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Artificial intelligence-driven safety assessment of scaffolding using LiDAR sensing

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The construction industry is embracing transformation through the integration of digitization, artificial intelligence (AI), and immersive technologies. On a construction site, continuous assessment is vital for ensuring both the reliability of assets and safety of workers. Scaffolding is a key structural support asset that requires regular inspections for detection and identification of alterations from the design rules that could compromise integrity and stability. At present, such inspections to identify deviations are primarily visual and conducted by the site managers or accredited personnel. However, visual inspection is time-intensive and susceptible to human errors, which can lead to unsafe conditions. This study explores the use of AI and digital technologies to automate and enhance scaffolding inspections process to contribute toward safety improvement. A cloud-based AI platform is developed to process and analyze 3D point-cloud data of scaffolding structures to detect modifications through comparisons as well as evaluate the certified reference scan with a recent scan. The proposed workflow incorporates prognostics and health management concepts with continuous monitoring to identify structural modifications and further assist with decision-making. The results indicate that the proposed approach can limit reliance on manual visual inspections. By enabling automated monitoring of scaffolding, the proposed approach reduces the time and effort required for inspection process, while enhancing the safety on a construction site.

KEYWORDS

3D point-cloud analysis, artificial intelligence, cloud-based monitoring platform, construction safety, prognostics and health management, scaffolding inspection

1 Introduction

Ensuring workers' safety on a construction site is a crucial concern that requires regular inspection and maintenance of the structural assets to avoid accidents. In these instances, site managers play key roles in making critical decisions that impact safety and operational efficiency. According to the accident causation model (Heinrich, 1941), accidents can be attributed to unsafe conditions and unsafe actions. Monitoring these two causes can reduce the safety risks on a construction site. Given the dynamic working conditions and complex nature of a construction site, workers are often progressively exposed to hazardous environments. Identifying the causes of unsafe conditions, implementing mitigatory actions, performing equipment inspections, and conducting safety evaluations are the main activities involved in safety and health monitoring (Reese and Eidson, 2006). Accidents occurring on construction sites may frequently result in fatalities, damage to assets, injuries to workers, financial losses, and delays (Hamdan and Awang, 2015).

Accidents are caused by various factors, including construction errors, insufficient protection equipment, inadequate technical specifications, excessive loads on scaffoldings, non-compliant components, improper physical actions, and distraction (Whitaker et al., 2003; Ismail and Ghani, 2012). The factors influencing accidents on construction sites are susceptible to changes over time (Hamdan and Awang, 2015). Scaffolding is a critical asset at a construction site that concerns safety-related risks. The majority of construction on a project is performed using scaffolding that comprises steel tubes and joints, where the tube axes describe the spatial configuration. Scaffolds serve as temporary structures that facilitate access to elevated areas during and after construction. The collapse of scaffolding can result in loss of life and financial costs and therefore requires strict compliance with safety protocols (Swedish Work Environment Authority, 2016). Regular inspections and maintenance are necessary to ensure good working conditions and safety for the workers operating at heights as well as prevent accidents involving pedestrians around the scaffolding.

Site managers play essential roles in coordinating and supervising operations at construction sites, ensuring the safety of workers, and completing projects in a timely manner while adhering to the budget. Site managers are also accountable for inspecting and monitoring the scaffolding. At present, scaffolding inspections rely mainly on visual procedures (Cho et al., 2018a), which are inefficient and may lead to errors, especially at large and dynamic construction sites. During construction, the scaffolding structure often undergoes modifications, which may sometimes lead to deviations from standard guidelines and necessitate regular inspections. Such modifications may result in missing or incorrectly replaced scaffolding components that could impact stability. Continuous monitoring of scaffolding to detect modifications and verify compliance requires investment of time and effort by the site manager. As construction operations progress and particularly at complex sites, manual inspection of scaffoldings becomes challenging and inaccurate (Wang, 2019), which may pose potential threats to the safety of workers and individuals situated on and around the scaffolding. Comparison of the scaffolding structure with a reference structure created according to established design rules is required to identify modifications. Additionally, periodic maintenance is needed to restore structural integrity. Beyond traditional inspection methods, there is rapid evolution in the field of digital transformation in construction. The integration of digital twin (DT) and building information modeling (BIM) with immersive technologies is changing the process of monitoring and managing structures in real time. Farsangi et al. (2024) discussed the transition from BIM to DT and the metaverse as well as highlighted the associated challenges and opportunities. Additionally, Ammar et al. (2022) examined the role of the DT in supporting transparency and enabling real-time feedback to enhance collaboration in construction projects. Thus, embedding scaffolding inspection into a digital ecosystem enables continuous data-driven monitoring that surpasses the limitations of periodic visual assessments.

Prognostics and health management (PHM) provides a framework focusing on the degradation mechanisms of an asset to forecast its health and enhance maintenance optimization. The PHM framework ensures optimal functioning, enhanced reliability,

and minimal maintenance cost of an asset (Soualhi et al., 2022). It involves steps like anomaly detection, where an alert is generated whenever the acquired data deviate from the required or desired performance. Later, diagnostics are performed to determine the probable causes for the deviations in terms of location and nature. Finally, given the current health and degree of degradation, prognostics is used to estimate the time when an asset will no longer be able to perform its intended functions (Soualhi et al., 2022). Figure 1 shows the workflow of the proposed scaffolding inspection system, which utilizes the concepts of PHM for asset monitoring and health management. The process begins with data acquisition, where 3D point-cloud data scans of the scaffolding structure are collected. When scaffolding is installed by experts, an initial scan is performed that serves as a reference or certified scan. During structural health monitoring, recently acquired data are continuously compared with the certified or reference data to highlight potential modifications in the scaffolding structure. If a structural modification is detected that could cause a potential safety concern, the system alerts the site manager. This workflow enables automated inspection of scaffolding to potentially reduce the repeated time and effort required from the site manager. Furthermore, the errors caused by manual visual inspections can be minimized, thereby assisting site managers in their decision-making.

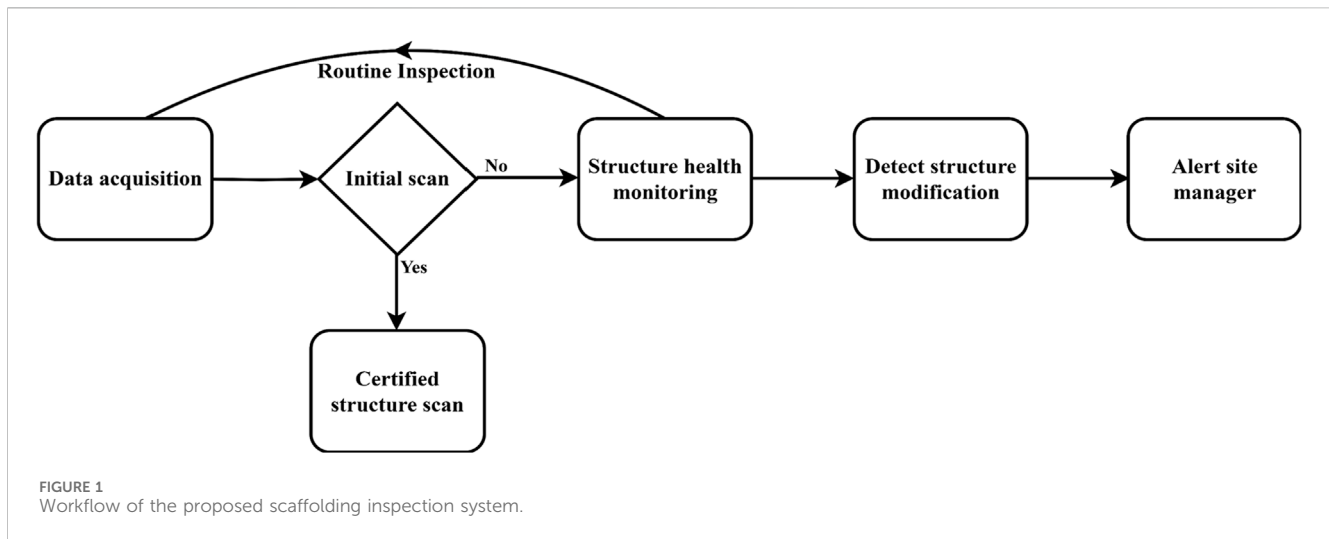
The key contributions of this study are as follows:

1. A cloud-based artificial intelligence (AI) platform is developed to process, analyze, and visualize scaffolding structure, thereby enabling automated inspection and decision-making.
2. A method for monitoring scaffolding using 3D point-cloud data is proposed, which facilitates detection of structural changes impacting stability and enhances safety at the construction site.
3. An approach representing the scaffolding using a graph data structure is presented, which enables the development of a design rule engine for compliance checking.

