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AUGMENTED REALITY AND COMPUTER VISION TO SUPPORT SCHEDULING AND MONITORING IN CONSTRUCTION: A MEP CASE STUDY

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Abstract

Mechanical, Electrical, and Plumbing (MEP) systems require complex spatial coordination and installation sequences, making scheduling and progress monitoring challenging. This paper presents a framework that integrates Augmented Reality (AR) and Computer Vision (CV) to support MEP scheduling and progress tracking. BIM-based plans are visualized on-site through AR to guide installers, while CV algorithms detect MEP components from images to measure progress and identify schedule deviations. A prototype developed in Unity for HoloLens 2 was tested in laboratory and construction site environments. Results demonstrate its potential to improve construction managers' situational awareness.

Introduction

Mechanical, electrical, and plumbing (MEP) construction projects are among the most complex phases of building delivery because they require the installation of numerous interdependent components within constrained spatial environments. As buildings become more technologically sophisticated, the density of MEP systems has increased, placing significant demands on coordination, sequencing, and precision during installation. Prior research highlights that MEP works often involve intricate spatial relationships and tolerance requirements, which make them particularly susceptible to coordination problems and rework if not managed carefully (Eastman et al., 2011). Moreover, these activities typically occur at later stages of a project, when structural and architectural elements are already in place, thereby limiting flexibility and amplifying the consequences of any errors or clashes discovered on-site.

Despite advances in Building Information Modeling (BIM) and digital design workflows, construction errors such as geometric clashes or incorrect installations are still frequently detected only at late stages of construction. Several studies have shown that while BIM-based clash detection is widely adopted, its benefits are reduced when updates to the model are not timely or when discrepancies between the as-designed and as-built conditions are not systematically captured (Hartmann et al., 2008). In practice, field conditions deviate from planned information for a range of reasons, for example design changes, unforeseen site constraints, or human error. These deviations are often discovered only during installation or inspection. By the time such issues emerge on-site, corrective actions may be costly, disruptive, or infeasible. This temporal gap between planning and execution remains a persistent challenge for effective project control.

The consequences of late error detection manifest in well-documented industry-wide problems of delays and cost overruns. Global construction performance studies indicate that time and budget deviations are widespread, with a significant portion of construction projects exceeding planned durations and costs (Flyvbjerg et al. 2002; Cantarelli et al., 2013). Highly integrated scopes such as MEP are particularly prone to such deviations because misalignments accumulate across trades and require iterative rework cycles. Furthermore, traditional monitoring techniques, such as manual inspections, paper-based checklists, or 2D drawings often limit the ability of project managers to obtain an accurate, real-time understanding of construction progress or emerging risks. As a result, decision-making tends to be reactive rather than proactive, reducing opportunities for early intervention.

In recent years, Augmented Reality (AR) has received growing attention to improve visualization and communication in construction environments. By superimposing digital information directly onto physical space, AR can provide workers and managers with intuitive insights into planned tasks, component locations, and spatial constraints (Billinghurst et al., 2015). Earlier research has demonstrated that AR can support construction activities such as layout, inspection, training, and safety management by making complex information easier to comprehend on-site (Kamat et al., 2011). When combined with sensor data or computer vision capabilities, AR systems can also help detect discrepancies between planned and actual conditions, thereby creating opportunities for early error identification. The integration of AR with BIM and progress monitoring tools has thus emerged as a promising direction for enhancing construction project management.

This paper proposes an integrated AR and CV approach aimed at supporting the scheduling and monitoring of construction projects, with a particular focus on MEP-intensive environments. The approach combines AR-based visualization of the construction schedule with automatic detection of installed components through CV techniques. This integration facilitates users to compare the planned and actual states of construction, facilitating earlier detection of deviations and more informed decision-making. The objective is to move beyond traditional, document-based progress tracking toward an immersive, data-driven project control system that can reduce errors, minimize rework, and improve adherence to schedule.

To demonstrate the feasibility and usefulness of the proposed approach, a prototype system was developed and tested partly in a laboratory setting and partly on-site within the construction of a large winery production and storage facility in northern Italy. This project provided a particularly relevant testing environment due to its complex MEP installations, tight construction timelines, and stringent quality requirements typical of industrial facilities. The pilot test allowed for an evaluation of the system's usability, accuracy, and potential benefits in supporting field operations. Preliminary findings suggest that AR-CV technologies can enhance situational awareness, streamline progress verification, and support proactive project control.

