Towards a Digital Twin construction system based on a data-centred approach for construction progress monitoring: Preliminary Results.

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Abstract:

Construction progress monitoring remains a challenge due to the limitations of manual inspection methods and fragmented information workflows, which can affect project control and decision-making. This paper presents a BIM-based Digital Twin framework that establishes a feedback loop between the physical construction site and its digital representation by integrating laser scanning, BIM-based scheduling, and simulation. A web-based system was developed to demonstrate the proposed concept and validate the integration of the different components within a unified workflow. The framework combines scan-vs-BIM progress assessment, schedule updating, and discrete-event simulation to connect observed construction status with future project analysis. Rather than aiming to implement fully automated algorithms, the proposed system focuses on demonstrating the feasibility of the approach using accessible data sources. The results highlight the potential of data-centred Digital Twins to support construction monitoring, schedule control, and informed decision-making.

1. Introduction

Construction progress monitoring (CPM) plays a critical role in ensuring project quality, safety, and cost control. Conventional monitoring methods primarily rely on manual inspections, paper-based reporting, and photographic documentation. These approaches are often time-consuming, prone to human error, and difficult to scale given the large volume of data generated on construction sites (Jiang et al., 2022; Zhang et al., 2025). Moreover, they often fail to accurately capture the actual state of the works, limiting the quality of information available for decision-making throughout the project lifecycle. Despite these operational challenges, continuous and reliable progress monitoring remains essential for ensuring compliance with project schedules, quality standards, and health and safety regulations (Li et al., 2022; Mirzaei et al., 2023).

Recently, Building Information Modelling (BIM) and Digital Twins (DTs) have been adopted in the construction industry, offering powerful capabilities for real-time progress monitoring and data-driven decision making (Saif et al., 2024). BIM has become the standard for managing design and planning information worldwide while DTs provide digital replicas of the built environment, continuously enriched with information captured directly from the construction site. Extending BIM to fully DT requires the integration of dynamic, geospatially accurate *as-built* data with the design model. Interoperability is a key requirement for this integration, ensuring that building information can be shared and utilized seamlessly across different software platforms and stakeholders.

Recent advancements in 3D data acquisition technologies have enabled quick capture of the construction sites. Point cloud data accurately represents *as-built* state of building, allowing progress monitoring with high geometry fidelity. In practice, however, the captured point clouds require the automatic processing, including segmentation, classification, and comparison with BIM elements, to assess the actual progress against the planned model.

This work proposes the development of a data-centred DT framework for the construction industry, with the primary objective of contributing to the automation of progress monitoring, and enabling managers to utilise geospatial data to support decision-making and improve project planning and scheduling. The proposed system overcomes the limitations of traditional progress monitoring approaches by establishing a closed-loop digital workflow that seamlessly integrates real-world data with digital planning and simulation models. Rather than focusing on the implementation of fully automated algorithms, this work presents a web-based system aimed at demonstrating the proof of concept and validating the proposed framework.

2. Related work

Given the importance of CPM to ensure compliance with schedules, quality requirements, and safety regulations, research has increasingly focused on automating CPM through the integration of reality capture technologies with BIM. Within this automated paradigm, site monitoring tasks are broadly divided into geometric quality assessment and progress monitoring, two complementary domains. While quality assessment provides the spatial baseline by verifying components against BIM tolerances (González-Cabaleiro et al., 2024), CPM extends this analysis over time to evaluate construction progress and identify schedule deviations before they lead to delays and cost overruns (Jiang et al., 2022, Kopsida et al., 2023).

The dominant paradigm for automated CPM is the Scan-vs-BIM workflow, where terrestrial laser scanning (TLS), photogrammetry, RGB imagery, or depth sensors are registered with 4D BIM models to compare the *as-built* and *as-planned* states (Jiang et al., 2022). Early approaches relied on manual or semiautomated point cloud registration and geometric comparisons (Bosche and Haas, 2008, Golparvar-Fard et al., 2011, Son and Kim, 2010), whereas recent studies increasingly exploit machine learning and deep learning techniques to improve segmentation, object recognition, and activity classification (Son et al., 2015). Representative solutions include SVM-based component classification after PCA/ICP registration (Kim et al., 2013), PointNet++ architectures for semantic feature extraction and BIM reconstruction (Huang et al., 2026), or Mask R-CNN combined with BIM to estimate indoor construction progress from image sequences (Wei et al., 2022), significantly improving automation and monitoring accuracy.