The remainder of this paper is structured as follows. Section 2 presents literature reviews on traditional and current approaches for scaffolding inspection as well as highlights the research gap. Section 3 presents the methodology of the proposed approach, and Section 4 presents the results. Section 5 includes the conclusions and future directions of this work.

2 Related work on scaffolding health monitoring

The digitalization of scaffolding inspection intersects with advances in sensor technologies, AI-driven analyses, and digital transformation in construction. To overcome the limitations of manual inspection, extant research on scaffolding inspections has adopted a range of technological approaches. The related works are further grouped under two categories as follows: (i) scaffolding inspection approaches that are not based on light detection and ranging (LiDAR) sensing technologies; (ii) LiDAR-based approaches using 3D point-cloud data for geometric and structural analyses.



2.1 Scaffolding inspections using non-LiDAR sensors and data-driven methods

Construction workers are often exposed to safety risks as the health assessments of scaffolding structures are still in the premature stages of development (Cho et al., 2018b). The variability of the design parameters depending on the load conditions, boundary conditions, and materials makes monitoring of scaffolding difficult. Cho et al. (2018b) employed wireless strain sensors to collect data from a scaffolding prototype and transmit them to a finite element machine (FEM) model that assesses the real-time structural conditions; these authors also explored a comprehensive approach to scaffold monitoring that integrated aspects like strain data, FEM, machine learning, and scaffolding (Cho et al., 2018a). The structural state was assessed using a strain gauge, and a data-driven approach was implemented to monitor the scaffolding. The FEM model was designed to replicate the structural response for a given load condition; hence, the training data for the machine learning model were generated using random loading scenarios. Finally, the structural condition was classified using a machine learning algorithm as safe, overloaded, unevenly settled, or risk of overturning. Machine learning has been highlighted as increasingly important to structural health monitoring, especially in support of damage detection and decision-making (Malekloo et al., 2022). Magnetic-flux-leakage-based 3D defect visualization was also employed by some researchers to detect the metal loss in scaffolding steel pipes using a custom Hall-sensor prototype (Yigzew et al., 2024).

Given the rapid developments in the field of data-driven approaches, advanced deep-learning architectures and generative AI methods have been leveraged for condition assessments (Wang et al., 2024; Shao et al., 2025). Scaffolding inspections are generally labor-intensive and subjective, sometimes resulting in inconsistencies. Computer vision and machine learning have been used to develop automated inspection processes (Kim A. et al., 2022). Both real and synthetic labeled datasets have been employed to train machine learning models to detect various conditions like rust, cracks, and deformations on scaffolding components. BIM and

image processing methods have been combined to estimate scaffolding progress through comparisons with site photographs (Chi et al., 2017). Safety monitoring models are frequently restricted to specific types of hazards; however, the dynamic nature of a construction site makes it impractical to detect hazards by type (Khan et al., 2021). Scaffolding inspections are intended to ensure structural stability and workers' safety. Furthermore, accidents may occur due to the workers' actions while on the scaffolding. To address worker-related risks on scaffolding, one approach proposed to detect unsafe actions by workers while situated on a mobile scaffolding by analyzing correlations drawn from safety rules. A deep-learning model was implemented for object detection and instance segmentation on manually labeled images of scaffolding with and without outriggers. The unsafe actions by workers were identified by integrating the classification and segmentation of workers' tasks with an object correlation detection module. This module determined the correlation between the predicted task and specific conditions (Khan et al., 2021). A related approach was proposed to mitigate the risk of construction-related falls from a height through a smart safety hook monitoring system; this system integrates computer vision with Internet of Things monitoring technologies and employs deep learning to identify workers and scaffolding from live camera feed. Upon detecting a worker in a risk zone, an Arduino Nano equipped with an inertial measurement unit and an altimeter sensor is activated to check the status of the safety hook (Khan et al., 2022).

The aforementioned approaches have been mostly implemented and evaluated on either scaffolding prototypes or parts of the scaffolding. Moreover, these models rely significantly on the quality of the collected image data, which can be affected by lighting conditions and image acquisition angles. Machine learning models require labeled data for training, which can be labor-intensive, and the model evaluations depend on their ground truths. All of these approaches require additional development and validation prior to real-world application.

2.2 LiDAR-based approaches

Among the sensor-based inspection technologies, LiDAR is a unique and powerful modality owing to its ability to acquire dense 3D geometric data (Wang and Kim, 2019). LiDAR or 3D laser scanning emits laser beams toward a target and detects the reflected signals to determine the distance. Scanners utilizing the time-of-flight principle emit laser pulses with predetermined velocities and measure the time elapsed before receiving the reflected pulses to estimate the target distances. LiDAR creates a 3D map of the physical environment by measuring distances and spatial interactions among the objects. 3D point-cloud data obtained by laser scanning technology can accurately and efficiently capture spatial structures (Wang et al., 2020). This technology allows high frame rates, an extended field of view, and the ability to operate under various lighting conditions, making it suitable for dynamic and complex construction environments (Teizer, 2008).

3D point-cloud data have emerged as invaluable tools in construction, offering applications to improve efficiency and accuracy through progress tracking as well as enhancing safety throughout the project lifecycle via quality inspections (Wang and Kim, 2019). Displacement mapping methods have been developed to analyze sequential point clouds of retaining structures (Zhao et al., 2021), demonstrating efficient detection of deformations and safety risks. LiDAR technology has been employed extensively for as-built inspections and building quality assessments (Styliadis, 2007; Bosché, 2010; Aydin, 2014; Yu-Fei et al., 2016). One study focused on deriving pictorial, geometric, spatial, topological, and semantic information from architectural objects like historical buildings and monuments; this work presented a practical demonstration of generating semantic models from high-resolution images to produce point-cloud data through calibration and alignment; the semantic models were subsequently integrated with computer-aided architectural design systems for advanced analysis and documentation (Styliadis, 2007). Another study employed high-resolution digital cameras and photogrammetry techniques to remodel building facades that were adversely affected by visual pollution owing to urban development (Aydin, 2014). Integration of 3D computer-aided design (CAD) models with laser scanning technologies has been proposed to address issues like progress tracking and quality control; in this approach, the CAD models are optimally registered with site scan objects to subsequently compute the as-built poses for verifying dimensional compliance with the specifications (Bosché, 2010). In a related approach, crack information was extracted from 2D images and reconstructed into 3D scenes using the structure-from-motion (SfM) algorithm by combining image processing and 3D modeling for structural health assessment (Yu-Fei et al., 2016).

