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Bridging Artificial Intelligence and Geotechnical Engineering through Education: A Social Framework for Disaster Risk Awareness and Preparedness

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Abstract

This paper addresses the critical gap between advanced technical analysis in Geotechnical Engineering and Artificial Intelligence (AI) and the actual level of societal disaster risk awareness and preparedness. While AI and Machine Learning (ML) techniques offer unprecedented accuracy in modeling complex ground hazards such as liquefaction and landslides, the resulting technical knowledge often remains confined to expert circles. This confinement leads to significant communication failure, hindering effective public preparation. To bridge this divide, we propose a novel AI-supported geotechnical risk education framework. This conceptual framework leverages AI's high-fidelity simulation and scenario generation capabilities to power a Pedagogical Translation Layer that converts complex analytical data into accessible, visually rich, and action-oriented educational modules. The final stage incorporates Interactive Public Engagement via immersive technologies, such as virtual reality (VR), to facilitate behavioral change and concrete preparedness for ground hazards. We argue that the success of modern disaster risk reduction is contingent upon this integration of scientific data into targeted public education. The framework carries profound policy implications, contributing directly to increased public safety and fostering robust national resilience against geotechnical disasters.

Keywords: Artificial Intelligence, Geotechnical Engineering, Disaster Risk Awareness, Educational Framework, Societal Resilience

Introduction

The increasing global scale of disaster risks and associated losses, particularly in the context of ground-related hazards (such as seismicity, landslides, and soil liquefaction), necessitates a redefinition of disaster management and resilience strategies (Feng & Liu, 2024). Accelerated globalization, the complexity of critical infrastructure, and extreme weather events triggered by climate change are exposing urban areas to unprecedented levels of risk. In this context, the importance of disciplines capable of in-depth analysis and prediction of these risks is increasing exponentially (Memiş et al., 2025).

In recent years, Artificial Intelligence (AI) and its subfields, Machine Learning (ML) and Deep Learning (DL), have offered revolutionary analytical tools in the field of Geotechnical Engineering. AI algorithms, by extracting meaning from large geological datasets, have revolutionized areas such as risk prediction models (Harle & Wankhade, 2025), site response simulations, and inverse engineering determination of soil parameters with a speed and accuracy not possible with traditional methods (Hu et al., 2023a). These technical advancements strengthen the technical dimension of disaster risk reduction by enabling data-driven engineering decisions. Thanks to the power of AI, high-resolution risk maps can be generated, and detailed potential damage scenarios can be identified.

However, despite this increase in high-level technical capabilities, the level of societal preparedness and awareness regarding disaster risks has not reached the expected level (Stewart, 2024). The complex information and predictions generated by AI and geotechnical sciences often remain inaccessible due to the technical jargon used in academia and expert circles. This information is not being conveyed to the at-risk local population, policymakers, and even relevant stakeholders outside of engineering in a clear, understandable, and actionable format. This situation creates a profound educational gap between technical expertise and public perception of risk (King, 2019). This deficiency in public education makes it difficult for the public to embrace the technical measures taken and reduces the effectiveness of response mechanisms during disasters.

This article presents a conceptual social education framework that aims to combine the analytical capacity of Artificial Intelligence with critical data from Geotechnical Engineering to translate this information into societal benefit. Our main thesis is that minimizing ground-related disaster risks depends not only on the accuracy of technical analyses but also on communicating these analytical results to the public through inclusive educational methods (Thekdi et al., 2023). In the following sections, we will first discuss the role of AI in geotechnical risk management beyond technical analyses, analyze the existing educational gaps in detail, present the proposed AI-supported educational framework, and finally evaluate the critical implications of this framework in terms of policy and societal resilience.

Artificial Intelligence And Geotechnical Risk: Beyond Technical Analysis

Artificial Intelligence (AI) is emerging as a transformative force in geotechnical engineering, with the potential to revolutionize traditional analysis methods. AI/ML models can solve complex problems such as soil classification, slope stability prediction, settlement analysis, liquefaction potential assessment, and inverse calculation of soil parameters with high accuracy using large datasets (Big Data) (Keskin & Memiş, 2025; Nguyen et al., 2025; Shahin, 2013a). The use of Deep Learning (DL) techniques, in particular, offers superior capabilities in integrating sensor data (IoT) and satellite imagery collected in the field to generate real-time risk predictions and regional soil response maps (Tiggeloven et al., 2025) (Keskin & Memiş, 2025). These capabilities shift the risk assessment process from reactive (post-event analysis) to a proactive and predictive approach.

