



FUSING POINT CLOUD AND MULTI-SOURCE DATA IN THE CONSTRUCTION INDUSTRY: A REVIEW

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Introduction

With the rapid digital transformation of the construction industry, high-fidelity 3D point clouds have become indispensable for site modeling. However, raw point clouds are unstructured and lack rich semantics (e.g., color, material, context), limiting their standalone utility (Wang et al., 2024). Integrating heterogeneous data sources (e.g. BIM models, RGB imagery, thermal maps, and sensor readings) with point clouds can enrich semantic content and improve task performance. Prior reviews have examined point-cloud applications, but they remain fragmented or domain-specific, lacking an overarching framework (Wang and Kim, 2019). This paper thus employs a PRISMA- guided systematic review to synthesize the literature on point cloud–multi-source fusion (2019–2025). Through this process we construct a unified three-dimensional knowledge framework (foundational technologies, fusion strategies, applications) and identify trends, typologies and gaps in the field.

Methodology

We performed a comprehensive literature search (Web of Science, Scopus) using keywords spanning point cloud, BIM, imagery, thermography, etc. Following PRISMA guidelines, 1,499 records were initially retrieved. After de-duplication and multi-stage screening (titles/abstracts, then full text, using predefined inclusion/exclusion criteria), 181 peer-reviewed articles (2019–2025) were deemed relevant (Figure 1). The final corpus was analyzed via bibliometrics and qualitative synthesis. Bibliometric analysis included: (1) publication trend analysis (2019– 2025) to reveal research growth (Figure 2), (2) venue and citation analysis to highlight key outlets and influential works, and (3) science mapping via keyword co- occurrence (using VOSviewer) to uncover thematic structure (Figure 3). Based on keywords and content, we classified fusion types (point cloud–BIM, imagery, thermography, pose data, SHM.) and examined their algorithms and implementations. Finally, we synthesized a three-dimensional knowledge framework (Figure 4) linking foundational elements (sensors, algorithms, data), fusion types, and application domains.

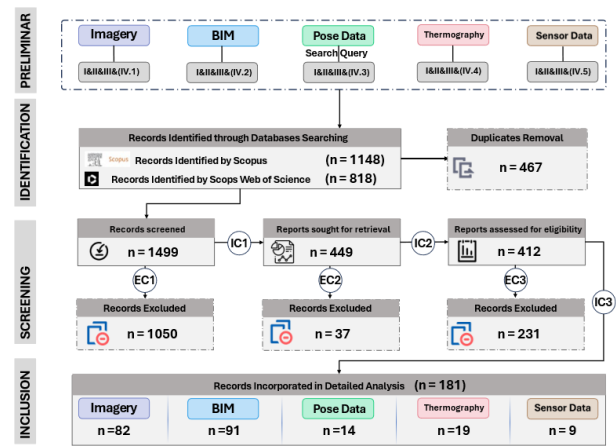


Figure 1: Systematic literature retrieval and screening process based on the PRISMA framework

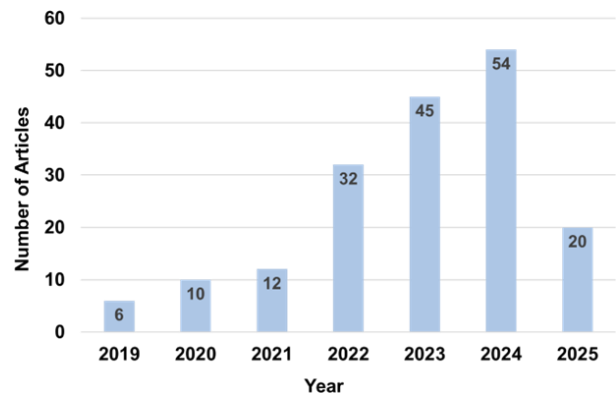


Figure 2: Annual distribution trend (2019-2025)

