Artificial Intelligence and Computer Vision for Construction Progress Monitoring: A Bibliometric and Thematic Review (2005–2026)

Kevin Torres [1], Luis A. Cristancho [1], Omar Sánchez [2], Rodrigo F. Herrera [1] and Karen Castañeda [1]

[1] School of Civil Engineering, Pontificia Universidad Católica de Valparaíso, Valparaíso 2374631, Chile
[2] Department of Civil Engineering, Pontificia Universidad Javeriana, Bogotá D.C., 111711, Colombia
torreskd@javeriana.edu.co, lcristancho@utb.edu.co, omar_sanchezr@javeriana.edu.co, rodrigo.herrera@pucv.cl, karen.castaneda@pucv.cl

Abstract - Reliable and timely construction progress monitoring remains challenging due to the dynamic, spatially complex, and visually cluttered nature of jobsite environments, where conventional inspection- and report-based approaches often yield subjective and intermittent assessments. This paper maps the adoption of artificial intelligence and computer vision for construction progress monitoring through a bibliometric and thematic review of 103 publications spanning 2005–2026. Using performance analysis and science mapping in Bibliometrix, the study characterizes scientific production, leading contributors, thematic structures, and topic evolution. Results indicate a marked growth and concentration of research output, led by the United States (61 publications) and China (43), followed by the United Kingdom (19), Germany (14), Australia (13), and South Korea (13). The thematic map reveals four interrelated research fronts: (1) computer vision as a transversal methodological core (e.g., machine learning, activity recognition, image processing, real-time monitoring), (2) construction progress monitoring as the primary application theme (strongly associated with deep learning, point clouds, object detection, and semantic segmentation), (3) photogrammetry and reality-capture pipelines as mature enabling technologies, and (4) BIM as an integration layer connecting field inference to planning and control. Trend analysis suggests a transition from early recognition and as-built modeling toward deep learning–driven, 3D-centric, and increasingly operational workflows. The findings provide an evidence-based agenda to strengthen benchmarking, generalize across sites, and tighten the coupling between vision outputs and project control systems.

Keywords – Artificial Intelligence; Computer Vision; Construction Progress Monitoring; Bibliometric Analysis; Trend Analysis

1 Introduction

The growing pressure to deliver construction projects within constrained schedules and budgets has heightened the need for reliable, objective, and continuous mechanisms to assess construction progress [1]. Conventional progress-monitoring practices, often reliant on manual inspections, periodic reports, and visual judgment, struggle to capture the dynamic and spatial complexity of construction activities [2]. As construction sites increasingly generate large volumes of visual data from fixed cameras, mobile devices, and aerial platforms, artificial intelligence and computer vision have gained prominence as technologies that transform visual information into structured indicators of project advancement [3]. Recent advances in deep learning and visual recognition enable automated detection of construction elements, activity states, and temporal changes directly from images and videos. These capabilities allow near-real-time progress evaluation, reduce subjectivity in reporting, and support more consistent performance tracking across project phases [4]. Furthermore, vision-based outputs can be aligned with planning and scheduling systems to provide data-driven insights into deviations between planned and actual progress. Despite the rapid expansion of technical solutions, research contributions remain dispersed across methods, application scenarios, and evaluation criteria, limiting the consolidation of knowledge in this field. A comprehensive understanding of how artificial intelligence and computer vision have been applied to construction progress monitoring, how research themes have evolved over time, and where methodological gaps persist is therefore essential. In this context, bibliometric and thematic analyses offer a systematic means to map scientific production, identify influential research streams, and highlight emerging directions in AI-enabled construction progress monitoring [5].

