Available online at www.CivileJournal.org

Civil Engineering Journal

(E-ISSN: 2476-3055; ISSN: 2676-6957)

Vol. 11, No. 01, January, 2025

Impact of the Application of Smart Sensor Networks for the Construction Management of Geotechnical Activities

Nimer Alselami [1], Khaled Aati [1], Mohammed Mutnbak [1], Khaled A. Alrasheed [2], Muhammad Basit Khan [3*]

[1] *Civil and Architectural Engineering Department, College of Engineering and Computer Sciences, Jazan University, Jazan 45142, Saudi Arabia.*

[2] *Department of Civil Engineering, College of Engineering and Petroleum, Kuwait University, Kuwait City, Kuwait.*

[3] *Department of Architecture and Civil Engineering, City University of Hong Kong, Kowloon, Hong Kong SAR, China.*

Received 03 August 2024; Revised 09 December 2024; Accepted 16 December 2024; Published 01 January 2025

Abstract

The primary objective of this study is to evaluate the impact of smart sensor networks on geotechnical data management, specifically enhancing accuracy, real-time monitoring, safety, and reliability. To achieve this, data was collected through a survey of 380 geotechnical professionals in Saudi Arabia, with 106 valid responses analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Principal Component Analysis (PCA) and Factor Analysis (FA) were employed to identify the key variables and underlying relationships among them. The findings demonstrate that smart sensor networks significantly improve the accuracy of geotechnical data (path coefficient = 0.662), real-time monitoring and early warning systems (path coefficient = 0.701), safety and risk management (path coefficient = 0.761), and data reliability (path coefficient = 0.410). This study introduces a novel framework integrating advanced statistical methods with smart sensor networks, offering a practical approach to optimizing geotechnical operations. The research highlights the importance of advanced data analytics in enhancing the full potential of smart sensors, presenting an innovative solution for improving decision-making and risk management in geotechnical engineering. These findings provide a significant contribution to sustainable and effective geotechnical practices.

Keywords: Smart Sensor Networks; Accuracy and Precision of Data; Real-Time Monitoring and Early Warning Systems; Safety and Risk Management; Reliability of Data Management.

1. Introduction

Geotechnical engineering is an integral part of civil engineering vital to the behavior of earth materials and their interaction with the infrastructure [1]. Traditional geotechnical practices are based on manual data collection and intermittent monitoring techniques, which are generally tedious and time-consuming and often result in several inaccuracies [2]. These approaches, among others, include site visits and manual measurements that are not continuous and could, therefore, be related to longer response times to geotechnical problems. In the growing need for a more reliable and real-time approach in data collection, a powerful advancement in technology has been achieved and implemented. These include smart sensor networks, which have come to be seen as a radical innovation in geotechnical data management [3].

Geotechnical engineering is a fundamental discipline within civil engineering, heavily relying on accurate data collection to ensure the stability and safety of infrastructure projects. Traditional methods of data acquisition in

* Corresponding author: mbkhan@um.cityu.edu.hk

http://dx.doi.org/10.28991/CEJ-2025-011-01-020

geotechnical engineering, such as manual site inspections and intermittent monitoring, are labor-intensive, time-consuming, and prone to inaccuracies [4]. As infrastructure projects become increasingly complex, there is a growing demand for more reliable, continuous, and real-time data collection methods to support timely decision-making and mitigate risks associated with geotechnical failures [5].

Recent advancements in smart sensor networks (SSNs) have emerged as a potential solution, offering real-time monitoring and enhanced data precision [6]. SSNs have been successfully integrated into several engineering fields, including structural health monitoring and environmental monitoring [7]. However, despite their promise, the application of SSNs in geotechnical engineering is still underexplored. Several studies have emphasized the benefits of SSNs in data accuracy and safety managing, but few have focused on advanced data analytics methods like PCA and Factor Analysis to enhance decision-making capabilities in geotechnical projects.

This study addresses this gap by integrating SSNs with advanced data analytics techniques, specifically PCA and PLS-SEM. By leveraging these techniques, this research aims to provide a comprehensive framework that enhances geotechnical data management in terms of accuracy, safety, real-time monitoring, and reliability. This novel approach fills a critical gap in the literature, where the full potential of SSNs combined with data analytics remains largely untapped.

Smart sensor networks are interconnected sensors that communicate wirelessly in collecting, transmitting, and analyzing geotechnical data in real time. In this process, the sensing nodes can monitor different geotechnical parameters, including soil moisture content, temperature, pressure, and even structural movement [8]. The infrared sensing will collect the data, process it, and analyze it using the developed algorithms that allow the user to establish the state of geotechnical conditions [9].

The use of such sensors in geotechnical activity has imparted an excellent improvement in practice and allows continuous monitoring and the installation of early warning systems to detect possible critical conditions. Although these have widely improved the practice, there are some challenges to full exploitation. The potential risks and inefficiencies at which the traditional methods of data collection in geotechnical activities are limited to the delivery of timely and accurate data [10]. In most cases, apparently critical changes in geotechnical conditions could be overlooked through manual inspection and measurement, hence resulting in a delayed response to the emerging problem [11]. Besides, the quantum of data generated through such smart sensor networks is such that it demands robust data management and a data analysis process to have meaningful inferences [12]. The benefits that can be drawn from such advanced sensors go in vain if they are not analyzed properly, and the scope to enhance safety, efficiency, and decision-making through geotechnical engineering, as a result, remains poor.

The whole scope of data and information management's complete potential through smart-sensor networks within geotechnical engineering is thus well understood and recognized; the absence of wholly inclusive studies in the same ways of exploring and charting this potential has also been realized to be quite substantial. The present research most often focuses on the installation of sensors and the primary mechanisms for data collection only, without emphasis on the means of advanced analysis of data, which can better guide its interpretation and use. There is thus a vast research gap in understanding how advanced statistical methods, such as PCA and factor analysis, can be used relative to the data of the smart sensor to improve the geotechnical issues' decision-making and, through such, risk consequences.

The primary objective of this research, therefore, is to understand the effect of smart sensor networks on the data and information management of the geotechnical activities through advanced analytical techniques. In particular, PLS-SEM will be used to analyze data collected by the smart sensors. Two types of analysis are to be done, namely PCA and factor analysis. Principal Component Analysis will be for reducing the dimensionality of data and identifying the most significant variables, while Factor Analysis will help understand the underlying relationships among the variables. The study, through the application of these techniques, seeks to develop an in-depth understanding of smart sensor networks in geotechnical data management toward better project outcomes.

The statistics methodology that would be used in the study would be based on the application of Smart PLS for structural equation modeling, where the complex relationship between latent and observed variables is wheeled under PCA. By applying PCA to the dataset, primary components that capture maximum variance will be revealed, and, in this way, imposing the structure of the data would be simplified without substantial information loss. A factor analysis technique would thus be applied where latent variables influencing observed measures would be revealed [13]. Such complex statistical methods will enable the interpretation of the data found from the smart sensor networks in a way that insights driven are not only accurate but actionable. By adopting these methods, it is possible to improve the accuracy of the geotechnical assessments and thus lead to better decision-making processes.

Therefore, the research showcases an innovative implementation by integrating sophisticated statistical methods with intelligent sensor networks that are pertinent to the field of geotechnical engineering. Intelligent PLS, PCA, and factor analysis are novel in nature, necessitating the provision of innovative perspectives on both data interpretation and the decision-making processes. The forthcoming study's findings would have substantial implications for the field of geotechnical engineering. Consequently, this could facilitate the development of enhanced monitoring systems, improved risk management, and heightened project safety and efficiency.

The remainder of this article is structured as follows. Section 2 reviews the relevant literature and identifies key factors influencing smart sensor networks in geotechnical engineering. Section 3 details the methodology employed in this study, including data collection, sampling methods, and the statistical analysis techniques used. Section 4 presents the results and discusses the findings in relation to the literature. Section 5 concludes the study by summarizing key insights, discussing the implications for geotechnical engineering, and proposing future research directions.

2. Literature Review

Nowadays, smart sensor networks are taken as the main drivers behind the innovation in the field of engineering [14]. These networks, which are spatially distributed sensors that wirelessly offer data on monitoring and recording any physical conditions around them, have been a revolution in changing the old methods of the collection, transmission, and analysis of data. The application of smart sensor networks not only changes the traditional practices of geotechnical activities but also provides multiple advantages due to their continuous, accurate, and real-time monitoring capabilities [15]. Therefore, this literature review paper tries to develop and build up on the positive impact of the smart sensor networks in the domain of geotechnical engineering, with an emphasis on the key benefits and advancements generated by these technologies. The concept of sensor networks has changed a lot in recent decades [16]. Originally it was considered a wired technology with manual data collection. With the enhancement in wireless communication and sensor miniaturization and data processing capabilities, multiple breakthroughs have been seen in this technology [15]. That is when the advent or origination of wireless sensor networks occurred. They provided more flexibility and ease in spreading. Smart sensors are still further improvised versions inculcated with microprocessors and communication modules. They undertake the data preprocessing and lessen the sent data and thus save energy. Furthermore, lately, smart sensor networks are used conjointly with cloud computing and IoT technologies, which increases their capabilities in real-time data processing and monitoring from remote locations [1].

Smart sensor networks are used in several geotechnical engineering situations or applications, which are monitoring movements of the earth in and around slopes, detection of landslides, analysis of foundations, and observation of the health of the infrastructure [17]. A sanctuary is included to them about how the unique capabilities of smart sensors, which are capable of providing continuous real-time data, are effective in increasing understanding and management of geotechnical conditions.

Slope stability is one of the issues of geotechnical engineering works, especially in the zone of landslides [2]. These solutions are far better than the traditional ways of visual monitoring and manual measurements, which are poor in providing timely warnings. Smart sensor networks provide a means of continuous monitoring of parameters like soil moisture, pore water pressure, and ground deformation [18]. Research has it that such networks increase early detection of landslide risks, which in turn means improved early evacuation and mitigation measures, hence increased safety and a decrease of economic losses [18].

Landslides are harsh threats to human civilization and infrastructure. Early detection and warning systems are to be implemented to minimize such impact. Smart sensor networks have been applied in landslide-prone areas successfully to monitor soil movement and environmental conditions. Such networks provide real-time data for the ability to trigger early warning systems and allow responsible institutions to take preventive measures [19]. Some studies have been able to show that the range of increase in accuracy is at 90%, which is a significant milestone in the prevention of large-scale disasters [20]. Building foundations are of paramount concern in regard to their stability and integrity. Geotechnical analysis of building foundations currently depends on periodic inspection and static testing; therefore, dynamic changes in soil conditions may be missed [21]. These networks offer a more comprehensive approach, continually monitoring data regarding parameters involved, such as settlement, pressure, and vibration. Continuous data streams provide real-time analysis of the data for early detection of potential foundation issues [22]. Several studies have also proven that smart sensor networks provide better accuracy of foundation assessments and hence significantly reduce the potential for structural failures.