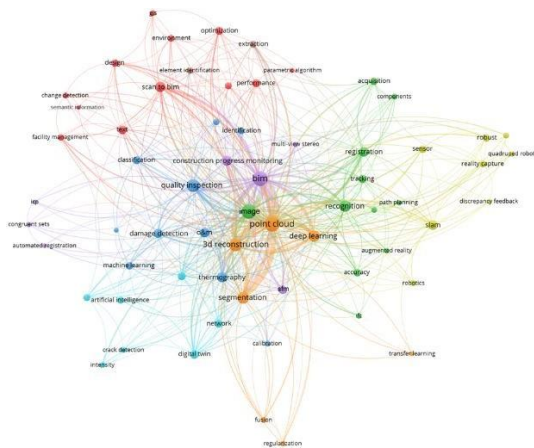


Figure 3: Keyword co-occurrence network analysis

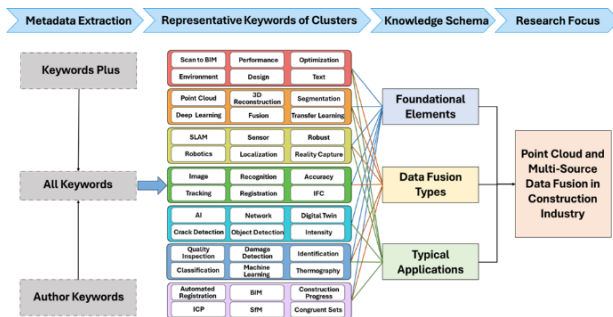


Figure 4: Three-dimensional knowledge framework

Results

The keyword co-occurrence network (Figure 3) identifies core terms – BIM, imagery, quality inspection, 3D reconstruction, deep learning, segmentation, etc. – which cluster into three dimensions: foundations (data, devices, algorithms), fusion types, and applications (Figure 4). Leveraging these insights, the comprehensive three-dimensional framework (Figure 5) was constructed to organize the field.

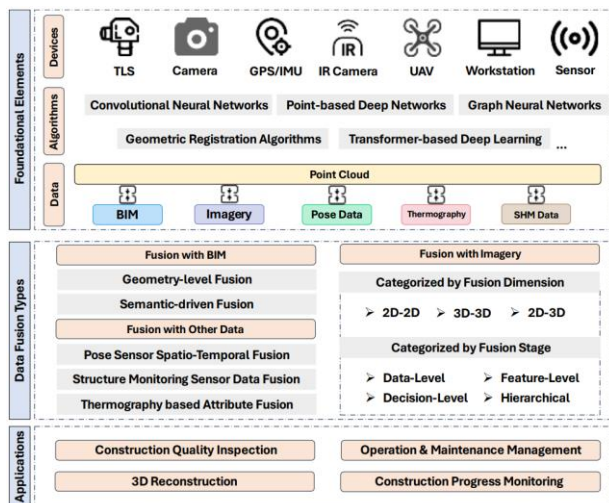


Figure 5: Comprehensive knowledge mapping framework

Among the various types of fusion, each integration pathway between point cloud and heterogeneous data exhibits distinct characteristics and technical strategies.

1. Point cloud–BIM fusion serves as a bridge between structured and unstructured 3D data. It is typically achieved through geometric registration—via planar constraints (Zong et al., 2019), feature descriptors (Wang et al., 2024), or deep learning-based alignment (Kim et al., 2020)—and semantic segmentation methods that leverage graph structures, rule-based grammars, or knowledge-graph reasoning (Yang and Hou, 2023).
2. Point cloud–imagery fusion combines 2D visual features with 3D geometric precision, enhancing object detection, scene interpretation, and texture reconstruction. To provide a systematic understanding, a dual-perspective taxonomy is adopted (Figure 6). From the fusion dimension, methods are categorized into 3D–3D (Chen et al., 2020), 2D–2D (Leahy et al., 2025), and 2D–3D (He et al., 2024) (Figure 7). From the fusion stage, approaches are further classified as data-level (Li et al., 2025), feature-level (Wang et al., 2024), decision-level (Liang and Xu, 2025), and multi-level fusion (Wan et al., 2025) (Figure 8).
3. Point cloud–thermography fusion enables thermal diagnostics by mapping surface temperature distributions onto spatial geometries, producing thermal-textured 3D models (De Pazzi et al., 2022).
4. Pose-data fusion aligns LiDAR data with GNSS/IMU streams for real-time mapping and motion compensation, often through tightly or loosely coupled SLAM architectures (Zhou et al., 2024).
5. Point cloud–SHM fusion integrates local sensor data with 3D spatial models to visualize and assess structural behavior. These fusions extend geometric modeling into performance-aware diagnostics (Luleci et al., 2024).