The rapid evolution of artificial intelligence and computer vision has significantly altered how construction processes are observed, measured, and analyzed, particularly in contexts marked by high visual complexity and continuous physical transformation. Vision-based technologies enable automated interpretation of site imagery, facilitating identification of construction elements, activity states, and temporal changes that are difficult to capture through conventional monitoring approaches [6,7]. Within construction management research, these developments have supported the transition from subjective, report-based progress assessments to data-driven, repeatable evaluation mechanisms. Deep learning architectures applied to images and videos have demonstrated the ability to track work execution, detect deviations from planned schedules, and provide quantitative indicators of progress with increasing accuracy [8]. At the same time, integrating visual outputs with planning, scheduling, and digital modeling environments has expanded the analytical capabilities of progress-monitoring systems. The advancement of Artificial Intelligence (AI) applied to construction progress monitoring is closely connected to the development of automation and robotics. Specifically, robotic inspection systems and autonomous monitoring platforms are increasingly playing a vital role in boosting efficiency and accuracy at construction sites. In recent years, automation has evolved from emerging technology to a key component of progress monitoring, especially through robotic inspection systems. Progress in this field enables the integration of AI for hazard prediction, real-time surveillance, and autonomous decision-making, leading to substantial improvements in tracking construction activities and reducing risk-related delays. Despite these advances, research remains fragmented across algorithms, data sources, and application contexts, often emphasizing technical performance without systematically relating findings to broader research trends. Furthermore, differences in evaluation metrics, validation strategies, and reporting practices hinder comparative assessment across studies. As a result, the absence of a consolidated view of how artificial intelligence and computer vision have been applied to construction progress monitoring limits the identification of dominant research streams and emerging thematic directions [9]. Addressing this limitation requires a structured synthesis of scientific production that captures methodological evolution, thematic concentration, and research gaps over time. In this regard, bibliometric and thematic analyses provide a robust framework for organizing existing knowledge and supporting the strategic development of AI-enabled research on progress monitoring.

Despite the increasing number of studies on artificial intelligence and computer vision in construction, the literature remains fragmented across methodologies, application scales, and analytical objectives, limiting a comprehensive understanding of the field's evolution [10–13]. Previous studies have developed algorithms for activity recognition, object detection, and progress estimation using images, videos, and sensor-based data [14–16], often demonstrating strong technical performance under controlled conditions. However, most research prioritizes algorithm development without systematically examining the evolution of research themes, evaluation methods, and application contexts over time. Consequently, it remains unclear which technological paradigms have driven the field, how dominant research streams have emerged, and where persistent gaps hinder practical implementation. To address these limitations, this study conducts a bibliometric and thematic review of publications from 2005 to 2026 on artificial intelligence and computer vision for construction progress monitoring. By integrating performance analysis, scientific mapping, and thematic evolution assessment, the study identifies influential contributions, dominant research clusters, and emerging thematic trends shaping the field's intellectual structure. Beyond descriptive analysis, the review highlights conceptual imbalances, methodological gaps, and underexplored connections between algorithmic development and real-world deployment in construction environments, providing a foundation for future research and the development of scalable, reliable, and data-driven progress-monitoring solutions.

2 Literature Background

The growing demand for objective, continuous assessment has positioned progress monitoring as a key area in digital construction. Conventional practices based on site visits and subjective reporting offer limited capacity to capture evolving spatial and temporal conditions [14,15]. The availability of visual data from cameras, UAVs, and mobile devices has driven adoption of AI and computer vision for automated evaluation [11]. Recent studies show that deep learning enables systematic interpretation of site imagery, identifying elements, activity states, and execution stages with reduced reliance on manual judgment [16,17]. These advances shift monitoring toward data-oriented paradigms, where measurable indicators replace qualitative descriptions. Yet diversity in analytical approaches, acquisition strategies, and validation procedures reveals fragmented trajectories, complicating knowledge consolidation.

A substantial body of work has developed vision methods to detect activities and estimate progress from images and videos. Early studies focused on object recognition and feature-based techniques, while recent contributions employ deep neural networks to capture complex spatial–temporal relation [18]. Several works report strong performance in recognizing work states and quantifying progress under controlled conditions [19]. Others link visual outputs with scheduling to detect deviations between planned and executed work [20]. Persistent challenges include limited transferability, sensitivity to environmental variability, reliance on context-specific datasets, and inconsistent evaluation metrics, which constrain comparability and generalization.