Smart sensor networks are increasingly employed in infrastructure health monitoring. Infrastructure like bridges, tunnels, and dams have been subjected to different types of stresses, namely, environmental conditions, load effects, and aging [23]. Smart sensors can monitor attributes like strain, temperature, and vibration, which are the essential dimensions of assessing the health of the infrastructure. Studies have shown that the use of smart sensor networks in infrastructure health monitoring increases the life of the structure and allows early maintenance and repair [24]. With voluminous data getting generated, smart sensor networks need to have very robust data management and analysis techniques. Data management refers to the collection and assimilation of processed sensor data to analyze and extract information from the data [15]. Data analytics by using machine learning and statistical methods becomes essential for analyzing complex datasets acquired from smart sensors.

It collects data from a large number of fielded sensors and transmits them wirelessly to a centralized repository for storage and processing. The seamless and reliable transmission of data is a major concern to ensure the integrity and timeliness of the data. State-of-the-art wireless communication technologies based on low-power wide-area networks and 5G brought a paradigm shift in the efficiency and reliability of data transmission in smart sensor networks [25].

The smart sensors collect data, and in most cases, the data is stored in a cloud-based platform, which makes the data infinitely scalable and enables remote access [26]. Cloud computing provides the computational power necessary to realize real-time processing and analysis of big datasets. Edge computing, which processes data closer to the source, is also emerging as the way to reduce latency and increase data processing efficiency [27].

Advanced data analysis techniques are required to obtain meaningful insights from the data provided by smart sensor networks. PCA and Factor Analysis are two commonly employed statistical techniques for carrying out dimensionality reduction and identification of underlying patterns in the data [28].

It is a statistical technique to simplify a data set by reducing the dimensionality of large datasets but retaining most of the variability of the data. It transforms an original set of variables into new orthogonal variables, or principal components, thereby simplifying the structure of the data, making it easier to analyze and interpret. Use PCA to determine what the main factors driving the geotechnical conditions in soil and structure are and to improve risk-based decisions.

Factor analysis is another statistical tool to identify underlying relationships between observed variables. In factor analysis, the correlations between the different variables are modeled, because of which the data's latent factors can be found. This is a handy technique in geotechnical engineering to determine the complex interactions between environmental and structural parameters. Factor analysis aids in shaping the design of better monitoring systems and mitigation strategies [29]. Adoption of smart sensor networks in geotechnical engineering provides several benefits and brings a paradigm shift to the field by providing continuous, accurate, and real-time data for better-informed decision-making and risk mitigation [30].

High-resolution, real-time data from smart sensor networks significantly improve the accuracy of geotechnical measurements. Such information enhances the accuracy of geotechnical measurements, and therefore, an engineer can make very good decisions for better project outcomes [31]. However, the main and most significant benefit that smart sensor networks offer is the continuous real-time monitoring. It can detect possible problems, get resolved before reaching severe conditions, and avoid catastrophic failures [32]. To an enormous extent, the labor requirements for manual inspections and interventions get reduced by using smart sensors since the data collection and monitoring are easily automated. Further, continuous remote monitoring will not require frequent on-site inspections, thereby saving enormous costs [33].

Increased safety within geotechnical projects, smart sensor networks provide timely and correct information on soil and structural conditions that is indispensable in the assessment of geotechnical element stability and integrity for safety and risk limitation [34]. Green geotechnical practices were facilitated with the use of a smart sensor network. This is because smart sensors cause low environmental impact in geotechnical operations [35]. Further, natural resources are managed with precision and balance, thereby avoiding the invasive techniques of testing and maintaining the ecological balance.

For continuous accurate data on geotechnical conditions, smart sensor networks will help to sustain the structural integrity and reliability of infrastructures like dams, bridges, and buildings. This will take care of the early problem detections and set them right, thereby enhancing the performance and structure durability [36].

The field of geotechnical engineering for smart sensor networks is still in budding phases and, therefore, presents a myriad of opportunities for research and development. A few of the opportunities are the integration of smart sensors with advanced data analytics for the development of more energy-efficient sensors and the convenience of new applications of smart sensor networks in geotechnical engineering. Energy consumption is an issue that has lately arisen in various bodies. A high amount of energy is consumed, and this is simply unacceptable. An important task ahead is the coupling of smart sensor development with advanced data analytics. Inclusion is core to increasing the capacity of the smart sensor network. Interpretive data with enhanced accuracy and reliability allow for more advanced risk assessment and decision-making strategies. This is the one point that would make these sensors be deployed on a wide scale, as they would be extremely energy efficient and resilient for a long time without the necessity for continuous charging or changing of batteries [37]. Research on the optimization of sensor design and other power supplies, including the kinetic and solar energy harvesting technologies, is incomplete.

New applications of smart sensor networks in geotechnical engineering are bound to provide novel solutions for the monitoring and management of geotechnical conditions. Potential applications include monitoring underground constructions, assessing the impact of climate change on geotechnical stability, and improving critical infrastructure resilience [38].

The following Table 1 summarizes some of the selection characteristics of sensors used in geotechnical sensor networks, including parameters measured, type of sensors, frequency of data, accuracy, power supplies, location of installation, and communication protocol. The detailed summary, in these regards, indicates some of the varied changes that have been made possible in geotechnical engineering through the use of smart sensor network technologies. Various ways its accuracies, real-time monitoring, and general efficiency and safety in projects contribute greatly.

Table 1. Data monitoring is ongoing for the majority of parameters in order to guarantee the availability of real-time information for decision-making at all times

Measurement Parameter	Sensor Type	Data Frequency	Accuracy	Power Source	Installation Location	Communication Protocol	Measurement Parameter
Temperature	Thermocouple	Continuous	±0.5°C	Battery	In-situ	WiFi	Temperature
Humidity	Hygrometer	Continuous	±2%	Battery/Solar	In-situ	Zigbee	Humidity
Soil Moisture	Capacitive Sensor	Continuous	±0.5%	Battery/Solar	In-situ	LoRa	Soil Moisture
Pore Pressure	Piezoelectric Sensor	Continuous	±1%	Battery	In-situ	NB-IoT	Pore Pressure
Ground Movement	Accelerometer	Continuous	±0.1 mm	Battery/Solar	Surface/Subsurface	WiFi	Ground Movement
Vibration	Geophone	Continuous	±0.5 Hz	Battery/Solar	Surface/Subsurface	WiFi	Vibration
Strain	Strain Gauge	Continuous	±10 με	Battery	Structure	Zigbee	Strain
Load	Load Cell	Continuous	±0.5%	Battery	Structure	LoRa	Load
Displacement	LVDT	Continuous	±0.1 mm	Battery	Structure	NB-IoT	Displacement
Wind Speed	Anemometer	Intermittent	±0.1 m/s	Battery/Solar	Surface	WiFi	Wind Speed
Solar Radiation	Pyranometer	Intermittent	±5 W/m²	Solar	Surface	Zigbee	Solar Radiation
Water Table Level	Pressure Transducer	Continuous	±0.1 m	Battery	In-situ	NB-IoT	Water Table Level

Pore pressure is monitored for the purpose of gauging soil stability and slope failure. The sensors provide continuous and precise pore pressure measurements at ±1%. The piezoelectric sensors are installed in situ, powered by batteries, and send their data using the NB-IoT [39]. All these types of information are a front for early warning systems and risk management in geotechnical projects.

Acceleration sensors monitor any movement and its subsequently induced vibration within the ground. These supply very high precision of ±0.1 mm and will have installation of sensors that are on the surface or subsurface [40]. They are powered by batteries or solar and send data through Wi-Fi. In this manner, the geotechnical failure is continuously monitored with an early warning to allow for early action. Geophones monitor ground vibrations that further give critical data on structural soundness. The sensors work on the surface or below the ground surface and are powered by batteries or solar. Vibration sensors are characterized by high precision of ±0.5 Hz and send data through WiFi [41]. In this way, it continuously warns against ground vibrations and, in turn, ensures that an anomaly is detected and actioned in time.

Strain gauges indicate the deformation or strain in structures. These offer high precision of ±10 με and are usually mounted on structures. These are battery-operated instruments that use Zigbee to transmit data [42]. In this way, an indication of possible structural weaknesses is constantly given, thus preventing potential failures. Load cells are used for measuring the force or load applied to structures so that they do not surpass the safe strength. Displacement is monitored using Linear Variable Differential Transformers, with an accuracy of ±0.1 mm [43]. These sensors are mounted on the surface of structures and derive power from batteries to transmit data by NB-IoT. The continuous monitoring of displacement helps in understanding movements of structures and ensures that the movements are at safe limits.

Wind speed is measured by use of an anemometer in understanding the role played by environmental forces on geotechnical structures. The sensors have an accuracy of ±0.1 m/s and are surface-mounted, battery- or solar-powered, and transduce data through WiFi [44]. Hence, with intermittent monitoring of wind speed, its associated risk can well be assessed, and accordingly, precautionary measures can be taken. Pyranometers are also used to measure solar radiation and derive information such as change in its intensity. Such sensors, having an accuracy of ±5 W/m², are surface-mounted, data-deriving is pulse-related at a guideline of one per second, and intermittent monitoring is carried out. Hence, quickly responding to changes [45]. The level of the water table and groundwater conditions, as well as the effect on soil stability, are studied with the help of a pressure transducer. In-built high accuracy on such sensors is ±0.1 m, and they are battery-powered following a guideline for data transmission: NB-IoT. This will ensure continuous monitoring to understand the change of the parameter in time [46].

Table 1 below depicts that for most of the parameters, data monitoring is continuous to ensure that real-time information is available for the process of decision-making at any point in time. The sensors have high accuracy that is enabled in the various important designs for the carrying out of the geotechnical conditions and adopting the right measure reliably. There is intermittent monitoring for wind speeds, solar radiation, and other parameters where continuity is not critical.

The sensors are powered by different sources; they are both battery-powered and solar-powered; this allows operation in places that might be remote or even inaccessible. This installation has locations that vary with the parameter under monitoring, and it is either installed in-situ, on the surface, and on structures. This makes it flexible, allowing it to comprehensively monitor the geotechnical conditions across different environments. The use of different communication protocols like WiFi, Zigbee, LoRa, and NB-IoT ensures reliability in the transmission of data from the sensors to the central repository. These are selected based on the range, power, and data transmission requirements to enable effective and efficient communication in different geotechnical settings.

