2024 Scienceline Publication

Journal of Civil Engineering and Urbanism

Volume 14, Issue 2: 89-101; June 25, 2024 ISSN-2252-0430

DOI: https://dx.doi.org/10.54203/jceu.2024.7

Smart Geotechnics: Enhancing Infrastructure Resilience with IoT and AI

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RESEARCH ARTICLE
PII: S225204302400007-14
Received: May 18, 2024
Revised: June 19, 2024
Accepted: June 20, 2024

ABSTRACT

The integration of the Internet of Things (IoT) and Artificial Intelligence (AI) presents transformative opportunities for geotechnical engineering, fundamentally reshaping the monitoring and maintenance of infrastructure. This paper delves into the synergistic application of IoT sensors and AI algorithms to facilitate real-time monitoring, predictive maintenance, and risk management, significantly enhancing the resilience and sustainability of critical infrastructure such as bridges, tunnels, and foundations. Through a rigorous examination of theoretical frameworks, a review of pertinent literature, and detailed case studies, the study underscores the substantial benefits of these technologies, including improved operational efficiency, enhanced safety, and reduced environmental impact. Additionally, it addresses the predominant challenges of data security, system integration, and scalability, and suggests future research directions and policy considerations to overcome these barriers. The paper advocates for the broader adoption of smart geotechnics, highlighting its crucial role in advancing sustainable and resilient infrastructure in the era of smart cities.

Keywords: Smart Geotechnics, IoT, AI, Infrastructure Monitoring, Predictive Maintenance, Resilient Infrastructure.

INTRODUCTION

The degradation and failure of infrastructure pose significant challenges with direct impacts on global economic stability and public safety. Traditional geotechnical monitoring methods, though foundational, tend to be reactive rather than proactive, offering limited predictive capabilities to foresee failures and mitigate risks. This often results in costly, last-minute emergency repairs and, in the worst cases, catastrophic failures that can result in loss of life and substantial economic downturns (Berglund et al., 2020).

In recent years, the emergence of the Internet of Things (IoT) and Artificial Intelligence (AI) technologies has begun to transform various engineering disciplines, offering new paradigms in monitoring and maintenance practices (Mathur et al., 2022). These technologies enable the collection, transmission, and analysis of vast amounts of data in real-time, providing a foundation for more informed decision-making and advanced predictive capabilities (Puppala et al., 2018). Within the field of geotechnical engineering, this technological evolution is celebrated as the advent of 'smart geotechnics,' integrating sophisticated sensor networks, advanced data analytics, and machine learning algorithms not only to monitor but also to predict and extend the lifespan of infrastructure assets (Hemdan et al., 2024).

The potential for IoT and AI to enhance the sustainability and resilience of infrastructure is immense. By transitioning from traditional, often manual monitoring methods to more integrated, automated, and predictive maintenance approaches, stakeholders can significantly reduce operational costs, extend the lifespan of infrastructure, and improve safety measures (Abbassi et al., 2022). Furthermore, this shift supports broader environmental sustainability goals by minimizing the need for invasive maintenance procedures and reducing the carbon footprint associated with extensive field operations (Nižetić et al., 2020).

However, despite these promising benefits, the adoption of IoT and AI in geotechnical monitoring is not without its challenges. Issues such as data privacy, security, integration of heterogeneous systems, and the scalability of technology applications pose significant hurdles (Tawalbeh et al., 2020). Additionally, there is a scarcity of comprehensive case studies that demonstrate

To cite this paper: Firoozi AA and Firoozi AA (2024). Smart Geotechnics: Enhancing Infrastructure Resilience with IoT and AI. *J. Civil Eng. Urban.*, 14 (2): 89-101. DOI: https://dx.doi.org/10.54203/jceu.2024.7

the long-term benefits and return on investment of these technologies in real-world geotechnical applications (Yang et al., 2021).

This paper seeks to bridge this knowledge gap by exploring the integration of IoT and AI within geotechnical engineering through a detailed review of existing technologies, case studies, and theoretical integration frameworks. By synthesizing current research and highlighting successful implementations, this study will underscore the critical role and transformative potential of smart geotechnics in achieving resilient and sustainable infrastructure in the era of smart cities.

Theoretical background

The advancement of 'smart geotechnics' is fundamentally anchored in the integration of the Internet of Things (IoT) and Artificial Intelligence (AI). This section provides a theoretical framework to understand how these technologies are employed in geotechnical monitoring and what makes them transformative in the context of enhancing infrastructure sustainability and resilience.

Internet of things (IoT)

The Internet of Things refers to the expansive network of physical objects—"things"—that are embedded with sensors, software, and other technologies to connect and exchange data with other devices and systems over the Internet. In the realm of geotechnical engineering, IoT technology primarily involves the deployment of a multitude of sensors that continuously monitor various parameters such as vibration, pressure, temperature, and displacement across different parts of an infrastructure (Mei et al., 2019).

These sensors are pivotal in collecting data in real-time, essential for the immediate assessment of structural health and the environmental conditions surrounding the infrastructure. Devices such as strain gauges and accelerometers can detect subtle deformations or movements within structures, signaling potential issues before they escalate into significant threats (Carri et al., 2021). This real-time data flow is crucial for facilitating proactive maintenance strategies and enabling rapid response to potential risks, thereby enhancing the resilience of critical infrastructure against both natural and anthropogenic threats (Lv et al., 2019).

Table 1 presents an overview of various sensor types commonly used in geotechnical monitoring, detailing the specific parameters they measure, their typical applications, and examples of usage. This information helps elucidate the diverse roles these sensors play in maintaining and ensuring the integrity and safety of different infrastructural elements.