Beyond algorithms, attention has turned to how AI and computer vision research has evolved as a domain. While individual studies provide technical insights, fewer examine publication dynamics, thematic concentrations, and intellectual structures [10,21–23]. Addressing this gap requires approaches tracing evolution across methods and applications. Bibliometric and thematic analyses systematically identify influential publications, dominant streams, and emerging topics. By reviewing output from 2005–2026, this study offers a comprehensive view of the maturation of AI and computer vision in progress monitoring, highlighting enduring challenges, methodological shifts, and opportunities for scalable, reliable, data-driven solutions.

3 Research Method

3.1 Methodological rationale and scope definition

Research on AI and computer vision for construction progress monitoring has expanded rapidly, producing a heterogeneous and methodologically dispersed body of literature. Contributions differ in data types, analytical pipelines, validation strategies, and monitoring objectives, complicating the identification of dominant trajectories and consolidated paradigms. In this context, bibliometric analysis offers a reproducible framework to examine scientific production collectively, revealing structural patterns, thematic concentrations, and temporal dynamics beyond narrative or technology-centered reviews.

This study adopts a bibliometric and thematic review of peer-reviewed publications from 2005 to 2026, spanning early visual inspection and object recognition to recent advances in deep learning, 3D sensing, and data-intensive workflows. Three objectives guide the analysis: (1) evaluate the evolution and performance of scientific output, (2) characterize the intellectual and thematic structure, and (3) identify dominant and emerging trends shaping AI-enabled progress monitoring. These objectives provide a coherent foundation for interpreting methodological evolution and research priorities over time.

3.2 Selection of bibliometric techniques

The bibliometric methodology was designed to align directly with the research objectives, ensuring consistency between the analytical procedures and the evidence generated. Performance analysis was used to characterize the development of the field by examining publication growth, citation patterns, and the geographical distribution of scientific output, thereby identifying the countries, institutions, and research contributions that have shaped the evolution of artificial intelligence and computer vision applications for construction progress monitoring. To complement this assessment, citation-based indicators and collaboration networks were analyzed to evaluate scientific influence and knowledge exchange within the domain, revealing the central role of leading institutions, authors, and technological paradigms. In particular, the prominence of terms such as machine learning and deep learning among highly cited publications reflects the growing importance of data-driven approaches for automation and real-time monitoring in construction environments. The conceptual structure of the literature was examined through science-mapping techniques, including co-word analysis and thematic mapping, which enabled the identification of recurrent concepts, thematic relationships, and the relative maturity and relevance of different research streams. Finally, temporal trend analysis provided insight into the evolution of the field, highlighting a transition from early recognition-based and as-built modeling approaches toward deep learning-enabled, three-dimensional, and increasingly operational frameworks for construction progress monitoring.

Data collection and filtering process

Scientific data were collected from Scopus, chosen for its broad coverage of peer-reviewed journals in engineering, construction, and computer science, and its robust indexing standards. A structured search strategy was refined iteratively, combining preliminary inspection with team input. Keywords on artificial intelligence, computer vision, and progress monitoring were combined with Boolean operators to balance sensitivity and specificity.

The final search equation — [("construction progress" OR "progress monitoring" OR "progress tracking") AND ("computer vision" OR "image-based" OR "video-based" OR photogrammetry OR "visual inspection")] — targeted publications on visual data analysis, automated monitoring, and progress assessment. Records were refined through multi-stage filtering to ensure relevance and quality. Temporal limits (2005–2026) captured long-term evolution. Filters retained journal articles and reviews, excluding conference and editorial material, and focused on engineering, construction, and computer science. Titles, abstracts, and keywords were reviewed independently, with full-text checks for ambiguous cases. Inclusion required explicit use of AI or computer vision in construction progress monitoring and sufficient metadata for bibliometric analysis. In this study, conference proceedings were excluded from the bibliometric analysis mainly because they usually present preliminary results. While conferences offer valuable information and advancements, they tend to highlight initial findings that often lack the depth needed for a thorough analysis. By focusing on articles from scientific journals, the goal is to ensure a more consistent and comprehensive examination of the field's impact and emerging trends, leading to a more reliable assessment of the research landscape. This systematic process resulted in a curated corpus that supports reliable, reproducible bibliometric analysis.

