological innovation but also socio-technical integration. Future research should therefore focus on developing holistic frameworks that align sensing capabilities, analytical models, and human-centered processes within a unified and scalable risk management strategy.

6 CONCLUSION AND FUTURE WORK

This study presented a comprehensive systematic review of IoT-based landslide EWS, integrating technological, analytical, and human-centered dimensions. The results demonstrate a clear transition from isolated monitoring solutions toward integrated and intelligent cyber-physical systems capable of supporting real-time monitoring and predictive analytics.

The findings highlight that current EWS architectures are primarily driven by advances in sensing technologies, communication infrastructures, and data processing frameworks. In particular, the widespread adoption of MEMS-based sensors, LPWAN communication technologies, and Edge–Cloud architectures has significantly enhanced the scalability and responsiveness of these systems. However, despite these technological advancements, critical structural gaps remain.

First, the absence of standardized validation frameworks limits comparability and reliability across different implementations. Second, interoperability challenges hinder the integration of heterogeneous system components, particularly in large-scale and multi-institutional deployments. Third, the limited incorporation of humancentered evaluation approaches reveals a disconnect between technological capabilities and real-world usability. Additionally, the underrepresentation of socio-environmental indicators suggests that current systems still prioritize physical monitoring over comprehensive risk assessment.

The conceptual framework proposed in this study contributes to addressing these limitations by providing an integrated representation of IoT-based EWS, structured into five interconnected layers: sensing, communication, data processing, validation, and human-centered evaluation. This framework offers a foundation for both future research and the design of more holistic and scalable early warning systems.

From a practical perspective, the results suggest that the next generation of landslide EWS should prioritize interoperability, standardized validation, and usercentered design. Achieving these objectives requires the integration of heterogeneous data sources, the development of unified validation protocols, and the incorporation of socio-environmental dimensions into predictive models.

Future research should focus on advancing the socio-technical integration of early warning systems through the following directions:

- Development of standardized validation frameworks that integrate physical, statistical, and operational criteria to ensure consistency and comparability across systems.
- Design of interoperable architectures that enable seamless integration of heterogeneous sensors, communication protocols, and data platforms.
- Integration of socio-environmental indicators, including community vulnerability and resilience metrics, into predictive modeling approaches.
- Adoption of human-centered design methodologies and standardized usability evaluation instruments to improve system acceptance and effectiveness.
- Exploration of Edge AI and real-time analytics to enhance predictive capabilities and reduce response latency in dynamic environments.

Overall, this study underscores that the future of landslide early warning systems depends not only on technological innovation but also on the development of integrated, interoperable, and human-centered frameworks capable of addressing the multi-dimensional nature of disaster risk.

Declarations

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- **Data availability** : No new data were created or analyzed in this study. Data sharing is not applicable to this article.
- **Code availability** : Not applicable.
- **Ethics approval** : Not applicable.
- **Consent to participate** : Not applicable.
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Figures