Recent research has expanded these approaches through the adoption of DT frameworks, which integrate BIM, reality capture, and data analytics into continuously updated virtual representations of construction sites.. For example, (Zhang et al., 2025) proposed a DT-based framework that combines BIM with multi-scale point cloud registration for automated bridge construction monitoring. More broadly, DTs enable anomaly detection, semantic progress tracking, and enhanced visualization by fusing point clouds, computer vision, and semantic information, supporting more informed and timely decision-making (Lu et al., 2020, Braun et al., 2020, Pal et al., 2023). In parallel, optimization techniques such as genetic algorithms have been proposed to support adaptive scheduling by combining project information with real-time progress and resource allocation (Yogi et al., 2026).

Despite these advances, most methods remain dependent on accurate BIM models, computationally expensive point cloud processing, and reliable registration between reality capture data and digital models (Kopsida et al., 2023). Their performance often deteriorates under occlusions, incomplete scans, cluttered environments, or non-standard construction elements (Kim et al., 2013, Huang et al., 2026). Moreover, most systems operate as periodic offline assessments rather than continuous monitoring platforms, delaying the identification of discrepancies and limiting their ability to support timely decision-making (Ekanayake et al., 2021). Consequently, despite significant advances in sensing, artificial intelligence, and DT technologies, existing approaches remain predominantly model-centred and focus on progress estimation rather than providing a fully data-centred, closed-loop framework capable of continuously integrating heterogeneous sensing data for proactive project control (Pal et al., 2023, Zhang et al., 2025).

3. Method

Automatic progress monitoring requires understanding the project status (*what it is done*) and the project intent (*what it is plan to do*). For this purpose, the system focuses on comparing the *as-designed* state of a construction project with its *as-built* condition, which is accurately captured using 3D laser scanning and evaluated by comparison against the BIM. This is achieved through the implementation of scan-vs-BIM matching, segmentation and classification algorithms. Then, the information extracted during this comparison is used to update the BIM in terms of status (geometry and semantics). At the same time, this information is used to define key performance indicators towards the redefinition of dependencies and reallocation of material and human resources. Although the concept of Digital Twin Construction is still under development, there is a common agreement in the need of using available standards and technologies. In this context, Industry Foundation Classes (IFC) is the core data model around which the DT system is extended.

The proposed method is implemented through a web-based system, with its functionalities organised into three computational modules that collectively form an integrated closed-loop workflow. These modules are described in detail in the following subsections. It should be noted that the developed algorithms are not intended to address the full complexity of real-world construction data processing; rather, they aim to demonstrate the feasibility of the proposed workflow and the integration of its key components. Accordingly, simplified implementations are adopted to validate the concept and evaluate the interaction between the different modules within the system.

3.1. Scan-vs-BIM module.

This module serves as the foundational data ingestion and comparison layer. At this stage, the web-based application performs automated geometric verification of construction progress. Two primary data sources are required as input:

- The *planned state*, represented by the BIM model as an IFC file format.
- The *as-built state*, captured as a 3D point cloud scan (in PLY format) from the construction site.

As the scanned data and the BIM are initially expressed in different coordinate systems, the first step of the process consists of establishing a common coordinate system between them (Figure 1). To achieve this, the algorithm samples the BIM mesh surfaces to generate a synthetic point cloud that serves as the reference geometry. A coarse registration is then performed using an Axis-Aligned Bounding Box (AABB) approach, which translates the scanned point cloud to approximately match the position of the synthetic BIM point cloud. The registration is subsequently refined using the Iterative Closest Point (ICP) algorithm, which iteratively minimises the distance between corresponding points. The ICP process is configurable through parameters such as the maximum correspondence distance and the maximum number of iterations, allowing the alignment accuracy to be adapted to different datasets.