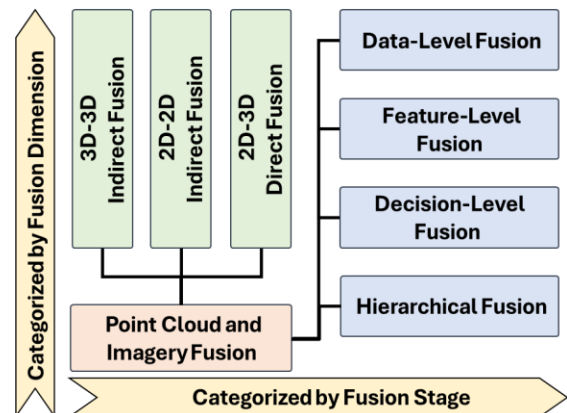


Figure 6: Dual-dimensional classification framework

Across all modalities, integration is typically supported by geometric algorithms such as ICP and RANSAC variants, as well as learning-based approaches including PointNet,

CNN backbones, GNNs, and Transformers. Implementation pipelines are supported by open-source platforms (e.g., Open3D, PCL) and commercial software (e.g., FARO Scene, Leica Cyclone), enabling robust and scalable multi-source fusion in construction settings.

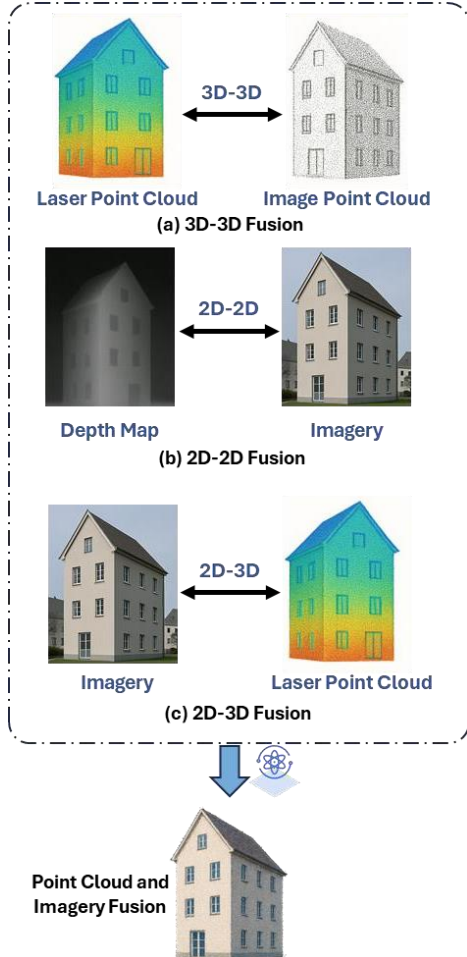


Figure 7: Schematic representation of point cloud-imagery fusion paradigms based on fusion dimensions: (a) 3D-3D fusion (b) 2D-2D fusion (c) 2D-3D fusion

The relationship between application demands and fusion types forms a multifaceted knowledge network linking core technologies to real-world deployment (Figure 9). Literature analysis highlights four primary application domains in the construction industry: quality inspection (Liang and Xu, 2025), progress monitoring (Zhang et al., 2024), 3D reconstruction (e.g., Scan-to-BIM) (Mahmoud et al., 2025), and operations and maintenance (O&M) management (Huang et al., 2024). Fusion technologies are driving a shift from experience-based practices to data-driven decision-making, improving accuracy in defect detection, timeliness in progress tracking, efficiency in reconstruction, and intelligence in lifecycle asset management. This transition reflects the growing role of multi-source integration in enabling smarter, more responsive construction workflows.