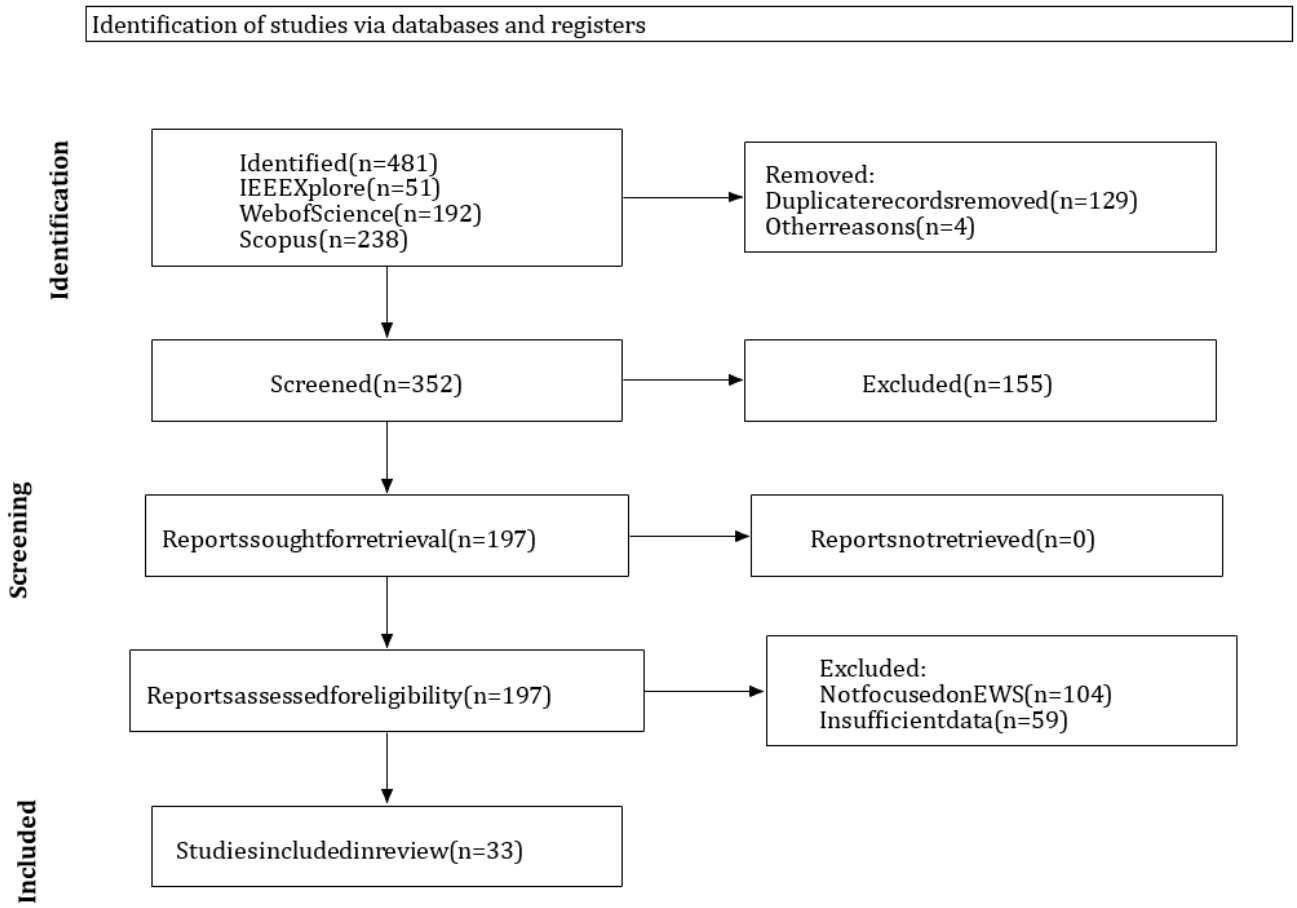


Figure 1

PRISMA-based study selection process.