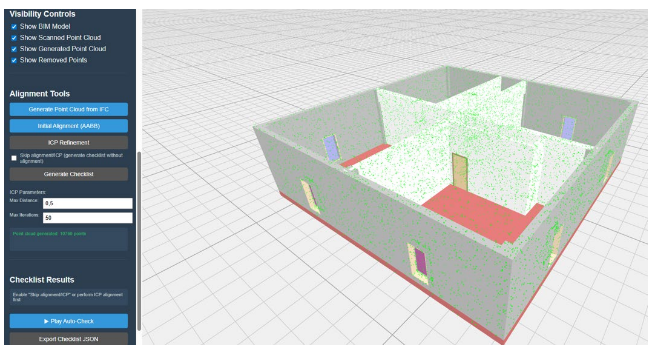

Figure 1. Aligment tools.

Once the two point clouds have been aligned, the algorithm compares the BIM geometry with the scanned point cloud to determine the construction status of each scheduled building element (e.g., walls, slabs, and beams) for a user-selected snapshot date, classifying them as either *Built* or *Not Built*.

Each element is evaluated independently based on a face coverage metric, which quantifies the proportion of the BIM surface detected in the scanned point cloud. The face coverage metric is computed by analysing the triangular faces of the IFC geometry and evaluating their correspondence with the *as-built* point cloud. First, the element mesh is cleaned to remove degenerate or duplicated geometry before analysis. After this preprocessing step, surface points are sampled from each triangular face and compared with nearby scanned points to determine whether the face is detected. A face is classified as detected when more than 50% of the sampled points are covered by the scanned point cloud. The element's detected area percentage is then calculated as the ratio between the area of detected faces and the total mesh surface area. Considering that, for convex three-dimensional elements, a single viewpoint typically captures at most approximately 50% of the total surface area, an element is classified as Built when the detected-face area exceeds 25% of its total surface area. The results are presented through a checklist interface that provides both project-level statistics and element-level information. The generated output is a structured JSON checklist containing the detected construction status and associated metrics for each element, which quantifies progress and serves as the evidence base for the subsequent modules.

At the project level, the system reports the total number of scheduled elements, the number and percentage classified as *Built*, the number classified as *Not Built*, the number of elements still *Pending evaluation,* and the number of elements for which the verification process generated an error. In addition, point cloud statistics are displayed, including the total number of points in the original scan, the number of points removed during the verification process, and the number of remaining points available for subsequent element matching. At the individual element level, the checklist reports the element identifier and IFC type (e.g., Wall_001 (IfcWall)), the element surface area, the percentage of the surface successfully matched with the scanned point cloud, and the number of mesh faces together with the number of faces identified as detected.

3.2. Schedule update module.

This module acts as the feedback loop, translating physical progress data from the scan-vs-BIM module into updates and analysis of the project plan. It is a Python-based module that takes the IFC file containing the original project schedule and the binary completion status of construction elements at a specified observation date as inputs. Its core function is to compare the observed construction progress with the planned schedule, identify deviations, and revise the project timeline by accounting for delays and propagating their effects through task dependencies and hierarchical relationships.

The algorithm estimates the impact of incomplete tasks on the remaining project schedule. For each task associated with a construction element classified as *Done* or *Not Done*, the module evaluates whether the planned duration remains valid or requires adjustment. When a task is identified as *Not Done* at the scan date and no additional progress information is available, its expected duration is estimated using a Mean Squared Error (MSE)-based approach. Assuming that task progress increases linearly over time and that the unknown progress level follows a uniform distribution between 0 and 1, the expected progress value that minimises the estimation error is p = 0.5. Therefore, the estimated total duration of an incomplete task is calculated as twice the elapsed time since its start.

Based on the updated task durations, the module recalculates the finish dates of delayed tasks and propagates the resulting changes to the start and finish dates of downstream activities dependent on their completion. The resulting schedule reflects the estimated impact of the observed construction status on the overall project timeline. The module generates an updated IFC file containing the revised schedule, a diff file documenting the changes, a detailed JSON report for auditability, and comparative Gantt charts (Figure 2). These outputs provide a traceable link between the observed construction status and the evolution of the BIM-based project schedule.