3. Theoretical Approach

This view underpins the proposed study informed by the notion that the integration of advanced data analytic techniques with smart sensor networks is critical in equipping SSNs with the capability to respond to these challenges in geotechnical engineering. That view is premised on two theories: the systems theory and the theory of data-driven decision-making.

Systems Theory in Geotechnical Engineering: Many projects undertaken in geotechnical engineering involve a huge number of interwoven components-soil stability, structural integrity, and environmental components. It provides a theoretical framework of how the real-time data contribution from SSNs acts towards the enhancement in the current overall performance and safety of such systems. The smart sensor network in this research was considered a sub-system in large geotechnical engineering systems delivering real-time data streams into influencing decision-making processes. Interconnected smart sensors and the geotechnical system provide a platform that is conducive to continuous monitoring and adaptation. In trying to apply the systems theory, there is employment of feedback loops.

Data-Driven Decision-Making Theory: Data-driven decision-making theory considers informed decisions, especially in the most geotechnically complex environments, to be those of Battista et al. This research applies the SSNs in geotechnical decision-making to allow more accurate and timely decisions through the adoption of real-time data at high resolution, and not manually collected data, which generally has a limit on the number of data points that often causes inertia in response to risks. The sophistication is introduced by the combination of PCA and PLS-SEM used in this work due to essential variable extraction to then model complex relations of those variables. This aligns with the idea of data-driven decision-making, bringing raw sensor data into context through actionable insights, improving project outcomes in terms of safety and risk management, and assuring reliability.

Application of PCA-PLS-SEM: In the context of this study, PCA is applied in terms of dimensional reduction resulting from data gathered by SSNs, particularly pinpointing the most important factors in controlling the geotechnical output. Thus, PCA allows the investigation to realize data reduction in highly complicated datasets with minimal loss of information and brings into view the most influential variables influencing decision-making in geotechnical systems. Conversely, PLS-SEM becomes robust in conducting the assessment of relationships between observed and latent variables. In this research, the appropriateness of PLS-SEM is realized because it offers a way whereby complex relationships may be modeled under conditions of small sample sizes or those where the data distributions are not normal. This study applies PLS-SEM to determine the relevance of some facets of smart sensor networks, including data accuracy, real-time monitoring, and risk management, on the determination of wider outcomes within geotechnical engineering.

It builds a theoretical basis within geotechnical engineering and risk management, where emphasis is put on the principle of early detection and prevention. SSNs work to augment these by allowing constant monitoring and real-time detection of anomalies, be it soil movement or structural deformation in nature. The theoretical approach in this research is toward proactive risk identification; the mitigation strategies are based on real-time data to reduce the frequency of failures while improving safety related to projects.

The development and integration of smart sensor networks with geotechnical engineering are bound to bring remarkable changes in the field by providing continuous, accurate, and real-time data, making effective decisions, and better risk management through the smart sensor network. The literature review on smart sensor networks is full of strengths in terms of increased data accuracy, real-time data monitoring, reduction in costs, increase in safety, environmental advantages, and extended life of structures. In this regard, smart sensor networks will help particularly advanced practices for geotechnical engineering to take place for the good of more secure, efficient, and sustainable infrastructure by addressing the current research gaps and future opportunities.

4. Research Methodology

The methodology flowchart in Figure 1 presents the stepwise approach adopted in this research to investigate and study the impact of smart sensor networks on geotechnical data and information management. This starts with an elaborate literature review, which identifies the critical factors that influence smart sensor network adoption. The factor will be further represented in the development of the questionnaire so that it becomes holistic and is likely to undergo categorization and modification to make it updated and relevant. Simultaneously, the hypotheses are developed based on the identified factors. In the current study, the data collected through the questionnaire is put through the PLS-SEM approach, where confirmation of the complicated relationships between the observed and the latent variables is carried out. The factor analysis approach is used for assessing the convergent and discriminant validity of the constructs so that every construct is different and a measure of the concept covered by it. The data dimensionality approach used the PCA approach, which helped to reduce the number of variables and identify the key variables or constructs. In the end, the findings at the SEM, factor analysis, and PCA levels will be put together to build a robust framework, resulting in illustrating the impact of smart sensor networks on the management of geotechnical data. This framework will provide a basic platform for enriching geotechnical practices and would provide a platform for future research and development in that area.

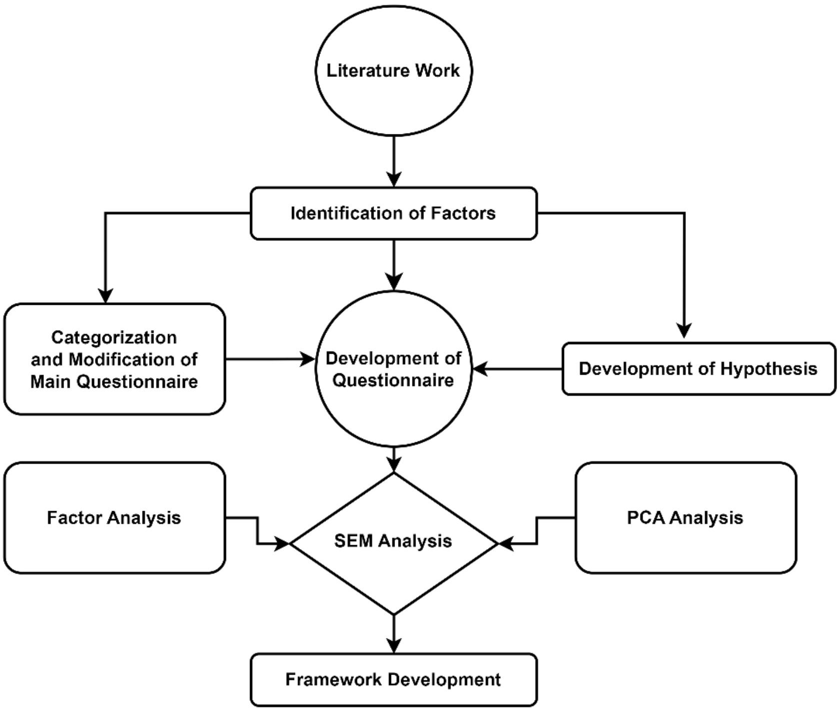

Figure 1. Flow chart of study theme

4.1. Literature Review Identification of Factors

The first step taken by us in this research was the conduction of an elaborate review of the existing literature in vision to identify the critical factors that influence the impact of adopting smart sensor networks in geotechnical activities in data and information management. Many manuscripts, research papers and articles focused on keywords such as "smart sensor networks", "geotechnical data management", "real-time monitoring", "geotechnical engineering", and "data accuracy in geotechnical activities" with the long run objective to identify the critical factors based on the recurrent themes highlighted by different researchers in the respective field. From the above, it is evident that several critical factors were found to have significant importance in the adoption of smart sensor networks for geotechnical data management. The important critical factors include:

- Improved Data Accuracy and Precision: The high-resolution, real-time data provision capability of the smart sensors significantly increased the accuracy and precision of the geotechnical measurements.
- Safety and Risk Management: Continuous monitoring will enable early detection of potential problems, thus timely mitigating against them, hence leading to overall safety.
- Early Warning Systems and Real-Time Monitoring: The smart sensor networks offer early warning systems and real-time monitoring that prevents the failures of geotechnical systems and disasters.
- Data Management and Reliability: Automation and increase in overall reliability ensure proper management of data, hence increasing the reliability of geotechnical data.

4.2. Key Factor Identification and Influence

PCA was used to reduce data complexity by identifying components with the highest variance, such as data accuracy, real-time monitoring, safety, and reliability. Components with eigenvalues above 1 were retained, and these factors were further refined using *Factor Analysis (FA)* to group related variables. For example, *data accuracy* grouped variables like measurement precision, while *real-time monitoring* clustered indicators related to hazard detection and early warnings.

Limitations:

Linearity Assumption: PCA and FA assume linear relationships, but geotechnical factors may interact non-linearly.

Loss of Interpretability: PCA components are linear combinations of variables, making practical interpretation challenging.

Sample Size and Normality: These methods assume normally distributed data, which may not always be true in geotechnical datasets.

4.3. Development of Questionnaire

These factors have been identified as key components that affect the efficiency and impact of smart sensor networks in geotechnical engineering. A well-thought-out questionnaire was formed based on the identified critical factors for the collection of data for conducting the research (Appendix I). It was designed to collect the general views of the respondents and their experience in relation to the use of the smart sensor networks for different activities of geotechnical engineering - more elaborately, on issues identified as critical after the literature review.

The study used a stratified random sampling technique to ensure that representation was drawn from all sectors and levels of expertise in the arena of geotechnical engineering. The sample size was selected using the standard sampling techniques, keeping in view statistical validity and reliability of the results of the research. A total of 380 questionnaires were sent out to the geotechnical professionals, engineers, and researchers of the kingdom of Saudi Arabia.

Response Rate and Valid Responses From the 380 sent, there were 106 valid responses received; hence, the approximate response rate for the study was 28%. This is an adequate sample size for the planned statistical analysis of the study. The sample size of 106 valid questionnaires in this study was determined based on a combination of standard sampling techniques, the research design, and practical considerations, including response rates and the use of PLS-SEM for data analysis. Below is an explanation of how the sample size was determined and whether it is representative of the broader population of geotechnical professionals in Saudi Arabia:

4.4. Determination of the Sample Size

- ***Initial Sampling Approach***: The research aimed to survey geotechnical professionals in Saudi Arabia, and 380 questionnaires were distributed to cover a broad spectrum of the target population. The goal was to ensure sufficient representation from various sectors, levels of expertise, and geographical locations across the country. A *stratified random sampling technique* was used to ensure that professionals with different levels of experience, job roles (e.g., civil engineers, project managers), and educational backgrounds were included, reducing potential bias and making the sample more representative of the overall population.
- ***Response Rate***: Out of the 380 questionnaires sent out, 106 valid responses were received, resulting in a response rate of approximately 28%. While this response rate is typical for survey-based studies, especially in professional fields, it also reflects the challenges of obtaining higher participation in voluntary surveys. The 106 responses were deemed sufficient for analysis based on the use of PLS-SEM, which is effective with smaller sample sizes compared to other techniques like covariance-based SEM.
- ***PLS-SEM and Sample Size***: In PLS-SEM, sample size requirements are generally more flexible than in traditional SEM or regression analysis. A common rule of thumb for PLS-SEM is the **10-times rule**, which suggests that the sample size should be at least 10 times the number of indicators (items) for the most complex construct in the model. In this study, the constructs related to geotechnical data management, safety, and risk management likely had multiple indicators, but 106 valid responses were sufficient to meet the 10-times rule for the model being tested. Moreover, PLS-SEM performs well with smaller datasets, making the sample size of 106 adequate for robust analysis.