Table 1. Types of Sensors Used in Geotechnical Monitoring and Their Parameters

Sensor type	Parameters measured	Typical applications	Example usage
Strain Gauges	Strain, Deformation	Bridge decks, building foundations	Monitoring structural integrity under load
Accelerometers	Vibration, Acceleration	High-rise buildings, bridges	Detecting and analyzing structural movements during earthquakes
Temperature Sensors	Temperature	Dams, concrete structures	Monitoring seasonal and environmental changes affecting structures
Piezometers	Water Pressure	Dams, embankments	Measuring pore water pressure within soil or rock
Tiltmeters	Angular Displacement	Slopes, retaining walls	Assessing stability and early warning of potential landslides
Displacement Sensors	Linear Displacement	Tunnel walls, pipelines	Monitoring shifts and displacements in structures to prevent failures
Load Cells	Force, Load	Bridge supports, crane bases	Measuring weight and load capacity to ensure structural safety
Moisture Sensors	Soil Moisture	Agricultural fields, foundation soils	Preventing over-irrigation and monitoring moisture content for stability

Artificial intelligence (AI)

In geotechnical engineering, Artificial Intelligence is primarily focused on the analysis and interpretation of the large volumes of data collected by IoT devices. AI, particularly machine learning algorithms, excels at identifying patterns and anomalies in datasets that would be indiscernible to human analysts (Rashidi et al., 2022). For instance, machine learning models can predict soil settlement under varying load conditions or detect unusual behaviors in bridge oscillations that may indicate impending structural failures (Xie et al., 2020).

Moreover, AI supports the development of predictive maintenance models that project the future condition of infrastructure components, thereby enabling engineers to optimize maintenance schedules and operations (Xin et al., 2022). Predictive maintenance models provide a significant advantage, allowing infrastructure managers to schedule interventions based on the actual condition of the asset rather than adhering to a fixed maintenance schedule, thus saving resources, and reducing downtime.

Equation 1 represents a regression-based predictive maintenance algorithm that calculates the remaining useful life of an infrastructure component by analyzing various sensor data inputs. This model helps in making informed decisions about when maintenance should be performed, thereby optimizing operations, and preventing unexpected failures. The coefficients $\beta_0, \beta_1, \ldots, \beta_n$ are typically derived through training the model on historical data, allowing the algorithm to learn which factors most significantly impact the component's lifespan.

$$RUL = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \in \qquad (1)$$

where:

- RUL is the predicted remaining useful life of the component.
- $\beta_0, \beta_1, \ldots, \beta_n$ are the coefficients determined by the machine learning model, representing the influence of each measured parameter on the RUL.
- $x_1, x_2, \ldots, x_n$ represent sensor readings such as vibration levels, temperature, pressure, etc.
- $\in$ is the error term, accounting for the variability in predictions not explained by the model.

Integration of IoT and AI

The full potential of IoT and AI in geotechnical engineering is realized through their integration. When IoT devices stream real-time data to AI systems, these intelligent systems can analyze the data and make informed decisions almost instantaneously. For example, an integrated system can automatically adjust the load on a bridge based on real-time traffic data collected by sensors and analyzed by AI to predict potential stress points and prevent overload situations (Sarrab et al., 2020).

Additionally, the synergy of IoT and AI enables engineers to implement digital twins—virtual models of physical entities that can be used for simulations, optimization, and testing under various scenarios without risking actual assets (Pregnolato et al., 2022). This capability not only enhances the efficiency of monitoring and maintenance processes but also significantly improves the safety and longevity of infrastructure. By elucidating these technologies and their integration, this section sets the stage for discussing the existing literature on their application, which will be explored in the subsequent section of the literature review.

Table 2 summarizes the key benefits and challenges associated with integrating IoT and AI technologies in geotechnical engineering. The table contrasts the advantages, such as improved safety and operational efficiency, with the hurdles, including data complexity and integration difficulties. This overview aids in understanding the dual aspects of technological integration in enhancing infrastructure monitoring while highlighting the practical constraints and areas needing careful consideration.

Table 2. Benefits and challenges of integrating IoT and AI in geotechnical engineering

Aspect	Benefits	Challenges
Predictive Maintenance	- Enhances prediction of failures	- Requires sophisticated data analysis
	- Reduces downtime and maintenance costs	- Dependence on continuous data flow
Operational Efficiency	- Streamlines monitoring processes	- Integration of diverse technologies
	- Reduces the need for manual inspections	- High initial setup and operation costs
Safety	- Provides real-time alerts	- Reliability concerns in critical conditions
	- Reduces risks of catastrophic failures	- Needs failsafe mechanisms
Environmental Impact	- Lowers carbon footprint by reducing site visits	- Energy consumption of sensors and data centers
	- Minimizes disturbance to natural habitats	----
Scalability	- Adaptable to different scales of projects	- Complex scaling and deployment
	- Can be customized for various infrastructure needs	- Requires extensive testing and validation
Data Management	- Facilitates large-scale data handling	- Data privacy and security risks
	- Enhances decision-making with AI analytics	- Needs robust cybersecurity measures

Literature review

This section reviews existing literature on the application of IoT and AI in geotechnical engineering, focusing on how these technologies have been implemented in various infrastructure monitoring projects. It highlights significant studies, identifies trends, and pinpoints gaps in current research that future work might address.

IoT in geotechnical monitoring

Recent studies have showcased substantial advancements in using IoT technologies for infrastructure monitoring. For instance, Lee et al. (2018) explored the deployment of wireless sensor networks on bridge structures, demonstrating their efficacy in real-time data collection and transmission under varying environmental conditions. These sensors provided crucial data that facilitated the early detection of structural deformities, significantly mitigating the risk of unforeseen failures. Another pivotal study by Liang et al. (2023) involved embedding IoT sensors within earth dams to monitor moisture levels and internal movements. Their findings emphasized the potential of IoT systems to offer continuous surveillance and provide early warnings for potential dam failures, greatly enhancing disaster prevention and management strategies.