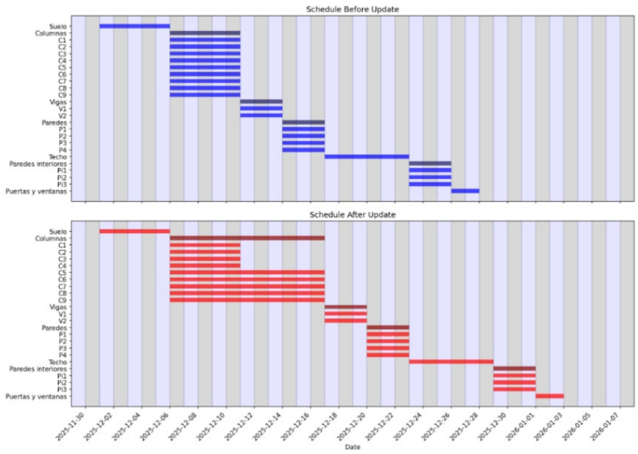

Figure 2. Gantt chart comparison example.

3.3. Prediction module.

This module provides forward-looking, predictive capabilities by transforming the updated digital schedule into a dynamic simulation model for construction performance analysis. The module uses the schedule information contained in the IFC file to automatically generate a Discrete Event System Specification (DEVS)-based simulation model of the construction process. The IFC file provides the baseline project structure, including task definitions, planned durations, temporal information, hierarchical relationships, and task dependencies, which are used to construct the simulation network.

The simulation represents construction progress through a discrete-event approach, where project evolution is modelled as a sequence of events, including task activation, task completion, resource allocation changes, and environmental condition updates. This approach enables the evaluation of how external factors and uncertainties influence project execution over time, combining historical progress information from the updated schedule with future projections to assess potential project outcomes under different scenarios.

The model incorporates configurable constraints related to weather conditions, resource availability, and task duration uncertainty. Environmental conditions are represented through a weather model that modifies task productivity, reducing efficiency under adverse conditions and suspending activities during extreme events. Resource availability is represented through a resource model that enables the simulation of different workforce scenarios, from unlimited resource availability to constrained team capacities. Additionally, an uncertainty model introduces stochastic variability in task durations through probability distributions, accounting for the inherent uncertainty associated with construction activities.

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Based on these constraints, the simulation follows a set of simplified rules governing task execution and schedule evolution. Under normal conditions, construction teams operate at full productivity (100% efficiency), and task durations are determined by their base durations modified according to a delay distribution derived from the empirical analysis reported by Anastasopoulos et al. (2012). During rainfall events, productivity is reduced by half, doubling task durations, while storm events suspend construction activities until suitable conditions are restored. Construction teams are modelled as homogeneous units, with each task requiring one complete team before execution can begin. Task sequencing follows a dependency-based logic, meaning that an activity can only start after all predecessor tasks have been completed. These assumptions provide a simplified representation of construction dynamics while enabling the simulation of schedule evolution under varying environmental, resource, and uncertainty conditions.

The DEVS formalism provides a modular and hierarchical framework in which individual construction tasks and influencing factors are represented as independent components that interact through predefined event exchanges. In the proposed implementation, construction task models are automatically generated from the IFC schedule topology, ensuring that the simulation structure remains consistent with the original project plan and preserving the relationships between activities defined in the BIM model. Independent modifier models, including weather, resource availability, and uncertainty, influence task execution through event interactions without altering the underlying task network.

The resulting DEVS-based simulation model enables Monte Carlo analysis by executing multiple simulation runs under different combinations of environmental conditions, resource constraints, and stochastic task durations. The collected results provide probabilistic information about project evolution, including expected completion times, project completion probability distributions, resource utilization metrics, and the estimated influence of external factors on schedule performance. By integrating the IFC-based DT representation with predictive simulation capabilities, the proposed module provides a decision-support framework for schedule forecasting, risk assessment, and the evaluation of potential project scenarios through *what-if* analysis.

4. Implementation and results

The implemented system follows a modular architecture, that enforces clear separation between feature modules and core modules, establishing a unidirectional dependency flow that promotes maintainability and testability (Figure 3).