3.3 Execution of bibliometric and thematic analysis

The bibliometric analysis was conducted in three stages: performance analysis, scientific mapping, and trend analysis. Performance indicators were computed using the Bibliometrix package in RStudio, enabling systematic assessment of annual publication output, citation trajectories, and country-level contributions. These metrics reveal how scientific activity has intensified and become more geographically distributed over time. The scientific mapping stage used author-provided keywords to construct co-occurrence networks that reflect the field's conceptual organization. To enhance consistency, synonymous terms and lexical variants were standardized using a controlled vocabulary developed collaboratively by the research team. Thematic maps were generated using centrality and density measures, allowing research clusters to be classified as motor, basic, emerging, or niche themes. Mathematical formulations for the equivalence index, centrality, and density were based on established bibliometric methodologies. The scientific mapping process was implemented using author keywords as the unit of analysis and co-word analysis as the relational technique. Prior to network construction, the keyword set was cleaned by normalizing spelling variants, singular and plural forms, and closely related expressions using a controlled vocabulary agreed upon by the research team. Only terms directly related to artificial intelligence, computer vision, and construction progress monitoring were retained for thematic interpretation. The thematic map was generated in Bibliometrix using Callon's centrality and density measures, which enabled classification of clusters as motor, basic, niche, or emerging themes. In parallel, the trend-topic analysis examined the temporal occurrence of keywords across the study period to identify shifts in conceptual emphasis and methodological development within the corpus. Finally, trend analysis examined temporal variations in keyword prominence, revealing shifts from early object recognition and as-built modeling toward deep learning–driven, three-dimensional, and operational monitoring workflows. This multi-layered analytical process supports a comprehensive interpretation of the maturation of AI and computer vision research for construction progress monitoring.

Evidence synthesis and analytical structure

The evidence synthesis was structured to directly reflect the three analytical dimensions defined by the research objectives. Performance analysis results describe growth patterns and the leading contributors shaping the field. Scientific mapping outcomes interpret the intellectual structure and thematic relationships among research fronts. Trend analysis findings highlight methodological transitions and emerging priorities in recent research. This organization ensures consistency between the analytical framework and the reported results, supporting transparent interpretation and replication. The methodological design emphasizes rigor, traceability, and reproducibility, providing a robust foundation for identifying future research opportunities in AI- and computer vision–based construction progress monitoring.

4 Results

4.1 Performance Analysis

The patterns of scientific production suggest both growth and concentration: from 2005 to 2026, the field has expanded rapidly as AI-driven monitoring capabilities have matured and diversified (**Error! Reference source not found.**).

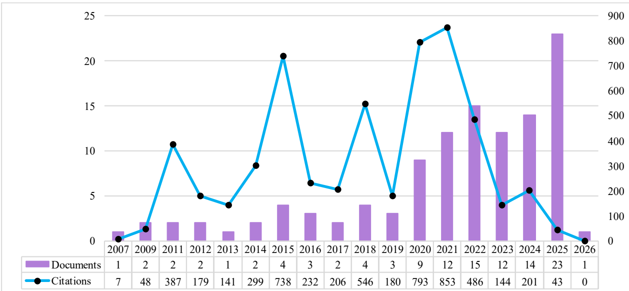

Figure 1. Scientific production by year.

The publication output indicates that the United States and China are the leading contributors in this area, with 61 and 43 publications, respectively, followed by the United Kingdom (19), Germany (14), Australia (13), and South Korea (13) (**Error! Reference source not found.**).