Overall, this research contributes to ongoing efforts to digitalize construction management by offering a practical solution for integrating AR and CV into project scheduling and monitoring workflows. By focusing on the challenges characteristic of MEP-intensive environments, the proposed approach addresses a critical gap in current construction management practices and offers new avenues for improving productivity, reducing errors, and enhancing coordination on construction sites.

Related works

In recent years, the literature on construction progress monitoring has increasingly focused on the development of digital pipelines integrating CV, BIM, Digital Twin (DT), and AR to support near real-time project control, effectively rendering traditional manual, episodic, and subjective approaches obsolete. Recent review studies highlight that the topic is no longer limited to the automation of data capture but is increasingly oriented toward the development of closed-loop control systems, in which as-built observations directly inform the comparison with as-planned data through BIM. Within this context, traditional monitoring methods based on site inspections and manual reporting are still widely used but are considered inadequate for complex and dynamic projects, particularly when frequent and objective assessment of progress is required (Reja et al., 2022; Pal et al., 2023; Samsami, 2024).

Research on CV applied to the construction industry primarily focuses on the comparison between as-built and as-planned conditions through BIM models. Recent advancements show a shift from simple recognition of whether an activity has been completed to more granular, activity-based methods. A representative example is the work of Yang et al. (2023), who proposed a YOLOv8-based system for the automated monitoring of window installation progress. Several studies emphasize that the reliability of CV models is strongly influenced by site conditions, such as lighting variations or the presence of occluding objects that may interfere with visual inspection, as well as by the limited availability of annotated datasets and the difficulty of recognizing partially installed elements (Yu et al., 2025; Yue et al., 2025). In the MEP domain specifically, point cloud-based approaches have shown that deep learning networks can accurately segment pipe components even from poorly scanned data, provided that the domain gap between BIM generated synthetic training data and real as-built scans is explicitly addressed through feature and label alignment strategies (Yu et al., 2025). In particular, point clouds of MEP scenes are inherently affected by severe occlusions due to the dense overlapping of components, which degrades the performance of downstream recognition and classification tasks if left unaddressed (Yue et al., 2025). Both Yu et al. 2025 and Yue et al. 2025 demonstrate that BIM models can serve as a scalable and cost-effective source of synthetic annotated training data, directly mitigating the scarcity of labeled industrial datasets that represents one of the primary bottlenecks in applying CV to MEP environments (Yu et al., 2025; Yue et al., 2025).

Pal et al. (2024) propose a framework, which combines BIM, semantic segmentation, and ortho-view synthesis, also leveraging Neural Radiance Fields (NeRF), to estimate activity completion percentages with an average error below 6%, overcoming the limitations of methods that only detect the presence or absence of elements. Many studies aim to optimize the acquisition of point clouds for integration and comparison with BIM models. Some approaches involve SLAM-based mobile mapping devices to capture point clouds and panoramic images in indoor environments. Vassena et al. (2023) highlight the potential of more continuous workflows but also the persistence of issues related to semantic interpretation and automated understanding of point clouds, which negatively affect the real-time capabilities of DT systems. Other research explores neural rendering techniques and lightweight, photorealistic 3D representations. Studies on NeRF show that construction site scenes can be used not only for visualization but also for BIM comparison and progress estimation, often relying on handheld smartphone-captured video (Jeon et al., 2024). More recent work is also exploring 3D Gaussian Splatting and hybrid workflows to improve coordination, immersive visualization, and the quality of as-built versus as-planned comparison (Liao et al., 2025). These developments indicate that CV for monitoring is no longer limited to 2D image detection and segmentation but is increasingly merging with scene representation techniques, digital twin systems, and visual analytics.

Regarding AR technologies, recent literature confirms that their main value lies not only in the visual overlay of BIM models onto the real environment, but also in their ability to make project information, construction sequences, geometric deviations, and coordination issues immediately interpretable on-site (Sidani et al., 2021). The review by Bhatarai et al. (2025) describes BIM-AR integration as a digital-physical bridge extending across the lifecycle, with expected benefits in design optimization, rework reduction, and contextual data access. At the application level, recent studies show that AR integrated with scheduling and BIM can support real-time progress tracking (Arvikar et al., 2025), while in the MEP domain AR has proven particularly promising for verifying complex installations, enabling direct comparison between the as-built condition and design geometry within the physical environment (Girgin et al., 2023).