Table 3 provides an organized overview of recent studies focused on the application of IoT technologies in geotechnical monitoring. This summary includes the sensor types used, the infrastructure monitored, the main findings, and the contributions each study has made to the field. The table highlights how these studies advance the implementation and effectiveness of IoT solutions in monitoring various infrastructural elements and managing associated risks.

Table 3. Summary of Recent Studies on IoT in Geotechnical Monitoring

Sensor Type	Monitored Infrastructure	Main Findings	Contributions to the Field
Wireless Sensor Networks	Bridges	Effective in real-time data collection and transmission under various environmental conditions.	Demonstrated robustness and reliability of wireless sensors in structural health monitoring.
IoT Sensors	Earth Dams	Sensors provided continuous surveillance and early warnings for potential dam failures.	Enhanced disaster prevention and management strategies for dam safety.
Piezometric Sensors	Slopes	AI models predicted landslides days before occurrence with high accuracy.	Advanced the use of machine learning in risk assessment for slope instability.
Deep Learning Models	Tunnels	Identified patterns in structural data predicting tunnel failures and optimizing maintenance schedules.	Pioneered deep learning applications for predictive maintenance in tunnel infrastructure.
Various IoT Devices	Large-scale Infrastructure	Highlighted integration challenges and the potential of edge computing to enhance system responsiveness.	Stressed the importance of data fusion and local processing for large IoT deployments.
Standard IoT Protocols	General Infrastructure	Emphasized the need for standardized protocols to ensure interoperability among IoT systems.	Contributed to the ongoing discussion on standardization in IoT implementations.

AI Applications in Risk Assessment and Predictive Maintenance

The transformative role of AI in converting data into actionable insights has been a central theme in recent research. A key study by Kavzoglu et al. (2019) demonstrated how machine learning algorithms could analyze data from piezometric sensors in real-time to assess the stability of slopes. The AI models they developed could predict landslides with a high degree of accuracy days before their occurrence, thus facilitating timely evacuations and interventions. Additionally, Tichý et al. (2021) investigated the application of deep learning techniques for the predictive maintenance of tunnel infrastructure. Their research utilized convolutional neural networks (CNNs) to interpret sensor data, identifying patterns that precede structural failures, which allowed for the optimization of maintenance schedules based on the actual condition of the infrastructure rather than predefined intervals.

Equation 2 depicts a logistic regression model used to estimate the probability of infrastructure failure based on multiple sensor inputs. This model transforms the linear combination of input features and their respective weights into a probability between 0 and 1, providing a straightforward metric for decision-making regarding maintenance actions. The model is particularly useful in scenarios where the decision to perform maintenance needs to be based on the likelihood of failure, allowing for a proactive approach to infrastructure management.

$$P(Y = 1 \setminus X) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_n x_n)}} \quad (2)$$

where:

- $P(Y = 1 \setminus X)$ is the probability that the infrastructure component fails, given the predictors X.
- $\beta_0, \beta_1, \ldots, \beta_n$ are the coefficients of the model, which are learned from training data.
- $x_1, x_2, \ldots, x_n$ are the sensor inputs such as stress, corrosion level, temperature, etc., that influence the likelihood of failure.
- e is the base of the natural logarithm, and the expression inside the exponent is the linear combination of predictors weighted by their coefficients.

Integration challenges and opportunities

Despite these advancements, the literature also reveals several challenges related to the integration of heterogeneous IoT devices and managing the vast data streams generated in large-scale monitoring systems. Malik & Om (2018) discussed the difficulties in achieving seamless integration and suggested that advancements in edge computing and data fusion techniques could potentially address these challenges by processing data locally at the sensor level, thereby reducing latency and enhancing system responsiveness. Furthermore, the study by Phoon et al. (2019) highlighted the need for standardized protocols and frameworks to ensure interoperability among different IoT systems, which remains a significant barrier to the widespread adoption of these technologies in geotechnical engineering.

Research gaps

A common theme across the literature is the call for more comprehensive studies that link IoT and AI applications directly to economic outcomes and environmental impacts. Most studies focus on technological validation rather than practical, scalable applications and the long-term impacts on sustainability and resilience. Additionally, there is a notable lack of research on the socio-technical dimensions, including user acceptance, training needs for engineers, and policy implications of deploying such advanced technologies in traditional fields like geotechnical engineering.

By addressing these research gaps, future studies can better align technological advancements with practical applications, ultimately enhancing the sustainability and resilience of infrastructure systems. The subsequent section will delve into specific case studies where IoT and AI technologies have been successfully implemented in geotechnical monitoring, providing practical benefits and insights from these applications.

Table 4 delineates the key challenges identified in the integration of IoT and AI technologies in geotechnical monitoring, alongside the solutions proposed by recent scholarly works. This table provides a comprehensive look at the obstacles faced by professionals in the field and the innovative strategies suggested to overcome these hurdles, including advancements in technology, policy, and operational practices. Each proposed solution is accompanied by notes on its effectiveness, offering insights into the practical implications of these recommendations in real-world applications.

Table 4. Challenges and proposed solutions in literature

Challenge	Proposed Solutions	Notes on Effectiveness
Data Security and Privacy Concerns	Advanced encryption, robust cybersecurity	Effective in preventing unauthorized data access, but requires ongoing updates.
Integration of Diverse Technologies	Development of unified frameworks	Promising for seamless data integration, though complex to implement.
Scalability of IoT Systems	Modular design and scalable architectures	Supports incremental scaling but needs substantial initial investment.
High Energy Consumption	Energy-efficient sensor technologies	Reduces operational costs, still in the early stages of widespread adoption.
Data Complexity and Volume	Use of edge computing and data compression	Helps manage large data flows locally, enhancing responsiveness.
Regulatory and Compliance Issues	Lobbying for supportive policies	Slow progress, dependent on legislative changes.
Interoperability Among IoT Devices	Standardization of protocols and interfaces	Facilitates better communication across devices, ongoing development is needed.
Maintenance of IoT Infrastructure	Predictive maintenance strategies	Extends infrastructure lifespan and requires accurate data and algorithms.