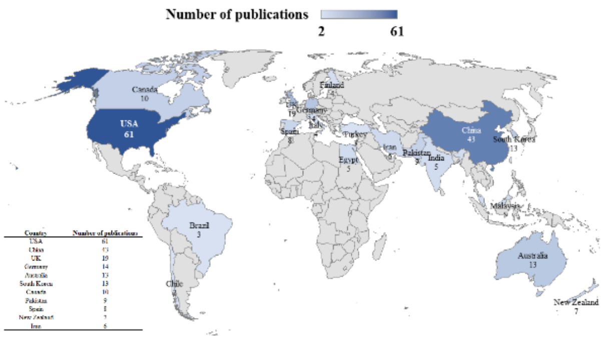

Figure 2. Scientific production by country.

Furthermore, the collaboration networks showed steady growth in international team interactions, indicating increased integration of global research in construction progress monitoring. The most frequently cited terms in the documents, such as 'machine learning' and 'deep learning,' were identified as the most influential in the field, highlighting the trend toward automating monitoring tasks with artificial intelligence. These results underscore the growing importance of AI and machine learning algorithms in improving the accuracy and efficiency of progress tracking on construction projects.

4.2 Science Mapping

The thematic map suggests that the intellectual structure of research on artificial intelligence and computer vision for construction progress monitoring is not dispersed across isolated topics but rather concentrated around four interrelated fronts. Their relevance and developmental intensity can be interpreted in terms of their positions with respect to centrality and density (**Error! Reference source not found.**). This configuration indicates that the field has evolved through a combination of conceptual consolidation and methodological specialization, with certain themes gaining prominence by shaping the broader research agenda, while others advance along more focused, internally cohesive trajectories. Notably, the right side of the map, associated with greater centrality, highlights themes that exert a stronger influence on the domain's overall organization. Within this area, two clusters emerge as the main anchors of the literature, suggesting that the field is shaped by dual logic: one oriented toward methodological development and the other focused on assessing application-driven progress. Rather than representing disconnected lines of inquiry, these clusters reveal how the domain is increasingly structured around the interaction between enabling analytical techniques and the practical demands of construction monitoring. The first cluster is computer vision, marked by high centrality and dense associations with machine learning, activity recognition, image processing, and real-time monitoring, as well as newer links to digital twins and segmentation models. This highlights computer vision as a transversal methodological backbone supporting diverse monitoring tasks rather than an isolated application.

The second cluster corresponds to construction progress monitoring, a basic theme with high relevance but moderate density. It represents the main application driving the domain, though still consolidating. Emphasis lies on deep learning and 3D representations, oftenconnected with point cloud, object detection, semantic segmentation, and image recognition. These terms reflect a shift toward automated, data-driven interpretations of site conditions, moving beyond visual documentation to structured progress assessments.

In contrast, the upper-left quadrant groups photogrammetry as a niche theme, linked to UAV, laser scanning, 3D reconstruction, reality capture, and automated measurement. Its high density but low centrality shows methodological maturity in acquisition and reconstruction, yet isolation suggests it is treated more as an enabling technology than a driver of semantic interpretation.

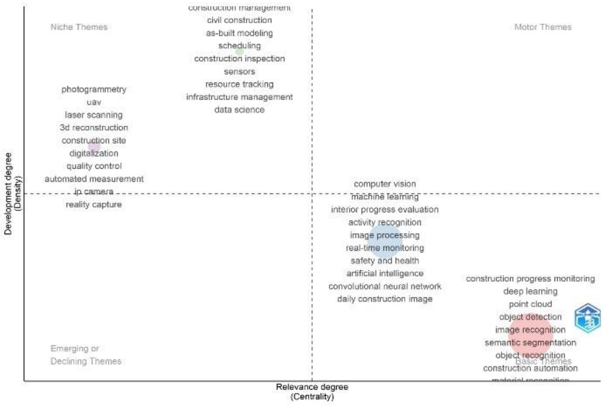

Figure 3. Thematic map analysis.