More recently, research has addressed the convergence of CV, BIM, DT, and AR. These technologies are no longer treated as independent modules but as components of a unified monitoring and inspection architecture. For instance, Tao et al. (2024a) propose a passive AR inspection framework that integrates object detection, 3D projection, digital twin-driven recognition, and AR visualization. Tao et al. (2024b) investigate different methods and their combinations for recognizing construction progress directly through AR, by overlaying BIM models onto captured images. At a broader scale, recent studies show that the integration of CAD, BIM, immersive technologies, and advanced scanning techniques can yield measurable benefits even in highly complex structural and MEP coordination scenarios, reducing rework and review times (Liao et al., 2025).

Within this context, the present work aligns with the most recent research direction by proposing an integrated AR-CV framework, in which AR is not used solely as a visualization tool, but as an operational interface for construction progress recognition, task visualization, and real-time monitoring, contributing to a more immediate and integrated connection between site conditions, BIM-based planning, and decision-making support.

AR-CV based Construction Management

The proposed approach consists of three modules: 1) Planning with AR, where the structure and level of detail is defined. 2) Scheduling with AR, where based on module "1 Planning" the components/objects that are scheduled for installation are visualized in AR. 3) Monitoring with AR and CV where the scheduled objects/components in AR are compared with the installed objects in reality by means of CV. In the proposed approach scheduling is based on monitoring implementing the so- called "rolling scheduling" approach. In this way, the construction work is scheduled in increasing levels of detail as the project progresses, rather than defining the entire schedule in detail from the start. The system was developed in Unity 2020.3.42f1 by using the Mixed Reality Toolkit (MRTK) 2.8 and deployed on the Head Mounted Display (HMD) Microsoft Hololens 2. Figure 1 shows the AR-CV based approach for construction management.

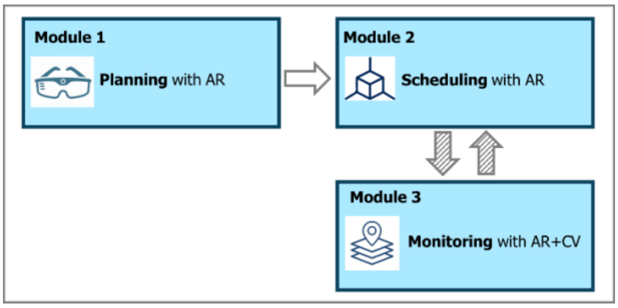

Figure 1: Schematic representation of the AR-CV based approach for construction management

Module 1 – Planning with AR

Module 1 is used to structure and define the Level of Detail (LoD) of the BIM, ensuring consistency between data acquisition, modelling, and downstream visualization processes. The definition of LoD within this module establishes clear modelling requirements aligned with the intended use of the digital model, particularly for AR visualization and CV–based monitoring. As a first step, a digital point cloud of the existing environment was generated using the Leica BLK2GO 3D laser scanner. This mobile scanning device enabled rapid acquisition of high-density spatial data while maintaining sufficient geometric accuracy for BIM modelling purposes. The resulting point cloud served as the primary geometric reference for the creation of the BIM model, which was developed using ArchiCAD version 27. The modelling process adhered to the LoD specifications defined in Module 1, ensuring that only the necessary geometric and semantic information was included.

The point cloud–based BIM model constitutes the foundation for the digital model used in AR visualization. By directly deriving the BIM geometry from the scanned data, spatial coherence between the physical environment and the virtual model is preserved, which is essential for accurate AR alignment and user interaction. This approach supports both visualization and spatial validation. In parallel, the planning module was employed to define the object structure and coding system required for AR visualization and monitoring. Each BIM object was assigned a standardized classification and unique identifiers, enabling seamless integration with the CV based monitoring approach. This structured coding framework allows selected elements to be visualized in AR and subsequently monitored in real time, supporting object recognition, status tracking, and progress analysis.