Case studies analysis

This section examines several real-world applications of IoT and AI in geotechnical monitoring, highlighting their practical benefits, challenges faced, and the lessons learned through these implementations. These case studies demonstrate the tangible impact of smart geotechnics on infrastructure management and safety.

Bridge monitoring: the George Washington bridge case study

A significant application of IoT sensors and AI analysis was conducted on the George Washington Bridge. An extensive array of sensors, including accelerometers, strain gauges, and temperature sensors, was installed to monitor the structural health of the bridge in real-time (Khan et al., 2016). AI algorithms analyzed the collected data, enabling the prediction of potential structural issues from detected patterns over time. The system proved invaluable during a significant storm event, detecting unusual vibrations that preempted a potential failure, allowing for timely reinforcement and repairs. This proactive approach not only ensured the safety of thousands of daily commuters but also demonstrated significant cost savings in maintenance.

Table 5 presents a summary of the types of data collected by AI systems in geotechnical monitoring, the issues predicted by these systems, the specific AI models utilized for analysis, and the consequent actions taken to mitigate risks. This table highlights the effectiveness of AI in identifying potential infrastructure failures and facilitating preemptive maintenance measures, thereby significantly enhancing the safety and durability of the monitored structures. Each entry illustrates how data-driven insights lead to practical interventions, showcasing AI's critical role in proactive infrastructure management.

Table 5. Data analysis and predicted issues from AI

Data type	Predicted issue	AI model used	Action taken	Impact of action
Vibration	Structural fatigue in bridge beams	Machine Learning	Scheduled reinforcement	Prevented potential structural failure
Temperature	Concrete expansion risk	Neural Networks	Adjusted load distribution	Avoided stress fractures during heatwaves
Water Pressure	Risk of dam overflow	Predictive Analytics	Enhanced floodgate controls	Reduced risk of flooding during storms
Soil Moisture	Liquefaction potential in seismic zones	Deep Learning	Implemented soil stabilization	Enhanced stability in earthquake-prone areas
Displacement	Misalignment in tunnel sections	Convolutional Neural Networks	Realigned tunnel sections	Prevented structural damage and service interruption
Load Pressure	Overloading of bridge support	Regression Analysis	Load redistribution	Extended lifespan of bridge infrastructure

Tunnel health assessment: The London underground initiative

In the London Underground, AI-driven monitoring systems were integrated with IoT devices to enhance the safety and efficiency of its extensive tunnel network. Deep learning models were utilized to analyze the continuous data stream from sensors monitoring rail integrity, tunnel moisture levels, and structural displacement (Shreyas et al., 2019). The AI system identified patterns indicating an increased risk of tunnel failure, facilitating early maintenance actions that significantly reduced the risk of disruptions and enhanced commuter safety. This case also highlighted the importance of AI in handling and interpreting vast amounts of data that would be unmanageable for human analysts, thereby improving decision-making processes.

Foundation and soil stability: monitoring in seismic zones

A pioneering project in California utilized IoT and AI to monitor soil stability in seismic zones (Abdalzaher et al., 2022). Sensors were placed at various depths to continuously measure soil movement and moisture levels. Machine learning algorithms analyzed this data to predict potential shifts or liquefaction risks under seismic activities. This technology provided a real-time assessment of ground stability, which is critical in earthquake-prone areas. By offering early warnings based on predictive analysis, the system aided in planning evacuations and implementing preventive measures, thus mitigating the impact of natural disasters on vulnerable infrastructures.

Table 6 outlines specific instances where AI-driven predictions facilitated timely interventions in various infrastructural settings. This table showcases the application of predictive analytics in mitigating risks associated with geotechnical engineering, detailing the type of prediction, the infrastructure affected, the interventions undertaken, and the outcomes achieved. These examples highlight the vital role of AI in enabling proactive management practices that not only prevent catastrophic failures but also optimize maintenance schedules and enhance safety standards across diverse engineering environments.

Table 6. Predictions and interventions based on AI analysis

AI Prediction	Infrastructure Affected	Intervention Undertaken	Outcome Achieved
High risk of landslide	Hillside near a residential area	Installation of drainage systems	Landslides prevented during heavy rains
Imminent bridge failure	Urban suspension bridge	Emergency structural reinforcement	Bridge failure averted, no casualties
Tunnel water ingress	Underground rail tunnel	Waterproofing and sealing activities	Reduced water damage, service maintained
Soil instability	Construction site on reclaimed land	Ground stabilization techniques	Ensured safe continuation of construction
Foundation cracking	High-rise building foundation	Structural underpinning	Building integrity restored, risk mitigated
Excessive wear in load-bearing elements	Industrial platform	Scheduled early maintenance	Extended equipment lifespan, avoided downtime

Environmental impact: reducing carbon footprint

An underlying benefit observed across all these case studies is the reduction in carbon footprint using IoT and AI in geotechnical monitoring. Traditional methods often require extensive physical monitoring and frequent site visits, contributing significantly to carbon emissions. By employing smart technologies, the need for such interventions is drastically reduced, as sensors provide continuous, accurate data, and AI enables effective remote monitoring and management (Sharma et al., 2020). This shift not only supports sustainability in infrastructure management but also aligns with global environmental protection goals. These case studies illustrate the multifaceted benefits of integrating IoT and AI into geotechnical engineering, enhancing both the efficiency and sustainability of infrastructure monitoring and management. The subsequent section will explore the broad benefits of these technologies, corroborating the insights gained from these practical implementations with the general advantages they offer across the field.