However, this revolutionary analytical depth provided by AI brings with it a significant communication paradox. Even the most sophisticated risk prediction model cannot be used as an effective risk mitigation tool unless its results are presented in a language that the public and decision-makers can understand (Capobianco et al., 2025a). Geotechnical risk analysis is fundamentally based on mathematical equations, probabilistic distributions, and complex parameter inputs. While artificial intelligence successfully addresses this complexity, the technical knowledge of the solution itself remains within the domain of experts (Nakano & Yamori, 2021a).

This situation creates a disconnect in the flow of information, which can be termed the "Last Mile Problem." AI and geotechnical models are interpreted and validated by experts; however, this interpretation encounters a gap when it comes to communicating the information to the at-risk community. As a result, the public, despite having access to highly accurate analytical information about soil risks in their environment, lacks the educational tools to understand and act upon this information. This disconnect leads to a low level of preparedness against ground hazards and becomes one of the biggest obstacles to social resilience (Rokvić & Stanojević, 2024).

To visualize this situation more clearly, the conceptual diagram shown in Figure 1 details the disconnect in the process of technical knowledge reaching the public from experts. Filling this gap between technical knowledge production and societal action is vital for AI and Geotechnical Engineering to fulfill their social mission. The main thesis of this article is that this gap can be closed through education, thereby creating a genuine social framework that extends beyond technical analyses (Jaimes, 2025).

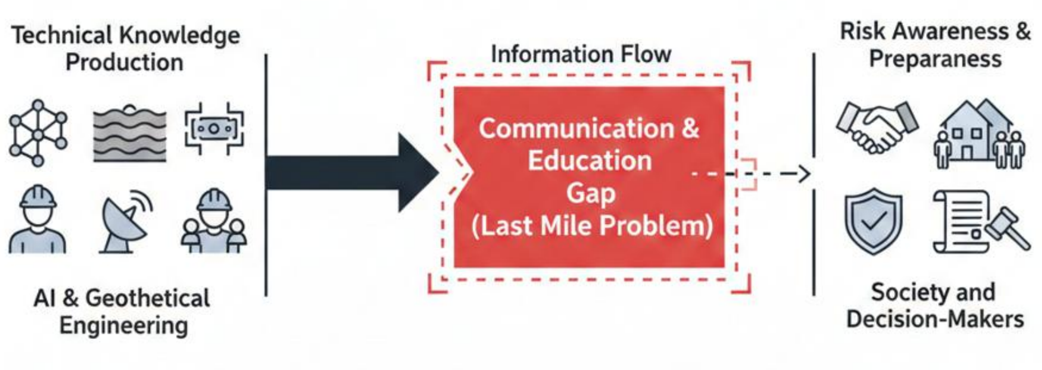

Figure 1: Conceptual illustration: The gap in technical knowledge flow

Educational Gaps in Geotechnical Risk Awareness

Despite the high-resolution analytical capabilities provided by Artificial Intelligence and Geotechnical Engineering, significant structural and methodological gaps exist in the process of delivering this information to the end-user. These gaps are observed in both the university education system and public risk communication mechanisms.

At the engineering and technical education level, AI/ML training and Geotechnical Engineering courses are generally conducted in separate silos. Geotechnical courses primarily focus on soil mechanics principles and traditional analysis methods (Das & Sobhan, 2006), while AI courses mainly teach algorithmic efficiency and big data processing techniques. This separation prevents future engineers from developing a holistic perspective on the societal risk communication and ethical implications of AI-generated outputs (Shahin, 2013b). Even if students understand soil behavior modeling, they lack the skills to effectively communicate the results of these models to a non-technical audience.

At the societal level, geotechnical risk perception is largely based on post-disaster experiences or speculative information. While risk education often emphasizes the effects of earthquakes (superstructure damage), the complex dynamics of soil-related risks, such as landslide potential, liquefaction, or different damage mechanisms caused by different soil types, are often neglected (Komac et al., 2020). Existing public education tools oversimplify complex geotechnical processes or fail to provide sufficient visualization. For effective risk communication, the public needs to connect the cause of the risk (soil behavior) and the consequence (potential damage) at a personal level; however, current educational formats fail to provide this (Himley et al., 2022a; Nakano & Yamori, 2021b). In this context, the visualization and scenario generation potential offered by Artificial Intelligence remains underutilized because it is not integrated into the education system. AI's ability to create risk maps and make region-specific damage predictions, if presented pedagogically correctly, could serve as a vital bridge to strengthen weak societal risk perception (Jin et al., 2021). However, currently, both academic and public education fall short of meeting this need.