Module 2 - Scheduling with AR

Figure 2 shows the interface for scheduling and monitoring the construction project by using the HMD Microsoft HoloLens 2. The buttons on the left side are used to show the scheduling for a specific week (KW = calendar week in German), the "tig" indicates if the installation of the scheduled week had been completed and by using the "Undo" sign the completion can be revoked. An important aspect is the accurate aligning and anchoring of the digital model to the real-world environment so that virtual objects appear in the correct position, orientation, and scale. This is also called AR registration. For this purpose, the Microsoft QR Code Tracking Package in Unity was used and 2 QR codes were set for the AR registration.

Figure 2. Interface for scheduling and monitoring by using the HMD

Module 3 - Monitoring with AR and CV

Module 3 is used to monitor the installation of the components on-site based on the scheduling. The complete system operates as a spatial correspondence estimator to quantify physical construction progress relative to the digital model through a multi-stage computation pipeline. The workflow begins with QR code detection, which establishes a spatial anchor that links Windows Perception Spatial Graph coordinate system to Unity's reference frame. This alignment ensures that the reference BIM and the spatial reconstruction produced are expressed in a common coordinate frame. Such normalization is essential as overlap estimation, and voxelization requires the same origin, orientation, and scale. To represent the real world, we used the HoloLens's 2 SLAM algorithm that generates view-dependent spatial mesh representing partial observations of the physical environment (SLAM, 2026).

In contrast, the reference BIM is deterministic and hierarchically structured, consisting of multiple geometric components that together encode construction elements, assemblies, and sections. Upon user-triggered comparison, both the reference geometry and the sensed spatial reconstruction are discretized through voxelization at a fixed spatial resolution of 5 centimeters. This process converts continuous surface meshes into discrete spatial occupancy representations that enable efficient comparison. Voxelization relies on the triangle-box intersection based on the Separating Axis Theorem (SAT), ensuring accurate surface coverage (Ericson, C., 2004). The SAT is a collision detection method, which determines intersection by testing for the existence of a separating axis such the projected intervals of the objects do not overlap. The system then computes the intersection over union (IoU) between the aggregated reference representation and the sensed environment to quantify spatial correspondence. Specifically, for each hierarchical node n , IoU is defined as the ratio between the number of voxels shared by the reference and sensed representations and the total number of voxels belonging to either representation. The reference voxel set V_n represents the aggregated spatial occupancy of node n in the reference hierarchy, while V_s denotes the voxel set corresponding to the sensed environment. Matched and total occupancy information is subsequently propagated recursively from lower-level components to higher-level nodes through bottom-up aggregation in the scene graph. Equation 1 shows the IoUn metric where n indexes a hierarchical reference node.

$$IoU_n = \frac{(|V_n \cap V_S|)}{(|V_n \cup V_S|)} \tag{1}$$

This bottom-up aggregation can be interpreted as a completion metric that estimates the degree of spatial correspondence for each construction unit. The resulting completion values are interpreted as empirical indicators of construction progress rather than exact geometric truth, explicitly accounting for the downward bias introduced by incomplete sensing. Module 3 was tested exclusively under laboratory conditions due to constraints encountered during the case study implementation. Immediately after installation, the pipes were covered as part of the standard construction process, preventing direct visual access required for the deployment and validation of the proposed approach on-site. As a result, laboratory testing was adopted to ensure controlled conditions for evaluating the functionality and performance of module 3.

Testing

The proposed approach was pilot tested partly in a laboratory setting and partly on-site within the construction of a large winery production and storage facility, where the construction intervention was focused on the realization of large underground cellar spaces dedicated to bottle storage. The case study company is a small enterprise located in Northern Italy and specialized in Heating, Ventilation and Air Conditioning (HVAC). The project considers the execution of technical installations within extensive subterranean open-plan environments. The industrial partner involved in the study was responsible for the on-site assembly of building services systems MEP, within these spaces.

Figure 3 shows the structuring of the BIM model as basis for the scheduling and monitoring of the case study. The size of section 1 is 17.80 m x 21.70 m, section 2 has a size of 13.50 m x 39.00 m and section 3 has a size of 13.00 m x 36.00 m.