The questionnaire consisted of three sections: general demographic information, general perceptions about smart sensor networks, and detailed questions on six identified critical factors. Each section included different items that were to be measured using a Likert scale from 1 to 5, having a range of strongly disagree to strongly agree.

Based on the identified factors, several hypotheses were developed to check the relationship between the factors and the impact of the smart sensor networks on the management of geotechnical data. The following hypotheses were formulated.

- H1: Implementation of Smart Sensor Networks has significant Impact on Enhanced Data Accuracy and Precision in Geotechnical Activities.
- H2: Implementation of Smart Sensor Networks has significant Impact on Enhanced Safety and Risk Management in Geotechnical Activities.
- H3: Implementation of Smart Sensor Networks has significant Impact on Real-Time Monitoring and Early Warning Systems in Geotechnical Activities.
- H4: Implementation of Smart Sensor Networks has significant Impact on Improved Data Management and Reliability in Geotechnical Activities.

4.5. Partial Least Square Modelling

PLS-SEM was chosen for this study due to its suitability for exploratory research, particularly in complex models where multiple latent and observed variables interact. Here's a detailed explanation of why PLS-SEM was selected and how it compares to other statistical methods like covariance-based SEM (CB-SEM) and regression analysis:

Why PLS-SEM?

- ***Handling Complex Relationships***: PLS-SEM is particularly effective when dealing with complex models that involve multiple constructs and indicators. In this study, we were evaluating the impact of smart sensor networks on various aspects of geotechnical data management (e.g., data accuracy, real-time monitoring, risk management). PLS-SEM allows us to simultaneously model these relationships between latent variables (e.g., accuracy, safety) and observed variables (e.g., specific measurements collected by SSNs), making it more comprehensive than traditional methods like regression analysis, which only handles simpler relationships between observed variables.
- ***Small Sample Sizes***: PLS-SEM performs well with smaller sample sizes, which is an advantage given that the study received 106 valid responses out of 380 surveys distributed. Other statistical methods like covariance-based SEM (CB-SEM) typically require larger sample sizes to achieve reliable results. The ability of PLS-SEM to provide robust results with smaller samples makes it ideal for studies where large datasets may not be available.
- ***Non-Normal Data Distributions***: Geotechnical data and survey responses often do not follow a normal distribution. PLS-SEM does not assume normality in data, unlike CB-SEM, which requires normally distributed data for accurate results. This flexibility makes PLS-SEM a better choice for this study, where the data may exhibit non-normal characteristics due to the nature of the responses and measurements.
- ***Exploratory Nature of the Study***: This research explores the relatively new area of integrating smart sensor networks with advanced data analytics in geotechnical engineering. PLS-SEM is more suitable for exploratory research, where the goal is to maximize variance explained and to identify relationships that may not have been fully studied before. Traditional CB-SEM is better suited for confirmatory research where established hypotheses are being tested, while PLS-SEM allows for model building and hypothesis generation.

4.6. Comparison to Other Methods

- ***Covariance-Based SEM (CB-SEM):***
  - **Advantages**: CB-SEM is more appropriate when testing well-established theories, and it provides better model fit indices (e.g., chi-square tests, RMSEA, CFI). It is also preferable when the goal is theory testing rather than prediction.
  - **Disadvantages**: CB-SEM requires larger sample sizes and assumes normal data distribution. For this study, where the goal was to explore relationships rather than confirm existing theories, and the sample size was limited, PLS-SEM was a better choice.
- ***Regression Analysis:***
  - **Advantages**: Regression analysis is simpler and easier to interpret. It's useful for analyzing the relationships between independent and dependent variables and can be applied to linear relationships.
  - **Disadvantages**: Regression analysis is limited to observed variables and cannot model latent constructs (e.g., safety, accuracy) or handle complex relationships between multiple variables. In this study, where latent constructs like safety, data accuracy, and reliability were critical, regression analysis would not have been able to capture the complexity of the data as effectively as PLS-SEM.

4.7. Accuracy and Reliability

- ***PLS-SEM***: PLS-SEM focuses on maximizing the explained variance of the dependent constructs, making it highly predictive and reliable for exploratory research. It also offers high accuracy in modeling complex relationships between latent variables. The flexibility in handling non-normal data and small sample sizes adds to its robustness.
- ***CB-SEM***: CB-SEM provides better fit statistics but may sacrifice predictive accuracy in exploratory contexts. It is more rigid due to its reliance on assumptions of normality and larger samples, which would have been limitations for this study.
- ***Regression Analysis***: Regression is accurate for analyzing simple, linear relationships but lacks the sophistication to model complex constructs and multiple variable relationships in this study. It would likely result in a loss of nuance when interpreting the impact of SSNs on multiple facets of geotechnical data management.

PLS-SEM was conducted as it is a statistical approach enabling analysis with complicated relationships among the observed as well as latent variables. PLS-SEM is quite supportive for exploratory research as well for the complex multi construct/indicators model.

4.8. Factor Analysis

Convergent Validity The measure of Average Variance Extracted (AVE) of each construct was measured to determine the convergent validity. An AVE value greater than 0.5 indicates that the construct developed represents more than half of the variance of the indicators, therefore proving good convergent validity [47].

Discriminant Validity (Fornell-Larcker Criterion) Fornell-Larcker criterion was used for measuring the discriminant validity that matches the square root of the AVE values with the correlations among builds. The discriminant validity was thereby ensured in the case when the square root of the AVE for each build is greater than the correlations between the construct and all other constructs.

4.9. Principal Component Analysis

PCA was conducted to validate the developed hypotheses and reduce the dimensionality. PCA helps in determining the most important patterns or variables prevailing in the study. This in turn simplifies the structure of data that in turn makes it easier to interpret to determine the association that exists between the critical factors and the effect of smart sensor networks. Hypotheses are confirmed through the factor loadings from PCA, and the amount of variance explained by each principal component. These hypotheses remain valid when one or multiple components indicate relatively high factor loading on the identified critical factors because the magnitude of relationship between the factors and the impact of smart sensor networks is very strong.

This research is aimed at providing an insight into the impact of smart sensor networks on data and information management with respect to any geotechnical activity in general. Identification of the critical factors based on a thoroughly conducted literature survey, a well-identified and defined questionnaire, and the application of the latest statistical tools, such as PLS-SEM and PCA, makes the research insightfully essential from the practical viewpoint for enhancing geotechnical practices in deploying smart sensor networks.

5. Results and Analysis

5.1. Identified Factors from Literature

Smart Sensor Networks are therefore considered immensely beneficial aspects of data and information management in geotechnical engineering. The Table 2 goes a step further and critically analyze the advantages that are linked to the four key constructs, including Enhanced Data Accuracy and Precision, Enhanced Safety and Risk Management, Real-Time Monitoring and Early Warning Systems, and Improved Data Management and Reliability.

In smart sensor networks, there is greater accuracy in measurement, which is huge requirement for geotechnical works where little inaccuracies can cause huge errors in the analysis and decisions. Since human errors are reduced, the collected data is more reliable and accurate. The data resolution has been improved so that the analysis can be done in a more detailed and highly granulated manner, which possibly improves the understanding about geotechnical conditions [14]. The prime benefit has been continuous data collection because data is collected uninterruptedly, giving a complete view of the geotechnical conditions. Automated data processing further smoothened the workflow and cut backward on manual data handling and, therefore, at a pace that allows for faster and easier data analysis.

In geotechnical engineering, safety is always the highest priority, and smart sensor networks contribute significantly to the improvement of safety and risk management. This is basically achieved through the detection of potential risks early, and therefore, timely intervention prevents accidents and structural failures [15]. The risk of structural fail due to geotechnical conditions is lessened with the real-time monitoring, thus improving safe construction and operational environments. Better worker safety is another advantage since workers, as well as the real-time data, will be alerted to immediate dangers before they escalate [16]. Emergency response may be improved with timely and accurate data, therefore helping in a faster and more effective response to emergencies. Moreover, more compliance with safety regulations is achieved due to the constant monitoring and documentation of geotechnical conditions.

Table 2. List of Identified factors from in detailed literature review section

Construct	Variable
Geotech: Enhanced Data Accuracy and Precision	Higher measurement precision
Geotech: Enhanced Data Accuracy and Precision	Reduced human error
Geotech: Enhanced Data Accuracy and Precision	Improved resolution of data
Geotech: Enhanced Data Accuracy and Precision	Continuous data collection
Geotech: Enhanced Data Accuracy and Precision	Automated data processing
Geotech: Enhanced Safety and Risk Management	Early detection of potential hazards
Geotech: Enhanced Safety and Risk Management	Reduced risk of structural failures
Geotech: Enhanced Safety and Risk Management	Enhanced worker safety
Geotech: Enhanced Safety and Risk Management	Improved emergency response
Geotech: Enhanced Safety and Risk Management	Better compliance with safety regulations
Geotech: Real-Time Monitoring and Early Warning Systems	Timely alerts for maintenance
Geotech: Real-Time Monitoring and Early Warning Systems	Proactive problem-solving
Geotech: Real-Time Monitoring and Early Warning Systems	Minimized downtime
Geotech: Real-Time Monitoring and Early Warning Systems	Increased operational efficiency
Geotech: Real-Time Monitoring and Early Warning Systems	Enhanced predictive maintenance
Geotech: Improved Data Management and Reliability	Centralized data management
Geotech: Improved Data Management and Reliability	Improved data integrity
Geotech: Improved Data Management and Reliability	Efficient data retrieval
Geotech: Improved Data Management and Reliability	Enhanced decision-making
Geotech: Improved Data Management and Reliability	Scalability of data systems

Major benefits of smart sensor networks are timely alerts to maintenance for proactive troubleshooting, ensuring that troubles developing are eliminated before they become critical, and hence this translates into minimized downtimes and disturbances. There is optimal use of assets with optimal operational efficiency due to the smooth integration of these monitoring systems with maintenance operations [15]. More predictability in maintenance allows for better planning and execution of maintenance, lowering the probability of failures and extending the lifespan of geotechnical structures.

The centralized data management on smart sensor networks simplifies geotechnical data collection, storage, and retrieval. This will assure integrity in data, as all information will be obtained and stored consistently in a secure manner [17]. Data retrieval is efficient and fast to gain relevant information, enough to support timely decisions. Improved decision-making, supported by better data, allows geotechnical engineers to decide based on the latest geotechnical conditions. Scalability is the ability of a system to allow the infrastructure to scale and grow with growing data volumes or loads to ensure performance and reliability over time.