One study aimed to reduce the time-consuming and error-prone manual inspections of highway retaining walls by extracting geometric features from laser scan data to identify displacements in mechanically stabilized earth (MSE) walls; here, the horizontal joints are extracted from point-cloud data of the MSE walls obtained at different time intervals that serve as the benchmarks for displacement measurements (Oskouie et al., 2016). Existing

approaches for safety planning at excavation sites susceptible to cave-ins and falls are manual and prone to errors; to address these limitations, a semi-automated approach was developed that utilizes the geometric characteristics of 3D point-cloud data to detect fall and cave-in hazards; to enhance safety planning, the hazards identified from point-cloud data and necessary safety rules were integrated with BIM (Wang et al., 2015). Active safety systems capable of real-time hazard detection have been explored to improve construction site safety, including the use of 3D range cameras for accident prevention; furthermore, algorithms have been developed to enhance the abilities of the 3D range cameras for detecting and tracking objects, such that real-time feedback can be provided to operators to enhance safety during heavy machinery operation (Teizer, 2008).

Scaffolding-related issues are a primary source of injuries and accidents at construction sites, so safety features like toe boards and guard rails are provided to avoid falls and other related injuries. Wang (2019) proposed an automated inspection method to ensure compliance with safety regulations. Here, upon detecting the locations of the vertical elements of scaffolding from point-cloud data, the planar and horizontal surfaces are identified for scaffolding platforms; the four sides of the detected work platforms are then considered for establishing toe boards and guard rails. Next, safety regulation assessments based on the heights of the toe boards as well as numbers and locations of the guard rails are conducted on the extracted toe-board and guard-rail components; however, this method primarily focuses on the toe boards and guard rails rather than the complete scaffolding structure (Wang, 2019). A 3D deformation monitoring model has been proposed for scaffolding to address limitations associated with the restricted scanning range of LiDAR using point-cloud data acquired from multiple stations, which is referred to as multithread LiDAR technology. The proposed model comprises point-cloud alignment and tube-axis modeling, where the geometric relationships of the planar features in the scans are used to compute the transformation parameters for point-cloud alignment; for scaffolding tube-axis modeling, the model integrates a least-squares approach with the RANdom SAMple Consensus (RANSAC) algorithm. The scaffolding deformations are monitored by comparing the tube-axis models at various time intervals; however, this alignment strategy requires the presence of sufficient planar surfaces in the scanned data (Rui et al., 2022). Kim et al. (2022b) proposed a 3D reconstruction approach for scaffolding monitoring using a semantic segmentation method called RandLA-Net, which detects scaffolding from point-cloud data collected using a robotic dog; this deep-learning model is trained from scratch as well as through transfer learning with the Semantic3D dataset. The 3D CAD model generated from the predicted scaffolding point cloud is more focused on the identification and 3D reconstruction of scaffolding at the construction site. For a large construction site, it is computationally inefficient to directly process point clouds to identify small objects. Accordingly, a methodology that integrates 3D point-cloud data with 2D image data has been reported for detecting and locating unsafe scaffold joints. In this approach, 3D semantic segmentation was applied to isolate scaffolding from the acquired point-cloud data, after which the scaffold joints were identified using the coordinates of uprights and guard rails to

TABLE 1 Previous studies on scaffolding inspections using point-cloud data.

Study	Objective	Methodology	Data acquisition	Focus
Wang (2019)	Detection of toe boards and guard rails	Using the geometric properties of point-cloud data, the four sides of a work platform were extracted after detecting the uprights (vertical) and platform (horizontal)	Terrestrial laser scanner	Toe boards and guard rails
Rui et al. (2022)	Monitoring scaffolding for deformations	Point-cloud data were aligned to compare the tube-axis model for deformations	Multithread LiDAR	Planar surfaces for alignment
Kim et al. (2022b)	Scaffolding extraction	3D semantic segmentation model was implemented to identify scaffolding	Mobile laser scanner	Scaffolding identification
Kim et al. (2023)	Inspection of scaffold joints	Semantic segmentation was performed to extract scaffolding, followed by point-to-image translation of the joints for safety inspection	Terrestrial laser scanner	Scaffold joints

generate joint images. Then, a deep-learning model was trained to detect ledger ends and tails from images of scaffolding joints to provide insights into the safety status of these joints (Kim et al., 2023).

To the best of our knowledge, there is limited research on integrating scaffolding monitoring with point-cloud data. This was also noted by Rui et al. (2022), who identified that there was a lack of studies employing point-cloud data for deformation monitoring of temporary structures. Table 1 demonstrates that extant studies incorporating point-cloud data for scaffolding are limited to either specific parts of the scaffold or detection of scaffolding. Hence, comprehensive methods for monitoring complete scaffolding structures using point-cloud data are lacking.

The aim of the present study was to explore the use of AI and digital technologies for scaffolding inspections to assist site managers with decision-making related to the safety of construction sites. Accordingly, our objective was to develop a cloud-based AI-driven platform that automates monitoring and safety assessments of scaffolding structures using 3D point-cloud data. The proposed approach is expected to contribute toward the ongoing digital transformation of the construction industry.

3 Methodology

This work focuses on identifying modifications to the scaffolding during the construction process. As discussed in Section 1, routine manual visual inspection of scaffolding is time-consuming and may be prone to errors, especially on complex sites and owing to human fatigue. The following insights are based on semi-structured interviews conducted with site managers, whose responsibilities include ensuring the safety of workers on construction sites. According to the managers, scaffolding inspections are repeated every few weeks, and the inspectors may struggle to recall specific changes made to the reference structures. The accuracy of inspection is also influenced by the inspector's familiarity with the design principles or rules. During construction, worker-structure interactions pose additional risks as workers occasionally remove the components or braces of the scaffolding for accessibility. The most common challenges encountered by site managers during scaffolding inspections are that the structural elements may not be replaced or that the replaced parts may not

be compliant with the design rules. These issues can compromise the structural integrity and eventually affect worker safety.

Our research seeks to automate the routine inspection processes necessary to maintain the structural integrity of the scaffolding and ensure safe working conditions. We further explore the roles of AI and digital technologies to assist site managers with informed decision-making on construction sites. As illustrated in Figure 1, the proposed scaffolding monitoring framework is structured into three parts, namely, acquiring the certified or reference structure and campaign-based data, performing a routine inspection for structural comparison and modifications, and assisting the site manager with decision-making. Figure 2 adapted from Karim et al. (2016) presents the comprehensive platform used in this study that encompasses the entire workflow from data acquisition to knowledge extraction and ultimately visualization. The platform follows a microservice-based architecture to enable seamless data acquisition, secure transfer, storage, processing, analytics, and visualization.

The proposed framework is designed to support various sensing devices like LiDAR scanners and robotics platforms like autonomous robot dog and drones. However, in the present work, the point-cloud data are exclusively acquired using a handheld LiDAR scanner. The acquired data are subsequently transferred to a binary large object (BLOB) storage, which is a cloud-based storage mechanism designed to efficiently handle large unstructured binary files like LiDAR point clouds within the proposed workflow. The point-cloud data represent the spatial configuration of the environment and contain extensive information that requires further processing. As shown in Figure 2, the knowledge extraction stage encompasses various operations like data preprocessing, structural comparison, and graph data structure representation. Data cleaning by eliminating irrelevant data points like outliers and isolating the object of interest, namely the scaffolding structure, ensure that only high-quality information is retained for further analysis. The scaffolding extracted from the raw data still contains a large number of points that must be represented effectively. Since scaffolding can be considered the interconnection of rods and joints, we employed a graph data structure as an effective representation method. This representation is well-suited to capture the relationships between the nodes (scaffolding joints) and edges (scaffolding rods or braces). Furthermore, graph-based approaches not only preserve the structural relationships but also enable the use of well-established