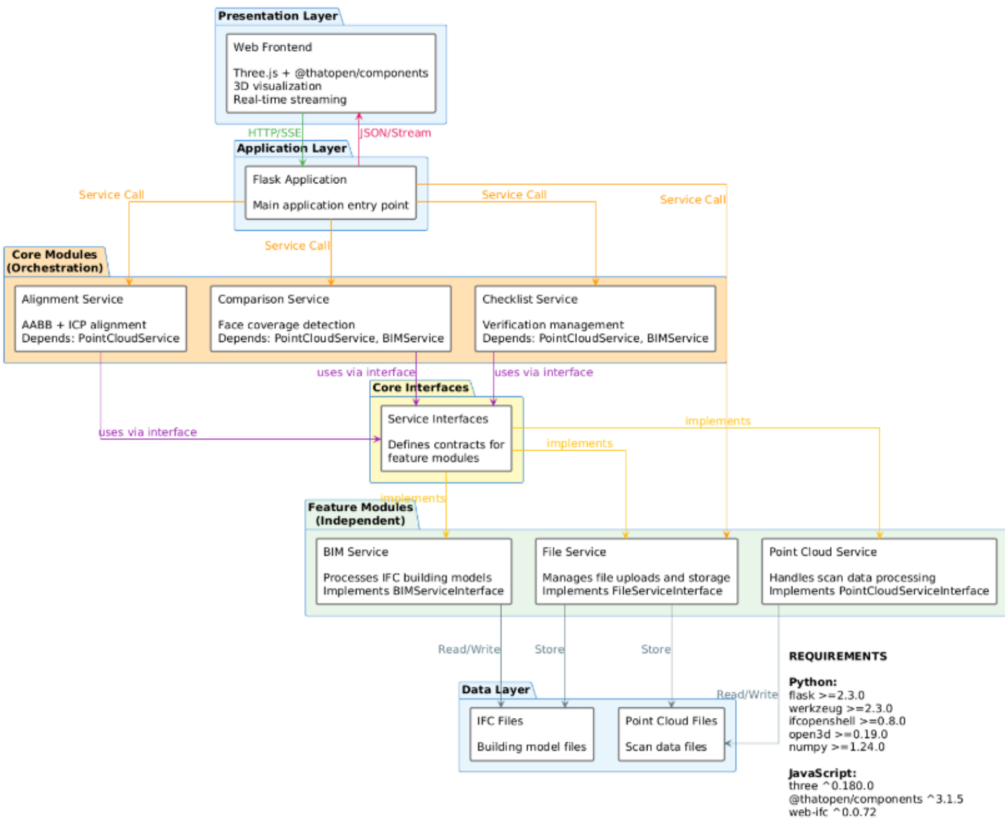

Figure 3. System architecture.

The point cloud and BIM models presented in the figures are based on a simulated construction scenario developed for testing and validating the proposed framework. The scan-vs-BIM comparison algorithm was implemented by processing IFC triangular faces and the *as-built* point cloud. Element meshes were first cleaned to remove duplicated geometry. For each triangular face, 50 surface points were sampled and evaluated against nearby scan points within a 0.1~m radius using projection and point-in-triangle validation. Faces were classified as detected when more than 50% of the sampled points were covered, and elements were classified as *Built* when the detected-face area exceeded 25% of the total surface area. Results are presented in a check-list as the one shown in Figure 4.

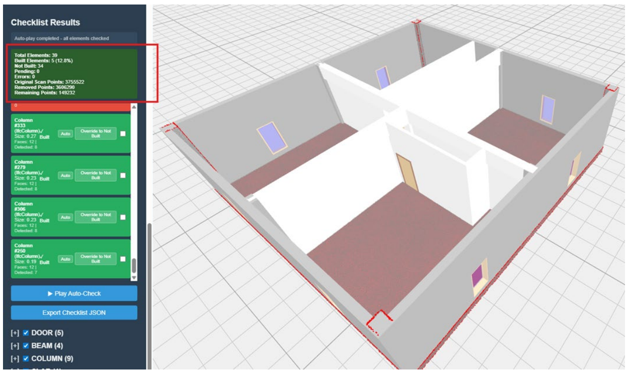

Figure 4: Results from the scan-vs-BIM module.