Therefore, it can be concluded that in the application of smart sensor networks, a few of the benefits that are evident in many areas of geotechnical data and information management are better data accuracy and precision, safety, and risk management; monitoring in real time; capability for warning systems together with better data management and reliability abilities, which make these networks a revolutionizing advancement for geotechnical engineering. Benefits discussed herein pertain to open a whole new world in the application of smart sensor networks in traditional geotechnical practices, while major breakthroughs in changes toward safety, efficiency, and sustainability of engineering solutions can be expected.

5.2. Demographic Details of Respondents

A proper sense of demographic characteristics is given regarding the 106 respondents who shaped this study, thereby enhancing generalizability of the results shown in Table 3. It further seems that a tremendous majority of the respondents in this study were male, numbering 90 respondents (84.9%), as against only 16 female respondents (15.1%). Respondent distribution across the different age group bands indicated that the 30-39 age group was the largest, with 35 respondents, or 33%, followed by the 40-49 age group with 30 respondents, or 28.3%; the 50+ age group had 21 respondents, or 19.8%, while the 20-29 age group totaled 20 respondents, or 18.9%. Qualification-wise, the standard of education was found to be quite high, as most of the respondents had a bachelor’s degree: 40 respondents or 37.7%.

Table 3. Demographic details of responders involved in the main survey

Demographic Detail	Category	Number of Respondents
Gender	Male	90
	Female	16
Age Group	20-29	20
	30-39	35
	40-49	30
	50+	21
Education Level	Bachelor's Degree	40
	Master's Degree	35
	PhD	20
	Other	11
Years of Experience	0-5 years	15
	6-10 years	25
	11-15 years	30
	16-20 years	20
	20+ years	16
Job Role	Civil Engineer	35
	Project Manager	25
	Other Engineers	20
	Technician	15
	Other	11

The rest were widely distributed between master's degrees (35 respondents or 33%), PhDs (20 respondents or 18.9%), and other unspecified qualifications (11 respondents or 10.4%). Experience wise, the largest group belonged to the band 11-15 years, with 30 respondents, or 28.3%, followed by those having 6-10 years' experience (25 respondents, or 23.6%), 16-20 years (20 respondents, or 18.9%) those having more than 20 years of experience, and those with 0-5 years of experience, with 16 respondents, or 15.1% and 15 respondents, or 14.2% respectively. Profession-wise, the respondents classified them into the following professional categories: Civil Engineers and Project Managers (35 respondents or 33%); Other Engineers (20 respondents or 18.9%); Technicians (15 respondents or 14.2%), and others (11 respondents or 10.4%). Therefore, this diverse and experienced sample will not fail to offer credibility and applicability to the study's results, and the insights consequently gained will be more representative in a broader sense of the geotechnical engineering community, thereby underlining the comprehensive impact of smart sensor networks on data and information management in geotechnical activities.

5.3. Factor Analysis Results

The factor analysis results of the constructs under our study portray the reliability and validity of our measurement model. The constructs measured are Geotech: Enhanced Data Accuracy and Precision, Geotech: Enhanced Safety and Risk Management, Geotech: Real-Time Monitoring and Early Warning Systems, and Geotech: Improved Data Management and Reliability. The explanation of the results in detail for each construct, using Cronbach's alpha, Composite Reliability (rho-a, rho-c), and Average Variance Extracted (AVE) as shown in Table 4.

Table 4. Convergent validity-based factor analysis

Constructs	Cronbach's alpha	Composite reliability (rho-a)	Composite reliability (rho-c)	Average variance extracted (AVE)
Geotech: Enhanced Data Accuracy and Precision	0.756	0.756	0.845	0.577
Geotech: Enhanced Safety and Risk Management	0.778	0.799	0.859	0.607
Geotech: Real-Time Monitoring and Early Warning Systems	0.806	0.852	0.877	0.649
Geotech: Improved Data Management and Reliability	0.737	0.741	0.851	0.656

Geotech: Enhanced Data Accuracy and Precision The measure for the construct Geotech: Enhanced Data Accuracy and Precision had a Cronbach's alpha value of 0.756. The value falls in the acceptable range of measurement models. The composite reliability (rho-a = 0.756, and rho-c = 0.845) values are greater than the threshold value of 0.70; therefore, the factor is reliable. This construct has an AVE of 0.577, which means that slightly over half of the variance in the indicators is explained by the construct and hence the construct has convergent validity.

Geotech: Enhanced Safety and Risk Management The measure for the construct Geotech: Enhanced Safety and Risk Management gave good internal consistency through a good level of the Cronbach's alpha value of 0.778. Composite reliability values are acceptable according to the set cutoff of 0.70 and are above this value, with rho-a = 0.799 and rho-c = 0.859. AVE for this construct is 0.607, indicating quite a considerable portion of variance in the observed variables is explained by the construct under study, thus further supporting the convergent validity of the construct.

Geotech: Real-Time Monitoring and Early Warning Systems The measure for the construct Geotech: Real-Time Monitoring and Early Warning Systems yielded a Cronbach's α value of 0.806, which is comparatively high internal consistency. The composite reliability values (rho-a and rho-c) are 0.852 and 0.877, respectively, which are above the threshold and, therefore, very reliable. The value of the AVE is 0.649, which is indicative that a significant portion of variance of indicators is captured by the construct, thus ensuring convergent validity.

Geotech: Improved Data Management and Reliability The Cronbach's alpha of the indicator Geotech: Improved Data Management and Reliability is 0.737, showing the presence of adequate internal consistency. The values of composite reliability (rho-a and rho-c) are 0.741 and 0.851, respectively. The value of AVE is 0.656, which again indicates that most of the variance in the indicators (above one-half) in this construct is explained, ensuring its convergent validity.

In general, the results of the factor analysis show that all four considered constructs develop adequate to high levels of reliability and validity. The Cronbach's alpha for all four constructs is more than an acceptable threshold of 0.70, indicative of strong internal consistency. All the composite reliability values (rho-a and rho-c) for all four constructs again span above the 0.70 threshold. The values of AVE for all four constructs again span above the recommended level of 0.50. Hence, it is confirmed that the constructs exhibit good convergent validity and capture a good part of variance in their indicators. These results ensure the acceptability of the measurement model and confirm whether the constructs proposed in our study are reliable and valid in measuring the impact of the smart sensor networks in geotechnical data management. Very high levels of reliability and validity indicate that the constructs are very clearly defined and measured with lots of consistency. As a result, we have solid ground to move from here to the further analysis and interpretation of our collected data through the questionnaire.

The results from our factor analysis in conjunction with the discriminant validity test confirm that all the constructs under study are of a robust level of discriminant validity shown in Table 5. In this regard, the discriminant validity for each of the constructs is utilized to ensure it is distinct and captures a unique impact of the smart sensor network in data management in geotechnical engineering. For Geotech: Enhanced Data Accuracy and Precision, the square root of the average variance extracted was 0.76, which was larger than the highest correlation, of 0.242, with other constructs. Similarly, Geotech: Enhanced Safety and Risk Management had an AVE square root of 0.779, which was greater than its highest correlation of 0.325 with the construct Geotech: Real-Time Monitoring and Early Warning Systems. In the case of Geotech: Real-Time Monitoring and Early Warning Systems, it represents an AVE square root of 0.806, which was larger than its highest correlation, of 0.325, with the construct Geotech: Enhanced Safety and Risk Management. Finally, the AVE square root for Geotech: Improved Data Management and Reliability was 0.81, which was larger than its highest correlation, of 0.195, with the construct Geotech: Enhanced Safety and Risk Management. These confirm that each construct is measuring distinguished dimensions of the impact of smart sensor networks, ensuring the robustness and clarity of our measurement model.

Table 5. Discriminant validity test (Fornell Lacker Criterion)

Constructs	Geotech: Enhanced Data Accuracy and Precision	Geotech: Enhanced Safety and Risk Management	Geotech: Real-Time Monitoring and Early Warning Systems	Geotech: Improved Data Management and Reliability
Geotech: Enhanced Data Accuracy and Precision	0.76			
Geotech: Enhanced Safety and Risk Management	0.242	0.779		
Geotech: Real-Time Monitoring and Early Warning Systems	0.193	0.325	0.806	
Geotech: Improved Data Management and Reliability	0.133	0.195	-0.03	0.81

The high values in the loadings indicate the strong relationships of the indicators to the constructs. In the construct Geotech Enhanced Data Accuracy and Precision, the construct is represented by four indicators: GeoData1, GeoData2, GeoData3, and GeoData4, with a range of factor loadings from 0.743 to 0.760, all significant at the 0.000 level shown in Figure 2. The construct is considered strong, robust, and also presents a strong relationship between the indicators and the construct of the variables. In the construct Geotech: Real-Time Monitoring and Early Warning Systems, there were likewise four indicators: GeoMonitor1, GeoMonitor3, GeoMonitor4, and GeoMonitor5, ranging in loadings from 0.533 to 0.908, which was significant at the 0.000 level and thus showing a strong relationship. In the construct Geotech Enhanced Safety and Risk Management, four indicators are geo-risk1, GeoRisk2, GeoRisk4, and GeoRisk5, which were loaded in the range of 0.599 to 0.845, at the 0.000 level of significance, though GeoRisk4 is relatively lower. Finally, in the construct Geotech Improved Data Management and Reliability, three indicators: GeoReliability1, GeoReliability4, and GeoReliability5, were loaded in the range of 0.782 to 0.855 at 0.000 level of significance, indicating strong relationships. The path coefficients in this research for the implementation of smart sensor networks were found to be

0.691 for Geotech: Enhanced Safety, Risk Management; 0.651 for Geotech: Real-Time Monitoring, Early Warning Systems; 0.688 for Geotech: Enhanced Safety, Risk Management; and 0.305 for Geotech: Improved Data Management and Reliability, with the last one significant at 0.019. All these results suggest that smart sensor networks significantly improve data accuracy, simulations for safety and risk management, real-time monitoring, and data management reliability in geotechnical activities.