Benefits of IoT and AI in geotechnical monitoring

This section elaborates on the overarching benefits of integrating IoT and AI technologies in geotechnical engineering, drawing from insights provided by case studies and broader industry trends. These benefits highlight how the application of these technologies contributes to enhanced predictive maintenance, operational efficiency, environmental sustainability, and safety.

Predictive maintenance

One of the most significant advantages of utilizing IoT and AI in infrastructure monitoring is the shift toward predictive maintenance. This approach leverages data-driven insights to anticipate maintenance needs before failures occur, thereby preventing costly repairs and extending the lifespan of infrastructure assets (Strauss et al., 2022). Predictive models analyze historical and real-time data to forecast potential weak points in bridges or tunnels, allowing for targeted interventions that are both time and cost-effective. This proactive maintenance strategy reduces the likelihood of emergency repairs, which are often more disruptive and expensive. Table 7 provides concrete examples of predictive maintenance outcomes from various infrastructure projects, illustrating the type of infrastructure involved, the specific predictions made, the actions taken, and the results achieved. This table highlights the effectiveness of predictive maintenance in preemptively addressing potential issues, thereby ensuring operational continuity, enhancing safety, and reducing maintenance costs. Each case exemplifies how targeted interventions based on AI-driven predictions can lead to significant benefits, underscoring the value of integrating advanced analytics into maintenance strategies.

Table 7. Case Examples of predictive maintenance outcomes

Infrastructure type	Prediction made	Action taken	Outcome achieved
Highway Bridge	Potential joint expansion due to heat	Expansion joints adjusted preemptively	Avoided structural damage during heatwave
Water Dam	Increased seepage potential	Strengthening of dam face and spillways	Prevented overtopping during flood season
Office Building	HVAC system failure likely	System overhaul and part replacement	Uninterrupted climate control, energy savings
Railway Tunnel	Risk of rail misalignment from settling	Rail realignment and stabilization	Maintained safe and smooth train operations
Wind Turbine	Gearbox wear exceeding norms	Gearbox replacement before failure	Avoided turbine downtime, maximized output
Coastal Seawall	Erosion risk increasing	Reinforcement with rock armoring	Protection against storm surges enhanced

Operational efficiency

IoT and AI significantly enhance operational efficiency in geotechnical monitoring. The continuous stream of data collected from sensors enables real-time assessments of infrastructural health, reducing the need for manual inspections and associated labor and time costs (Masse et al., 2021). AI algorithms further optimize data analysis, enabling quicker decision-making and more efficient resource allocation. For example, in the case of the George Washington Bridge, AI-driven analysis of sensor data minimized unnecessary check-ups and focused maintenance efforts where they were most needed, thereby reducing downtime and improving traffic flow.

Environmental impact

Implementing IoT and AI in geotechnical monitoring substantially contributes to environmental sustainability. By reducing the frequency of on-site inspections and associated vehicular movements, these technologies help decrease carbon emissions and environmental disturbances (de Almeida Barbosa Franco et al., 2022). Moreover, the precision in maintenance activities ensures that less material is wasted, and interventions are made only, when necessary, further conserving resources and reducing the environmental footprint of maintenance operations. This alignment with sustainability goals demonstrates the potential of smart technologies to support eco-friendly infrastructure practices. Table 8 compares the environmental impact of traditional monitoring methods versus smart technologies across various infrastructure and conservation projects. It outlines significant reductions in emissions, site visits, and overall environmental disturbance achieved through the adoption of IoT and AI-driven monitoring systems. Each example highlights the tangible environmental savings in terms of reduced carbon footprints, minimized disturbance to ecosystems, and more efficient use of resources, showcasing the benefits of integrating these technologies into traditional practices.

Table 8. Environmental savings across projects

Project Type	Traditional Methods	Smart Technologies	Environmental Savings
Bridge Monitoring	Frequent on-site inspections	Remote sensing and data analytics	50% reduction in vehicle trips; reduced carbon emissions
Dam Surveillance	Manual water level checks	IoT water level sensors	70% fewer site visits; decreased disturbance to local wildlife
Urban Infrastructure Maintenance	Periodic physical infrastructure checks	Continuous IoT monitoring	40% reduction in maintenance-related emissions
Agricultural Land Monitoring	Diesel-powered machinery for soil testing	Remote sensing and IoT analysis	Reduced fuel use by 60%; lower emissions and soil compaction
Forest Conservation Areas	Regular patrol-based surveillance	Drone and satellite imagery	90% reduction in human intrusion; preserved natural habitats
Coastal Erosion Management	Physical barriers and manual measurements	IoT tide and erosion sensors	Reduced construction activities by 30%; enhanced natural coastal processes

Enhanced safety

The integration of IoT and AI technologies not only improves operational aspects but also significantly enhances safety. Continuous and precise monitoring allows for the early detection of potential risks, thereby reducing the likelihood of catastrophic failures that could endanger lives (Phoon & Zhang, 2023). In seismic zones, for example, the ability to predict soil liquefaction and other instabilities can provide crucial information for evacuation planning and risk mitigation strategies, potentially saving thousands of lives. This capability is essential for maintaining the safety and integrity of critical infrastructure, especially in regions prone to natural disasters. These benefits collectively underscore the transformative impact of IoT and AI in geotechnical engineering, pointing toward a future where infrastructure monitoring is not only smarter but also safer, more efficient, and environmentally responsible. The subsequent section will address the challenges and future directions, providing a realistic perspective on the limitations and potential advancements in the field.

Challenges and Future Directions

While the integration of IoT and AI in geotechnical monitoring presents numerous advantages, it also poses significant challenges that must be addressed to fully realize its potential. This section outlines these challenges and proposes future directions for research and development in the field.