Table 1 summarizes the key educational gaps identified in light of these analyses. This table provides a roadmap for which problems the educational framework, to be presented in the fourth section of this article, will address (Salifu et al., 2025).

Table 1. Identified Training Gaps

Area	Current Status	Gap (Deficiency)
AI Education	Algorithmic and technically focused, big data analysis.	Societal connection, ethical responsibilities, risk communication practices.
Geotechnics Education	Analysis-focused, traditional modeling and design principles.	Risk communication pedagogy, socialization of AI outputs, scenario-based learning.
Public Awareness	Low, dependent on post-disaster experiences, focused on superstructure.	Effective, visual, ground behavior-based educational tools and accessibility.

Ai-Supported Geotechnical Risk Education Framework

Addressing the gaps in geotechnical risk awareness requires not only generating more information but also fundamentally changing the methodology of information delivery and interaction. The proposed AI-Powered Geotechnical Risk Education Framework is built upon three main pillars that translate technical analysis into societal action: High-Fidelity Simulation, Pedagogical Translation Layer, and Interactive Public Engagement. This framework is conceptually illustrated in Figure 2.

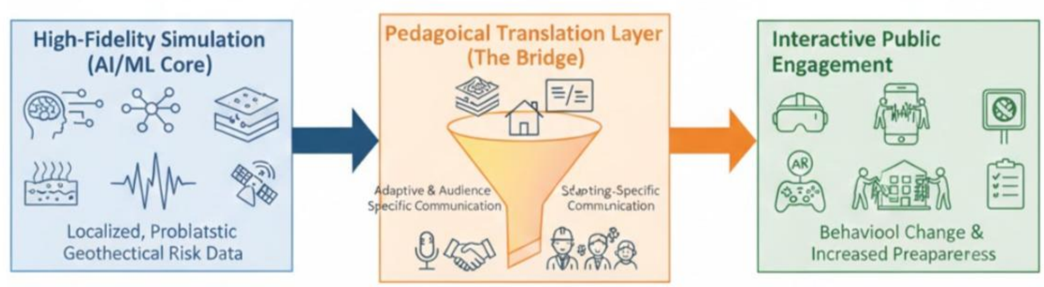

Figure 2: Conceptual structure of the AI-supported geotechnical risk training framework

High-Fidelity Simulation (AI/ML Core)

The starting point of the framework is the use of Artificial Intelligence and Machine Learning models in soil behavior analysis. This stage, unlike traditional geotechnical models, produces localized risk predictions with high spatial and temporal resolution (Hu et al., 2023b). AI integrates seismic, hydrogeological, and meteorological datasets to model the potential for landslides, liquefaction, or differential ground response in a specific geographical area using probabilistic scenarios (Memis & Memis, 2026). This output is more than just a map; it is a rich dataset reflecting the dynamic and time-varying nature of the risk. The data generated in this stage forms the basis for the high-quality and reliable content required for the next stage.

Pedagogical Translation Layer (The Bridge)

This is the most critical and innovative component of the proposed framework. It is the stage where technical analytical outputs (e.g., 3D finite element analysis results or probabilistic distributions) are transformed into meaningful and actionable educational modules tailored to the target audience. This layer acts as an interface that translates complex AI models into metaphors, analogies, and story-based scenarios that the public can understand (Himley et al., 2022b). The Translation Layer includes algorithms that automatically optimize the complexity and presentation format of the content according to different user groups (e.g., Local Governments, Civil Engineers, Elementary School Students, the General Public). For example, a soil liquefaction potential map is presented to an engineer as a technical threshold value. At the same time, for the public, it is visualized using the metaphor of "soils that will behave like waterlogged sand during a disaster" and linked to building damage predictions (Capobianco et al., 2025b).

Interactive Public Participation

The final stage is where the translated pedagogical content directly engages with the community. This layer moves away from passive information transfer (such as brochures and presentations) and focuses on interactive experiences that trigger behavioral change (Lindell & Perry, 2012). Localized risk scenarios generated by AI are experienced using technologies such as Virtual Reality (VR), Augmented Reality (AR), and Serious Games. Users can experience the effects of a potential liquefaction event on the soil type of their own homes within a VR simulation. This experience transforms the abstract concept of risk into a personal and concrete threat perception, increasing the willingness to adopt pre-disaster preparedness actions (building reinforcement, choosing assembly areas) (Maragkou et al., 2023). This interactive methodology is an indispensable strategy for increasing community resilience.