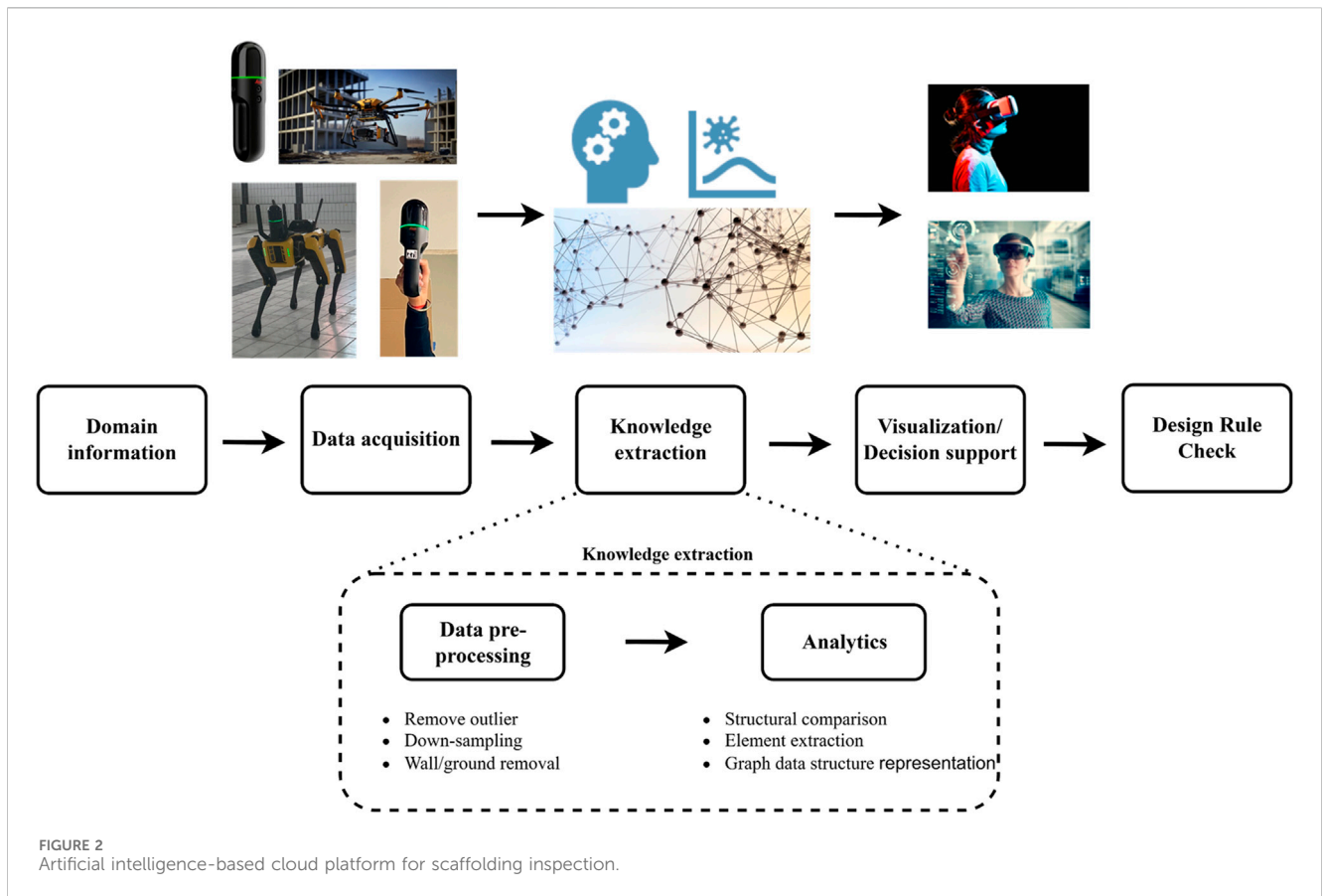


FIGURE 2
Artificial intelligence-based cloud platform for scaffolding inspection.

methodologies in network analysis to better understand the scaffolding structure. Structural changes occurring during the construction process can affect stability; therefore, the processed and extracted scaffolding point-cloud data are compared against the certified reference scaffolding design to detect structural changes or deviations. To this end, continuous monitoring of the scaffolding is essential so that any structural alterations can be highlighted and reported promptly. By drawing attention to these modified areas, the site manager can prioritize inspections to critical zones and implement targeted corrective actions, optimizing both time and resource allocations. Hence, digital technologies are valuable tools that can assist site managers in making informed decisions on the health of the scaffolding and safety of the workers. Finally, the visualization stage employs immersive technologies like augmented reality (AR) and virtual reality (VR) to present the extracted knowledge and support decision-making through intuitive interactions with the processed data. Prior to data acquisition, construction domain knowledge is incorporated into the platform to guide both data collection and processing. Although the platform developed herein focuses on data acquisition, knowledge extraction, and visualization, it can be extended to incorporate the design rule check module. Such an addition would validate the extracted scaffolding model against established design rules and regulatory requirements to strengthen compliance and enhance worker safety.

The point-cloud data uploaded to the BLOB storage serve as the primary inputs for all subsequent processing steps. All data preprocessing and analytical algorithms, including noise removal, downsampling, structural comparisons, and graph-based

scaffolding representation, are executed on cloud infrastructure as part of the proposed platform. These algorithms are applied directly to the stored .e57 point-cloud files. The cloud-based processing steps are triggered upon the arrival of a new point-cloud data file to initiate the knowledge extraction stage. The processed results are subsequently reused at the visualization stage, including AR- and VR-based interfaces. Overall, this work presents a computational intelligence system that transforms raw sensory inputs into structured representations, evaluates structural integrity through algorithmic inference, and generates decision-support information for scaffold safety assessments without human intervention.

In the following section, we present detailed results corresponding to the three stages shown in Figure 2, namely, data acquisition, knowledge extraction, and visualization, to demonstrate the effectiveness of the proposed AI-based platform.

4 Results and discussion

This section demonstrates the results achieved during different stages of the developed AI-based platform.

4.1 Data acquisition

Figure 3 illustrates the raw point-cloud data of the scaffolding from a construction site that was acquired using a LiDAR device.

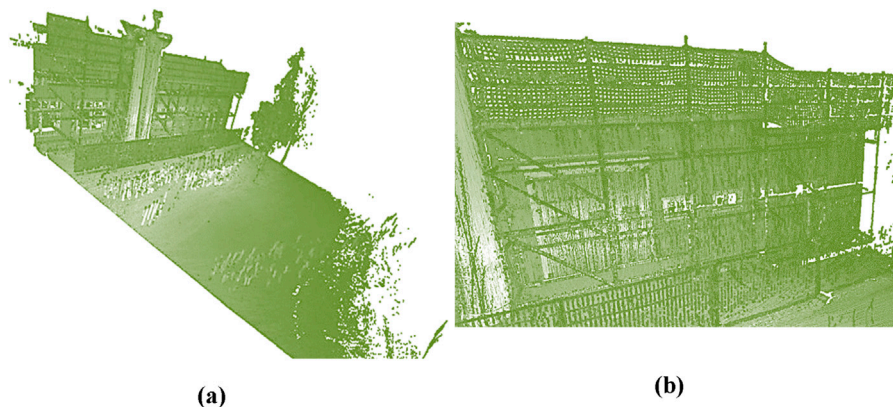


FIGURE 3
Raw point-cloud data of the scaffolding from (a) perspective 1 and (b) perspective 2.

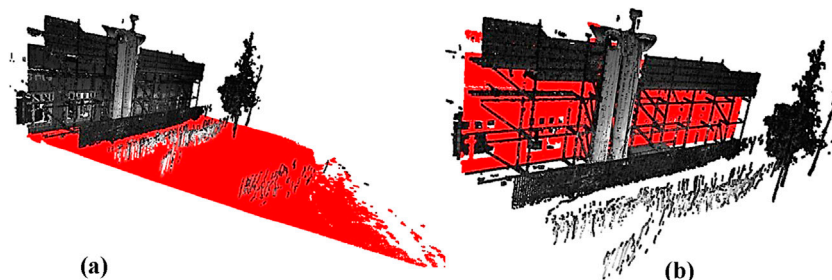


FIGURE 4
Processing of the point-cloud data to detect (a) the ground and (b) walls.