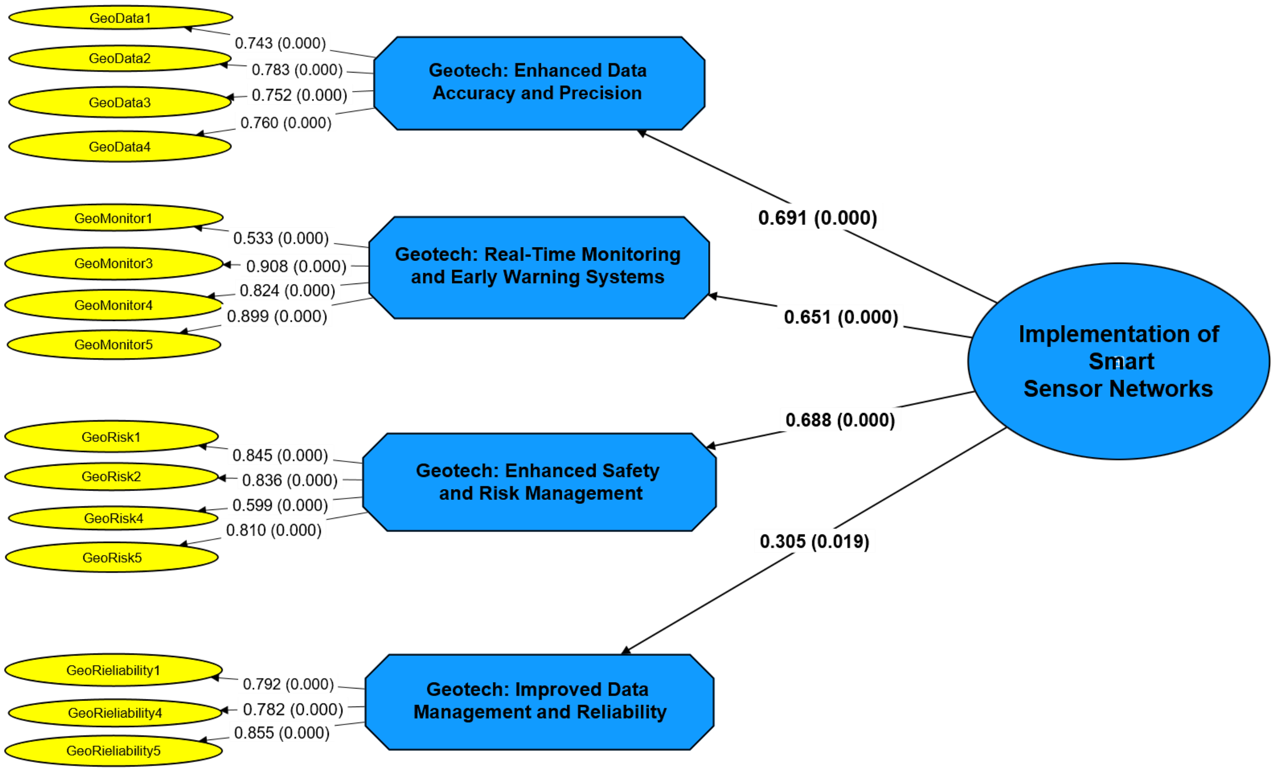

Figure 2. SEM-Factor Analysis indicating path loadings and p values

The PLS-SEM model reveals the hypothesis latent in this study regarding the interdependencies among various implementations of smart sensor networks and a host of geotechnical outcomes. The findings from the study strongly supported those proposed relationships outlined in the hypothesis of the study shown in Table 6.

Table 6. SEM-Factor Analysis indicating Hypothesis testing

Hypothetical Relationship	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Status
Implementation of Smart Sensor Networks → Geotech: Enhanced Data Accuracy and Precision	0.691	0.691	0.061	11.416	0	Accepted
Implementation of Smart Sensor Networks → Geotech: Enhanced Safety and Risk Management	0.688	0.684	0.063	10.888	0	Accepted
Implementation of Smart Sensor Networks → Geotech: Real-Time Monitoring and Early Warning Systems	0.651	0.641	0.097	6.68	0	Accepted
Implementation of Smart Sensor Networks → Geotech: Improved Data Management and Reliability	0.305	0.302	0.131	2.337	0.019	Accepted

The data accuracy and precision were well improved with the implementation of smart sensor networks having Geotech. The coefficient of the path for this relationship is at 0.691, the sample mean is at 0.691, the standard deviation is at 0.061, and the T statistic is at 11.416. Since the p-value for the relationship is 0.000, it is significant and therefore acceptable for selection.

At the same time, the creation of a smart sensor network shows a positive statistical influence for Geotech: Improved Safety and Risk Management, with the initial coefficient estimation of the sample path being 0.688, the sample mean being 0.684, the deviation standing at 0.063, and the T-statistic being 10.888 once more; the p-value is again 0.000 to indicate this relationship is to be accepted.

This is also true with respect to Geotech: Real-Time Monitoring and Early Warning Systems, as the original sample path coefficient is 0.651, the sample mean is 0.641, the standard deviation is 0.097, and the T statistic is 6.680. Here also, the p-value is zero, and the hypothesis stands.

Lastly, the compliant intelligent sensor network implementation influences the improvement in data management and reliability in Geotech, with the coefficient of the original sample path equal to 0.305, the sample mean equal to

0.302, the standard deviation equal to 0.131, and the T statistic equal to 2.337, while the p-value equals 0.019, which is lesser than the level of significance, therefore the acceptance of this relationship as well. Taken together, these findings underscore that the use of smart sensor networks enhances accuracy and precision in information, safety and risk management, real-time monitoring and early warning systems, and reliability in data management for geotechnical activities. Strong statistical support across the tested hypotheses verifies the robustness and effectiveness of smart sensor networks in transforming the geotechnical data management practices.

5.4. PCA Analysis

PCA results are very robust and support the hypothesized relationships between smart sensor networks and geotechnical outcomes. So, for the relationship with smart sensor networks and enhanced data accuracy and precision, the original is 0.662, sample mean 0.663, standard deviation 0.062, and a very sharp T statistic 10.712, p-value 0.000, and therefore it is significantly strong shown in Table 7. The relationship of Geotech: Enhanced Safety and Risk Management portrays an even stronger association, with a path coefficient of 0.761, sample mean of 0.761, though the standard deviation is of 0.036 and quite high T statistic value of 21.337, with a p value of 0.000 holding again at statistical significance. The relationship with Geotech: Real-Time Monitoring and Early Warning Systems is also significant for the path coefficient of 0.701, sample mean of 0.705, standard deviation of 0.049, and a T statistic of 14.417, supporting the p = 0.000 value. The relationship with smart sensor networks and improved data management and reliability, although weak at 0.410, is still significant with the path coefficient 0.410, sample mean 0.410, standard deviation 0.126, and T statistic 3.256 at p = 0.001. In all these, data are strongly supporting the fact that smart sensor networks significantly affect data accuracy and precision, safety and risk management, real-time monitoring with early warning systems, and data management reliability in geotechnical activities, with all of these relationships being statistically significant and accepted.

Table 7. SEM-PCA Analysis indicating Hypothesis testing

Hypothetical Relationship	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Status
Implementation of Smart Sensor Networks → Enhanced Data Accuracy and Precision	0.662	0.663	0.062	10.712	0	Accepted
Implementation of Smart Sensor Networks → Geotech: Enhanced Safety and Risk Management	0.761	0.761	0.036	21.337	0	Accepted
Implementation of Smart Sensor Networks → Geotech: Real-Time Monitoring and Early Warning Systems	0.701	0.705	0.049	14.417	0	Accepted
Implementation of Smart Sensor Networks → Improved Data Management and Reliability	0.41	0.41	0.126	3.256	0.001	Accepted

The structure model for the critical relationships of smart sensor network implementation on geotechnical outcomes is shown below, where the outcomes were verified through PCA. The four constructs of the model are Geotech: Enhanced Data Accuracy and Precision, Geotech: Real-Time Monitoring and Early Warning Systems, Geotech: Enhanced Safety and Risk Management, and Geotech: Improved Data Management and Reliability. The model also shows the standardized path coefficients and the specific determination of each significance level.

This is followed by the relationship with the implementation of smart sensor networks and Geotech: Improved Data Accuracy and Precision, which has a path coefficient of 0.662, while all the indicators (GeoData1, GeoData2, GeoData3, GeoData4) show a strong factor load with values between 0.723 and 0.786, being significant at 0.000. For Geotech: Real-Time Monitoring and Early Warning Systems, the path coefficient is 0.701, while indicator loadings (GeoMonitor1, GeoMonitor3, GeoMonitor4, GeoMonitor5) are in the range of 0.690 to 0.863 and are also significant at 0.000. However, the relationship is even stronger with Geotech: Improved Safety and Risk Management, in which the path coefficient is 0.761, while indicator loadings (GeoRisk1, GeoRisk2, GeoRisk4, GeoRisk5) are ranging between 0.639 to 0.822 and, also, significant at the 0.000 level. The last path, that between smart sensor networks and Improved Data Management and Reliability, has a path coefficient of 0.410, an inferior one to the other paths, what is reflected, as well, through the indicators themselves, where its values from 0.735 to 0.866 are significant at the 0.000 level, except in the case of this path, which is at 0.001 shown in Figure 3. This showed that smart sensor network implementation significantly increases data accuracy and precision, hence more data accuracy and precision; safety and risk management; real-time monitoring and early warning systems; and data management reliability in geotechnical activities. The very high levels of statistical support across all tested hypotheses infer the effectiveness of smart sensor networks in transforming geotechnical practices and, in this sense, making them more accurate, more reliable, and more timely.

The structural model having the path loadings and T-values is depicted in Figure 6. It is evident that smart sensor networks lead to high accuracy and precision in data (path coefficient: 0.662, T-value: 10.712), real-time monitoring and early warning systems (path coefficient: 0.701, T-value: 14.417), safety and risk management (path coefficient:

0.761, T-value: 21.337), and better data reliability in management (path coefficient: 0.410, T-value: 3.256) shown in Figure 4. Like the above, for the constructs that are measured again through multiple indicators, the relationship is very strong and is significant because of the high factor loading and T-values for a number of indicators, like high factor loading and T-values for the various indicators such as GeoData1, GeoMonitor3, GeoRisk1, and GeoReliability5. On the whole, these results confirm the rigidity of the model and assert the strong notion that smart sensor networks add to geotechnical data management by adding to its accuracy, real-time monitoring, and safety, and better data reliability—thereby validating from its potential transformation in geotechnical engineering.