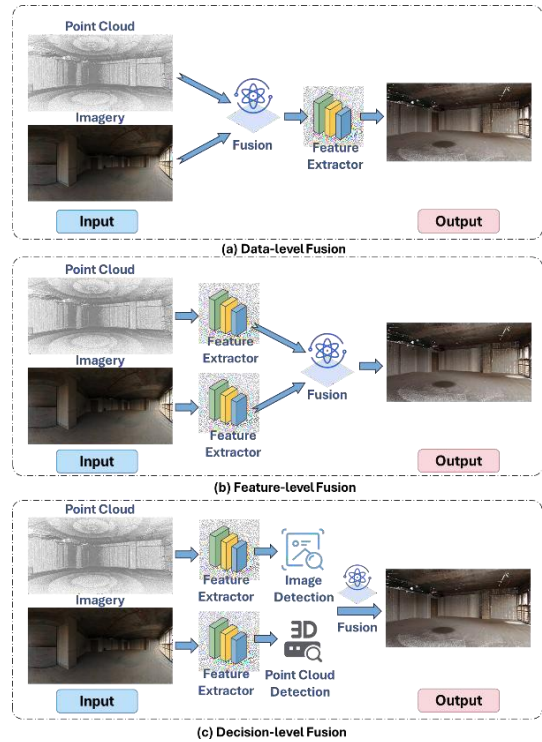


Figure 8: Categorization of point cloud-imagery fusion technologies based on processing stages: (a) data-level fusion (b) feature-level fusion (c) decision-level fusion

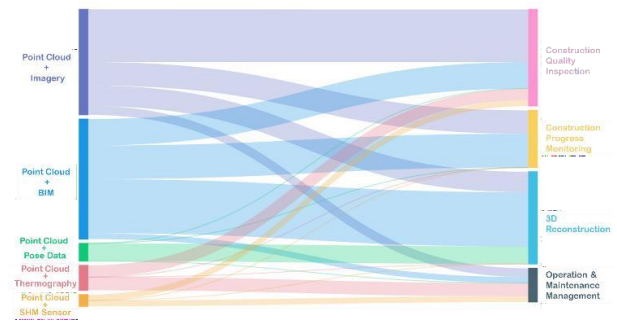


Figure 9: Association matrix between data fusion types and construction application scenarios

Conclusion

This review synthesizes recent advances in point cloud and multi-source data fusion in the construction industry and proposes a knowledge framework integrating theoretical foundations and technical pathways. The analysis reveals that BIM and visual data remain dominant fusion targets, with rapid progress in deep learning and multimodal perception. Key challenges—summarized in Figure 10—include accuracy, scalability, and interoperability. Future research should prioritize robust, scalable AI-driven fusion frameworks, open platforms, and standardized workflows to advance intelligent sensing and integrated computation in construction.

Range	Research Limitations	Future Directions
	<ul style="list-style-type: none"> ❑ Cross-modal Misalignment ❑ Semantic Uncertainty ❑ Calibration & Resolution Limits 	<ul style="list-style-type: none"> ➤ Multi-scale semantic matching ➤ Hierarchical registration ➤ Enhanced sensor calibration ➤ End-to-end integrated fusion
	<ul style="list-style-type: none"> ❑ Limited Real-time Capability ❑ High Data Complexity ❑ Inefficient Resource Allocation 	<ul style="list-style-type: none"> ➤ GPU-accelerated Algorithms ➤ Adaptive Compression ➤ Distributed Incremental Processing
	<ul style="list-style-type: none"> ❑ Insufficient Annotated Datasets ❑ Poor Cross-domain Generalization 	<ul style="list-style-type: none"> ➤ Synthetic Data Augmentation ➤ Multi-branch Neural Networks ➤ Semi-supervised / Unsupervised Learning
	<ul style="list-style-type: none"> ❑ Format Incompatibility ❑ Fragmented Software Tools ❑ Missing Common Semantics 	<ul style="list-style-type: none"> ➤ Unified Data Standards ➤ Standardized Multi-source APIs ➤ Expanded Fusion Scope ➤ Open-source Frameworks

Figure 10: Limitations and future development directions

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