The figure presents different perspectives of the acquired data. The raw 3D point-cloud scan obtained from the construction site consists of approximately 16 million points and includes not only the scaffolding but also other objects like the nearby trees and surrounding structures, which are not of interest to this work. The raw point-cloud data are next processed to isolate the primary object of interest.

4.2 Data preprocessing

The preprocessing step discussed herein is applied to both the initial and periodic data acquired. Raw data often contain noise, outliers, and redundant points; therefore, preprocessing ensures that the dataset is cleaner and more interpretable. To extract the object of interest, preprocessing involves several operations like removal of the ground plane, elimination of outliers, and voxelization to reduce the density of data points to make the data more manageable for further processing. During the voxelization step, the point-cloud data are partitioned into uniformly sized grids such that the points within each grid can be aggregated to achieve a manageable resolution. For planar surface removal, iterative algorithms like RANSAC (Fischler and Bolles, 1981; Rui et al., 2022) are commonly used to identify and separate the planar surfaces from

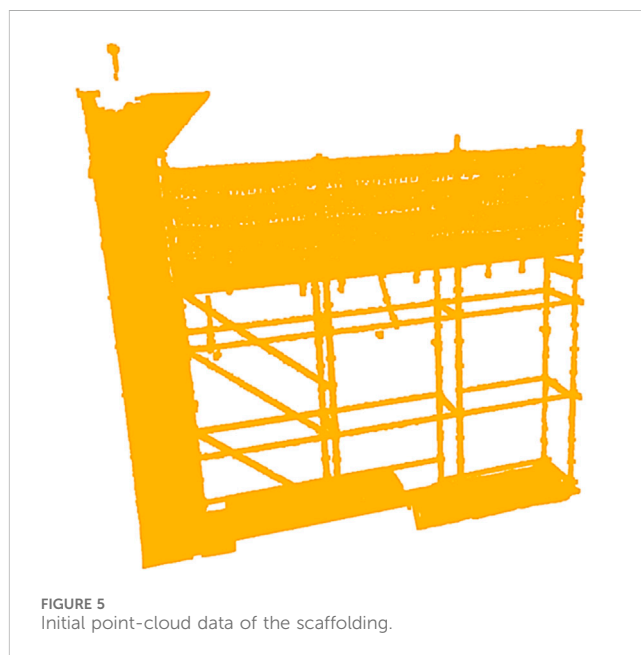
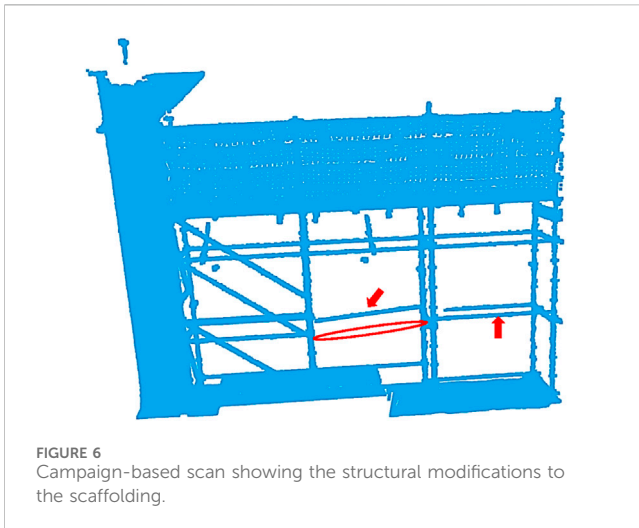


FIGURE 5
Initial point-cloud data of the scaffolding.

the point-cloud data. In this study, RANSAC was employed by repeatedly fitting planes to some random subsets of data points and

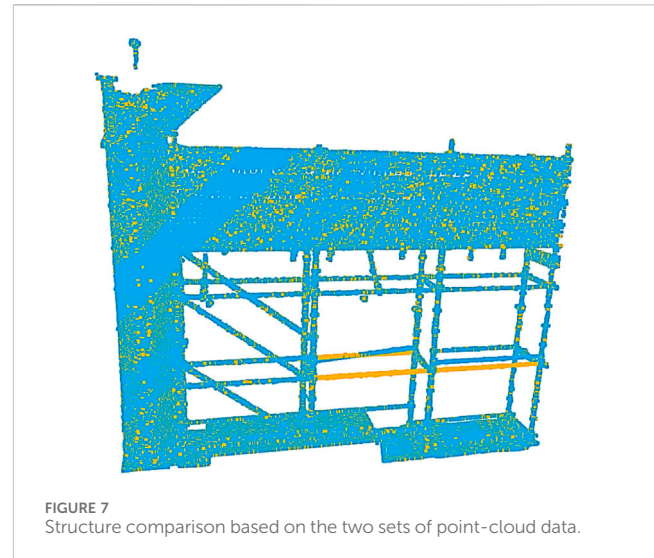


selecting the planes with the highest number of inliers; this allowed identification and removal of the planar surfaces, leaving only the scaffolding structure as the primary object of interest. Figure 4 shows the detected ground plane and walls in red color. Since the scaffolding is installed at a predefined distance from the wall, all data points beyond this distance are eliminated to obtain the object of interest, as shown in Figure 5. In this work, the certified scaffolding structure is considered as the initial or reference scan.

4.3 Structure comparison

This step replicates the routine inspection process typically undertaken by the site manager, where a LiDAR scan of the construction site is obtained every 2 weeks or as required. For periodic monitoring, campaign-based LiDAR scans are acquired and compared with the certified reference scan to detect modifications to the scaffolding. Each newly acquired set of point-cloud data undergoes the preprocessing steps mentioned in Section 4.2. The two most common issues faced by the site manager during inspections are missing and deviated scaffolding braces or elements; such changes usually occur as the construction progresses and workers modify the temporary structure for ease of access, as shown in Figure 6. In the figure, the missing element is shown by the red circle, whereas the shifted or deviated elements are indicated by red arrows.

The recently extracted and cleaned scaffolding point-cloud data are compared with the reference data to detect modifications so that the site manager can focus on the modified sections. The iterative closest point algorithm (Li et al., 2021) is used to align and minimize the distance between the two sets of point-cloud data; this algorithm estimates the transformation matrix, which is a combination of a rotation matrix R and a translation matrix T , that minimizes the mean-squared error, as given in Equation 1. Here, I represents the initial data from the certified scan, C is the current scan, and N_p denotes the total number of data points.



$$Error(R, T) = \frac{1}{N_p} \sum_{i=1}^{N_p} \|I_i - RC_i - T\|^2 \quad (1)$$

For each point in C , the algorithm identifies the closest point in I to establish a point correspondence; these correspondences are then used to estimate the optimal transformation matrix that best aligns the two sets of point-cloud data. To assess convergence, the algorithm evaluates the change in error and iterates until convergence or the maximum iteration limit is reached. Figure 7 shows the output from the algorithm, where the matching or identical points between the scans appear in blue color, while the modified points are highlighted in yellow color. This enables the site manager to focus on the sections requiring attention, which is particularly beneficial for a large complex construction site with scaffolding at multiple locations.

To further evaluate and visualize the alignment accuracy between the current and reference point-cloud data, the distance between the corresponding point data is computed. A threshold is applied to distinguish well-aligned from poorly aligned points, and the result is color-coded depending on the severity level. If the distance between the current and reference data points is within the threshold, the points are colored green, while those exceeding the threshold are displayed in red to signal possible misalignments for closer inspection. By tuning the threshold parameter in the point-cloud distance calculation, the percentage of deviation or modification can be adjusted. The flexibility of tuning the threshold allows site managers to adapt the severity levels to site-specific requirements and professional judgment. Figure 8 shows the points having distances less than the defined thresholds in green, whereas points exceeding the threshold distances are shown in red. Figure 8a shows the result for 10% threshold, where small deviations are acceptable and do not compromise the structural integrity; Figure 8b demonstrates the result for 5% threshold, where even small deviations are unacceptable.