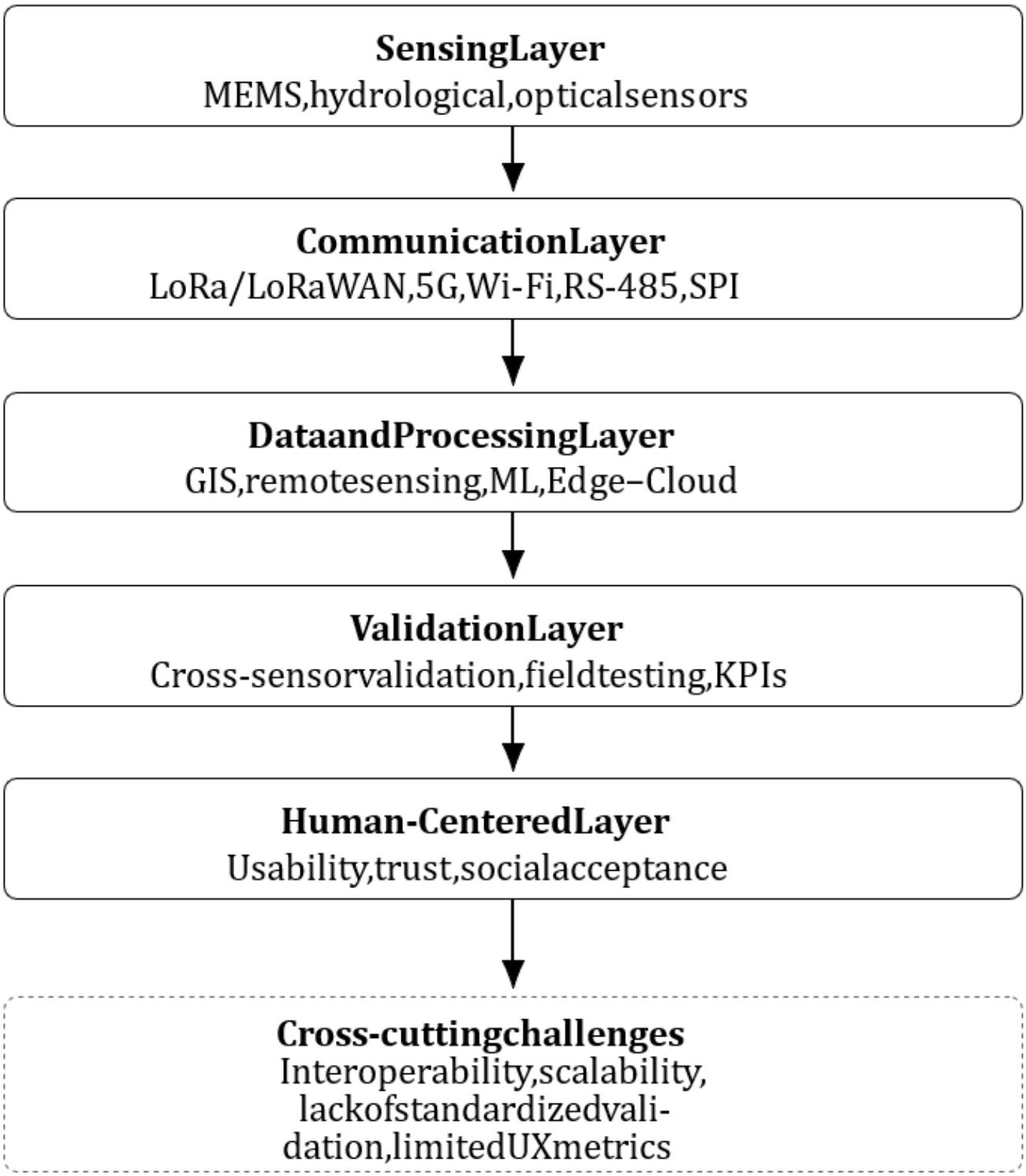


Figure 2

Conceptual framework of IoT-based landslide early warning systems, structured into five interconnected layers: sensing, communication, data processing, validation, and human-centered evaluation. The framework highlights key cross-cutting challenges affecting system integration and scalability.