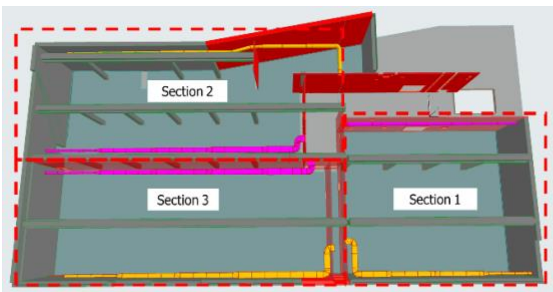

Figure 3. BIM model and structure of the case study

This case study introduced two main challenges: (i) the exceptionally large scale of the environments, characterized by open spaces, and (ii) the limited lighting conditions present during on-site testing activities. The solution deployed on site demonstrated high accuracy in hologram-to-reality alignment, maintaining geometric consistency between the physical environment and the digital model. However, the HMD initially experienced reduced spatial tracking performance due to insufficient illumination. This critical aspect was successfully addressed by installing temporary artificial lighting, which restored stable tracking conditions and enabled the continuation of the experimental activities.
Figure 4 shows module 2 and specifically the weekly scheduling in AR of the installation of air exchange pipes in sector 3 by using the Microsoft Hololens 2 HMD.

The results demonstrate that the AR–based visualization has great potential, even when applied to large-scale construction sectors. The spatial alignment between the digital model and the physical environment enables immediate identification of clashes and intersections among building elements, supporting rapid detection of potential conflicts. Furthermore, according to the foreman of the case study company, the integration of scheduling information into the visualization environment made construction sequencing tangible, allowing temporal aspects of the project to be intuitively understood and facilitating improved comprehension of planned activities and their spatial implications.

Figure 4. Module 2 weekly scheduling in AR of the installation of air exchange pipes in sector 3

Figure 5 shows the testing of module 3 in the laboratory environment.

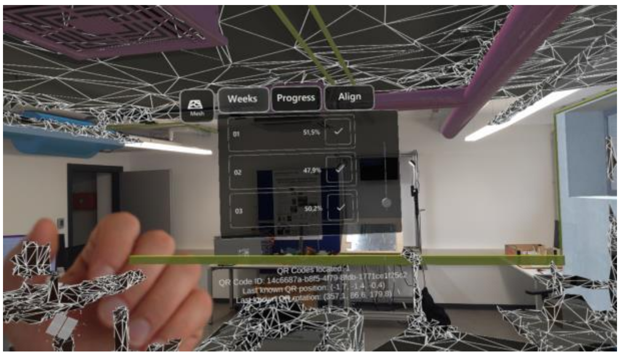

Figure 5. Testing of module 3 in laboratory settings

Figure 6 shows the 5 main component groups that were used to test module 3: A) The fan coil unit, B) the fan pipe supply connected to the unit, C) the wall channel for covering electrical wires, D) electrical pipes for the ventilation system and the writing desk plugins and E) the air exchange pipe system.

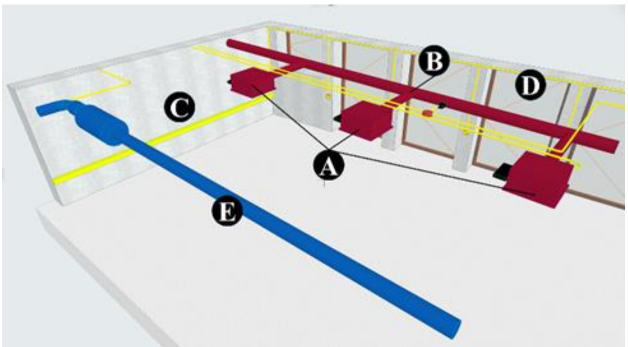

Figure 6. Component groups used for the testing of module 3

Table 1 shows the results of the lab tests where the IoU indicator was used according to Equation 1. Two tests in August 2026 were done.

Table 1: Lab test results of module 3

Object name and acronym	Intersection over Union IoU [%] – test 1	Intersection over Union IoU [%] – test 2
Fan coil unit (A)	48.00	77.80
Fan pipe supply (B)	78.10	62.30
Wall channel (C)	75.00	37.50
Electrical pipes (D)	54.7	45.60
Air exchange pipe (E)	91.4	63.60

According to the test results, electrical pipes D) and wall channels C) exhibit comparatively lower values of the Intersection over Union (IoU) ratio, indicating greater difficulty in achieving accurate spatial overlap for these elements. This behaviour can be attributed to their reduced cross-sectional dimensions and partial occlusions within the scene. In contrast, air exchange pipes E) and fan supply components B) demonstrate relatively high IoU values, reflecting more reliable detection and spatial correspondence. The larger geometric dimensions and clearer visibility of these elements contribute to improved detection, confirming the sensitivity of the IoU indicator to object scale and visual accessibility.