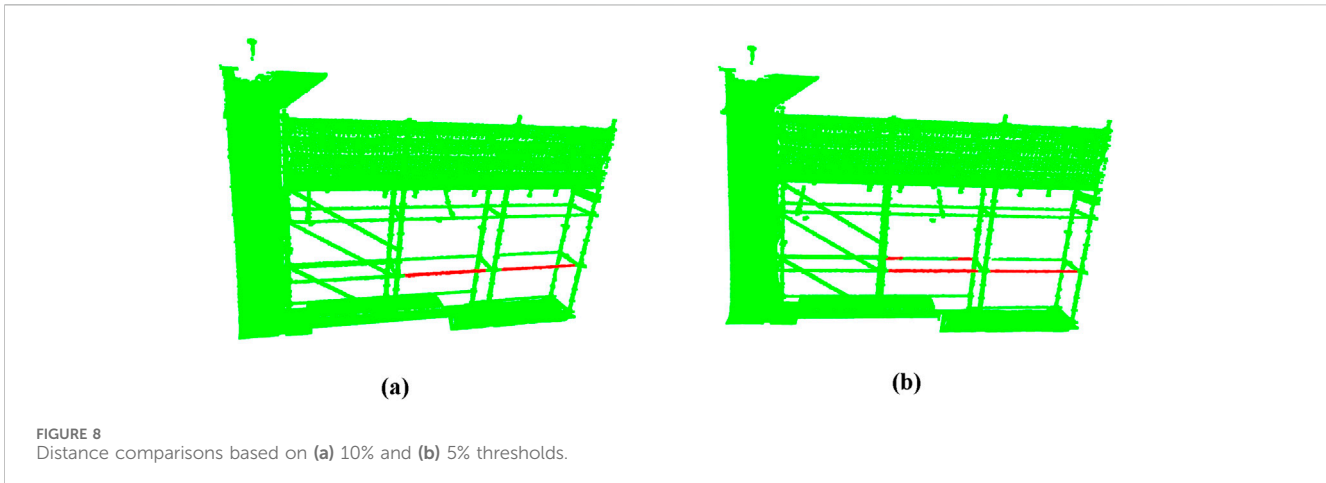


FIGURE 8
Distance comparisons based on (a) 10% and (b) 5% thresholds.

4.4 Graph representation

Scaffolding structures are composed of interconnected elements like tubes or braces and joints, which can naturally be represented using a graph data structure. The physical elements of the scaffolding like rods or braces represent the edges in the graph, whereas the joints represent the nodes. This approach allows representation of the complex point-cloud data of scaffolding efficiently and systematically.

Figure 9 illustrates the steps involved in the process of representing the graph data structure of a scaffolding from its raw point-cloud data. First, the scaffolding is extracted from the raw point-cloud data by segmentation according to local geometric characteristics; here, the KDTree algorithm (Guo et al., 2017; Lin et al., 2020) was employed to identify neighboring points within a predefined radius. Singular value decomposition was then applied to compute the principal components that were then used to determine the distribution of the selected points and classify their shapes as linear, planar, or spherical. This classification allows the braces to be identified as linear features, platform and safety sheets as planar structures, and joints as spherical features. The result of this step is shown in Figure 9 under the element extraction block, where the braces are represented in green, joints are shown in red, and planar surfaces like the safety sheet are depicted in blue. Second, the density-based spatial clustering of applications with noise (DBSCAN) (Ester et al., 1996; Kim et al., 2024) algorithm was used to cluster the point-cloud data and isolate the linear features corresponding to the scaffolding braces. To reduce the data and computational complexity, the two farthest points were determined for each cluster along with the alignment of the braces. For each of these farthest points, the corresponding close data points were identified and their mean was computed to represent a physical joint of the scaffolding. As shown in the figure, the braces are represented in green, while the joints shown in red are the mean values derived from the bounding boxes represented by the dotted lines. The last row of Figure 9 presents the color coding for each brace in the horizontal x direction, horizontal y direction, and vertical z direction of a scaffolding.

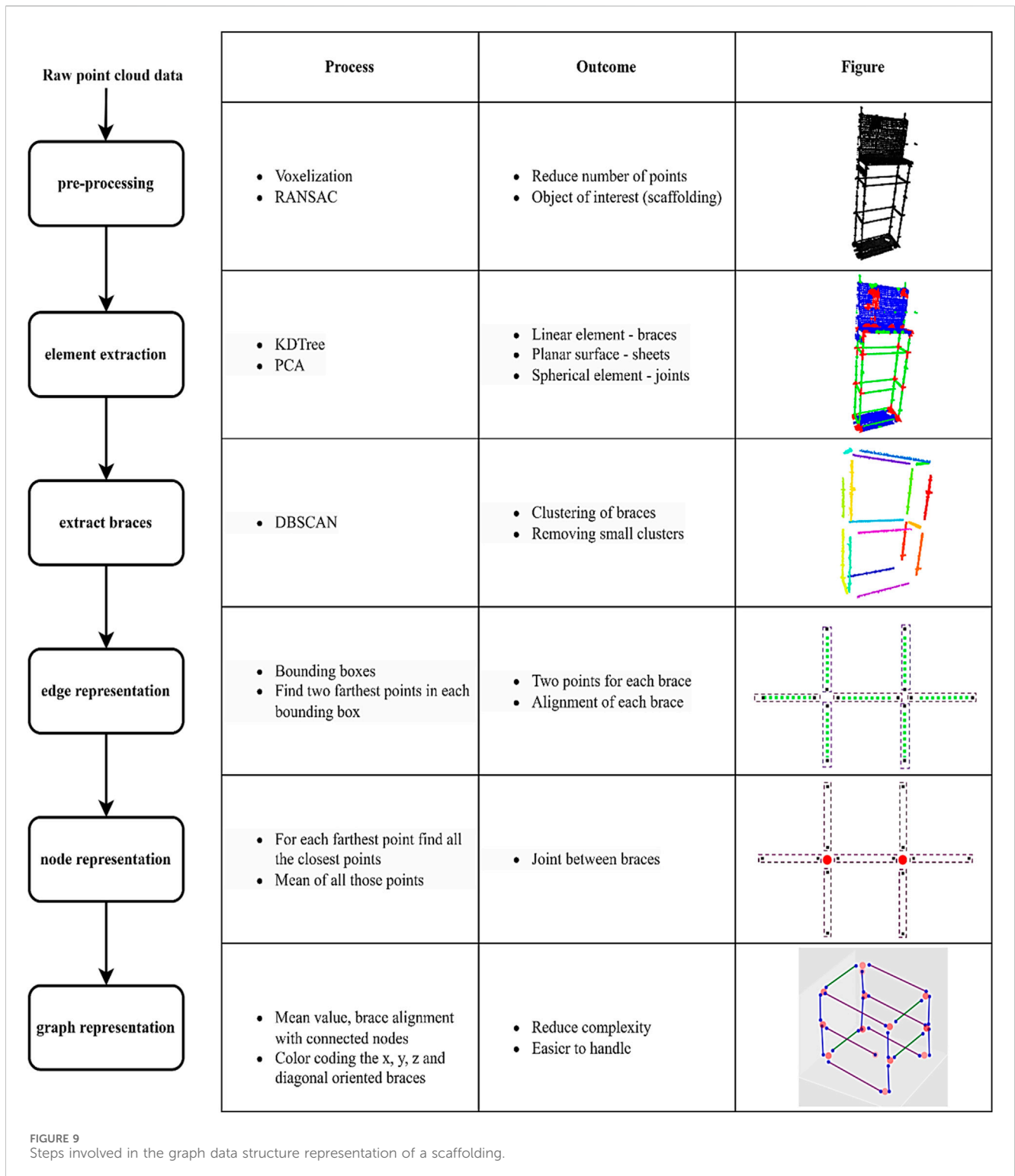
4.5 Hybrid clustering

In the element extraction block, the linear elements (i.e., braces) are separated from the spherical elements like joints, after which the DBSCAN algorithm is applied to cluster the braces. However, as shown in Figure 10a, certain clusters contain both vertical and horizontal braces under one label. Such edge cases require further refinement before clustering. Accordingly, an additional normal vector-based separation is introduced to specifically target incorrect or misclassified clusters. The normal vector representation for the edge case is shown in Figure 10b. Thus, two-stage or hybrid clustering is adopted for edge cases, where the first stage is based on spatial distance and second stage employs normal vector direction. As shown in Figure 10c, the results generated from the two clustering stages are combined for more accurate differentiation between the vertical and horizontal braces of the scaffolding structure.