With the *schedule update module*, the IFC-based project schedules were modified according to the completion status of building elements obtained from the checklist. The implementation automatically adjusted task durations and dates for elements classified as not built, propagated changes through parent-child task relationships, and updated dependent activities according to the defined task dependencies (Figure 2).

Finally, the prediction module requires the definition of a set of user-defined parameters before execution. Weather conditions can be modelled using either a *random* mode, where transitions between weather states are generated according to a probability matrix, or a *fixed* mode, where a constant condition is maintained throughout the simulation. Resource availability can be configured as *fixed*, representing a predefined team capacity, or *unlimited*, allowing tasks to be scheduled solely according to their dependencies. Additionally, a temporal cutoff timestamp is defined to separate the fixed phase, based on available planned or updated schedule information before the cutoff date, from the simulated phase used to project future project evolution.

Figure 5 presents the Gantt chart of the project simulation under ideal conditions, assuming perfect weather, unlimited resource availability, and no uncertainty in task durations, resulting in the original planned schedule. In contrast, Figure 6 shows the same project simulated under random weather conditions, a fixed availability of four construction teams. The cutoff timestamp splits the timeline, creating a fixed phase using planned data before the cutoff date and the simulation phase after it.

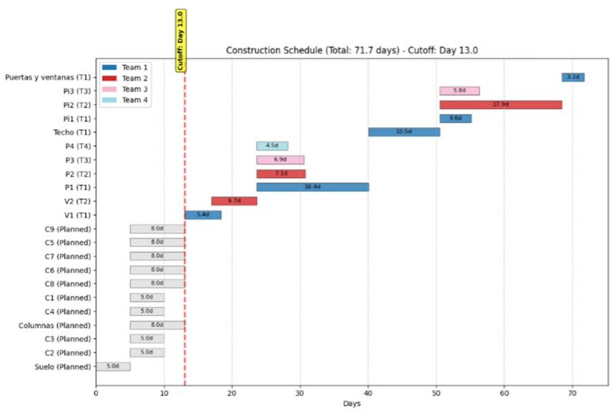

Figure 5. Perfect conditions simulation example.

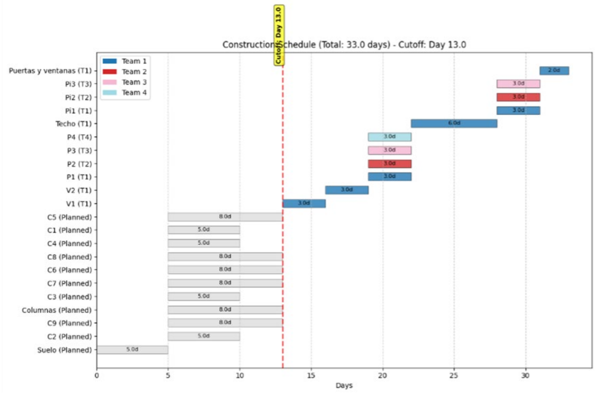

Figure 6. Scenario simulation example.

5. Conclusions

This paper presents a BIM-based DT framework that establishes a feedback loop between the physical construction site and its digital representation by integrating laser scanning, BIM-based scheduling, and simulation capabilities. The proposed approach supports progress verification, schedule adaptation, and future performance analysis within a unified workflow.

Rather than aiming to implement fully automated algorithms, this work develops a web-based system to demonstrate the feasibility of the proposed concept and validate the integration of the different components within the framework. The results show that a practical DT feedback loop can be established using limited and accessible data sources. By connecting progress monitoring, schedule updating, and predictive simulation, the proposed framework provides a foundation for enhanced construction control and data-driven decision-making.

Future work will focus on extending the framework to more complex construction scenarios by implementing automated registration approaches capable of handling the variability associated with different construction phases. Instead of relying solely on geometric information, future developments will incorporate semantically enriched and instance-segmented elements to improve the assessment of component completion levels, including partially constructed elements. Additionally, the simulation capabilities will be enhanced by incorporating further construction constraints and sources of uncertainty to better represent project execution dynamics.

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References

Anastasopoulos, P. C., Labi, S., Bhargava, A., & Mannering, F. L. (2012). Empirical assessment of the likelihood and duration of highway project time delays. *Journal of Construction Engineering and Management*, 138(3), 390–398.