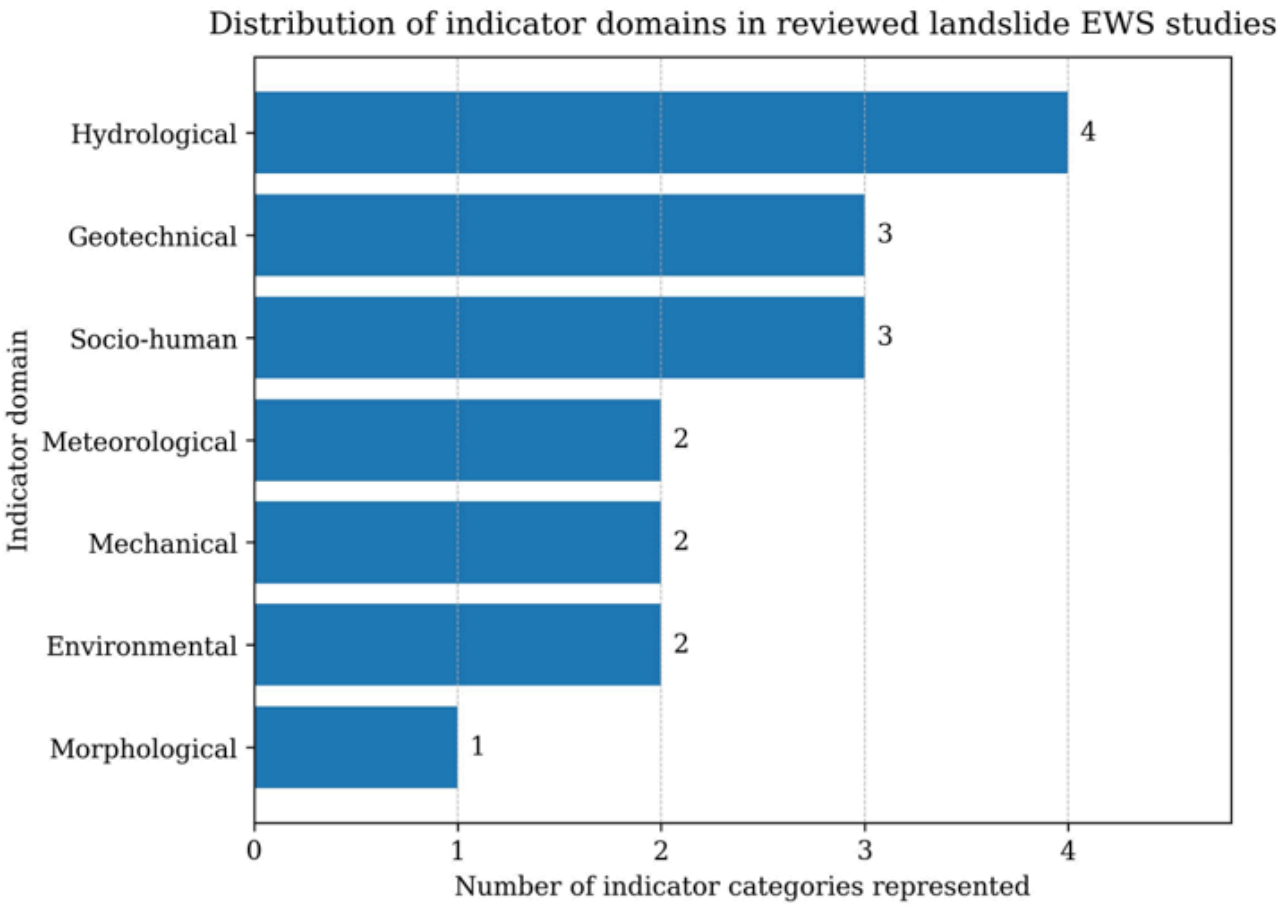


Figure 3

Distribution of indicator domains identified in the reviewed landslide early warning studies. Hydrological and geotechnical domains show the highest representation, confirming the predominance of physically measurable parameters in current IoT-based EWS. In contrast, morphological, environmental, and socio-human domains remain comparatively less represented, highlighting the need for more holistic risk assessment frameworks.