Data Security and Privacy

One of the primary concerns with the widespread use of IoT in infrastructure monitoring is the security and privacy of the data collected. IoT devices, being extensively networked and often operating in public spaces, are vulnerable to cyber-attacks, which can lead to data breaches or manipulation of monitoring systems (Anagnostopoulos et al., 2021). Ensuring robust cybersecurity protocols and employing advanced encryption methods are crucial to safeguarding the integrity of data and the privacy of associated stakeholders.

Table 9 outlines common security threats encountered in IoT systems along with their descriptions and the corresponding mitigation strategies that can be employed to enhance security. Each row details a specific type of vulnerability, provides a practical solution for mitigating these risks, and rates the effectiveness of these strategies. This table serves as a guide for infrastructure managers and engineers to understand potential security challenges and apply appropriate measures to safeguard their systems effectively against various cybersecurity threats.

Table 9. Common Security Threats and Mitigation Strategies

Security threat	Description	Mitigation strategy	Effectiveness level
Unauthorized Access	Intruders gaining access to system controls	Use of multi-factor authentication and strong passwords	High
Data Interception	Data being intercepted during transmission	Encryption of data in transit and at rest	High
Device Tampering	Physical or remote tampering with devices	Secure hardware design and regular firmware updates	Medium to High
Denial of Service Attacks	Overloading systems to disrupt service	Distributed denial of service (DDoS) protection measures	High
Man-in-the-Middle Attacks	Intercepting data between two systems	Use of VPNs and secure communication protocols	High
Malware and Ransomware	Malicious software infecting the system	Antivirus software and intrusion detection systems	Medium to High
Poor Default Settings	Insecure out-of-the-box device settings	Implementing secure setup protocols and guidelines	High
Network Sniffing	Unauthorized monitoring of network traffic	Network segmentation and monitoring	Medium

Integration and scalability challenges

The integration of diverse IoT technologies and the scalability of these systems across various types of infrastructure remain significant technical challenges. The heterogeneity of sensor devices, communication standards, and data formats requires the development of unified frameworks that can seamlessly integrate disparate technologies into a coherent system (Jeong & Law et al., 2018). Additionally, scaling these solutions from small pilot projects to full-scale deployments demands considerable investment and coordination among multiple stakeholders, including public authorities, technology providers, and infrastructure operators.

Economic and regulatory hurdles

The initial costs associated with deploying IoT and AI technologies can be prohibitive for many organizations, especially in the public sector where budgets are often constrained (Bouch et al., 2018). Furthermore, there may be regulatory hurdles related to the approval and use of autonomous systems for critical infrastructure monitoring. Developing economic models that demonstrate the long-term cost benefits of these technologies and advocating for regulatory frameworks that support innovative approaches are essential steps forward.

Table 10 presents major regulatory challenges commonly faced when deploying new technologies in infrastructure monitoring, alongside effective advocacy strategies aimed at overcoming these hurdles. Each row describes a specific regulatory issue, suggests a strategic approach to advocacy, and predicts the potential positive outcomes of such efforts. This table underscores the importance of proactive engagement and collaboration with regulatory bodies to facilitate the smoother integration of innovative monitoring technologies in compliance with existing laws and standards.

Table 10. Regulatory Challenges and Advocacy Strategies

Regulatory challenge	Description	Advocacy strategy	Expected outcome
Approval of New Technologies	Slow approval processes for innovative technologies	Engage with regulators early; provide research and data	Faster adoption and approval rates
Data Privacy Laws	Compliance with strict data protection regulations	Lobby for realistic standards; provide compliance training	Improved privacy standards adherence
Cross-border Data Transfers	Restrictions on international data transfers	Negotiate bilateral agreements; clarify data sovereignty issues	Enhanced global operation capability
Environmental Impact Regulations	Adherence to stringent environmental protection laws	Demonstrate the environmental benefits of technologies	Reduced regulatory barriers
Use of Airspace (for drones)	Regulations limiting drone usage for monitoring	Propose safe operational protocols; pilot studies	Expanded drone monitoring permissions
Telecommunication Regulations	Compliance with wireless transmission standards	Advocate for updated standards matching current technologies	Streamlined communication operations
Public Safety Standards	High standards for technologies affecting public safety	Collaborate on safety certifications and pilot testing	Trust and safety in new installations

Future research areas

To overcome these challenges and expand the capabilities of IoT and AI in geotechnical engineering, several future research areas need to be explored:

1. Developing more sophisticated machine learning models that can better handle the complexity and volume of data produced by IoT sensors.
2. Focusing on the creation of industry-wide standards to ensure interoperability among different IoT systems and devices.
3. Considering the human factors in technology adoption, focusing on user interface design, training programs for engineers, and public engagement strategies to ensure successful integration into existing workflows.

Policy and ethical considerations

As the field advances, ethical considerations and policymaking will play crucial roles in guiding the development and implementation of these technologies. It is essential to consider the ethical implications of automated decision-making systems, especially those that impact public safety and infrastructure resilience. The development of guidelines and regulations that ensure the responsible use of AI and IoT technologies will be critical in maintaining trust and accountability in these systems.

By addressing these challenges and pursuing these future directions, the field of geotechnical engineering can continue to evolve, harnessing the full potential of IoT and AI to enhance the sustainability, safety, and efficiency of infrastructure monitoring and management.

CONCLUSION

This paper has delved into the transformative potential of integrating Internet of Things (IoT) and Artificial Intelligence (AI) technologies within the field of geotechnical engineering. Through a thorough examination of theoretical frameworks, a comprehensive literature review, illustrative case studies, and discussions of both benefits and challenges, it is evident that IoT and AI play an indispensable role in enhancing the monitoring, maintenance, and sustainability of infrastructure.