Policy And Societal Implications

The success of the proposed AI-supported Geotechnical Risk Education Framework lies not only in technological and pedagogical innovations but also in the support this framework receives from public policies and legal regulations. This innovative approach, focusing on bridging the gap between technical knowledge and societal action, has profound social and policy implications for urban management and disaster risk reduction strategies. The framework's primary and most significant impact is its direct influence on public safety and quality of life. Increased cognitive risk awareness through education allows communities to internalize ground-related risks (such as liquefaction and landslide potential) through interactive simulations, encouraging proactive preparedness actions at the individual and community levels, even without mandatory legal enforcement (Karanci et al., 2024). This facilitates a paradigm shift from 'passive acceptance' of risk to 'proactive management,' significantly enhancing pre-disaster preparedness levels. Policymakers, by transparently sharing high-quality AI-supported risk data with the public, can facilitate the necessary social consensus and participation for risk-based zoning plans and structural reinforcement programs (Reduction, 2025).

The increased public awareness also indirectly creates positive pressure on infrastructure resilience. Local governments and the private sector are compelled to adopt higher geotechnical safety standards in critical infrastructure projects in the face of tangible risks visualized by AI data (Godschalk, 2003). The demands of an informed public lead to the prioritization of risk mitigation measures in the design and construction processes of critical structures such as roads, bridges, and dams. This education-based risk reduction strategy directly contributes to the national economy in the long term by significantly reducing the costs of post-disaster emergency response, recovery, and reconstruction. International development agencies and research have repeatedly shown that every unit spent on pre-disaster education yields a significant return on investment (ROI) by reducing post-disaster losses many times over (Hazards, 2010). The dimensions and expected impacts of the policy and societal benefits derived from this framework are summarized in detail in Table 2.

Finally, the successful institutionalization of this framework creates a necessary collaborative ecosystem among universities, local governments, and civil society organizations. Universities should contribute their AI and geotechnical expertise, local governments their policy implementation and authority, and civil society organizations their community outreach and educational methodology expertise to this common goal. At the policy level, a standardized data access and privacy protocol should be established to translate AI outputs into educational materials. This protocol should ensure the transparency and public accessibility of technical data while simultaneously guaranteeing the protection of sensitive personal or commercial information. Without this institutional integration, even the most advanced AI model will fail to function as a social framework and will remain within a technical silo (Pielke Jr, 2007). In conclusion, this framework supports a vision of a more resilient society against disasters by creating a cycle where scientific knowledge is not only produced but also effectively consumed and translated into societal benefit.

Table 2: Dimensions and impacts of policy and social benefits

Focus Area	**Mechanism of Impact**	**Expected Benefit / Impact**
Public Safety	Increased cognitive and behavioral awareness, shift to proactive action.	Reduction of personal losses and panic situations during a disaster.
Infrastructure Resilience	Adoption of risk-based standards through public pressure, informed site selection.	Minimization of critical infrastructure damage and indirect economic losses.
Policy and Management	Data-driven, transparent decision-making processes; institutional cooperation requirement.	Focused and effective use of resources for risk reduction, social consensus (approval).

Conclusion

This article strongly argues that the comprehensive technical knowledge generated by the convergence of Artificial Intelligence (AI) and Geotechnical Engineering disciplines must be socialized through education to serve societal risk reduction fully. Despite the revolutionary advancements of AI in risk analysis and prediction, the confinement of this knowledge within academic and technical circles creates a critical gap between technical expertise and public awareness and preparedness levels. These identified educational gaps stem from both disciplinary silos in engineering education and inadequacies in public communication of ground-related risks.

The proposed AI-Supported Geotechnical Risk Education Framework offers a conceptual roadmap designed to bridge this gap. Its three core elements—High-Fidelity Simulation, Pedagogical Translation Layer, and Interactive Public Engagement—aim to fundamentally transform risk perception by translating technical data into personal experiences and actionable information. Through this system, local communities can concretely experience potential ground behavior in their living spaces using tools such as Virtual Reality (VR), rather than relying on complex probabilistic models.

The policy and societal implications of this education are significant. Increased public awareness proactively strengthens public safety, encourages risk-based decision-making in infrastructure investments, and reduces the long-term economic burden of post-disaster recovery. The article emphasizes the crucial need for collaboration between universities, government agencies, and civil society, as well as the establishment of transparent data management protocols, for the successful implementation of this framework.

In conclusion, resilience against disasters will be achieved not only through the excellence of engineering calculations but also through the equitable and accessible dissemination of scientific knowledge to society. Future research should conduct pilot implementations of this conceptual framework, identify the most appropriate pedagogical translation methodologies for AI outputs, and empirically measure the effects of educational interventions on behavioral change. This holistic approach offers a sustainable path forward in managing future geotechnical disaster risks.

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