Bosche, F., & Haas, C. (2008). Automated retrieval of 3D CAD model objects in construction range images. *Automation in Construction*, 17(4), 499–512.

Braun, A., Tuttas, S., Borrmann, A., & Stilla, U. (2020). Improving progress monitoring by fusing point clouds, semantic data and computer vision. *Automation in Construction*, 116, 103210.

Ekanayake, B., Wong, J. K.-W., Fini, A. A. F., & Smith, P. (2021). Computer vision-based interior construction progress monitoring: A literature review and future research directions. *Automation in Construction*, 127, 103705.

Golparvar-Fard, M., Peña-Mora, F., & Savarese, S. (2011). Integrated sequential as-built and as-planned representation with D4AR tools in support of decision-making tasks in the AEC/FM industry. *Journal of Construction Engineering and Management*, 137(12), 1099–1116.

González-Cabaleiro, P., Túñez Alcalde, R. M., Albadri, M. S. A., Fernández, A., & Díaz-Vilariño, L. (2024). Control analysis of building under construction from indoor mobile mapping systems. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLVIII-4-2024, 213–220.

Huang, J., Xiao, Z., Ji, A., & Zhang, L. (2026). Lightweight semantic segmentation for construction progress monitoring using 3D point clouds. *Automation in Construction*, 183, 106765.

Jiang, Z., Shen, X., Ibrahimkhil, M. H., Barati, K., & Linke, J. (2022). Scan-vs-BIM for real-time progress monitoring of bridge construction project. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, X-4/W3-2022, 97–104.

Kim, C., Son, H., & Kim, C. (2013). Automated construction progress measurement using a 4D building information model and 3D data. *Automation in Construction*, 31, 75–82.

Kopsida, M., Brilakis, I., & Vela, P. A. (2023). A review of automated construction progress monitoring methods. *Proceedings of the 32nd CIB W78 Conference on Construction IT*.

Li, D., Liu, J., Hu, S., Cheng, G., Li, Y., Cao, Y., Dong, B., & Chen, Y. F. (2022). A deep learning-based indoor acceptance system for assessment on flatness and verticality quality of concrete surfaces. *Journal of Building Engineering*, 51, 104284.

Lu, Q., Xie, X., Parlikad, A. K., & Schooling, J. M. (2020). Digital twin-enabled anomaly detection for built asset monitoring in operation and maintenance. *Automation in Construction*, 118, 103277.

Mirzaei, K., Arashpour, M., Asadi, E., Feng, H., Mohandes, S. R., Bazli, M., (2023). Automatic compliance inspection and monitoring of building structural members using multitemporal point clouds. *Journal of Building Engineering*, 72, 106570.

Pal, A., Lin, J. J., Hsieh, S.-H., & Golparvar-Fard, M. (2023). Automated vision-based construction progress monitoring in built environment through digital twin. *Developments in the Built Environment*, 16, 100247.

Saif, W., RazaviAlavi, S., & Kassem, M. (2024). Construction digital twin: a taxonomy and analysis of the application-technology-data triad. *Automation in Construction*, 167, 105715.

Son, H., Bosché, F., & Kim, C. (2015). As-built data acquisition and its use in production monitoring and automated layout of civil infrastructure: A survey. *Advanced Engineering Informatics*, 29(2), 172–183.

Son, H., & Kim, C. (2010). 3D structural component recognition and modeling method using color and 3D data for construction progress monitoring. *Automation in Construction*, 19(7), 844–854.

Wei, W., Lu, Y., Zhong, T., Li, P., & Liu, B. (2022). Integrated vision-based automated progress monitoring of indoor construction using mask region-based convolutional neural networks and BIM. *Automation in Construction*, 140, 104327.

Yogi, M. R. A., Berawi, M. A., Latief, Y., & Sucahyo, Y. G. (2026). Construction task priority development using genetic algorithm: A numerical approach for progress and resource allocation. *Journal of Soft Computing in Civil Engineering*, 10(1).

Zhang, H., Yan, J., Yang, J., Meng, W., & Chen, S. (2025). Two-stage point cloud registration using multi-scale edge convolution for digital twin-based bridge construction progress monitoring. *Automation in Construction*, 178, 106415.