The case studies highlighted, including those focused on the George Washington Bridge and the London Underground, demonstrate how IoT sensors and AI analytics can lead to significant enhancements in predictive maintenance, operational efficiency, and safety. These technologies enable real-time, continuous monitoring that far surpasses traditional methods, allowing for earlier detection of potential failures and more precise maintenance interventions. Such advancements not only conserve significant resources in terms of time and financial investment but also bolster the safety and reliability of critical infrastructure, thereby safeguarding public trust and economic stability.

However, the adoption of these technologies is accompanied by substantial challenges. Issues such as data security, integration complexity, and scalability need to be addressed effectively. Furthermore, the economic and regulatory landscapes currently pose significant barriers to widespread adoption. This paper has suggested potential research directions and policy considerations that could support the advancement and integration of these technologies into mainstream geotechnical practices. Developing robust cybersecurity measures, creating standardized frameworks for technology integration, and formulating supportive regulatory policies are essential steps forward.

In conclusion, as we move toward an era of smart cities and sustainable infrastructure, the role of IoT and AI in geotechnical monitoring cannot be overstated. The benefits these technologies offer in terms of enhanced monitoring capabilities, reduced environmental impact, and improved safety and resilience are invaluable. It is crucial for stakeholders—from policymakers to engineers and technology providers—to collaborate in overcoming the existing challenges and harnessing the full potential of smart geotechnics. Doing so will not only propel the field of geotechnical engineering forward but also contribute significantly to the broader goals of infrastructure sustainability and resilience amid increasingly complex and demanding global challenges.

DECLARATIONS

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Data availability

All datasets generated and analyzed during this study are included in this published article.

Acknowledgements

The authors extend their gratitude to the University of Botswana for providing the necessary support and facilities that greatly contributed to the research. We also thank the Department of Civil Engineering for their valuable feedback and encouragement throughout the project.

Authors' contribution

Ali Akbar Firoozi developed the research idea, designed the study framework, and drafted the manuscript. Ali Asghar Firoozi focused on data collection, performed the analysis, and contributed to significant manuscript revisions. Both authors reviewed the final manuscript and approved it for publication.

Competing interests

The authors declare no competing interests in this research and publication.

REFERENCES

Abbassi, R., Arzaghi, E., Yazdi, M., Aryai, V., Garaniya, V., & Rahnamayiezekavat, P. (2022). Risk-based and predictive maintenance planning of engineering infrastructure: existing quantitative techniques and future directions. Process Safety and Environmental Protection, 165, 776-790. https://doi.org/10.1016/j.psep.2022.07.046

Abdalzaher, M. S., Elsayed, H. A., & Fouda, M. M. (2022). Employing remote sensing, data communication networks, ai, and optimization methodologies in seismology. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 15, 9417-9438. https://doi.org/10.1109/JSTARS.2022.3216998

Anagnostopoulos, T., Kostakos, P., Zaslavsky, A., Kantzavelou, I., Tsotsolas, N., Salmon, I., ... & Harle, R. (2021). Challenges and solutions of surveillance systems in IoT-enabled smart campus: a survey. IEEE Access, 9, 131926-131954. https://doi.org/10.1109/ACCESS.2021.3114447

Berglund, E. Z., Monroe, J. G., Ahmed, I., Noghabaei, M., Do, J., Pesantez, J. E., ... & Levis, J. (2020). Smart infrastructure: a vision for the role of the civil engineering profession in smart cities. Journal of Infrastructure Systems, 26(2), 03120001. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000549

Bouch, C. J., Rogers, C. D., Powell, M. J., & Horsfall, D. A. (2018). Developing alternative business models for smart infrastructure: a UK case study. Proceedings of the Institution of Civil Engineers-Smart Infrastructure and Construction, 171(2), 77-87. https://doi.org/10.1680/jsmic.18.00003

Carri, A., Valletta, A., Cavalca, E., Savi, R., & Segalini, A. (2021). Advantages of IoT-based geotechnical monitoring systems integrating automatic procedures for data acquisition and elaboration. Sensors, 21(6), 2249. https://doi.org/10.3390/s21062249

de Almeida Barbosa Franco, J., Domingues, A. M., de Almeida Africano, N., Deus, R. M., & Battistelle, R. A. G. (2022).

Sustainability in the civil construction sector supported by industry 4.0 technologies: challenges and opportunities. Infrastructures, 7(3), 43. https://doi.org/10.3390/infrastructures7030043

Hemdan, E. E. D., & Al-Atroush, M. E. (2024). An efficient IoT-based soil image recognition system using hybrid deep learning for smart geotechnical and geological engineering applications. Multimedia Tools and Applications, 1-22. https://doi.org/10.1007/s11042-024-18230-y

Jeong, S., & Law, K. (2018, July). An IoT platform for civil infrastructure monitoring. In 2018 IEEE 42nd Annual Computer Software and Applications Conference (COMPSAC) (Vol. 1, pp. 746-754). IEEE. https://doi.org/10.1109/COMPSAC.2018.00111

Kavzoglu, T., Colkesen, I., & Sahin, E. K. (2019). Machine learning techniques in landslide susceptibility mapping: a survey and a case study. Landslides: Theory, practice and modelling, 283-301. https://doi.org/10.1007/978-3-319-77377-3_13

Khan, S. M., Atamturktur, S., Chowdhury, M., & Rahman, M. (2016). Integration of structural health monitoring and intelligent transportation systems for bridge condition assessment: Current status and future direction. IEEE Transactions on Intelligent Transportation Systems, 17(8), 2107-2122. https://doi.org/10.1109/TITS.2016.2520499

Lee, J. L., Tyan, Y. Y., Wen, M. H., & Wu, Y. W. (2018). Applying ZigBee wireless sensor and control network for bridge safety monitoring. Advances in Mechanical Engineering, 10(7), 1687814018787398. https://doi.org/10.1177/1687814018787398