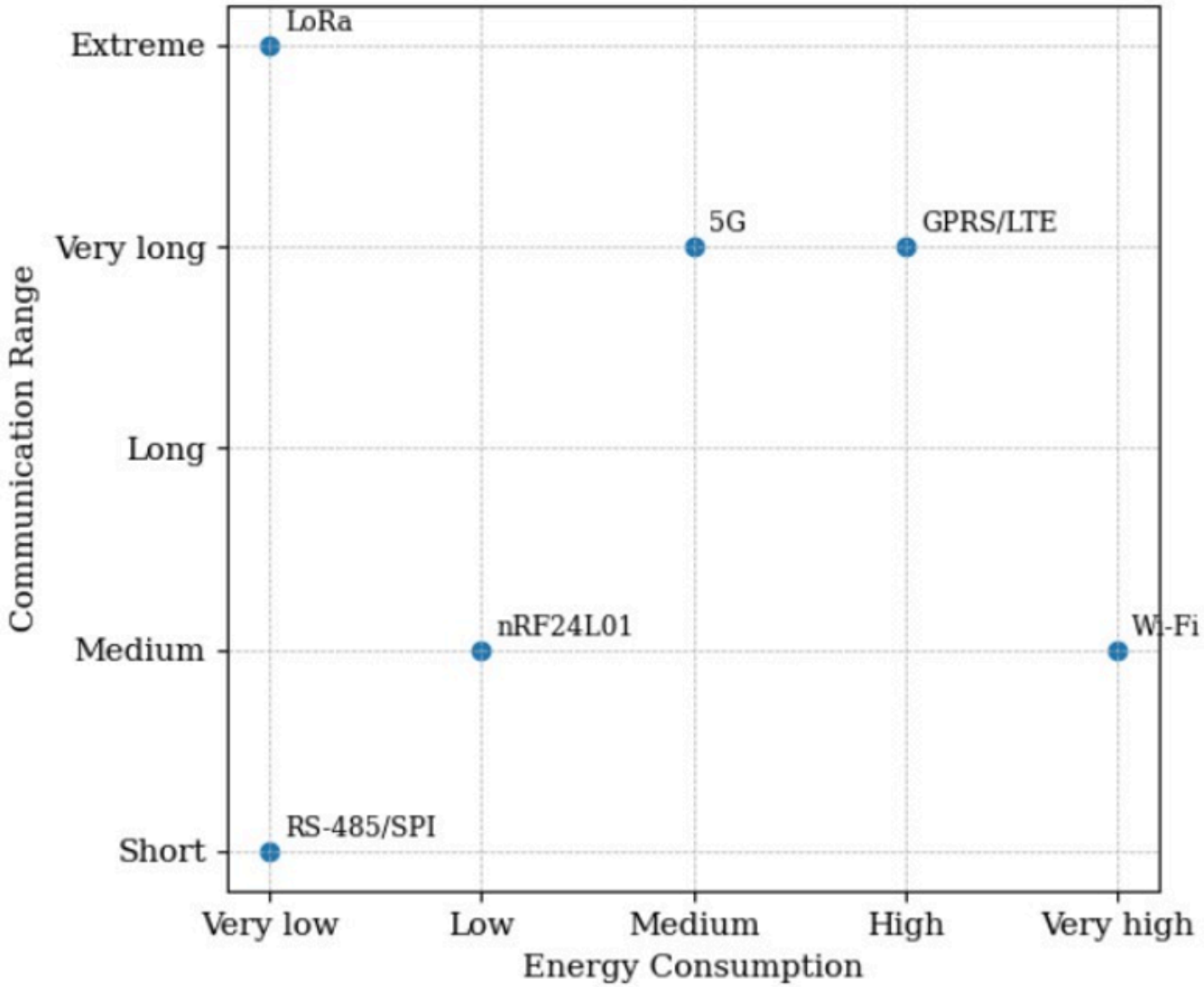


Figure 4

Trade-off between energy consumption and communication range in IoT protocols used in landslide early warning systems. LoRa is positioned as the most balanced alternative for remote deployments due to its low energy demand and long-range coverage, whereas 5G provides higher performance at the cost of greater energy consumption. Wired and short-range protocols remain suitable for local or embedded configurations.