Discussion

The results indicate that the proposed AR–CV system enables a significantly faster detection of potential planning and execution errors when compared to traditional inspection and coordination methods. By superimposing digital information directly onto the physical environment, discrepancies between the planned and the as-built conditions can be identified in real time, supporting prompt corrective actions and reducing the risk of error propagation during construction.

The findings further demonstrate that the visualization approach remains effective even in large-scale construction projects. Despite the increased spatial complexity and scale, the system maintained sufficient clarity and spatial accuracy, allowing users to navigate extensive construction sectors while preserving meaningful contextual information. This highlights the scalability of the AR-based visualization framework for complex construction environments.

The proposed AR–CV system addresses key limitations in current methods for scheduling and monitoring MEP construction projects. Unlike traditional approaches that rely heavily on large, annotated datasets, which are often scarce or costly to obtain in construction contexts, the proposed approach operates without the need for pre-labeled training data, enhancing its scalability and practical deployment. Furthermore, the AR–CV system tightly integrates scheduling with real-time monitoring, enabling dynamic adaptation to the inherent variability and uncertainty of construction processes. This interlinking facilitates more responsive progress tracking and decision-making. Additionally, while existing CV approaches struggle to accurately recognize partially installed components, Module 1 of the proposed system introduces a flexible level-of-detail definition, allowing robust detection and classification even in intermediate installation states. Collectively, these features contribute to a more adaptable and reliable solution for managing complex MEP construction workflows.

However, the analysis also reveals that the perspective of visualization plays a critical role in the evaluation of the IoU indicator (Table 1). Variations in viewing angle and distance influence the apparent overlap between detected objects and their corresponding digital representations, thereby affecting IoU values. This becomes also evident considering the discrepancies between test 1 and test 2 visualized in Table 1. This suggests that IoU-based performance assessment in AR–CV applications should account for viewpoint-dependent effects.

Moreover, the performance of the AR–CV construction management system was found to be highly sensitive to low-light conditions. Insufficient illumination negatively impacts image quality and feature extraction, leading to reduced detection accuracy and lower IoU values. This limitation highlights the need for controlled lighting conditions or the integration of additional sensing modalities to improve robustness in real-world construction environments.

Finally, the results indicate that the IoU indicator is particularly sensitive to objects that are not spatially free or detached on all sides, such as elements attached to walls or partially occluded components. In such cases, limited visible surfaces reduce the measurable overlap between detected and reference objects, leading to lower IoU values. This observation suggests that complementary evaluation metrics may be required to fully assess system performance for attached or constrained building elements.

Conclusion and outlook

Mechanical, Electrical, and Plumbing (MEP) systems involve spatial coordination and often complex installation sequences, making schedule adherence and progress monitoring particularly challenging in construction projects. This paper proposes a framework that leverages Augmented Reality (AR) and Computer Vision (CV) to enhance scheduling support and real-time monitoring in MEP construction. The approach combines BIM-based planning data with on-site AR visualization to provide field personnel with intuitive, context-aware guidance on installation tasks and sequencing constraints. By using CV algorithms an automatically detection of MEP components from site images and video streams becomes possible. This enables objective progress measurement and early identification of deviations from planned schedules. By fusing AR-enabled human-centric decision support with automated CV-based performance tracking, the system facilitates more accurate schedule updates, reduces rework caused by miscoordination, and improves communication on-site. The paper proposes a prototype that has been developed in Unity for the Head Mounted Display HoloLens 2. The AR-CV prototype had been pilot tested partly in a laboratory setting and partly on-site by using as case study the construction of a large winery production and storage facility in northern Italy.

Future research will focus on further enhancing the monitoring capabilities of the proposed system. First, Module 3 will be improved to understand the user's point of view, increasing robustness to viewpoint misalignment and occlusions during on-site data capture. Second, complementary evaluation metrics will be investigated to more comprehensively assess system performance, particularly for attached or geometrically constrained building elements where standard detection measures may be insufficient. Finally, extensive empirical testing of the monitoring module will be conducted on active construction sites to evaluate its accuracy, reliability, and practical usability under real-world conditions.

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