The node interaction map (Figure 4) further supports these identified patterns, illustrating how construction progress monitoring acts as a central hub, intricately connected to point cloud data and deep learning techniques. Meanwhile, computer vision functions as a comprehensive aggregator, linking various recognition and inference tasks. This central role of progress monitoring within the network highlights its vital part in the ongoing development of AI-enabled monitoring systems. BIM (Building Information Modeling), in this context, serves as a key integration layer that connects technical innovations with management-focused objectives, helping to translate real-time data into actionable insights for decision-making. The structure shown in the map indicates an ongoing shift toward integrated monitoring pipelines, where 3D data capture, deep learning–based inference, and BIM-enabled environments work together. This shift suggests moving from isolated, independent technologies to a more operational, traceable, and decision-oriented approach to progress monitoring in construction projects. The implication is clear: the future of construction progress monitoring is evolving into a unified, adaptive system that tracks progress while continuously adjusting to the project's changing needs in real time.

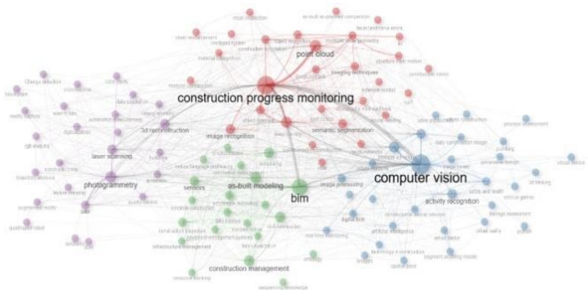

Figure 4. Node interaction map.

Beyond identifying thematic clusters, analyzing node interactions reveals a layered structure in AI-enabled progress-monitoring systems. At the core, technologies like photogrammetry and three-dimensional reconstruction are essential for creating increasingly precise and reliable geometric models of site conditions. These form the basis for higher-level analytical processes. Next, computer vision and deep learning conduct semantic inference, transforming raw visual data into recognizable construction components, activity states, and work progress assessments. This layer is crucial for converting large volumes of unstructured visual information into organized, usable data that supports progress evaluation. At the system-integration level, BIM functions as the backbone of a unified environment, connecting visual outputs with planning, scheduling, and control mechanisms. This link is vital to ensure that the insights produced by monitoring systems are not only accurate but also actionable within broader project management contexts. Connecting real-time data with decision-making tools in BIM creates a feedback loop that helps continuously assess and adjust project progress to meet overall goals. However, despite these advancements, the thematic structure also uncovers ongoing fragmentation in current research. Although the layers composing the monitoring pipeline are becoming more interconnected, they still tend to operate separately. While notable breakthroughs have been achieved in vision-based inference and geometric reconstruction, fewer studies have addressed interoperability and feedback mechanisms necessary to close the loop in progress monitoring systems. This fragmentation partly explains why many systems report high accuracy in controlled environments or pilot projects but face difficulties when scaled for real-world construction applications. The lack of a unified framework that integrates these components into operational systems may be a significant barrier to the widespread adoption of advanced monitoring solutions. Lastly, although individual parts of AI-driven construction progress monitoring have advanced markedly, further research into integrating these components into a seamless, closed-loop system remains vital. Moving beyond isolated technical innovations toward a fully operational, scalable system suitable for diverse construction environments presents the next challenge for research in this field.

4.3 Trend Analysis

The trend-topic analysis reveals a clear methodological and thematic transition in AI- and computer vision–based construction progress monitoring between 2009 and 2025 (**Error! Reference source not found.**). Early studies focused on as-built modeling and object recognition, emphasizing the alignment of site conditions with design intent through constrained recognition tasks. As the field evolved, topics such as laser scanning, daily construction images, image analysis, and imaging techniques became prominent, reflecting increased attention to reliable visual data acquisition and processing pipelines. From 2020 onward, the research focus shifted toward integrated progress assessment, with growing emphasis on BIM, 3D reconstruction, photogrammetry, and construction progress monitoring and evaluation. This evolution indicates a transition from isolated perception tasks to integrated monitoring workflows combining data capture, reconstruction, and interpretation. Recent trends further demonstrate the consolidation of contemporary AI paradigms.