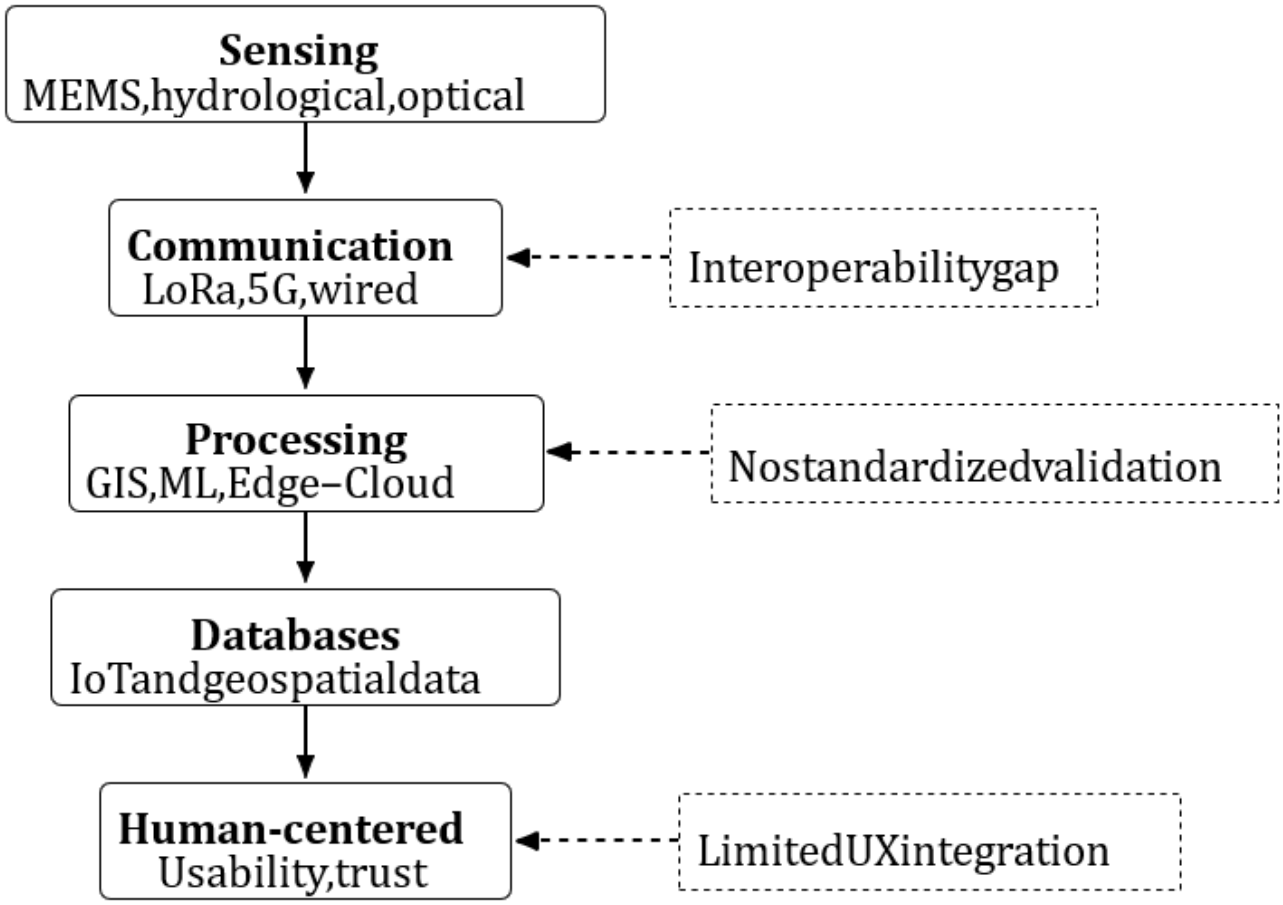


Figure 5

Minimal analytical representation of IoT-based landslide early warning systems, highlighting system layers and key structural gaps.