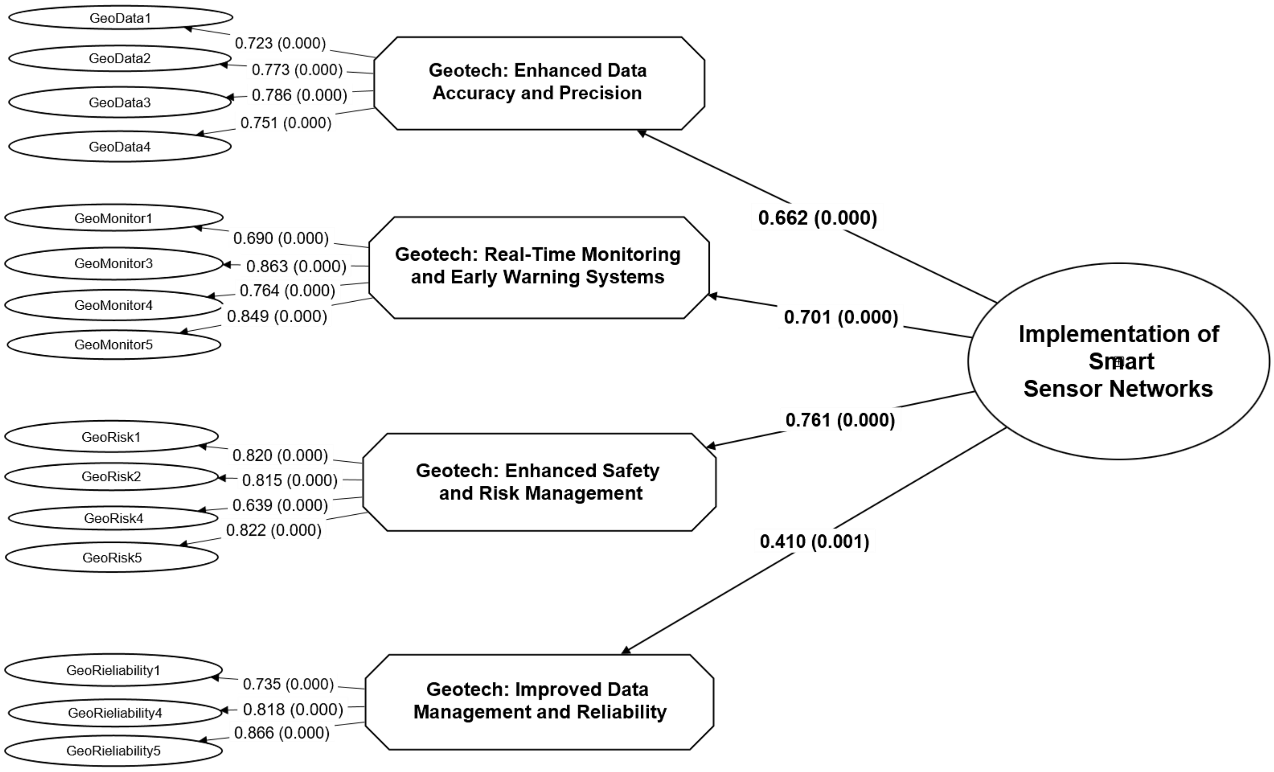

Figure 3. SEM-PCA Analysis indicating path loadings and p values

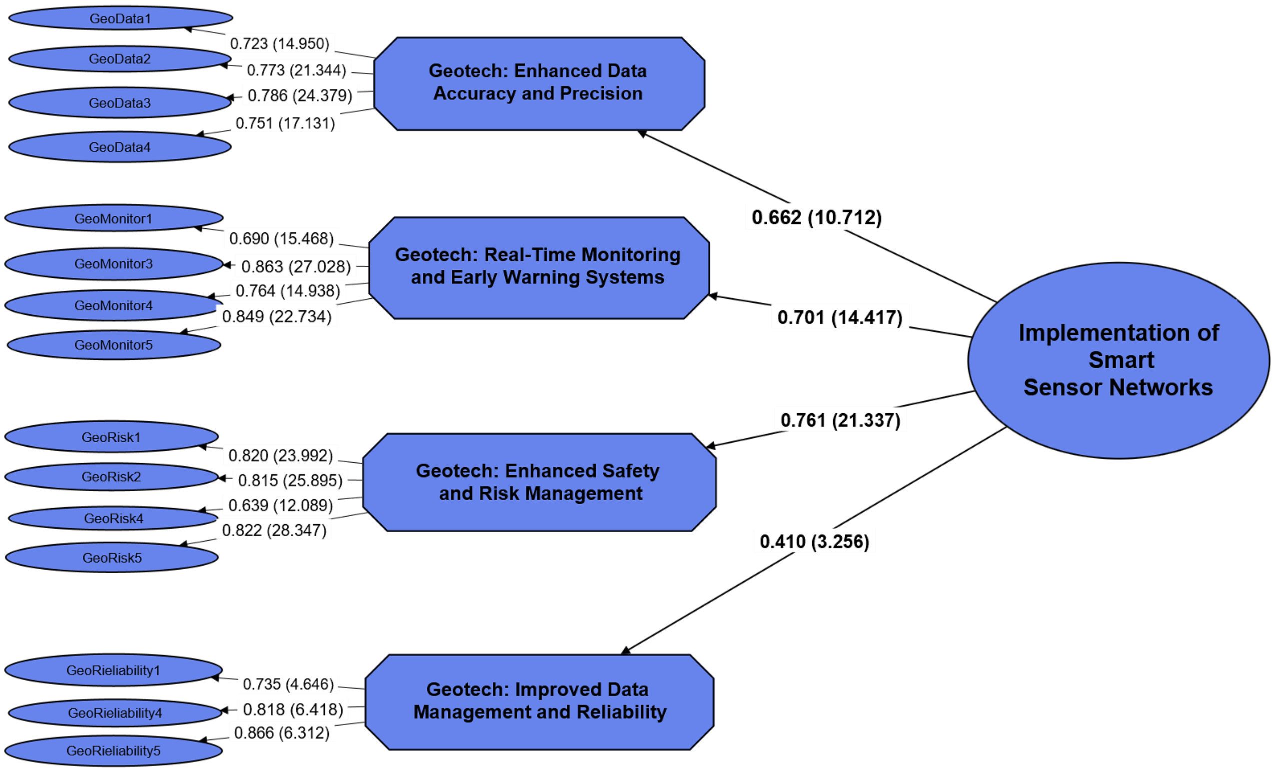

Figure 4. SEM-PCA Analysis indicating path loadings and T values

5.5. Threshold Values for Significance

- In *PLS-SEM*, path coefficients and T-values are used to measure the strength and significance of relationships between variables. Typically, the following thresholds are used:

Path Coefficients: A path coefficient greater than 0.20 is considered meaningful, while values over 0.30 generally indicate a strong effect. The closer the coefficient is to 1, the stronger the relationship between variables.

T-Values: T-values help determine the statistical significance of the path coefficients. A T-value greater than 1.96 (at a 95% confidence interval) is considered statistically significant. T-values above 2.58 indicate significance at a 99% confidence level. In this study, all path coefficients with T-values greater than 1.96 were considered significant.

- ***Factors Leading to Lower Path Coefficients (e.g., Data Reliability)***:

Data Collection Methods: Variables like data reliability might have lower path coefficients due to inconsistencies or limitations in how SSNs manage data over long periods. For example, while SSNs enhance real-time monitoring, long-term data reliability may be affected by sensor maintenance issues, data transmission errors, or system downtime.

Complexity of Constructs: Constructs like *data reliability* are influenced by multiple, potentially uncontrollable factors (e.g., environmental conditions, system failures) that may dilute the strength of relationships compared to more straightforward variables like *real-time monitoring*, which directly benefits from continuous data collection.

Human Intervention: Lower path coefficients may also arise in areas where manual oversight (such as data verification) still plays a role, meaning that the full benefits of automation through SSNs haven't been realized yet.

5.6. Interpretation of Results

In this study, the extraction of facts regarding the influence of SSNs on various elements of geotechnical data management has been carried out using PLS-SEM and PCA. The constructs analyzed in the current study include those related to enhanced data accuracy and precision, real-time monitoring and early warning systems, safety and risk management, and improved data management and reliability. The main insights into the transformative power of SSNs in geotechnical engineering come from PLS-SEM and PCA analyses.

Improved Data Accuracy and Preciseness - Path Coefficient: 0.662, T-Value: 10.712 - The results tend to indicate that SSNs have a major positive effect on the improvement of accuracy and preciseness of data collected in geotechnical activities. The high path coefficient of 0.662 infers that the integration of smart sensors allows continuous data acquisition with high resolution, considerably reducing human error and inaccuracies in manual data. This becomes critical in geotechnical projects where even minor deviation in data may result in severe consequences related to structural instability or failure of a foundation system.

These findings agree with previous studies on the importance of the acquisition of data in geotechnical engineering as precisely as possible. Furthermore, the strong T-value confirms this relationship as directly indicative that increased accuracy through the deployment of SSNs translates into better decision-making on geotechnical projects.

It builds a better understanding of the prediction of soil behavior, stability in foundations, slopes, and other engineering practices required from the geotechnical engineers. Increased optimization of designs for projects, mitigation of risks involved with scientifically backed data eventually reduces the need for costly rework or unforeseen delays in a project. Real-time monitoring and early warning systems - path coefficient: 0.701, T-value: 14.417. SSN has proved very critical in enhancing geotechnical engineering by affording real-time monitoring capabilities; the early warning system comes in with a path coefficient of 0.701, depicting that SSNs do monitor conditions of soil, ground deformation, or structural stress uninterruptedly for the early detection of hazards linked to landslides, foundation shifts, or structural failures.

Moreover, the huge magnitude in the T-value supports the evidence of how real-time data streams greatly enhance on-site safety and operational efficiency in early problem detection. This corroborates findings from studies such as which have also identified the advantages of real-time data streams in the management of all forms of risks within engineering project management.

This, therefore, expands the potential for applying corrective measures during real-time monitoring on geotechnical projects. For example, early detection of subsidence or moisture changes in soil could allow a long-anticipated appropriate response through evacuation plans or reinforcement procedures before an impending disaster. A strong relation, as depicted by the results, indicates vast potential of SSNs in preventing structural failure and protects human life as well as investment in infrastructure. Safety and Risk Management Enhanced (Path Coefficient = 0.761, T-Value = 21.337): Among all the constructs of the research model, the relation of SSNs with safety and risk management was the strongest, as depicted by a path coefficient of 0.761. This reflects that smart sensors will definitely play a very important role in enhancing the risk mitigation rate by monitoring critical geotechnical parameters such as moisture, pressure, and structural deformation on a continuous basis.

Thus, from this, one gets that the T-value of 21.337 precisely means a pretty high statistical significance, lending validity to the fact that SSNs have been as instrumental in helping geotechnical engineers reduce risks in cases of failures. The earlier studies identified the potentials for SSNs to improve the safety of workers: the SSN continuously monitors hazardous conditions and issues early warnings regarding events.