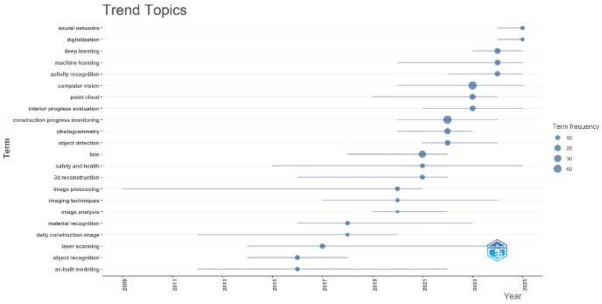

Figure 5. Trend analysis.

The increased frequency of computer vision and point cloud signals a maturation of 3D-driven monitoring. At the same time, the rise of deep learning, machine learning, and activity recognition reflects broader adoption of data-driven models capable of capturing complex spatial–temporal patterns in site environments. The emergence of digitalization and manual annotation near the end of the period suggests growing attention to dataset construction, labeling burden, and the governance of visual data at scale. Together, these trends depict a field moving beyond proof-of-concept to scalable, operational monitoring solutions that rely on robust 3D representations, learning-based inference, and tighter coupling with project information environments.

The trend analysis reveals not only technological advancements but also a progressive redefinition of construction progress monitoring. Early research approached progress assessment primarily as a visual correspondence problem, emphasizing object detection and the comparison between as-built conditions and design intent. As sensing and data acquisition technologies matured, the focus expanded toward automated spatial representation through photogrammetry and 3D reconstruction techniques, enabling more comprehensive and scalable monitoring workflows. More recently, the emergence of deep learning and activity recognition has shifted the field toward dynamic interpretations of construction progress, where monitoring is increasingly associated with evolving work states rather than static measures of completion. Despite these advances, the continued reliance on manual annotation and dataset preparation highlights a persistent challenge, as the rapid development of model architectures has not been matched by the availability of standardized and transferable training datasets, limiting model generalizability and large-scale implementation.

The corpus indicates that benchmark inconsistency is not merely a reporting issue, but a structural characteristic of the field. The analyzed studies address markedly different analytical targets, ranging from training image database development [6] and BIM-linked indoor progress monitoring [8] to semantic information extraction [19], ontology-based image enrichment [20], and RTLS-integrated monitoring workflows [21]. This heterogeneity is also reflected in the thematic structure, where deep learning, point cloud, object detection, semantic segmentation, and BIM-related terms coexist within the same research domain. Trend analysis reinforces this interpretation, as the recent visibility of manual annotation and digitalization suggests continued dependence on project-specific data curation, while the relatively late prominence of BIM indicates that many studies still evaluate perception modules in isolation rather than within comparable end-to-end monitoring workflows. Consequently, reported performance is often tied to different tasks, datasets, validation settings, and deployment contexts, thereby weakening cross-study comparability and limiting the accumulation of transferable evidence.

5 Conclusions

This study contributes to the understanding of AI and computer vision applications in construction progress monitoring by consolidating research across methodologies, data acquisition strategies, applications, and evaluation approaches. The thematic analysis identifies four main research directions: construction progress monitoring, computer vision, photogrammetry and 3D reconstruction, and BIM integration with project information systems. The review also shows a methodological transition from conventional feature-based approaches to deep learning models capable of addressing the spatial and temporal complexity of construction environments. These findings reflect the evolution of monitoring systems from isolated analytical tools into integrated frameworks that support construction management and decision making.

The study also highlights practical implications for implementing automated monitoring systems in real construction projects. Effective monitoring frameworks require the integration of capture technologies such as fixed cameras, mobile devices, and UAVs with analytical models adapted to different monitoring levels, including activities, elements, operational states, and temporal changes. The integration of AI outputs with planning processes and BIM environments can improve performance tracking, reduce subjectivity, and support earlier detection of project deviations. However, some limitations remain. Bibliometric and thematic reviews depend on metadata quality, keyword consistency, and search strategies, which may restrict the inclusion of relevant studies. The absence of standardized datasets, evaluation metrics, and benchmarking practices also limits comparability across studies. Future research should focus on standardized evaluation protocols, open datasets, domain adaptation methods, and multimodal AI frameworks integrated with BIM-based management systems to improve robustness and applicability in real construction environments.

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