4.6 Visualization

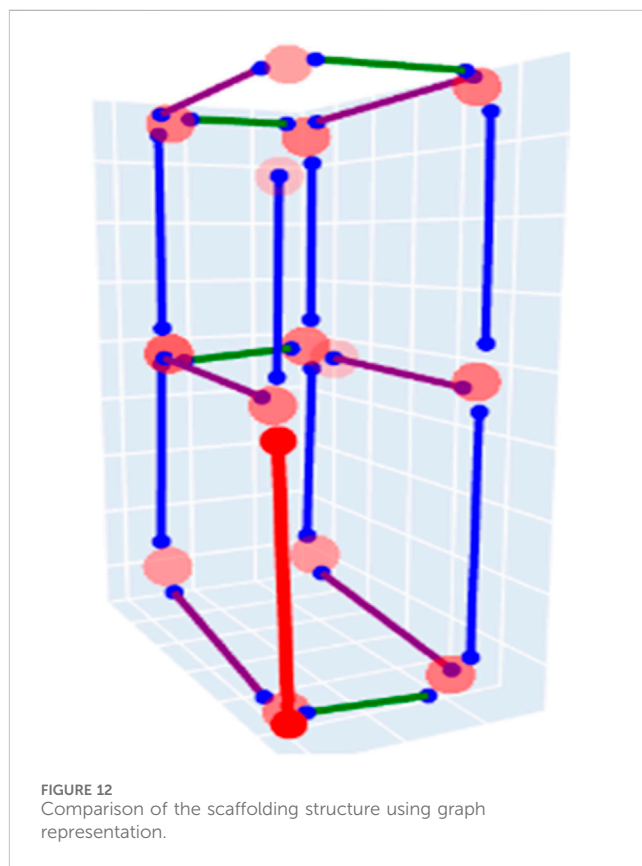
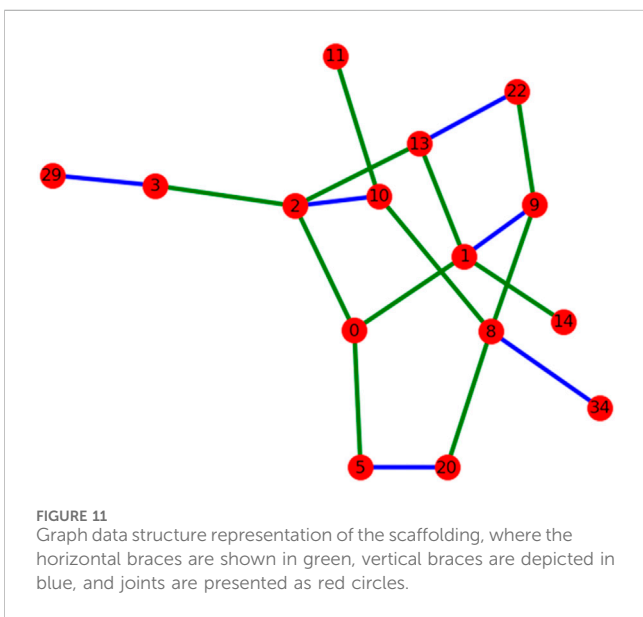
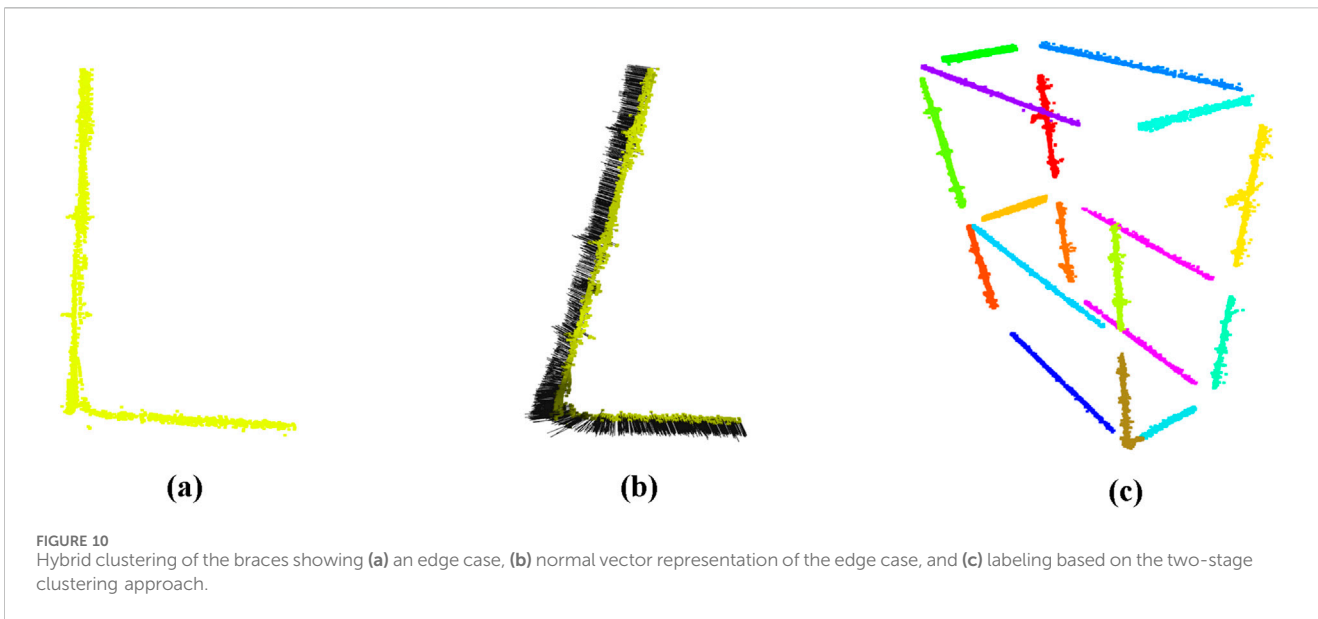
Once the scaffolding is represented as a graph data structure, its layout is as shown in Figure 11. In this representation, the horizontal braces are colored green, whereas the vertical braces are shown in blue and joints are denoted by small red circles. Although Figure 11 may not visually resemble a physical scaffolding structure, it effectively captures the connectivity and relationships between the components. As discussed previously, one of the major issues during inspection is missing scaffolding elements. Figure 12 demonstrates this case by comparing the graph representations of the reference scan with the recent scan in which a brace is missing. Figure 12 shows the graph representation of a scaffolding with a missing brace highlighted in red.