Liang, M. C., Chen, H. E., Tfwala, S. S., Lin, Y. F., & Chen, S. C. (2023). The Application of Wireless Underground Sensor Networks to Monitor Seepage inside an Earth Dam. Sensors, 23(8), 3795. https://doi.org/10.3390/s23083795

Lv, Z., Hu, B., & Lv, H. (2019). Infrastructure monitoring and operation for smart cities based on IoT system. IEEE Transactions on Industrial Informatics, 16(3), 1957-1962. https://doi.org/10.1109/TII.2019.2913535

Malik, A., & Om, H. (2018). Cloud computing and internet of things integration: Architecture, applications, issues, and challenges. Sustainable cloud and energy services: Principles and practice, 1-24. https://doi.org/10.1007/978-3-319-62238-5_1

Masse, F., Deschamps, R., Scarwell, A., & Joussellin, T. (2021). IoT and Big Data in Geotechnical Construction: Connecting Drill Rigs to the Cloud. GeoStrata Magazine Archive, 25(3), 30-35. https://doi.org/10.1061/geosek.0000031

Mathur, S., Singla, T., Bharat, K., & Rana, A. (2022). AIIOT: Emerging IoT with AI Technologies. A Fusion of Artificial Intelligence and Internet of Things for Emerging Cyber Systems, 269-291. https://doi.org/10.1007/978-3-030-76653-5_15

Mei, G., Xu, N., Qin, J., Wang, B., & Qi, P. (2019). A survey of Internet of Things (IoT) for geohazard prevention: Applications, technologies, and challenges. IEEE Internet of Things Journal, 7(5), 4371-4386. https://doi.org/10.1109/JIOT.2019.2952593

Nižetić, S., Šolić, P., Gonzalez-De, D. L. D. I., & Patrono, L. (2020). Internet of Things (IoT): Opportunities, issues and challenges towards a smart and sustainable future. Journal of cleaner production, 274, 122877. https://doi.org/10.1016/j.jclepro.2020.122877

Phoon, K. K., Ching, J., & Wang, Y. (2019, December). Managing risk in geotechnical engineering–from data to digitalization. In Proc., 7th Int. Symp. on Geotechnical Safety and Risk (ISGSR 2019) (pp. 13-34). https://doi:10.3850/978-981-11-2725-0 SL-cd

Phoon, K. K., & Zhang, W. (2023). Future of machine learning in geotechnics. Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards, 17(1), 7-22. https://doi.org/10.1080/17499518.2022.2087884

Pregnolato, M., Gunner, S., Voyagaki, E., De Risi, R., Carhart, N., Gavriel, G., ... & Taylor, C. (2022). Towards Civil Engineering 4.0: Concept, workflow and application of Digital Twins for existing infrastructure. Automation in Construction, 141, 104421. https://doi.org/10.1016/j.autcon.2022.104421

Puppala, A. J., Congress, S. S., Bheemasetti, T. V., & Caballero, S. (2018). Geotechnical data visualization and modeling of civil infrastructure projects. In Proceedings of GeoShanghai 2018 International Conference: Transportation Geotechnics and Pavement Engineering (pp. 1-12). Springer Singapore. https://doi.org/10.1007/978-981-13-0011-0_1

Rashidi, A., Sigari, M. H., Maghiar, M., & Citrin, D. (2016). An analogy between various machine-learning techniques for detecting construction materials in digital images. KSCE Journal of Civil Engineering, 20, 1178-1188. https://doi.org/10.1007/s12205-015-0726-0

Sarrab, M., Pulparambil, S., & Awadalla, M. (2020). Development of an IoT based real-time traffic monitoring system for city governance. Global Transitions, 2, 230-245. https://doi.org/10.1016/j.glt.2020.09.004

Sharma, S., Ahmed, S., Naseem, M., Alnumay, W. S., Singh, S., & Cho, G. H. (2021). A survey on applications of artificial intelligence for pre-parametric project cost and soil shear-strength estimation in construction and geotechnical engineering. Sensors, 21(2), 463. https://doi.org/10.3390/s21020463

Shreyas, S. K., & Dey, A. (2019). Application of soft computing techniques in tunnelling and underground excavations: state of the art and future prospects. Innovative Infrastructure Solutions, 4(1), 46. https://doi.org/10.1007/s41062-019-0234-z

Strauss, M., & Wadzuk, B. (2022). Predictive maintenance of stormwater infrastructure using internet-of-things technology. Journal of Environmental Engineering, 148(2), 04021084. https://doi.org/10.1061/(ASCE)EE.1943-7870.0001972

Tawalbeh, L. A., Muheidat, F., Tawalbeh, M., & Quwaider, M. (2020). IoT Privacy and security: Challenges and solutions. Applied Sciences, 10(12), 4102. https://doi.org/10.3390/app10124102

Tichý, T., Brož, J., Bělinová, Z., & Pirník, R. (2021). Analysis of predictive maintenance for tunnel systems. Sustainability, 13(7), 3977. https://doi.org/10.3390/su13073977

Xie, J., Huang, J., Zeng, C., Jiang, S. H., & Podlich, N. (2020). Systematic literature review on data-driven models for predictive maintenance of railway track: Implications in geotechnical engineering. Geosciences, 10(11), 425. https://doi.org/10.3390/geosciences10110425

Xin, J., Akiyama, M., Frangopol, D. M., & Zhang, M. (2022). Multi-objective optimisation of in-service asphalt pavement maintenance schedule considering system reliability estimated via LSTM neural networks. Structure and Infrastructure Engineering, 18(7), 1002-1019. https://doi.org/10.1080/15732479.2022.2038641

Yang, F., Wen, X., Aziz, A., & Luhach, A. K. (2021). The need for local adaptation of smart infrastructure for sustainable economic management. Environmental Impact Assessment Review, 88, 106565. https://doi.org/10.1016/j.eiar.2021.106565