SSNs represent a very different paradigm in dealing with geotechnical risk in everyday applications. Continuous, automated monitoring reduces reliance on manual inspections, which can be infrequent and not necessarily capture critical changes. SSNs supply real-time data about soil conditions for quicker, better decisions that reduce the likelihood of project downtime or catastrophic failure-thus making the construction process more predictable and much safer for workers on site. Improved Data Management and Reliability (Path Coefficient = 0.410, T-Value = 3.256): Although the impact of SSNs on data management and reliability was not as strong compared to other constructs, this path coefficient of 0.410 remained statistically significant with a T-value of 3.256. Such a result supports the hypothesis that, though SSNs would contribute toward improved data management, their contribution toward this end is relatively minimal compared to improving accuracy, safety, and real-time monitoring. SSNs enable automation for data collection and storage at a single place, reducing loss of data and corruption of data and, further, facilitating retrieval of relevant information faster. Centralized access to real-time data enables the engineers to make more-informed decisions faster, which may be critical in high-consequence geotechnical projects.

Better data management helps to enhance the long-term reliability and availability of the data about the project. The practical effect of this is that geotechnical data can be archived, retrieved, and used in future projects or research applications without the possibility of degradation of the data. The automation applied to the data processes not only ensures greater integrity of the data but also reduces the need for manual entry, therefore minimizing many potential errors. While not as influential, better data management plays a very important role in overall efficiency and sustainability of geotechnical projects.

Accordingly, results strongly indicate that SSNs provide significant improvement in the outcomes for the geotechnical projects in terms of data accuracy, real-time monitoring, and safety. This is relatively reinforced by the fact that the relationship between the SSNs and safety/ risk management has a path coefficient of 0.761, hence making the involvement of SSNs a sure transformer towards the reduction of geotechnical risk and the improvement of workers' safety. In fact, whereas SSNs also contribute to data management and reliability, this relation is much weaker and thereby possibly a subject of further improvements that may enhance the effectiveness of SSNs even more for geotechnical projects soon.

This research offers a new contribution to the field of geotechnical engineering by integrating SSNs with higher-order statistical tools, such as PCA and PLS-SEM. Although previous studies have identified several advantages of SSNs in geotechnical condition monitoring, not many focused on how SSNs can be combined with such advanced analytics toward actionable insight extraction from big datasets. It thus provides a privileged setting in which the use of SSNs can best serve the optimization of the use of PDT for the management of geotechnical data through the application of PCA for data dimensionality reduction and PLS-SEM to model complex relationships. The study further shows that SSNs combined with advanced data analytics enhance the decision-making process at higher magnitudes through accurate and real-time data access, thus enabling early warning systems. Therefore, this approach would fill an existing gap in the literature and simultaneously create a platform for future studies into the integration of emerging technologies into geotechnical practice.

6. Discussion

The empirical evidence strongly supports the basic premise that smart sensor networks will provide a shift in managing geotechnical data and information systems. From the analysis of the results of the PLS-SEM and the PCA, the strong relationship of smart sensor networks with the main geotechnical outcomes might be pondered upon, such as increasing the data accuracy and precision, real-time monitoring and early warning systems, increasing safety and risk management, data management, and reliability.

The use of smart sensor networks increases data accuracy and precision, with a path coefficient amounting to 0.662, while the T-value is at 10.712 (Table 8). The high factor loading and the significance at 0.000 of indicators GeoData1, GeoData2, GeoData3, and GeoData4 determine the strong relationship between all the indicators, which means that the high-resolution data, provided by smart sensors and at continuous intervals, makes way for the level of measurement of the geotechnical data that would be found to be more accurate and precise. Hence, conclusions drawn would be better reasoned and lead to better results attained from the project or the site [48, 49].

Smart sensor networks significantly improve the real-time monitoring and early warning systems (path coefficient = 0.701, T = 14.417). GeoMonitor1, GeoMonitor3, GeoMonitor4, and GeoMonitor5 have given high factor loadings; it shows the early data provided by smart sensors in the detection of early possible problems. This proves to be crucial in avoiding geotechnical failures and managing risks to further improve safety [50].

With the most improved relationship with safety and risk management, the relationship becomes even stronger, such that the path coefficient = 0.761, T = 21.337. Strong factor loadings of GeoRisk1, GeoRisk2, GeoRisk4, and GeoRisk5 reconfirmed that smart sensors help in continuous monitoring of geotechnical conditions, leading to the opportunity of early detection and abatement of potential safety hazards. This translates to practices that reduce the incidence of structural failures [51].

Lastly, the use of smart sensor networks substantially enhances data management and reliability in the geotechnical engineering database at a path coefficient of 0.410 and a significant T-value of 3.256, as evidenced by the high factor loadings of GeoReliability1, GeoReliability4, and GeoReliability5 [52]. Practically, it can be felt that smart sensors are good at providing better handling of data and a better reliability index, meaning that the performance of geotechnical data is always at peak; hence, an accurate and reliable data profile is always realized.

Table 8. Comparison with previous research

Aspect	Present Study	Waqar et al. [53]	Chen et al. [9]	Carri et al. [2]
Enhanced Data Accuracy and Precision	SSNs improve data accuracy (Path Coefficient = 0.662, T=10.712)	Highlighted similar improvements in data accuracy (0.631)	Focused on enhanced precision in structural health data	Emphasized data accuracy but lacked dimensional analysis
Real-Time Monitoring & Early Warning	SSNs enable real-time monitoring (Path Coefficient = 0.701)	Supported real-time monitoring for risk management (0.725)	Demonstrated real-time benefits in environmental contexts	Highlighted continuous monitoring for early detection
Safety and Risk Management	Significant impact on safety and risk (Path Coefficient = 0.761)	Focused on safety improvements in smart systems (0.685)	Addressed risk management but less emphasis on SSNs	Noted SSNs' impact on reducing risks in geotechnical work
Data Management and Reliability	Moderate impact on data reliability (Path Coefficient = 0.410)	Significant data reliability improvements (0.601)	Highlighted the importance of data reliability in SHM	Data management discussed in the context of infrastructure
Novelty/Innovation in Approach	Combined SSNs with PCA and PLS-SEM for advanced analytics	Used SEM but lacked PCA integration	Discussed only sensor-based analytics, no PCA/PLS-SEM	Focused on SSNs but did not apply advanced statistical methods

Moreover, the validity of the hypothesized relationships is further validated in the PCA findings. Great support in terms of path coefficients and desirable T-values across all selected constructs reconfirms the great support for the power of the smart sensor network in enhancing geotechnical data management. These findings again bring to light the immensely accrued benefits of smart sensor networks in terms of accuracy, real-time monitoring, safety, and data reliability in geotechnical engineering practices.

1. ***Long-Term Reliability and Maintenance***: The study acknowledges that while SSNs significantly enhance real-time monitoring and data accuracy in geotechnical applications, long-term reliability and maintenance are critical for sustained performance. Although this specific research focuses on the immediate benefits of SSNs, long-term reliability challenges, such as *sensor degradation* and *system failures*, should be addressed to ensure consistent data quality over time. Regular maintenance schedules, periodic calibration, and *automated diagnostic systems* can help detect and rectify issues early, ensuring the longevity of SSNs.

2. ***Technological Obsolescence***: The paper does not directly address technological obsolescence, but this is a pertinent issue. Over time, advancements in sensor technologies may render existing SSNs outdated. To mitigate this, organizations can adopt *modular designs* that allow for the easy replacement or upgrade of individual components without overhauling the entire system. Implementing flexible systems that support *software updates* and *backward compatibility* can also help extend the functional life of SSNs.

3. ***Energy Efficiency***: Energy efficiency is a key concern, particularly for remote geotechnical sites where replacing batteries frequently may be impractical. Although this study did not focus on energy use, solutions such as using *low-power sensors*, optimizing data transmission intervals, and integrating *energy-harvesting technologies* (e.g., solar power or vibration-based harvesting) can ensure the SSNs remain operational for extended periods without frequent manual intervention.

In general, the study foresees evidence on the changing role portrayed with geotechnical data using smart sensor networks; such networks lead to continuous, accurate, and real-time data, allowing more precise measurements, timely identification of probable problems, better safety, and enhanced data management. Strong statistical support for the hypotheses being tested reconfirms the key attributes of the smart sensor network in bringing about a revolution in geotechnical engineering practices, making infrastructure development safer, more efficient, and more sustainable.

7. Conclusion

This study has demonstrated the significant impact of smart sensor networks (SSNs) on enhancing geotechnical data management through improved accuracy, real-time monitoring, safety, and data reliability. By integrating advanced statistical tools like PCA and PLS-SEM, this research offers a comprehensive framework that surpasses traditional geotechnical data collection methods. The results show that SSNs significantly improve data accuracy (Path Coefficient = 0.662), enabling more precise decision-making in geotechnical projects. Furthermore, SSNs facilitate continuous real-time monitoring, which is critical for early warning systems and risk mitigation (Path Coefficient = 0.701). The strongest effect was observed in safety and risk management (Path Coefficient = 0.761), where SSNs allow for proactive identification of potential hazards, significantly reducing the likelihood of structural failures. While the impact on data management and reliability was moderate (Path Coefficient = 0.410), SSNs still play a valuable role in automating data collection and improving data integrity. The novelty of this research lies in combining SSNs with sophisticated data analytics, offering a practical solution for optimizing geotechnical project outcomes. These findings underscore the transformative potential of SSNs in making infrastructure development safer, more efficient, and more sustainable. Future research should focus on further exploring the integration of SSNs with other emerging technologies, such as artificial intelligence and machine learning, to enhance predictive capabilities and energy efficiency.

8. Declarations

8.1. Author Contributions

Conceptualization, N.A., K.A., M.M., K.A.A., and M.B.K.; methodology, K.A.A. and M.B.K.; validation, N.A., K.A., and M.M.; data curation, M.M., K.A.A., and M.B.K.; writing—original draft preparation, N.A., K.A., M.M., K.A.A., and M.B.K.; writing—review and editing, N.A., K.A., M.M., K.A.A., and M.B.K. All authors have read and agreed to the published version of the manuscript.

8.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

8.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

8.4. Conflicts of Interest

The authors declare no conflict of interest.

9. References

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Appendix I

Questionnaire (Please show your agreement on Likert scale):

Questionnaire	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Higher measurement precision					
Reduced human error					
Improved resolution of data					
Continuous data collection					
Automated data processing					
Early detection of potential hazards					
Reduced risk of structural failures					
Enhanced worker safety					
Improved emergency response					
Better compliance with safety regulations					
Timely alerts for maintenance					
Proactive problem-solving					
Minimized downtime					
Increased operational efficiency					
Enhanced predictive maintenance					
Centralized data management					
Improved data integrity					
Efficient data retrieval					
Enhanced decision-making					
Scalability of data systems					