VR and AR are increasingly being recognized as transformative technologies that are changing the construction industry through better visualization capabilities (Li et al., 2018). VR creates an experience by immersing the users in a fully simulated environment to effectively isolate them from the physical world; this allows the users to engage in natural interactions and navigation within the virtual environment in a manner that closely resembles reality. However, AR superimposes the digital information directly



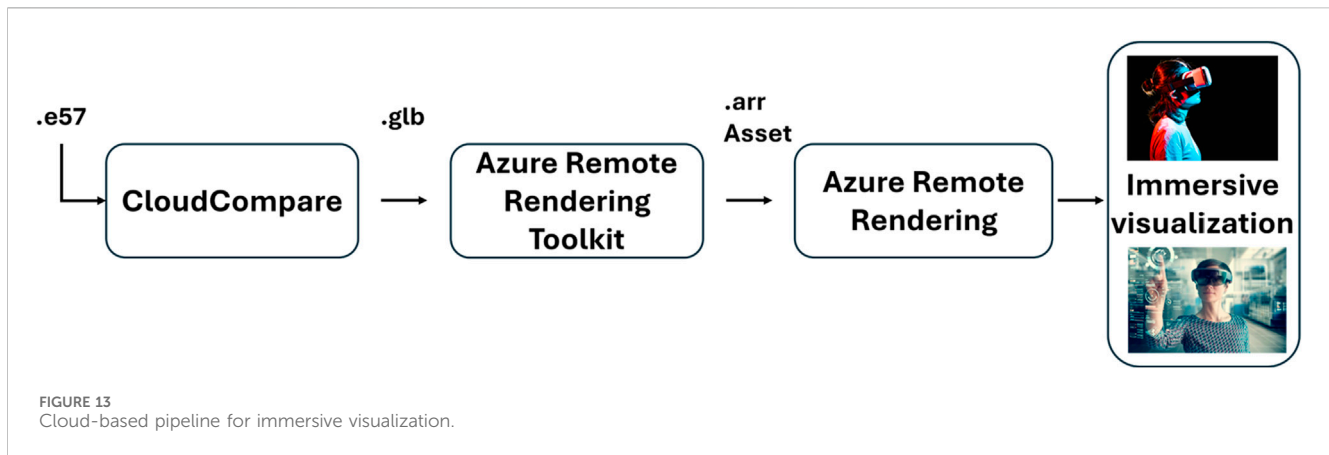
onto the physical environment to enhance the user’s interactions with their surroundings. These immersive tools enable site managers to conduct virtual inspections of the scaffolding and specifically focus on critical sections to ensure structural integrity. To enable immersive visualization, the point-cloud files (.e57 format) from the knowledge extraction stage are transformed into optimized 3D representations suitable for real-time rendering. Azure remote rendering (ARR) service was used in this work to facilitate the

rendering of high-quality and interactive 3D content for seamless real-time streaming to AR and VR devices. Figure 13 illustrates the conversion pipeline used in the visualization stage; here, the processed point-cloud data are converted to AR/VR-friendly “arrAsset” format using ARR. This conversion involves exporting the .e57 format file to a standard intermediate format like .glb as the .e57 format is a vendor-neutral exchange format; however, arrAsset is a runtime asset format for cloud-based AR/VR applications.



An illustrative screenshot captured using AR glasses is shown in Figure 14, where a missing brace is shown in red color and a deviated scaffolding element is shown in yellow color. This example demonstrates the conceptual visualization of the detected scaffolding anomalies and is intended to present the inspection results in an immersive environment. Since the 3D model is not rigidly aligned with the physical environment, it allows the users to freely reposition and rotate the AR scaffolding. This enables inspection from multiple viewpoints and improved perception of all spatial dimensions. Although Figure 14 illustrates the AR-based visualization using the HoloLens glasses, the ARR service also supports rendering of 3D scaffolding models in VR

glasses. These technologies eliminate geographical barriers to support problem-solving and coordination as well as extend collaborative practices by diving into 3D models and performing hands-on tasks that go beyond computer screens. This, in turn, promotes real-time discussions among experts, resulting in improved decision-making.



5 Conclusion and future work

This work proposes a cloud-based AI platform for monitoring scaffolding at construction sites. The proposed method processes the raw 3D point-cloud data acquired using a 360° LiDAR scan to isolate the scaffolding; then, it compares the certified reference scan of the scaffolding structure with recent scans acquired at regular intervals. Deviations or missing elements of the scaffolding are then detected using alignment algorithms. To quantify the difference between the reference and recent scans, the distance between their point-cloud data is computed for precise identification of structural modifications. By automating scaffolding monitoring on complex construction sites, the proposed approach reduces the time and effort required from the site manager. Additionally, this work also suggests an efficient method of representing scaffolding using a graph data structure, which not only captures the connectivity between the joints and braces but also allows integration of numerous well-established graph algorithms for advanced

analyses. Highlighting the structural modifications to the scaffolding during construction progress can direct the site manager's attention to focus on these sections, thereby reducing human errors during inspection. By providing data-driven insights into scaffolding structural modifications, the proposed approach assists site managers with critical decision-making. Moreover, the integration of advanced visualization tools like VR and AR can further enhance remote visualization, foster real-time discussions, and facilitate informed decision-making. The proposed cloud-based platform demonstrates the use of AI and digitization technologies to automate scaffolding inspections, which currently rely heavily on manual visual inspections. Traditional visual inspections can be time-consuming, error-prone, and inconsistent, potentially compromising the safety on a construction site. The proposed approach is one method of enhancing the safety of the workers and other individuals at a construction site by reducing errors associated with visual inspections. By linking LiDAR-based data acquisition, AI-driven analysis, and immersive visualization within a connected platform, our work contributes to the broader digital transformation within the construction industry.

From the perspective of practical implementation, the proposed approach can be adapted to real-world construction environments. Although LiDAR-based sensing involves an initial cost, its ability to acquire high-resolution spatial data can be utilized to monitor multiple assets at construction sites to improve long-term cost efficiency. The cloud-based processing pipeline enables execution of computationally intensive algorithms and supports scalability. However, there may be some barriers to adoption of methods like those proposed herein, include the need for trained personnel, integration with existing site workflows, and regulatory acceptance of digital inspection methods.

Within this digital framework, continuous monitoring and predictive capabilities are essential components of proactive safety management. To enhance safety at construction sites, there is a critical need to detect wear, damage, or unintended changes at the earliest. The present work aligns with the PHM concept by enabling continuous monitoring of scaffolding to track changes or modifications against the certified reference structure, thereby supporting the prediction of potential failures or safety hazards. Continuous monitoring of the health of the scaffolding also assists with forecasting when the elements may require maintenance, thereby enhancing the overall safety and reliability. Our work is

expected to be a foundation for future advances in scaffolding condition monitoring. When scaffolding structures are installed, they must adhere to the established design rules to ensure structural stability and integrity. One promising extension of the proposed approach is the integration of design rule verification, which enables the system to automatically assess the current condition of the scaffolding against predetermined safety specifications. Furthermore, implementing an expert system framework could advance the platform toward a higher degree of autonomous decision support.

Beyond the technical contributions, the proposed approach supports broader societal goals by promoting consistent safety practices through data-driven inspection. Increasing accessibility to digital inspection tools can reduce reliance on subjective manual assessments and improve protection for construction workers. In addition, continuous digital monitoring may enable early detection of deviations in the scaffolding even under adverse environmental conditions, thereby contributing toward a more resilient system.

Data availability statement

The datasets presented in this article are not readily available because of confidentiality issues and cannot be shared at the moment. Requests to access the datasets should be directed to corresponding author at sameer.prabhu@ltu.se.

Ethics statement

Ethical approval was not required for the studies involving humans in accordance with the local legislation and institutional requirements. The Institutional Review Board of Luleå University of Technology waived the requirement of written informed consent for participation from the participants or their legal guardians/next of kin because the interactions with site managers were part of the approved project activities and no separate written consent was required from the participants. Involvement in the project inherently included the sharing of domain knowledge and professional insights.

Author contributions

SP: Formal analysis, Writing – review and editing, Visualization, Data curation, Software, Validation, Investigation, Writing – original draft, Methodology, Conceptualization. AP: Formal analysis, Software, Data curation, Conceptualization, Writing – review and editing,

Validation, Investigation. RK: Writing – review and editing, Supervision, Conceptualization, Validation.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that generative AI was used in the creation of this manuscript. During the preparation of this work, the authors used ChatGPT, a language model developed by OpenAI, to assist with grammar refinement and text clarity. All contents have been reviewed and edited by the authors, who assume full responsibility for the published version.

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